The
HANDBOOK
of
TRADING

STRATEGIES FOR NAVIGATING AND PROFITING FROM CURRENCY, BOND, AND STOCK MARKETS

Edited by **Greg N. Gregoriou**
Co-editor of *The Handbook of Credit Portfolio Management*

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Greg N. Gregoriou

Editor

CONTENTS

CHAPTER 26 STRATEGIC FINANCIAL
INTERMEDIARIES WITH
BROKERAGE ACTIVITIES   389

Laurent Germain, Fabrice Rousseau, and Anne Vanhems

CHAPTER 27 FINANCIAL MARKETS, INVESTMENT
ANALYSIS, AND TRADING IN
PRIMARY AND SECONDARY
MARKETS   403

André F. Gygax

CHAPTER 28 TRADING AND OVERCONFIDENCE   417

Ryan Garvey and Fei Wu

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EXECUTION AND MOMENTUM TRADING

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PERFORMANCE LEAKAGE AND VALUE DISCOUNTS ON THE TORONTO STOCK EXCHANGE

Lawrence Kryzanowski and Skander Lazrak

ABSTRACT

Various measures of liquidity are estimated for common and preferred shares (individual firms and exchange-traded funds), units (trusts and limited partnerships), notes (index linked and principal protected), and warrants listed on the Toronto Stock Exchange. We document significant differences in potential and actual trade execution costs intra- and inter-security type and across time that impact on the net benefits of trading for different levels of trading patience, the valuation discounts of non-granular portfolios under various more or less patient exit strategies, and the likely performance drag from investments in different security types or the average security in that security type. We also provide an illustration of how trade execution costs are affected adversely by worries of a global recession.

INTRODUCTION

Since the performance of all investment decisions are directly affected by the quality of effecting such decisions in the marketplace and varies within and across security types, all investors must carefully balance the marginal benefits and costs of each transaction. Such costs include commissions, fees, execution, and opportunity costs. Execution quality reflects various trading demands for immediate liquidity (speed) based on different investment styles and on the availability and cost of such liquidity at each point in time. The latter includes the expected and actual impact of investor trade on market prices and on the cost and likelihood of concluding the remainder of a trade. Since execution quality is most often unobservable, it is imputed from the data either as the difference between the actual trade execution price and the price that would have existed in the absence of the trade or as the difference (referred to as performance leakage) between the quoted or actual trade price and its counterpart in the absence of trade costs (referred to as the "fair" price). The time to complete a trade for a fixed concession from the "fair" price is another dimension of execution quality, which can not be measured using most available databases (such as the one used herein) that do not provide information on order submissions and their subsequent fill history. Execution quality also affects the pricing of securities through its impact on value discounts.

Trade activity measures of liquidity include (un)signed number and dollar value of shares traded and the number of trades. Metrics for measuring expected or actual trade execution costs include quoted, effective and realized spreads, and quoted depths. Hasbrouck (2009) provides a good review of various measures of trade and market impact costs using daily data.

Earlier research focuses on the measurement of execution cost (e.g., Collins and Fabozzi, 1991), on the impact of execution costs on the speed and method by which institutional investors should implement buy and sell decisions (e.g., Bodurtha and Quinn, 1990; Wagner and Edwards, 1993; Wilcox, 1993), and on trading costs in different international markets (e.g., Kothare and Laux, 1995). More recent studies examine the effects of changes in exchange rules on execution costs across trading platforms (e.g., Venkataraman, 2001; SEC, 2001; Bessembinder, 2003; Boehmer, 2005) and on institutional differences (Eleswarapu and Venkataraman, 2006).

To our knowledge, few published studies examine the trade execution cost performance of security types other than stocks, bonds, and highly liquid

derivatives. This study is the first to examine trade execution costs for all the security types on the Toronto Stock Exchange (TSX). We expect to find significant differences in execution costs for a dichotomization of trades by security type.

The remainder of this chapter is organized as follows. The second section of this chapter discusses the sample and data. This chapter's third section presents the measures of market quality. The fourth section presents the empirical estimates of market quality; and the fifth section concludes the chapter.

SAMPLE AND DATA

Our initial sample contains all 2,300 listed securities on the TSX for the first two calendar months of 2008; namely, 1,300 common shares, 15 shares listed in USD, 256 preferred shares, 396 units including income trusts units, 149 debentures,[1] 119 warrants, and 65 NT_NO notes including asset-linked, principal protected notes sponsored by the Royal Bank.[2] As is common practice in the literature and reporting in the financial press (e.g., *Globe and Mail*) and following the definition of the SEC regarding penny shares available at http://www.sec.gov/answers/penny.htm, the common share sample is split in two based on those trading at or above $5 per share (Common >$5) and those trading at less that $5 per share (Common <$5) based on the time-series mean price of each common share.

Trading data are extracted from the TSX's Trades and Quotes (TAQ) database. As in Chordia, Roll, and Subrahmanyam (2001), the data are cleaned by removing: (i) quotes/trades outside regular trading hours of 9:30 to 16:00 EST; (ii) trades with negative numbers of shares or trading prices; (iii) trades with delayed delivery, special settlement and/or delivery, or subject to special restrictions and conditions; (iv) bids exceeding offers or either with nil prices or volumes; and (v) quoted percentage spreads exceeding 30 percent.[3] These filters delete 2.74 percent and 5.41 percent of the initial 202,710,358 quotes and 27,276,955 trades, respectively.

MEASURES OF PERFORMANCE LEAKAGE AND VALUE DISCOUNTS

Our first measure is the quoted spread, $QS_{i,t}$, for security i at time t or $QS_{i,t} = (Ask_{i,t} - Bid_{i,t})/[0.5(Ask_{i,t} + Bid_{i,t})]$, where the denominator is the midspread. Our second measure is superior to the first for a patient investor

given that limit orders can improve on the posted quotes of registered trad-
ers on the TSX. Thus, the effective spread, $ES_{i,tk}$, is given by $ES_{i,t} = 2 \times$
$[(Price_{i,t} - MidSpread\ Pre_{i,t})/MidSpread\ Pre_{i,t}] \times I_{i,t}$ where $I_{i,t}$ is a trade indi-
cator variable equal to $+1$ for buyer initiated (purchase) trades and -1 for
seller initiated (sale) trades. Since benchmark quotes need to be observed
when the trade decision is made and these times are not observable and
quotes may move after submitting even small orders, a five-second lag is
used to determine the pretrade benchmark midspread as recommended by
Bessembinder (2003).

Since the identity of the trade initiator is unobservable empirically, the
Lee and Ready (1991) algorithm is used to sign the transactions. The trade
is assumed to be buyer- (seller-) initiated when the traded price is higher
(lower) than the prevailing midquote or if the last nonzero price change
(tick) is positive (negative) for trade prices at the prevailing midquote (tick
rule). Contemporaneous quotes (i.e., quotes for a zero-second lag) are used
to compute benchmark midquotes for trade signing purposes (Ellis,
Michaely, and O'Hara, 2000; Bessembinder, 2003).

Effective spreads are compensation for both the probability of adverse
information and order execution. The former represents the loss incurred
by market makers to better informed traders as prices move against the
market makers. The realized spread is not only a better measure of com-
pensation for trade execution but a better indicator of market liquidity and
trading quality from the market-maker's perspective. To estimate the real-
ized spread and thus eliminate the loss to better informed traders, the trad-
ing price is compared with a benchmark or a midquote that occurs
sometime after the trading takes place. This measures the market-maker's
profit if she or he rebalances inventory after making the initial trade. As in
Huang and Stoll (1996) and Bessembinder (2003), benchmark quotes for
both $k = 5$ and 30 minutes after trades (i.e., $MidSpreadPost_{i,t,k}$) are used
herein. Daily closing quotes are used for trades occurring within the last
$k = 5$ or 30 minutes of a trading session. The realized spread, $RS_{i,t,k}$, is
given by: $RS_{i,t,k} = 2 \times [(Price_{i,t} - MidSpreadPost_{i,t,k})/MidSpread\ Pre_{i,t}] \times I_{i,t}$.
Thus, the price impact of a trade, $PI_{i,t,k}$, is given by the difference between
the effective spread and the realized spread, $ES_{i,t} - RS_{i,t,k}$, or $PI_{i,t,k} = 2 \times$
$[(MidSpreadPost_{i,t,k} - MidSpreadPost_{i,t,k})/MidSpread\ Pre_{i,t}] \times I_{i,t}$.

Since the effective/realized spreads or price impact can be negative
due to the measurement of the trade sign variable at a different time

compared with the prevailing or subsequent quote, we also use an alternative for these spread measures that relies on their absolute values. For instance, the alternative measure of the effective spread, $AES_{i,t}$, is: $AES_{i,t} = 2 \times |(Price_{i,t} - MidSpread\ Pre_{i,t})/MidSpread\ Pre_{i,t}|$.

The quoted dollar depth, which is the capacity of a market to absorb trades with little or no price impact, also is measured to assess liquidity and market execution quality. As quotes represent prices at which market makers are willing to trade at a prespecified maximum trading size, we assume that this size is the highest possible volume before an order eats up the available liquidity at the inside quotes and quotes need to be moved up or down depending on trade direction. We measure depth $QD_{i,t,}$ as the average quoted order flow size at both the inside bid and ask or $QD_{i,t,} = 0.5\ (Bid_{i,t} \times BidSize_{i,t} + Ask_{i,t} \times AskSize_{i,t})$.

EMPIRICAL ESTIMATES FOR THE TSX

The relative quoted and effective spreads for all the securities listed on the TSX and seven subsamples differentiated by security type (and price in the case of common shares) are reported in Table 1.1. As expected, the lowest median spreads are for common shares with prices above $5 (Common >$5), followed by the asset-linked notes (NT_NO) for relative quoted spreads (QS) and preferred shares for the two measures of relative and average effective spreads (ES and AES). The highest median spreads are for Warrants. To illustrate, the median effective spreads are 0.31 percent and 6.88 percent for Common with prices above $5 and Warrants, respectively.

NT_NO and Common >$5 are among the two lowest mean spreads with Common >$5 only occupying the lowest mean spread for the ES measure. Warrants have the highest mean spreads for each of the three measures. The relatively high trading costs associated with Warrants is primarily due to the relatively low traded prices of Warrants (mean of $1.79 compared with $13.24 for all other securities). Securities denominated in USD have the second highest mean and median spreads for all three measures. To illustrate, the median USD effective spread is 4.19 percent.

As expected, considerable variation exists in the spread measures within each security type. The NT_NO followed by Common >$5 have the lowest

Table 1.1 Quoted and Effective Spreads for Canadian Securities

Table 1.1 provides summary statistics for relative (%) quoted spreads or QS and effective spreads or ES (as defined in the text where the prefix A when added to ES refers to alternate measure) for TSX listed securities during the first two months of 2008. The final data set consists of 197,159,687 quotes and 25,800,483 trades.

Statistic	Sample	QS (%)	ES (%)	AES (%)	Sample	QS (%)	ES (%)	AES (%)
Min		0.03	−17.14	0.03		1.53	1.11	1.32
Median		2.14	1.03	1.65		5.92	4.19	5.09
Mean	All	3.87	2.25	3.30	USD	8.53	6.24	7.02
Max		28.57	34.39	36.89		22.08	19.83	20.90
SD		4.55	3.69	4.46		6.89	6.27	6.23
Min		1.89	−17.14	1.22		0.09	−0.55	0.09
Median		12.91	6.88	11.75		1.07	0.92	1.03
Mean	Warrant	13.09	8.59	12.30	NT_NO	1.69	0.93	1.21
Max		28.57	30.23	36.89		5.85	3.56	3.58
SD		5.94	7.21	7.31		1.43	0.76	0.73
Min		0.22	−1.91	0.20		0.03	−1.98	0.03
Median		1.15	0.59	0.97		0.97	0.31	0.62
Mean	Preferred	1.88	1.05	1.52	Common >$5	1.82	0.84	1.34
Max		22.93	22.49	22.49		16.45	10.43	11.87
SD		2.68	2.23	2.41		2.09	1.22	1.61
Min		0.09	−0.49	0.04		0.39	−6.71	0.36
Median	Unit	1.76	0.88	1.33	Common <$5	4.67	2.31	3.89
Mean		2.49	1.32	1.94		5.86	3.53	5.15
Max		18.76	10.23	16.68		28.57	34.39	36.08
SD		2.49	1.48	2.04		4.72	4.16	4.74

variation (e.g., effective spread sigmas of 0.76 percent and 1.22 percent, respectively). Warrants and USD have the highest variations for all three spread measures with USD in the top spot only for QS (6.89 percent). As expected, the spread distributions are right-skewed so that the medians are always lower than their mean counterparts. While a small percentage of the effective spreads using the signing algorithm are negative, as expected due to signing error, this is not the case when the alternate measure of the effective spread AES is calculated.

A comparison of the mean, median, and sigma values for common shares trading below and above $5 exemplifies the much higher trade costs associated with so-called "penny" stocks (e.g., median ES of 2.31 percent versus 0.31 percent and sigma of 4.16 percent versus 1.22 percent, respectively). This may have implications for small cap investing in national markets smaller than in the United States.

The relative realized spreads for the various samples are reported in Table 1.2. With four exceptions (RS5 and RS30 for both USD and

Table 1.2 Realized Spreads

Table 1.2 provides summary statistics for (%) realized spreads or RS (as defined in the text where the prefax A refers to alternate measure and the suffix 5 and 30 refer to quotes 5 and 30 minutes, respectively, after trades) for TSX listed securities during the first two months of 2008.

Statistic	Sample	RS5 (%)	ARS5 (%)	RS30 (%)	ARS30 (%)	Sample	RS5 (%)	ARS5 (%)	RS30 (%)	ARS30 (%)
Min		−28.57	0.00	−48.89	0.00		−8.63	1.29	−10.23	1.39
Median		1.20	1.84	1.16	2.11		1.23	6.06	2.79	4.92
Mean	All	2.28	3.70	2.18	3.97	USD	0.60	8.18	1.64	6.05
Max		39.33	65.37	45.06	117.81		8.22	20.34	5.10	15.73
SD		3.65	5.49	3.88	6.04		5.24	6.69	4.31	4.16
Min		−28.57	1.81	−33.58	2.26		−1.05	0.00	−1.03	0.00
Median	Warrant	6.03	12.28	5.52	13.00	NT_NO	0.83	1.25	0.96	1.21
Mean		7.13	14.91	6.97	16.01		0.75	1.74	0.86	1.66
Max		34.09	54.58	45.05	117.81		2.59	5.57	2.58	5.60
SD		8.42	10.66	9.41	14.69		0.82	1.45	0.75	1.34
Min		−2.00	0.19	−2.00	0.20		−2.72	0.03	−3.97	0.03
Median		0.72	1.03	0.71	1.05		0.43	0.90	0.41	1.37
Mean	Preferred	1.19	1.56	1.17	1.61	Common >$5	1.00	1.59	0.94	1.90
Max		21.43	21.43	21.43	21.43		10.58	10.98	10.58	11.44
SD		1.98	2.28	1.98	2.35		1.37	1.64	1.30	1.55
Min		0.03	0.04	−0.60	0.05		−19.05	0.37	−48.89	0.36
Median		1.08	1.43	1.02	1.53		2.78	4.02	2.67	4.37
Mean	Units	1.59	2.16	1.51	2.28	Common <$5	3.62	5.55	3.41	5.86
Max		9.68	18.85	10.75	18.86		39.33	65.37	43.71	70.05
SD		1.66	2.34	1.61	2.29		4.07	5.87	4.48	5.84

NT_NO), the means are greater than their median counterparts, which indicates right-skewed distributions. The median relative realized spreads are lowest for Common >$5 followed by Preferreds for all but the ARS30 (Alternative Realized Spread based on quotes 30 minutes after trades) measure where the lowest median is for Preferreds followed by NT_NO. To illustrate, the median RS5 and RS30 values are 0.43 percent and 0.41 percent, respectively, for Common >$5. The highest median relative realized spreads are for Warrants. This is followed by Common <$5 for RS5 and by USD for the other three relative realized spread measures.

The lowest mean RS5 and RS30 are for USD and NT_NO, respectively, followed by respectively NT_NO and Common >$5. In contrast, the lowest mean ARS5 and ARS30 are for Preferreds followed by Common >$5 and NT_NO, respectively. Warrants always have the highest mean relative realized spreads followed by Common <$5 for RS5 and RS30 and by USD for ARS5 and ARS30, respectively. Thus, the choice of how to calculate the relative realized spread has an impact on the rankings of this measure across security types.

The lowest sigmas are found for NT_NO for all four relative realized spread measures, followed by units for RS5 and Common >$5 for the other three measures. Once again, Warrants have the highest relative realized spreads followed by USD for the two 5-minute measures and Common <$5 for the two 30-minute measures. To illustrate, the sigmas for RS5 and RS30 for Warrants are 8.42 percent and 9.41 percent, respectively.

The quoted depth-traded volumes (share numbers and dollars) and the number of trades for the various samples are reported in Table 1.3. All the distributions are right-skewed. The lowest mean, median, and sigma of quoted depth (QD), share volume (Shares vol) and number of trades are for Warrants, NT_NO, and NT_NO, respectively. With two exceptions, the highest mean, median, and sigma of these three measures are for Common >$5. The exceptions are NT_NO for the median QD and Common <$5 for the median Shares vol.

The high depth for the index linked notes shows that dealers have minimal concerns about trading against informed traders as private information is negligible about the entire index compared with individual securities. The high median of penny stock trading volume measured in number of shares is due to the larger round lot sizes of stocks trading below $1 and the need to trade more shares of a lower priced share to achieve a comparable dollar

Table 1.3 Quoted Depth and Trading Activity

Table 1.3 provides summary statistics for quoted depth (QD ($)), share volume (Shares vol), and dollar traded volume ($ Vol) in thousands, and number of trades (Nb_trades) for TSX-listed securities during the first two months of 2008.

Statistic	Sample	QD ($)	Shares vol	$ Vol	Nb_trades	Sample	QD ($)	Shares vol	$ Vol	Nb_trades
Min		0.023	0.100	0.390	1.000		3.115	0.465	2.890	1.500
Median		9.761	25.550	93.318	12.929		12.066	3.321	31.706	5.033
Mean	All	23.442	195.475	3,356.594	297.921	USD	15.324	36.295	96.264	5.675
Max		1,415.986	11,170.279	259,932.309	18,540.071		36.073	363.262	597.645	15.929
SD		73.373	663.623	17,206.560	1,222.051		9.441	108.491	174.238	3.831
Min		0.062	0.667	0.495	1.000		8.727	0.830	7.924	1.000
Median	Warrant	1.138	24.578	14.767	5.099	NT_NO	26.003	2.750	29.576	1.857
Mean		4.445	75.745	70.674	11.646		32.595	4.066	44.990	2.357
Max		31.628	2,127.875	784.184	142.750		162.306	20.800	241.305	9.000
SD		6.912	211.431	147.433	19.117		27.205	3.971	45.936	1.604
Min		0.045	0.100	0.425	1.000		1.393	0.180	1.239	1.000
Median		15.395	4.042	76.289	6.225	Common >$5	14.472	49.815	523.919	61.664
Mean	Preferred	18.977	6.924	135.580	9.343		50.722	358.856	9,990.020	809.795
Max		107.109	85.414	2,154.335	57.333		1,415.986	8,686.755	259,932.309	18,540.071
SD		12.090	9.514	204.020	8.798		118.336	893.362	30,241.782	2,111.872
Min		0.358	0.425	2.079	1.125		0.023	0.350	0.390	1.000
Median		11.070	14.754	123.071	15.190		3.595	59.620	51.275	14.110
Mean	Unit	16.178	79.108	1,300.092	153.898	Common <$5	6.384	216.275	327.037	79.110
Max		1,261.424	2,074.231	52,655.592	3,884.548		148.640	11,170.279	2,2652.803	1,965.429
SD		63.361	185.596	4,357.675	429.569		13.721	750.003	1,240.112	204.073

volume as for non-penny shares.[4] Despite their high depths and low trading costs compared with other security types, the notes offered by the Royal Bank are not heavily traded as the exchange-traded funds are more popular instruments. Units are the second most actively traded security type on the TSX. The income trust vehicle, which passes through its income untaxed, was a popular investment choice due to yields considerably higher than those on fixed income securities (Kryzanowski and Lu, 2009).

All of the nonparametric (distribution-free) Kruskal-Wallis tests of the equality of the medians as well as the ANOVA tests of equality of means across the seven security types for each of the 11 liquidity measures are significant at better than the 0.001 level. Based on tests of the means and medians for all pairs of security types for each of the 11 liquidity measures, as summarized in Table 1.4 (further details available from the authors), we find the following to be significant at better than the 0.05 level: (i) all pairings of Common <$5 with Common >$5 and with Preferreds; (ii) all but one of the pairings of Common <$5 or Common >$5 with Units (i.e., median Nb_trades for Common <$5) and with Warrants (i.e., mean QD for Common <$5); and (iii) all but one of the pairings of Warrants with Preferreds (i.e., mean and median Nb_trades), with Units (mean Share vol) and with NT_NO (mean $ Vol).

Although comparisons across markets (and especially for different time periods) are only indicative due to interexchange differences in design features (e.g., tick and board lot sizes, order handling rules, and regulatory rules and their enforcement), Warrants on the TSX have higher mean relative quoted spreads (13.086 percent versus 7.308 percent) and lower quoted dollar depths (4,445 CAD versus 171,990 HKD) based on the values reported for company warrants by Brockman and Chung (2007) for Hong Kong for the period of May 1996 to August 1997. As expected, the relative quoted and effective spreads for TSX Common >$5 are inferior to the cross-sectional statistics for time-series means reported by Roll (2005) for NYSE-listed securities. The mean, median, and sigma for the TSX (NYSE) are 1.82 percent (1.60 percent), 0.97 percent (1.15 percent), and 2.09 percent (1.36 percent) for relative quoted spreads, and are 1.82 percent (1.11 percent), 0.84 percent (0.77 percent) and 1.34 percent (1.32 percent) for the alternative relative effective spreads. Not surprisingly, the mean relative quoted and effective spreads of 1.82 percent and 1.34 percent are considerably higher than their respective counterparts of 0.54 percent and 0.50 percent for the TSX and

Table 1.4 Tests of Pairwise Means and Medians for the Various Liquidity Measures

Table 1.4 reports the liquidity measures with p values > 0.05 for tests of pairwise means and medians, which are reported in the lower and upper diagonals, respectively. Thus, they are not reported (such as between Common $>$\$5 and Common $<$\$5) if they are significant at the 0.05 level. They are underlined if the pairwise differences are significant at the 0.10 level.

	Warrant	Preferred	Unit	USD	NT_TO	Common <$5	Common >$5
Warrant		Nb_trades		$ Vol, Nb_trades, ES			
Preferred	Nb_trades			QD, Shares vol, Nb_trades, RS5	QS, ES, AES, (A)RS5 & 30		QD
Unit	Shares vol	QD, ES		QD, RS5, RS30	QS, ES, AES, ARS5, (A)RS30	Nb_trades	
USD	Shares & $ Vol, Nb_trades, ES, RS30	QD, $ Vol, Nb_trades, RS5 & 30	QD, Shares & $ Vol, Nb_trades, RS5, RS30		Shares & $ Vol, RS5	QS, $ Vol, AES, (A)RS5 & 30	QD, RS5
NT_NO	$ Vol	QS, Shares vol, (A)ES, (A)RS5, (A)RS30	QD, $ Vol, ES, ARS5, ARS30	$ Vol, RS5&30			QS, (A)RS5 & 30
Common <$5	QD			QS, Shares & $ Vol, Nb_trades, AES, ARS5, (A)RS30	Shares & $ Vol		
Common >$5		QS, ES, AES, (A)RS5, RS30		QD, Shares & $ Vol, Nb_trades, RS5 & 30	QS, QD, (A)ES, (A)RS5 & 30		

13

considerably lower than their respective counterparts of 2.32 percent and 2.13 percent for the average exchange, which are reported by Jain (2003) based on closing daily values for the 25 highest market capitalization stocks for each of 51 major exchanges for the first four months of 2000.

Time-series plots of six of the liquidity measures for the various samples are depicted in Figures 1.1 to 1.6. We examine the intertemporal variation in these series using the standard deviation (sigma) and coefficient of variation (i.e., the sigma divided by the mean).

Based on untabulated results, the three security types with the highest spread sigmas are Warrants followed by USD and NT_NO for QS and an interchange of Warrants and NT_NO for ES and RS30. The three security types with the highest spread Coefficients of Variation (CVs) are NT_NO followed by USD and Preferreds for QS, and USD followed by NT_NO

Figure 1.1 Time-Series of Median Relative Quoted Spreads (%)

Date—Daily first 2 months 2008
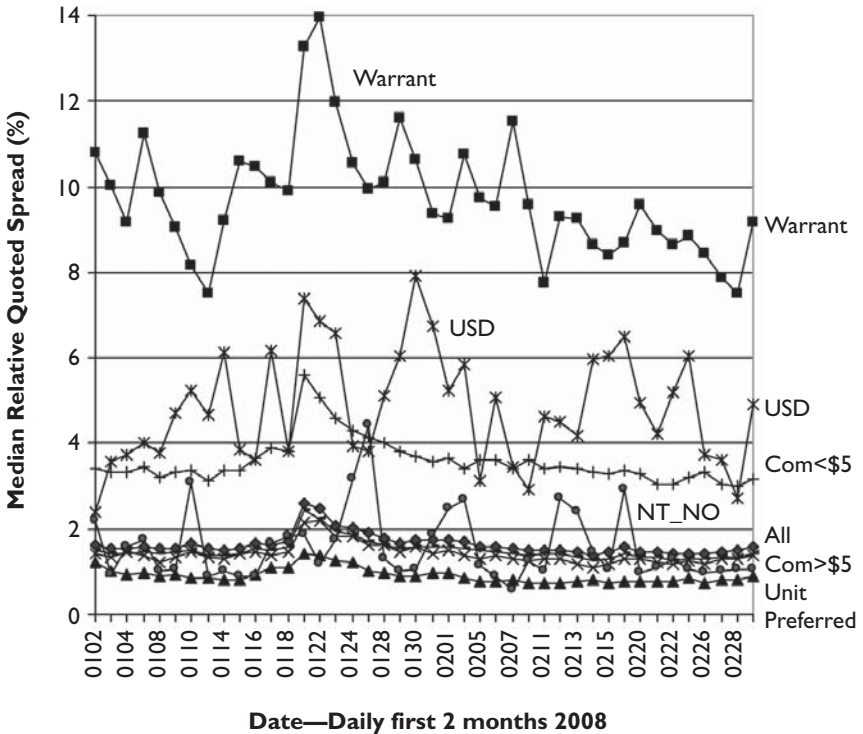
Figure 1.2 Time-Series of Median Quoted Depths (in thousands of $)
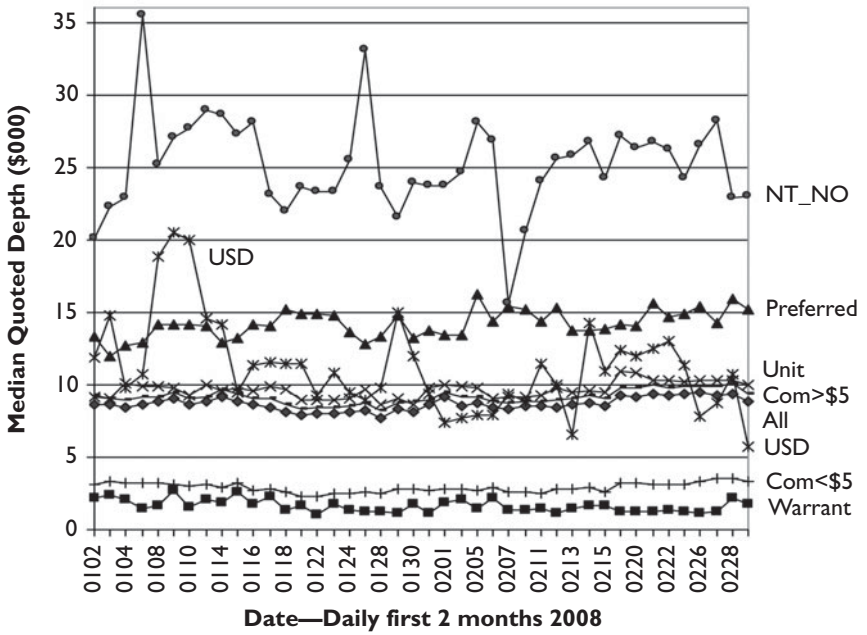
Figure 1.3 Time-Series of Relative Effective Spreads (%)
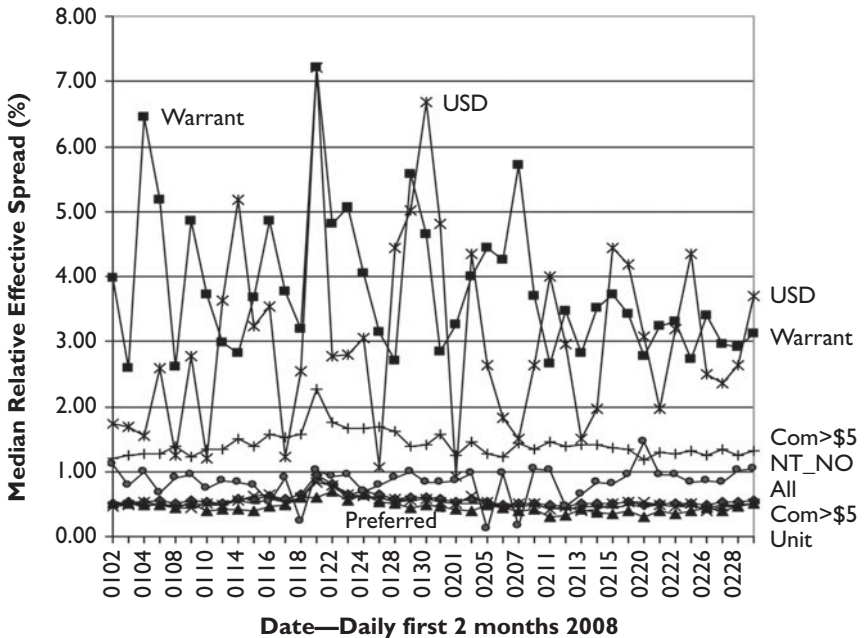
Figure 1.4 Time-Series of Relative 30-Minute Post-Realized Spreads (%)

Date—Daily first 2 months 2008
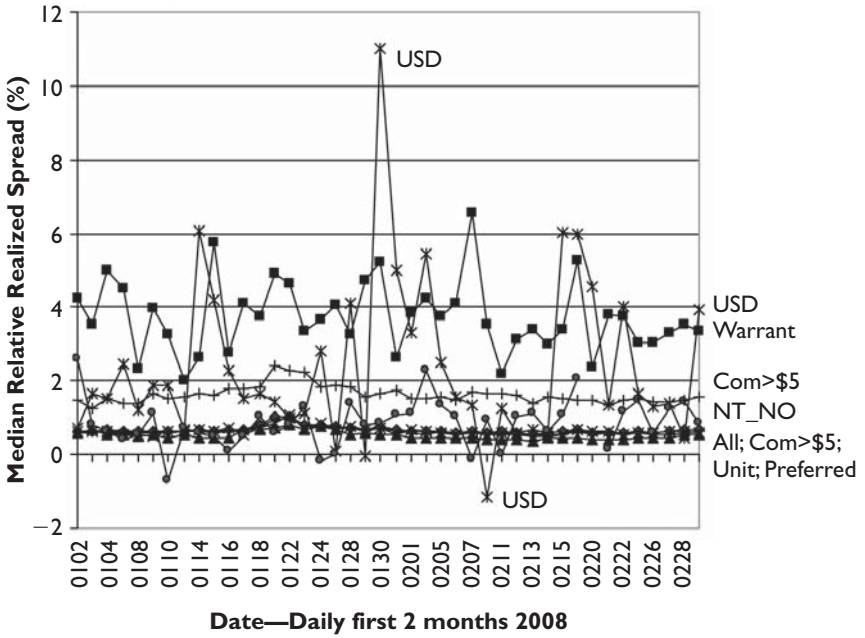
Figure 1.5 Time-Series of Dollar Volume (in thousands of $)

Date—Daily first 2 months 2008
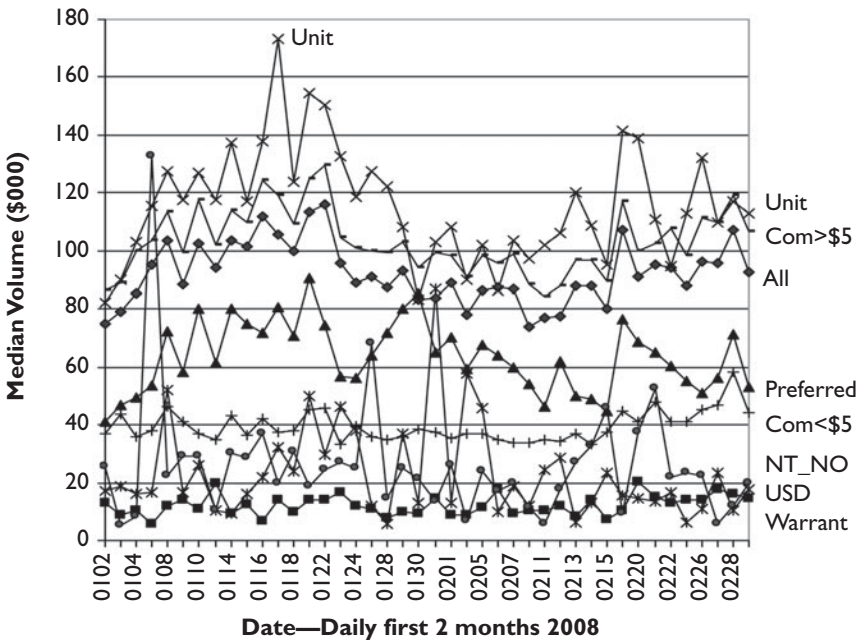
Figure 1.6 Time-Series of Number of Trades

Date—Daily first 2 months 2008
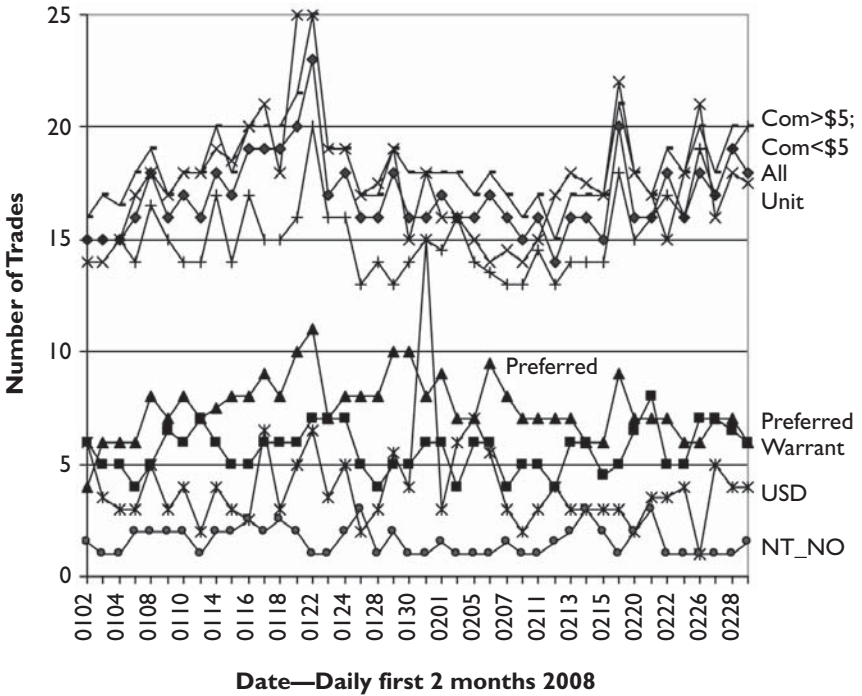
and Warrants for ES and RS30. The security types with the largest QD ($) sigmas are NT_NO followed by USD and Preferreds, and with the largest QD ($), CVs are USD followed by Warrants and NT_NO. The security types with the largest $ Vol sigmas are NT_NO followed by Units and USD, and with the largest $ Vol CVs are NT_NO followed by USD and Warrants. The security types with the largest Nb_trade sigmas are Units followed by USD and Common <$5, and with the largest Nb_trade CVs are USD followed by NT_NO and Preferreds.

Thus, Common >$5 never appear and Common <$5 only appears once in the top three ranks for intertemporal variation for all six depicted liquidity measures. Units appear in the top three ranks for intertermporal variation for only the two trade-activity measures of liquidity. While NT_NO has relatively low spreads and high quoted depths compared with the other security types, it has relatively lower trade-activity measures of liquidity and relatively higher intertemporal variation for all six liquidity measures.

The behavior of the six liquidity measures in Figures 1.1 to 1.6 around Monday, January 21, 2008 is interesting. Just prior to and on this date, world equity markets were affected adversely due to worries of a global recession. There was an upward spike in relative spreads (quoted and effective and especially for Warrants), and an upward spike in dollar traded volume.

CONCLUSION

This chapter makes four major contributions to the literature and practice. First, this study provides estimates of various measures of trade execution quality that investors must seriously consider when deciding to effect investment decisions, and documents significant differences in potential and actual trade execution costs as measured by various market quality measures intra- and inter-security type and across time (intertemporally). This information should be of considerable interest to investors (especially technical traders) who must carefully balance the marginal benefits and costs of each transaction. Second, this study provides estimates of the magnitudes of the discounts required when valuing various security types under a hold scenario and under less and more patient liquidation scenarios. This information should be of considerable interest to asset valuators and to investors when assessing the value of mutual funds with concentrated or nongranular portfolios under various exit strategies for specific security holdings. Third, this study provides estimates of the discounts required when assessing reported portfolio performance. This performance-drag information should be of considerable interest to investors in all funds that actively trade, and particularly in those funds with aggressive and nongranular holdings and limited liquidity provisions under down-market scenarios. Fourth, this study documents how trade execution costs vary on a daily basis and how they are affected adversely by worries of a global recession (i.e., prior to and on Monday, January 21, 2008).

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NOTES

1. This security type is not examined subsequently because no trading activity for debentures (ticker suffix DB) is found in the TAQ database.

2. Using the TSX eReview, only one security is identified as having a ticker symbol change. On January 21, 2008, the ticker of Nord Resources Corporation changed from NRD.U to NRD. Similarly, only two securities (Absolute Software Corporation and Corus Entertainment Inc B class) had subdivisions during the studied period.

3. Quotes with extremely high spreads are usually passive in the sense that either the bid or the offer (or both) are posted away from competitive prices.

4. On the TSX, board lot sizes are 100, 500, and 1,000 units for trading prices per unit of $1 or more, $0.10 to $0.99, and less than $0.10, respectively.

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INFORMED TRADING IN PARALLEL AUCTION AND DEALER MARKETS
The Case of the London Stock Exchange

Pankaj K. Jain, Christine Jiang, Thomas H. McInish, and Nareerat Taechapiroontong

ABSTRACT

In this chapter, we examine trading on the London Stock Exchange where the same stocks trade side-by-side on the computer-based Stock Exchange Electronic Trading Service (SETS) and the dealer market (DM). SETS has more trades overall, but the DM has larger trades and dominates the execution of very large-sized trades. The permanent price impact of trades is much larger on SETS than on the DM. However, the temporary price impact of trades is significantly larger on the DM than on SETS. The two effects together indicate that informed trades are likely routed to SETS for immediate execution, whereas informed trades are screened or trade prices are appropriately negotiated ex-ante to reflect information in the DM.

INTRODUCTION

We study trading on the London Stock Exchange (LSE) where, unlike most other exchanges, the same stocks trade on the computer-based Stock Exchange Electronic Trading Service (SETS) and the dealer market (DM).

SETS is the fully computerized automated trading system where liquidity is provided by traders who submit limit orders. The purpose of our chapter is to analyze informed order flows and price impact of trades in this parallel market structure.

At the time of our study, dealers had no affirmative obligation to offer quotes. Yet, the DM accounts for a significant share of trading volume. Dealers can also provide liquidity on SETS. There is no requirement for formal interaction between SETS and the DM. Yet SETS and DM are very closely integrated and may often have the same dealer serving as counterparty. Nevertheless, there are several important distinctions between the two systems in terms of anonymity and direct agency crosses. The hybrid structure of the LSE has not yet been examined in the context of informed trading, although other studies analyze the interaction of order flow between the two markets (see Friederich and Payne, 2007) and the dynamics of the market open and close (see Ellul, Shin, and Tonks, 2005).

We provide a number of findings. Both the SETS and the DM are active with the SETS market executing more trades, but the DM executing larger trades overall and dominating the execution of very large trades. The permanent price impact of trades is not only significantly lower on the DM than on SETS, but is actually negative. However, the temporary price impact of trades is significantly larger on the DM than on SETS. The two results together suggest that dealers on the DM are able to effectively identify informed trades ex-ante. Such identification of trade motives enables dealers to either screen out the informed trades avoiding losses or trade effectively with them, and in the process learning the information with which they can trade profitably for their own accounts, as suggested by Naik, Neuberger, and Viswanathan (1999).

TRADING SYSTEMS AND VENUES

Competing yet Complementary Trading Systems

Madhavan (1995) proposes a model that provides a rationale for the existence of fragmented markets, focusing on the impact of disclosing trading information to market participants. He shows that informed traders and large traders who place multiple trades obtain lower expected trading costs in fragmented markets where their trades are not disclosed. On the other hand, dealers benefit from nondisclosure by decreasing price competition.

Contrary to this view, Chowdhry and Nanda (1991) provide a theoretical model in which if more than one market for a security exists, one market will emerge as the dominant market, a "winner takes most" phenomenon. This prediction occurs as liquidity traders seek thick markets with the lowest execution costs and informed traders maximize their profits by hiding trades in the most liquid markets. Glosten (1994) suggests that the open electronic limit order book such as SETS is inevitable because it provides as much liquidity as possible in extreme situations and does not invite competition from third market dealers, while other trading institutions do.

Our empirical analysis presented later is consistent with the coexistence hypothesis instead of the market dominance hypothesis.

Permanent Price Impact in Coexisting Markets

Another branch of literature allows for coexistence and deals with either upstairs versus downstairs markets or auction versus dealer markets. Seppi (1990), Easley and O'Hara (1987), and Easley, Kiefer, and O'Hara (1996) developed models in which dealers (such as upstairs block traders in New York or the dealers in London) are able to differentiate uninformed traders from informed traders based on reputation signals or other implicit commitments. This non-anonymous feature in dealer markets enables ex-ante identification, relationship based information sharing as suggested by Hansch, Naik, and Viswanathan (1999), or potential cream skimming of uninformed trades and screening out of informed traders. This ability of the dealers lowers adverse selection costs for large liquidity traders. Seppi (1990) argues that the lack of anonymity in off-exchange block trading enables investors and the dealers to make "no bagging the street" commitments and face penalties on any subsequent trades if they fail to divulge information.

Grossman (1992), Pagano and Roell (1996), and Schwartz and Steil (1996) focus on order transparency in limit order books like SETS. They suggest that many large traders do not want to expose their orders to the public since large trades may adversely impact the market price, may invite front running by other traders, and may introduce a free-option problem (the risk of being picked off if market conditions change). A large order sent to the DM is less exposed than one sent to the SETS market and may be matched with other unexpressed liquidity. As a consequence, dealers serve as a repository of information on large investors' latent trading interest.

Premiums paid to the dealers by informed traders are justified if they are less than costs of marching up or down the order book to execute large quantities. We examine these predictions of the theoretical models in out univariate analysis of the unique hybrid LSE market structure. Additionally, Franke and Hess (2000) propose that the information differential between an anonymous screen-based trading system and a non-anonymous floor trading system should increase the attractiveness of the latter in the times of high information intensity (proxies for information intensity include trading volume and price volatility). We study these ideas in our cross-sectional regression.

A few country specific empirical studies are closely related to ours. Heidle and Huang (2002) investigate whether auction markets (NYSE, AMEX) or dealer markets (NASDAQ) are better able to identify informed traders. Gramming, Schiereck, and Theissen (2001) examine the relation of degree of trader anonymity and the probability of informed trading on the two parallel markets at the Frankfurt Stock Exchange. Booth et al. (2002) and Smith, Turnbull, and White (2001) find that upstairs trades have a lower permanent price impact than those executed downstairs in Helsinki and Toronto, respectively. Our chapter extends the analysis to the hybrid LSE market and also analyzes both permanent and temporary price impacts. The former unveils the informativeness of trades, whereas the latter represents the transaction cost for investors.

Temporary Price Impact in Auction and Dealer Markets

As addressed in Seppi (1990) and Grossman (1992), off-exchange dealer markets involve a process of searching and matching of order flow. Temporary price concessions are needed to induce dealers to accommodate orders due to inventory holding risk. On the other hand, SETS is fully automated implying that additional liquidity cannot be negotiated by the offer of price concessions. Hence, trade sizes and temporary price impacts should be larger for an off-exchange DM than for an anonymous SETS market. In addition, for small sizes, dealers may not offer significant price improvement because of less intensive competition. For large orders, dealers have the ability to extract additional information about the motivation behind the order flow and benefit from such reputation effects, and significant price improvements are often achieved as a result. Thus, temporary price

impact is a decreasing function of trade size for orders on the DM market. Bernhardt et al. (2005) also develop a model along these lines where larger orders have lower transaction costs on the LSE.

INSTITUTIONAL BACKGROUND, DATA, AND METHODOLOGY

The London Stock Exchange

The London Stock Exchange, which is one of world's leading stock exchanges, has experienced significant transformation to maintain and compete for order flow and to improve price discovery. Before October 1997, the LSE was a pure quote-driven dealer market (Stock Exchange Automated Quotation, SEAQ) with relatively nontransparent order flow. Retail investors complained that they were subsidizing large traders, which caused order flow to migrate to other European markets.

In 1997, the LSE began to implement a phased introduction of a more transparent order-driven auction market called the Stock Exchange Electronic Trading System. At first, SETS traded stocks in the FTSE 100 index, but over time the stocks covered increased and in 2003 roughly 217 stocks from the FTSE 250 index were traded. Thin stocks that have never been components of these two indices are traded only on an old quote-driven market (SEAQ) and are not included in our study.[1]

Dealers on the LSE can compete voluntarily for trades on SETS' stocks on an off-exchange DM, but are no longer obliged to post firm bid and ask prices as they did earlier, and their quotes are no longer available to investors through a publicly available price-display mechanism. Trades on the DM are not constrained by limit order prices on SETS or required to be partially executed against the limit order book. This arrangement differs from other hybrid markets such as the NYSE, Toronto Stock Exchange, Paris Bourse, or Helsinki Stock Exchange where the public orders in the limit order take priority over specialist market maker's own trades. Investors can choose their trading venues depending on their motivation. Investors, who require prompt and anonymous transactions, may prefer to execute market orders against the book in SETS. Passive customers may choose to place limit orders on the book. Large traders, who do not want their trades to create extensive impact on prices in an order book market, may prefer to trade off-book on the DM. For additional institutional details about the LSE, see Board and Wells (2001) and Friederich and Payne (2007).

Data Selection and Processing

This study uses data provided by the London Stock Exchange for stocks that are components of either the FTSE 100 or FTSE 250 indices in 2000, designated as SET1 or SET2. These stocks are traded on both the SETS and the DM. We include only trades during normal hours (08:00 to 16:30). All trades are in GBP.

These data comprise a number of files. For each trade, the Trade Reports File has the firm symbol, date, time, price, number of shares, whether the trade is buyer or seller initiated, which market was used for the trade (SETS or DM), type of order (market, limit), special designations (such as fill or kill), and the settlement date. We note that in determining trade direction on the DM we take the viewpoint of a trader. We exclude trades with settlement dates greater than SETS' standard settlement date, trades with a price or volume of zero, and trades with size greater than 8 NMS and trades designated "WT" (which are ≥8 NMS and are subject to a Work Principal Agreement), "UT" (occurring during opening and closing call period), "RO" (resulting from an option exercise), "SW" (resulting from a stock swap), "CT" (contra trades), and "PN" (work principal portfolio notification). We also exclude trades for which the quantity $|(p_t - p_{t-1})/p_{t-1}| > 0.5$ where p_t is the trade price at time t, as this condition might result from potential data entry errors.

All quote data are from SETS. The DM does not provide quote data. The Best Prices File includes the time and price (but not the depth) of all quote updates that are better than an existing bid or ask on SETS. We exclude quotes with either ask, bid, ask size, or bid size less than or equal to zero, and for which $|(a_t - a_{t-1})/a_{t-1}| > 0.5$ or $|(b_t - b_{t-1})/b_{t-1}| > 0.5$, where a_t is the ask quote and b_t is the bid quote.

For all orders submitted to SETS, the Order History File contains details about the date and time when the order is entered, deleted, cancelled, or executed, along with its order type, quantity, and limit price. We use these details to obtain aggregate depth at each best limit price.

Due to mergers, new listings, and delistings, stocks leave and join the index during the year and to ensure a sufficient sample period, we use only stocks that are members of either index for at least 80 days during the year 2000. The final sample comprises 177 firms after deleting 16 stocks not meeting the requirements enumerated above. The average market capitalization for these firms, obtained from the Compustat global file, is 7.5 billion pounds and the average stock price is 6.59 pounds.

Measurement of Price Impact

To measure whether there is a difference in how trades affect prices on SETS and the DM, we use the method of Keim and Madhavan (1996) and Booth et al. (2002). This method uses trade prices rather than quotes, which is helpful because we do not have quotes for the DM. The total price impact can be decomposed into the permanent price impact and the temporary price impact. The permanent price impact reflects changes in beliefs about a security's value due to new information conveyed by trades.[2] The temporary price impact measures liquidity effects from transitory price reversals. The total price impact reflects the difference between the trade price required to absorb the order and the preceding price.

We assume that a trade occurs at time t with price PT. The equilibrium price observed at time $t - b$ *before* trade at time t is PB and the equilibrium price observed at time $t + a$ *after* trade at time t is PA. The sequence of trades is $b < t < a$. We measure price impact as

$$\text{Permanent price impact (\%)} = BS \times ln\,(PA/PB) \times 100 \qquad (2.1)$$

$$\text{Temporary price impact (\%)} = BS \times ln\,(PT/PA) \times 100 \qquad (2.2)$$

$$\text{Total price impact (\%)} = BS \times ln\,(PT/PB) \times 100 \qquad (2.3)$$

where BS equals plus (minus) 1 for buyer (seller) initiated trades. We also study differences in price impact by trade size. We categorize trades by percentiles of all trades for each firm. This ensures a representation of all stocks in each trade size category rather than bunching of trades from a stock in one category. Note that the trade size cut-off varies from firm to firm. To identify the equilibrium prices before and after a trade, we plot the price movement around large GBP trades (top 5 percent in terms of GBP) in Figure 2.1. We calculate cumulative returns as follows. Each trade is labeled as trade 0, in turn. The previous 20 trades (regardless of trade location, size, buy/sell) executed prior to trade 0 (-1, -2, . . .,-20) and 20 trades executed after trades 0 ($+1$, $+2$, . . ., $+20$) are obtained. Then trade-to-trade returns calculated as the difference in log prices are estimated from each trade from trade -20 to trade $+20$. These returns are averaged and cumulated.

We identify the 5 percent of trades that have the greatest GBP value. We label each of these trades, in turn, as trade 0. For each trade 0, we identify the 20 previous trades, trades -1 through -21, and the subsequent 21

Figure 2.1 Cumulative Average Returns Around Large GBP Trades
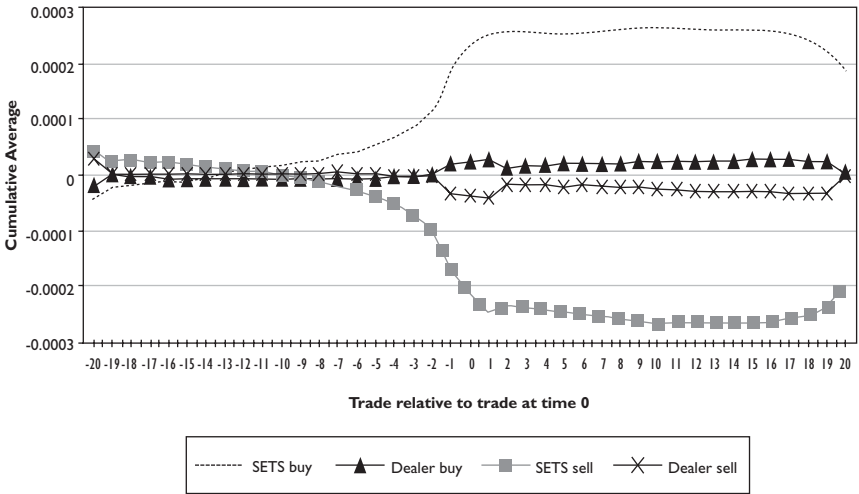
trades, trades +1 through +21. We calculate the return for each trade from −20 to +20 as the difference in the log of the trade price minus the log of the previous trade price. These returns are averaged and cumulated beginning with trade −20. Mean values of cumulative average returns are plotted. Percentage cumulative returns are shown on *y* axis and prior and subsequent trades relative to trade 0 are shown on *x* axis.

Figure 2.1 shows that there are large price movements prior to trade 0 for trades on SETS for both seller- and buyer-initiated trades, indicating information leakage before trade 0. Conversely, price movements before trades on the DM started immediately prior to trade 0. Prices after trade 0 stay high for later trades for SETS, but after dealer trades prices reverse. We find similar patterns for 30 trades and 10 trades. Following Booth et al. (2002), we choose equilibrium price *PB* before trade *t* at *t* – 12 and equilibrium price after trade *t* at *t* + 3 where *PB* is P_{-12} and *PA* is P_{+3}.[3] Price movements in other trade value groups show similar patterns.

EMPIRICAL RESULTS

Table 2.1 shows that the average daily number of trades per stock is higher on SETS than on the DM, but the size of each trade in terms of both number of shares and monetary value is higher on the DM. The size advantage

Table 2.1 Summary Statistics

	All	SETS	DM	t test of Mean Difference between SETS and DM
Number of trades per day per stock	294	163	131	32*
Thousands of shares traded per stock per day	3,201	1,496	1,706	−210*
GBP trading volume in thousands	19,520	9,266	10,256	−990*
Return volatility (%)	1.60	1.20	1.58	−0.38*
Trade size	10,696	8,536	14,539	−6,003*
GBP trade size	50,560	40,347	68,901	−28,554*
SETS' relative quoted-spread (%)	0.987	0.933	1.046	−0.114*
Effective − spread (%)	0.705	0.201	0.617	−0.416*
SETS depth	48,693	55,669	40,298	15,371*
GBP SETS depth (000s)	239,295	273,024	189,550	83,475*

* Significant at the 0.01 level.

of the DM is evident even though these data exclude trades that are greater than 8 NMS, which are mostly DM trades. Both quoted and effective spreads are higher on SETS at the time orders are submitted to the DM than at other times. The higher effective spread on SETS at the time when orders are sent to the DM shows that many traders are actually timing their trading venue and switching to the DM under particular conditions. We view this as the purchase of (high-cost) liquidity when this liquidity is not available on SETS.

For 2000, we present summary statistics for our sample of 149 firms. The overall SETS and DM results are presented in columns 2 to 4. The first three rows present the daily number of trades, number of shares traded and GBP trading volume. Return volatility is the standard deviation of hourly returns in percentage. Trade size is the average number of shares for each trade and GBP trade size is the monetary value of each trade. SETS' relative quoted-spread (%) is computed as (ask − bid)/(ask + bid)/2×100 immediately prior to the trades. SETS Effective spread is the absolute value of the difference between the trade price and the midpoint of the spread at the time of the trade. Depth at best bid and ask immediately prior to the

trade is aggregated and presented in both number of shares and GBP. Quotes from dealer markets are not archived. Therefore, we use SETS spreads to measure market liquidity at the time of each dealer trade. The last column presents the t statistic for the test of the mean difference between the SETS and DM.

Table 2.2 reports and compares the permanent, temporary, and total price impact of trades between the two parallel markets. There is a significantly smaller permanent price impact on the DM compared with SETS both

Table 2.2 Price Impact on SETS and SM

GBP Trade value (percentile)	All	SETS	DM	t-test of Mean Difference between SETS and DM
Permanent price impact (%)				
All orders sizes <25%	0.100	0.219	−0.019	0.239*
	0.003	0.122	−0.055	0.177*
25%–50%	0.055	0.157	−0.032	0.189*
50%–75%	0.141	0.224	−0.002	0.227*
75%–90%	0.227	0.296	0.032	0.264*
90%–95%	0.204	0.311	0.025	0.285*
>95%	0.118	0.340	0.052	0.288*
Temporary price impact (%)				
All orders sizes <25%	0.169	0.073	0.260	−0.187*
	0.277	0.123	0.351	−0.228*
25%–50%	0.202	0.096	0.288	−0.192*
50%–75%	0.134	0.067	0.234	−0.167*
75%–90%	0.067	0.043	0.125	−0.081*
90%–95%	0.054	0.037	0.080	−0.043*
>95%	0.055	0.036	0.062	−0.026*
Total price impact (%)				
All orders sizes <25%	0.262	0.294	0.226	0.068*
	0.260	0.244	0.267	−0.023*
25%–50%	0.251	0.254	0.244	0.010
50%–75%	0.274	0.294	0.226	0.068*
75%–90%	0.293	0.340	0.155	0.185*
90%–95%	0.258	0.349	0.105	0.244*
>95%	0.174	0.365	0.115	0.249*
GBP trade size	**50,560**	**40,347**	**68,90I**	**−28,554***

* Significant at the 0.0I level.

overall and for each size category. This is quite contrary to the notion that theoretical models and empirical works suggest, that is, informed traders prefer to trade in anonymous dealer systems where they do not have to disclose their trading interest ex-ante to the public. Barclay, Hendershott, and McCormick (2003) report that there is a tendency for informed trades in NASDAQ to migrate to anonymous electronic communication networks. Our explanation for the lower permanent price impact lies in that the unique features of the DM. The DM on the LSE does not permit open access. Therefore, long-term relationships are essential and traders cannot afford to conceal that a particular trade is informed.

For the 149 firms in our sample, we present the permanent, temporary, and total price impact of trades on SETS and the DM both overall and by relative trade size category. The permanent price impact of trade at time t is computed as $BS \times ln\ (PA/PB) \times 100$ where BS equals plus (minus) one for buyer (seller) initiated trade and if a trade occurs at time t, designate the price of that trade as PT, the price of the third subsequent trade as PA and the price of the twelfth previous trade as PB. The temporary price impact of trade at time t is computed as $BS \times ln\ (PT/PA) \times 100$, and total price impact of trade at time t is calculated as $BS \times ln\ (PT/PB) \times 100$. The last column presents the test of the mean difference between the SETS and DM.

Turning to temporary price impact, we find that it is significantly lower on SETS than on the DM. In addition we find that the temporary price impact declines as order size increases. This is consistent with dealers offering significant price improvement because of lack of intensive competition for smaller trades. For large orders, dealers have the ability to extract additional information about the motivation behind the order flow and benefit from such reputation effects, and significant price improvements are often achieved as a result. The smaller temporary price impact of large orders in the DM is also consistent with the findings of Bernhardt et al. (2005) who advance a price discount hypothesis.

Next, we investigate whether these differences in permanent and temporary price impacts across trading systems survive after controlling for firm-specific and trading characteristics. We control for the variables that are known to affect transaction costs (Stoll, 2000) while estimating the following cross-sectional regression:

$$Y = b_0 + b_1\ \text{SETS} + b_2\ \text{Cap} + b_3\ \text{Price} + b_4\ \text{Volatility} \\ + b_5\ \text{Freq} + b_6\ \text{Size} + \varepsilon \tag{2.4}$$

where Y is the permanent price impact and temporary price impact, in turn, SETS is an indicator dummy variable that is assigned a value 1 for SETS and 0 for the DM, Cap is the natural log of the market capitalization (millions of GBP), Price is the natural log of the price, Volatility is the natural log of the hourly return volatility (%) from the SETS or DM, Freq is the natural log of the daily number of trade (000s) from the SETS or DM, and Size is the natural log of share trade size from the SETS or DM.

Table 2.3 presents the regression results. Examining the regression with the permanent price impact as the dependent variable, the adjusted R-square exceeds 70 percent. The SETS dummy has a statistically significant positive coefficient indicating that permanent price impact is greater for SETS trades, whereas dealers are able to learn about the information contained in an order and negotiate the trade price for supplying liquidity. Price, volatility, and trade size are significantly positively related to the permanent price impact and trading frequency is significantly negatively related to permanent price impact.

In Table 2.3 we present the results of cross-sectional regressions of the price impact of trades for both the SETS and the DM. The sample comprises 298 observations (149 firms times 2 markets). The regression equations are: $Y = b_0 + b_1 \text{ SETS} + b_2 \text{ Cap} + b_3 \text{ Price} + b_4 \text{ Volatility} + b_5 \text{ Freq} + b_6 \text{ Size} + \varepsilon$, where Y is permanent and temporary price impact, in turn. The permanent price impact of a trade at time t is computed as $BS \times ln$

Table 2.3 Cross-sectional Regression Analysis on Price Impact of Trade

Independent variables	Permanent Price Impact		Temporary Price Impact	
	Coefficient	t statistics	Coefficient	t statistic
Intercept	−0.2224	−1.74	1.3699*	12.19
SETS	0.2849*	21.62	−0.1956*	−16.92
Cap	0.0008	0.08	−0.0024	−0.26
Price	0.0274*	2.00	−0.1060*	−8.82
Volatility	0.1031*	4.90	0.1176*	6.37
Frequency	−0.0399*	−4.77	−0.0180*	−2.45
Size	0.0311*	2.28	−0.0948*	−7.93
Adj. R²	0.7062		0.7836	
F value	119.97		175.58	

*Asterisk represents a statistically significant positive or negative coefficient

(*PA/PB*) × 100 where *BS* equals plus (minus) one for buyer (seller) initiated trade and if a trade occurs at time *t*, designate the price of that trade as *PT*, the price of the third subsequent trade as *PA* and the price of the twelfth previous trade as *PB*. The temporary price impact of a trade at time *t* is computed as *BS* × *ln* (*PT/PA*) × 100. SETS is a dummy variable that equals 1 if the observation is aggregated from the SETS market. Cap is the natural log of the market capitalization (millions). Price is the natural log of the price. Volatility is the natural log of the hourly return volatility (%) from the SETS or DM. Freq is the natural log of the daily number of trade (000s) from the SETS or DM. Size is the natural log of share trade size from the SETS or DM.

Examining the regressions with the temporary price impact as the dependent variable, the adjusted R-square is 78 percent. The SETS dummy has a statistically significant negative coefficient indicating that the liquidity is cheaper on SETS and costly on the DM. However, not all trades will automatically gravitate to SETS because total price impact is lower on DM markets for larger trade sizes. Moreover, large trades may simply be impossible to execute on SETS. Temporary price impact is lower for firms with a higher price, more frequent trading, and larger-sized trades. But higher volatility is associated with an increase in the temporary price impact of trades.

Regression results in Table 2.3 are consistent with those presented in Table 2.2 for SETS versus dealer comparisons as well as trade size comparisons. Coefficients for the control variables are also consistent with previous microstructure literature such as Stoll (2000).

Qualitatively similar results in terms of adjusted R-squares, and direction, magnitude, and statistical significance of coefficients are obtained when we estimate Equation 2.4 separately for the SETS and DM and, therefore, these results are not reported in tables for brevity.

CONCLUSION

We examine trading on the London Stock Exchange where the same stocks are traded on a computer-based trading system called SETS and on a DM. Dealers have no obligations to post quotes or to support the market in any way. We find that the SETS market has more trades overall, but the trades are larger on the DM and the DM dominates very large sized trades.

We find significantly greater permanent price impact on SETS compared with the DM for both the overall sample and for each size category. Consequently, we believe that the informed trades are routed to SETS while the DM is able to effectively identify informed trades ex-ante. Such identification of trade motives enables dealers to either screen out the informed trades, avoiding losses, or trade effectively with them. In the process, dealers learn information useful for their own trading.

Further, we find that the temporary price impact on the SETS market is less than on the DM. However, we note that only small quantities are traded on SETS so the temporary price impact could be large on SETS if an order marched up the book. For larger trades, liquidity can be purchased on the DM at a premium. Premiums paid to the dealers are justified if they are less than the cost of marching up or down the order book to execute large quantities. A multivariate investigation shows that our findings of higher permanent and lower temporary price impacts on SETS hold after we control for firm and trading characteristics.

ACKNOWLEDGMENTS

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NOTES

1. A few stocks that have been deleted from these indexes continue to be traded on SETS.

2. Of course, participants can disagree on interpretation of common information and thus an informed trader can trade with another informed trader in real world trade settings. Most theory models, however, simplify trades to include either one informed and one liquidity trader or both liquidity traders.

3. Booth, Lin, Martikainen, and Tse (2002) find insignificant price movement five trades before and three trades after trade t.

MOMENTUM TRADING FOR THE PRIVATE INVESTOR

Alexander Molchanov and Philip A. Stork

ABSTRACT

This chapter explores the potential profitability of a momentum strategy for a private investor. Such a strategy is based on price continuation and requires buying stocks that have performed well in the past while short selling under-performing stocks. In order to replicate a trading strategy readily attainable by individual investors, we only select constituents of major worldwide indexes. Consistent with prior work, we document strong momentum in shares around the world. However, we also find that when trading costs are accounted for, momentum profits disappear in some markets. Nevertheless, in Australia and Canada, momentum profits remain positive and significant.

INTRODUCTION

Since the seminal paper by Jegadeesh and Titman (1993), who analyze returns to buying winners and selling losers, the so-called "momentum effect" has been highlighted by both academics and practitioners alike.[1] The main presumption behind the momentum effect theory is that it is possible to predict future price movements based on past price trends. More specifically, past winners keep outperforming past losers. The momentum effect is of particular interest to researchers, as it is one of the best documented challenges to the efficient market hypothesis which, in its basic form, tells

us that price changes should be unpredictable. While several potential explanations for the momentum effect have been proposed, a general consensus is yet to be reached.[2]

The apparent simplicity of a momentum strategy implementation makes it an attractive choice for an individual investor. After all, one only needs to rank stocks according to their past performance. This chapter analyzes the profitability of the momentum strategy for such an investor. The next question is which shares to select for inclusion in the momentum portfolio. We select 220 of the world's largest shares—constituents of well-known stock indexes. We have two main reasons for making such a choice. First, these shares are likely to have low transaction costs compared to other stocks. Second, as Barber and Odean (2008) point out, individual investors, when faced with a choice of thousands of stocks, tend to select those that catch their attention. Index constituents are more likely to do that.

Consistent with prior studies, we document medium-term momentum in all the markets we consider, including those of Western Europe, the United States, Northern Europe, Australia, and Canada. Additionally, and to no surprise, once trading costs have been accounted for then some of the profits disappear. However, momentum profits in Australia and Canada remain statistically and economically significant, indicating that following a simple momentum strategy could potentially generate abnormal returns, even for a private investor.

DATA

We use only the largest shares that are traded in some of the most liquid markets. For a private investor it is relatively easy to find out which shares make up any of the main share indexes available. In these largest shares, a private investor will encounter very few, if any, problems when trading. Going short will usually be possible at reasonable costs, as there is ample supply. Moreover, the available price data will contain only a minimal amount of the distortions that are often found in the share prices of smaller stocks, including bid-ask bounces, unrepresentative prices due to infrequent trading or other illiquidity related issues.

From Datastream, we download end-of-month return indexes and trading volumes of the constituent shares of five main equity indexes. The sample period runs from December 1991 to January 2008, comprising 193 observations in total. We have selected three indexes from Dow Jones &

Company, Inc. (Dow Jones) and two exchange-generated indexes. The first index is the Dow Jones EURO STOXX 50, which consists of the 50 stocks with the highest free-float market capitalization of the 600 largest stocks traded on the major exchanges of 18 European countries.[3] Second, the Dow Jones Industrial Average 30 Index represents large and well-known U.S. companies. All industries are covered and the components are selected at the discretion of *The Wall Street Journal* editors. Third, the Dow Jones STOXX Nordic 30 provides a blue-chip representation of the super sector leaders in the Nordic region, covering 30 stocks from Denmark, Finland, Iceland, Norway, and Sweden. The S&P/ASX 50 index places an emphasis on liquidity and comprises the 50 largest stocks by market capitalization in Australia. Finally, the S&P/TSX 60 index is a list of the sixty largest companies on the Toronto Stock Exchange in Canada as measured by market capitalization. Together, these five indexes comprise 220 of the world's largest and most liquid stocks. This approach contrasts with other momentum studies which usually focus either on all shares listed on a national exchange or on a sample of national indexes.

Prior to its announcement, an investor cannot know which shares will be added or removed from the list of constituents. We have removed this potential survivorship bias from our sample using proprietary data kindly provided to us by Dow Jones. Stepwise, we assess per individual index which shares are added and deleted monthly based on the information retrieved from Dow Jones and the websites of the two exchanges. We manually adjust the lists of constituent shares accordingly. Each monthly list of constituent shares that comprise the index thus reflects only the information available up until that date. This procedure ensures that the survivorship bias is removed from the data. Of the five indexes chosen, we were unable to obtain all additions and deletions for only the S&P/ASX 50 and the S&P/TSX 60 indexes. We are thus unable to adjust those two indexes prior to January 2000 and therefore some survivorship bias may remain for the period between 1992 and 1999. We have no reason to believe that this has significant affects on our results.

MOMENTUM TRADING RESULTS

We execute the following procedure to calculate momentum returns. The ranking period is defined as the period during which returns are calculated in order to rank the shares according to their relative return levels. The

holding period is defined as the period after the ranking period, during which the returns from holding the shares are realized. Every month, for a specific ranking period, the returns of all shares are calculated and ranked. The top five winners are bought and the bottom five losers are sold short, and we thus hold these 10 shares in position. We initially choose the minimum number of shares per long or short portfolio to equal five, as other momentum trading studies also often use deciles. Furthermore, we below analyze the effects of changing this number and show that a reduction increases the momentum returns generated but at the same time lowers the statistical reliability of the results.

We vary both the ranking and the holding period between 1 and 12 months. We utilize the investment rule that equally weighted momentum strategies of varying vintages are simultaneously in effect at all times, following Jegadeesh and Titman (1993, 2001) and Griffin, Ji, and Martin (2003). For comparison purposes, we apply the most commonly used return calculation method. We acknowledge that the implicit monthly rebalancing is potentially oversimplifying and may, in practice, increase transaction costs, as pointed out by Liu and Strong (2008). Moreover, we follow the common practice of skipping one month between ranking and holding periods in order to minimize microstructure price distortions. As a robustness test, we also calculated momentum returns without skipping one month. The results obtained contain few surprises and are broadly in line with, for example, the findings of Griffin, Ji, and Martin (2003), and are available from the authors upon request. For each of the five data samples, the annualized momentum returns are calculated. Table 3.1 reports the returns for the highest versus lowest portfolio across several ranking and holding period combinations. Corresponding t values are given in parentheses.

Table 3.1 shows for all five geographical areas that positive momentum returns are generated for the most commonly used ranking and holding period combinations of 6, 9, and 12 months. Apparently, a sample size of 30 to 60 shares suffices to convincingly demonstrate the pervasive presence of momentum effects. For three of the five samples (Europe, Nordic, and the United States), the returns are statistically not significant. For Australia and Canada, the returns are markedly higher and significant, as confirmed by the t statistics. For these samples, the annualized returns range between 20 percent and 30 percent for various ranking and holding periods.

Table 3.1 Momentum Returns

Panel A. S&P/ASX 50 (Australia)

		Holding Period in Months				
		1	3	6	9	12
Ranking period in Months	1	7.36%				
		(1.14)				
	3	13.52%	19.74%			
		(1.82)	(3.26)			
	6	24.09%	24.02%	23.82%		
		(2.99)	(3.59)	(3.95)		
	9	31.17%	27.73%	23.71%	20.24%	
		(4.31)	(4.03)	(3.81)	(3.72)	
	12	29.82%	27.58%	23.98%	20.67%	17.06%
		(3.82)	(3.87)	(3.84)	(3.65)	(3.34)

Panel B. ASX/TSX 60 (Canada)

		Holding Period in Months				
		1	3	6	9	12
Ranking Period in Months	1	1.15%				
		(0.12)				
	3	0.40%	15.82%			
		(0.03)	(1.51)			
	6	26.46%	24.63%	27.72%		
		(2.13)	(2.15)	(2.65)		
	9	31.00%	31.48%	29.34%	24.38%	
		(2.63)	(2.77)	(2.71)	(2.49)	
	12	29.79%	29.82%	23.37%	20.89%	19.55%
		(2.40)	(2.55)	(2.02)	(1.87)	(1.81)

Panel C. Dow Jones Industrial Average 30

		Holding Period in Months				
		1	3	6	9	12
Ranking Period in Months	1	−0.72%				
		(−0.13)				
	3	−4.08%	−6.24%			
		(−0.75)	(−1.35)			
	6	−3.72%	−2.16%	2.16%		
		(−0.67)	(−0.45)	(0.50)		
	9	1.56%	2.88%	5.04%	6.24%	
		(0.22)	(0.48)	(0.90)	(1.11)	
	12	−1.20%	4.08%	6.24%	5.04%	5.16%
		(−0.18)	(0.64)	(0.96)	(0.83)	(0.95)

(Continued.)

Table 3.1 (Continued)

<div align="center">

Panel D. Dow Jones STOXX Nordic 30

</div>

		Holding Period in Months				
		1	**3**	**6**	**9**	**12**
Ranking Period	**1**	−16.80%				
in Months		(−0.85)				
	3	−4.56%	1.80%			
		(−0.44)	(0.23)			
	6	8.76%	10.44%	10.20%		
		(0.82)	(1.12)	(1.19)		
	9	−2.64%	7.08%	4.56%	3.60%	
		(−0.26)	(0.81)	(0.54)	(0.47)	
	12	2.76%	2.88%	5.76%	4.68%	4.44%
		(0.28)	(0.32)	(0.68)	(0.58)	(0.57)

<div align="center">

Panel E. Dow Jones EURO STOXX 50

</div>

		Holding Period in Months				
		1	**3**	**6**	**9**	**12**
Ranking Period	**1**	−6.84%				
in Months		(−0.85)				
	3	2.04%	5.64%			
		(0.24)	(0.75)			
	6	1.92%	5.64%	5.64%		
		(0.22)	(0.71)	(0.82)		
	9	5.76%	8.28%	7.44%	7.44%	
		(0.63)	(0.98)	(1.00)	(1.05)	
	12	4.68%	6.35%	7.20%	3.72%	3.48%
		(0.49)	(0.74)	(0.89)	(0.50)	(0.48)

A second observation is that the strength of the momentum effects depends on the duration of the ranking and holding period. For the shorter ranking periods of one and three months, the momentum returns for several samples turn negative, although the amounts are statistically insignificant. Our finding of lower momentum returns for the short-term ranking periods is in line with prior empirical studies; see, for example, Jegadeesh and Titman (2001).

ROBUSTNESS TESTS

In this section we conduct a number of robustness tests in order to analyze in more detail the behavior of the momentum effect. We commence by analyzing the behavior of the momentum returns over time. Could it be that this is a disappearing phenomenon, or is it still present in the most recent data? Figure 3.1 shows the average of all five areas' cumulative (12 × 6) momentum returns over the full duration of the sample.

The cumulative momentum returns in Figure 3.1 show a continuing upward movement, albeit with several periods of severe volatility. In 2002, for example, the returns strongly increased only to fall again in 2003. The peak in cumulative returns of 2002 was not reached again until 2007. Although the volatility of the returns is apparently quite high, the strong positive trend nevertheless suggests that the momentum effect is still going strong in recent years.

However, a further analysis, as seen below, indicates that the above conclusion is premature and that the true story is more nuanced. Instead of averaging out the cumulative returns over the five samples, we now analyze the results per individual sample. We split the period into two subperiods, namely, 1992 to 1999 and 2000 to 2008. The respective average momentum returns are presented in Figure 3.2.

Figure 3.1 Average of All Cumulative Momentum Returns
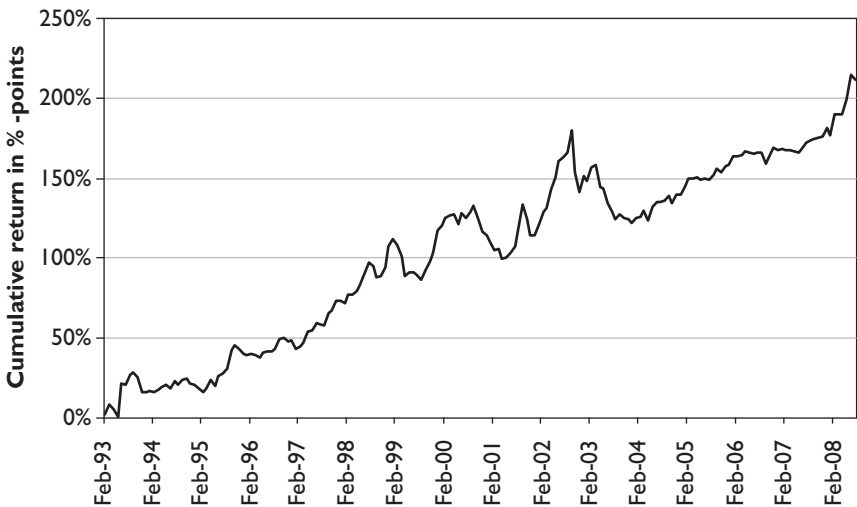
Figure 3.2 Individual Momentum Returns per Subperiod

	Nordic	Euro	DJIA	Australia	Canada
1992-1999	6.10%	12.99%	10.27%	13.15%	29.64%
2000-2008	5.37%	0.74%	1.95%	35.28%	16.83%
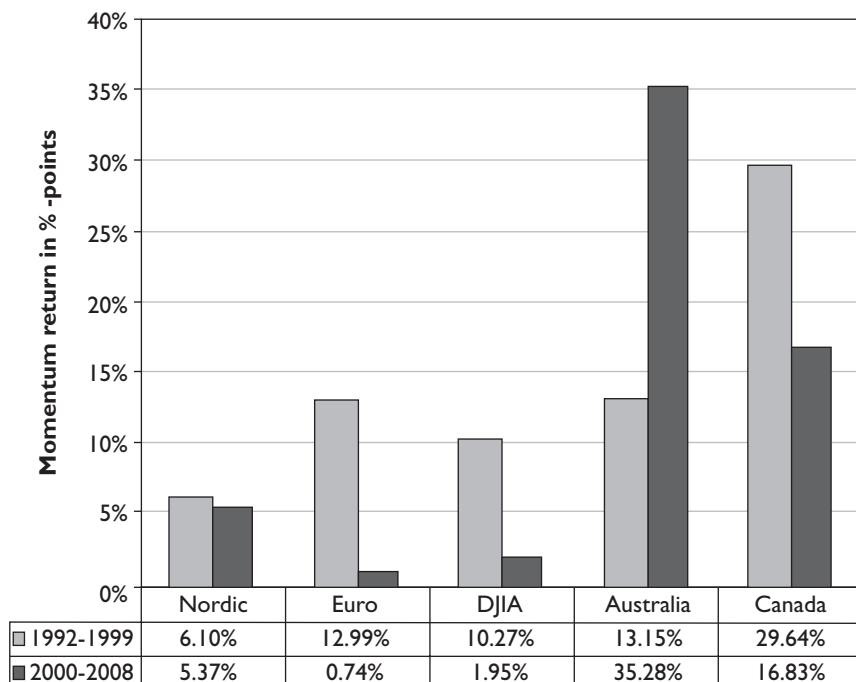
A surprising picture emerges from Figure 3.2. For the first subperiod 1992 to 1999, four of the five samples generate average momentum returns in excess of 10 percent. Only in the Nordic sample do the momentum returns remain subdued at a meager 6.10 percent. However, in the second subperiod 2000 to 2008, four of the five samples show markedly lower momentum returns. For the Dow Jones Euro STOXX 50 and the Dow Jones Industrial Average 30 samples, the returns are less than 2 percent and have thus almost totally disappeared. Only in the Australian sample did the momentum returns increase during the second subperiod.

Next, we analyze to what extent the results depend on the number of shares being used in the trading strategy. In the above calculations we took a position of five shares long and five shares short, thus a total of 10. We now reduce the number of shares in the portfolios. It is of course easier and cheaper to trade fewer shares, but if we do that we can expect more erratic trading results due to less averaging out of the returns. To ensure

consistency, we continue to conduct the above-used (12 × 6) combination of ranking and holding periods.[4]

For most samples, the most extreme losers and winners tend to show the strongest momentum effects, which is in line with the results found in Stork (2008). The cumulative momentum returns tend to reduce stepwise from the first ranked shares to the fifth ranked shares. The average momentum return is depicted in Figure 3.3. Although the details are not discussed here, we find a corresponding decrease in cumulative momentum returns for most other holding and ranking periods. Our conclusion is that the common practice used by momentum studies of dividing the shares within the sample in deciles increases the statistical reliability yet, at the same time, reduces the absolute size of the momentum effect. Raising the number of shares in the momentum portfolio reduces both the expected level and volatility of the returns. The investor who utilizes a momentum investment strategy in the market faces this tradeoff.

TRADING WITH A VOLUME FILTER

In this section we present the results of applying a simple volume filter to the positions. Several authors have already linked momentum and trading volume. Conrad, Hameed, and Niden (1994) use weekly NASDAQ stock prices between 1983 and 1990 and find that for past losers, high trading volumes predict high future returns. For winners, this relationship is less evident. Momentum returns are higher if low volume losers are sold as opposed to high volume losers.

The change in trading volume is calculated as the last month's volume divided by the average volume of the three preceding months. Lee and Swaminathan (2000) show that most of the predictive power of trading volume is attributable to *changes* in the level of trading activity rather than lagged volume. This result supports our choice of trading volume measurement. We have arbitrarily chosen a length of three months. However, we find that increasing the length to 6 or 12 months has only marginal impact on our key findings.

We build on the Conrad, Hameed, and Niden (1994) study and filter out those shares for which the trading volume changes more than a specified threshold. We set these filter-limits somewhat arbitrarily in order to ensure that volume can neither have increased more than 10 percent nor

fallen more than 50 percent. Although we find that the filtered momentum returns do not depend strongly on the thresholds used in the volume filters, a more detailed sensitivity analysis falls outside the scope of this chapter.

In some months, all winners or losers are filtered out: for those months, the strategy cannot be executed and no momentum return is calculated. Table 3.2 shows the filtered momentum trading returns, the number of monthly returns, and the t statistics in parentheses for the (12 × 6)-strategy.

Table 3.2 shows an interesting picture. In line with the results in Table 3.1, we find that for most samples the highest filtered returns are generated when using only a minimal number of shares. The returns are widely dispersed, ranging from a maximum of 64 percent to a minimum of −9 percent. Unsurprisingly, the volatility decreases when the portfolio size is augmented. Moreover, use of the volume filter tends to cause the number of observations to decrease and the returns to become more erratic. As a result, it is difficult to draw any consistent conclusions per individual sample. As a next step, we calculate average filtered momentum returns for each portfolio size, which enables us to better compare the filtered versus unfiltered trading strategy results.

Table 3.2 Filtered Momentum Returns and Portfolio Size

	Number of shares				
	1	2	3	4	5
S&P/ASX 50 (Australia)	40.88%	41.50%	34.63%	25.38%	25.61%
	143	164	181	183	183
	(2.44)	(2.85)	(3.13)	(2.87)	(3.35)
S&P/TSX 60 (Canada)	30.35%	24.43%	23.52%	15.63%	13.10%
	128	162	175	179	181
	(1.31)	(1.41)	(1.80)	(1.38)	(1.24)
Dow Jones	−8.82%	−0.22%	12.58%	7.92%	9.56%
Industrial Average 30	124	158	165	178	178
	(−0.60)	(−0.02)	(1.12)	(0.70)	(1.03)
Dow Jones	63.56%	18.21%	7.55%	−2.66%	1.88%
STOXX Nordic 30	37	69	89	122	132
	(1.51)	(0.48)	(0.2)	(−0.10)	(0.08)
Dow Jones	59.43%	54.55%	22.38%	10.93%	4.74%
EURO STOXX 50	88	119	140	163	166
	(1.87)	(2.24)	(0.99)	(0.58)	(0.27)

Figure 3.3 Comparison of Filtered and Unfiltered Trading Strategies

Number of shares used	1	2	3	4	5
Unfiltered	21.76%	18.31%	17.23%	14.47%	13.31%
Filtered	37.08%	27.69%	20.13%	11.44%	10.98%

Number of shares used
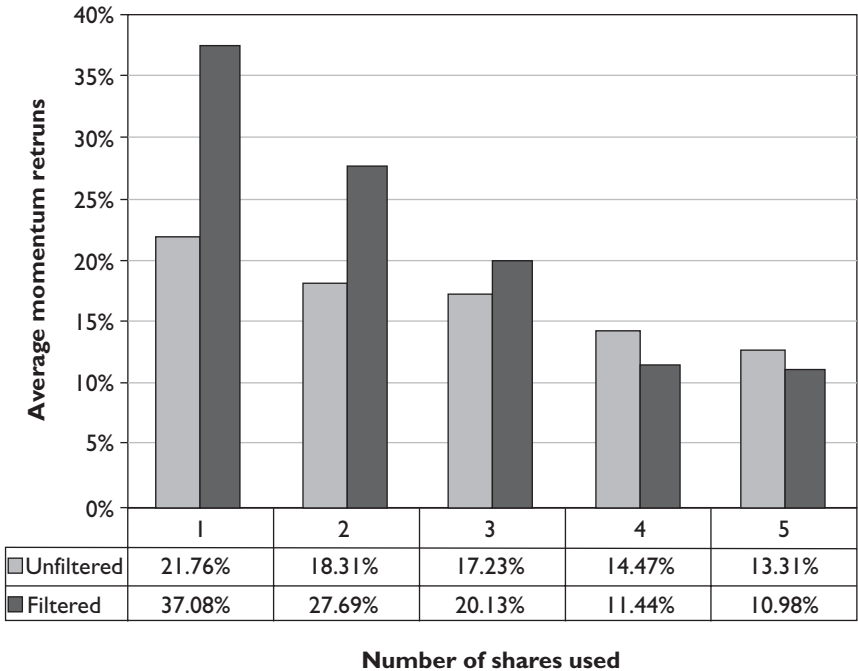
Figure 3.3 shows that for the smaller portfolios the average momentum return increases after applying a volume filter. Even though marginal, the difference for the (relatively) large sizes of four and five shares favors the unfiltered strategy. The highest average momentum returns are apparently obtained by applying a volume filter on very small portfolios. These returns fluctuate wildly and are thus quite risky.

PRIVATE INVESTOR TRADING

Because of its simplicity, the momentum strategy with or without a filter should in practice be tradable fairly easily and without too many costs. We assume one-sided trading costs of 0.3 percent and a bid-offer spread of 0.3 percent as well. For consistency we continue to focus on the (12 × 6)-strategy. For ease of exposition we first focus on the smallest portfolios which consist of one share long and one share short. We simultaneously buy and sell these two shares and after six months conduct an offsetting trade.

We thus conduct four trades for each portfolio. Per portfolio, this means that we pay four times the transaction costs of 0.3 percent and we lose two times the bid-offer spread of 0.3 percent for a total of 1.8 percent. These "costs" are incurred per portfolio that is held for six months, thus twice per year, so that the overall trading costs equal 3.6 percent per year. On top of these costs we must add the stock lending fee, usually expressed as a percentage spread of, for example, 1 percent. Finally, we have to pay some miscellaneous costs for events such as corporate actions, a fixed-account fee and a fee dependent on the number of shares registered with the broker. In total, the miscellaneous fees should not exceed 0.4 percent. The total costs amount to around 5 percent per year.

Our cost-estimates are fairly conservative and are likely to be lower in practice for an experienced and savvy private investor. For example the bid-offer spread in blue chip shares usually is less than 0.3 percent. Moreover, if somewhat larger amounts are traded, the trading costs will be lower as well. Finally, we have assumed that each consecutive trading portfolio is different. In reality, however, shares stay in or out of market favor for prolonged periods of time. In such scenarios the composition of the portfolio remains unaltered and the number of trades comes out lower.

If total trading costs amount to around 5 percent, we conclude that for the period since the year 2000 the unfiltered momentum trading results obtainable for the private investor were nil or even negative for the Euro, Nordic, and U.S. areas. In Australia and Canada, however, a private investor could have made significant momentum profits in excess of 10 percent per annum even after deduction of all costs.

CONCLUSION

The momentum effect—past winners continuing to outperform past losers—has been one of the main challenges to the efficient market hypothesis. Following a simple strategy of buying past winners and selling past losers seems to generate significantly positive abnormal returns in all the markets we consider in this chapter. Our findings are robust to a number of tests. We confirm that momentum profits do not disappear over time; they are more pronounced for extreme winners and losers; and they are amplified with an application of a simple volume filter.

We are looking at the viability of the momentum strategy from the perspective of the private investor who is likely to encounter significant trading

costs. Indeed, consistent with conventional wisdom and academic evidence, once the trading costs are accounted for, some of the momentum profits disappear. Nevertheless, these profits remain significant in the Australian and Canadian markets. However, one has to exercise caution in implementing such a strategy, as there is no guarantee these profits will repeat themselves in the future.

ACKNOWLEDGMENTS

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NOTES

1. Other prominent papers documenting momentum in stock returns are, for example, Grundy and Martin (2001) and Nijman, Swinkels, and Verbeek (2004).

2. Daniel, Hirshleifer, and Subramanyam (1998) attribute momentum to traders' overconfidence; they ascribe the performance of ex-post winners to superior stock selection, while ex-post losers are explained by bad luck. Therefore, delayed overreaction will drive the momentum profits. Hong and Stein (1999) assume that investors use only partial information to update their expectations. This will cause short-run underreactions and long-run overreactions, resulting in momentum profits.

3. See www.stoxx.com for an overview of the methodology. The market has chosen this index as one of the standards for exchange-traded funds, derivatives, and other European index products.

4. In order to save space we do not tabulate the results; however, they are available from the authors upon request.

TRADING IN TURBULENT MARKETS
Does Momentum Work?

Tim A. Herberger and Daniel M. Kohlert

ABSTRACT

Identifying ways to successfully predict security returns based on past returns is a major objective of investment research. One of the most important strategies, that of momentum (Levy, 1967; Jegadeesh and Titman, 1993; Oehler et al., 2003), is employed in this chapter. Using NYSE data from December 1994 to May 2009, we analyze whether buying stocks that have performed well in the past and selling stocks that have performed poorly in the past can generate significant positive returns, even in a turbulent market phase. Our findings suggest that investors using momentum strategies could have indeed generated superior returns during that time period.

INTRODUCTION

Since it was first reported by Jegadeesh and Titman (1993), the momentum phenomenon has been extensively discussed in the literature. Based on the concept of "Relative Strength" by Levy (1967), the authors argue that contrary to the neoclassic efficient market hypothesis, stock prices are autocorrelated. For the U.S. stock market they find that trading strategies that buy stocks which have performed well in the past and sell stocks that have performed poorly in the past can achieve abnormal market-adjusted returns that could not exist if the market was efficient. After Jegadeesh and Titman (1993), many studies tried to reproduce their results by testing momentum investment strategies in other stock markets: For example, Rouwenhorst

(1998) shows that momentum can be found in a sample of 12 European stock markets. Chui, Titman, and Wei (2000) confirm momentum for eight Asian stock markets (without Japan), and Glaser and Weber (2003) show that investment strategies based on momentum can be profitable in the German stock market. In an experimental study, Oehler et al. (2003) identify momentum traders and disposition investors.

This chapter uses NYSE data from December 1994 to May 2009 to examine whether momentum can still be found on the U.S. stock market. This is particularly interesting as the sample period covers extreme market moves resulting from the rise and fall of dot-com stocks at the beginning of this century and from the current financial crisis. We find significant positive abnormal returns on a market-adjusted basis for a short-term strategy with equally long ranking and holding periods of 3 months as well as for a medium-term strategy based on 6-month-long ranking and holding periods. This holds true even after transaction costs are considered. A long-term strategy based on 12-month-long ranking and holding periods, however, does not produce significant abnormal returns.

The chapter is organized as follows. The second section of this chapter provides a literature review, and in the third section we explain the dataset and introduce the methodology adopted. The presentation of the empirical results follows in this chapter's fourth section, and the fifth section concludes.

LITERATURE REVIEW

Although the profitability of momentum strategies is rarely disputed, there is still a great deal of controversy over the reasons for such abnormal returns. Neoclassical economists attempt to explain momentum as a rational compensation for risk, a liquidity premium and/or an illusion induced by market frictions (Fuertes, Miffre, and Tan, 2009). Lesmond, Schill, and Zhou (2004), for instance, argue that momentum cannot be profitably exploited when transaction costs are considered. Korajczyk and Sadka (2004), however, find that transaction costs can only partially explain the profits of momentum strategies. Conrad and Kaul (1998) argued that cross-sectional variation can potentially explain the profitability of momentum strategies, and Moskowitz and Grinblatt (1999) find that it is for the most part attributable to momentum in different industries. After controlling for momentum across industries, the authors hardly find a profit

in individual stock returns. Another explanation is offered by Wu (2002) and Wang (2003) who assume that the profitability of momentum trading is a result of time-variation in expected returns. Grundy and Martin (2001) and Karolyi and Kho (2004) show, however, that neither industry effects, time-variation in expected returns, nor cross-sectional disparities are the main reasons for the momentum effect and that these factors can explain it only partially. Also, while Chordia and Shivakumar (2002) indicate that some macroeconomic variables (e.g., the yield on a three-month T-bill) predict the momentum phenomenon and the associated payoffs, Griffin, Ji, and Martin (2003) show that this approach also offers an only incomplete explanation.

Behavioral economists follow another approach. They argue that momentum is a consequence of cognitive biases and/or limits to arbitrage. In the model of Barberis, Shleifer, and Vishny (1998), momentum results from conservatism while representativeness leads to overvaluation and consequently to price correction. Daniel, Hirshleifer, and Subrahmanyam (1998) argue that biased self-attribution and overconfidence are the reasons for the predictability of equity returns. Chan, Jegadeesh, and Lakonishok (1996) as well as Hong and Stein (1999) attributed momentum to an only gradual distribution of new information on the market.[1] Chui, Titman, and Wei (2009) find indications in their analysis of 55 countries that cultural differences affect stock return patterns and the extent of the success of momentum trading. They argue that individuals from different countries respond differently to risk. Hwang and Rubesam (2008), however, note that at least for the U.S. stock market momentum profits have slowly eroded since the early 1990s.

DATA AND METHODOLOGY

Monthly stock prices over the period December 31, 1994 to May 31, 2009 are obtained from Datastream for all common stocks listed on the NYSE, excluding American depository receipts (ADRs), real estate investment trusts (REITs), closed-end funds, and companies which were delisted during the evaluation period. For our analysis we use returns adjusted for capital gains and dividends. An equally weighted NYSE Index that consists of all shares of the dataset is used as a market proxy. The momentum strategy is intended as a zero-cost portfolio strategy that buys stocks that have performed well in the past and sells stocks that have performed poorly in the past.

We basically follow the methodology of Jegadeesh and Titman (1993). We couch everything in terms of raw returns, and we equally weight these returns. However, in contrast to Jegadeesh and Titman (1993), we do not analyze 16 but three trading strategies: we use a short-term strategy with a ranking period J of 3 months and an equal holding period K ($J = 3/K = 3$), a medium-term strategy consisting of a 6-month ranking period as well as a 6-month holding period ($J = 6/K = 6$), and a long-term strategy with a ranking period of 12 months and a holding period of 12 months ($J = 12/K = 12$). To increase the power of our tests, we construct overlapping test runs like Moskowitz and Grinblatt (1999), Jegadeesh and Titman (2001), and Fuertes, Miffre, and Tan (2009). This results in 167 test runs for the 3/3 trading strategy, 161 test runs for the 6/6 strategy, and 149 test runs for the 12/12 strategy. While Jagadeesh and Titman (1993) sort stocks into 10 deciles according to past performance, and then measure the return differential of the most extreme deciles which they denote by P10 – P1, we place even more emphasis on the tails of the performance distribution.

One month after the ranking takes place, we sort our sample into only two parts based on past performance: P1, which includes the worst-performing 1 percent, and P2, which includes the best-performing 1 percent of NYSE stocks in the ranking period. Our basic measure of momentum is then P2 – P1. The top 1 percent portfolio is the winners' portfolio and the bottom 1 percent portfolio is the losers' portfolio. The stocks in the individual portfolios are equally weighted. Contrast to Jegadeesh and Titman (1993), Jegadeesh and Titman (2001), and most former studies, the two extreme portfolios are formed in order to maximize performance and to minimize transaction costs. This, however, implies fewer diversification benefits in the portfolios. In order to avoid biases because of low-priced stocks, which are documented for example in Conrad and Kaul (1993), particularly for January, we follow the method of Jegadeesh and Titman (2001) and Fuertes, Miffre, and Tan (2009) by (temporarily) excluding stocks which are priced below $5 at the end of the ranking period.

By skipping a month between the end of the ranking period and the beginning of the holding period like Rouwenhorst (1998), we avoid some of the bid-ask spread, price pressure, and lagged effects, which could skew our results. These effects are documented for example in Jegadeesh (1990) and Lehmann (1990). The gross return of a test run (cumulative return of a holding period of T months in test run i, $CR_{i,T}$) is defined as follows:

$$CR_{i,T} = \sum_{t=0}^{T} \left[R_{W,t} - R_{L,t} \right] \tag{4.1}$$

where $R_{W,t}$ is the monthly return of the winners' portfolio and $R_{L,t}$ represents the monthly return of the losers' portfolio.

The market-adjusted return of a test run (cumulative abnormal return of a holding period of T months in test run i, $CAR_{i,T}$) is defined as follows:

$$CAR_{i,T} = \sum_{t=0}^{T} \left[\left(R_{W,t} - R_{L,t} \right) - R_{M,t} \right] \tag{4.2}$$

where $R_{W,t}$ is the monthly return of the winners' portfolio and $R_{L,t}$ represents the monthly return of the losers' portfolio. $R_{M,t}$ is the monthly return of the equally weighted NYSE Index.

For evaluating the success of a trading strategy it is essential to consider transaction costs, which are incurred when the portfolios are assembled and when the strategy closes out the positions at the end of a test run.[2] In our study we consider three different rates of transaction costs that depend on the type of investor employing the momentum strategy. Following Bromann, Schiereck, and Weber (1997), we assume that institutional investors face transaction cost of 0.2 percent for every purchase or sale (4x), wealthy private clients 0.5 percent (4x), and private clients 1.0 percent (4x).[3] The market-adjusted return after transaction cost of a test run (cumulative abnormal return after transaction costs with a holding period of T months in test run i, $CART_{i,t}$) is defined as follows:

$$CART_{i,T} = \sum_{t=0}^{T} \left[\left(R_{W,t} - R_{L,t} - T_{C,t} \right) - R_{M,t} \right] \tag{4.3}$$

where $R_{W,t}$ is the monthly return of the winners' portfolio and $R_{L,t}$ represents the monthly return of the losers' portfolio. $R_{m,t}$ is the monthly return of the equally weighted NYSE Index and $T_{C,t}$ is the rate of transaction costs per month.

RESULTS

Table 4.1 presents the average monthly returns on the composite portfolio strategies between December 1994 and May 2009. The returns have been obtained based on the methodology discussed in the previous section.

Table 4.1   Average Monthly Returns of Momentum Portfolios in the Period from 1994 to 2009

Table 4.1 presents average equally weighted monthly returns in percentages for price momentum portfolio strategies involving NYSE stocks from December 1994 to May 2009. At the end of each month, all stocks are ranked in ascending order based on the actual t and the past $J - 1$ months' cumulative returns. One month after the ranking takes place, two equally weighted, monthly rebalanced, extreme portfolios are constructed that consist of the 1 percent of NYSE stocks with the highest returns and the 1 percent with the lowest returns in the ranking period. P1 represents the low-return loser portfolio, and P2 represents the high-return winner portfolio. Overlapping portfolios are constructed to increase the power of the tests. K represents holding periods where K = 3, 6, or 12 months. Returns of the winner and loser portfolios in t are simply the average of J portfolio returns. The momentum portfolio (P2 – P1) is the zero-cost, winner minus loser portfolio. For monthly returns, t statistics are shown in parentheses.

Ranking Period (J)	Portfolio	Holding Period (K)		
		3	6	12
3	Loser (P1)	−0.0167		
	Winner (P2)	0.0038		
	Winner − Loser (P2 − P1)	0.0205		
	(t statistic)	(4.16)		
6	Loser (P1)		−0.0187	
	Winner (P2)		0.0032	
	Winner−Loser (P2 − P1)		0.0219	
	(t statistic)		(5.93)	
12	Loser (P1)			−0.0091
	Winner (P2)			−0.0064
	Winner − Loser (P2 − P1)			0.0027
	(t statistic)			(1.12)

The table shows that for the strategy with a 3-month ranking and a 3-month holding period ($J = 3/K = 3$), an equally weighted portfolio formed from the stocks in the bottom percentile of previous 3-month performance returns –1.67 percent per month, 2.05 percent less than the top percentile portfolio which returns 0.38 percent. In the case of the second strategy with a ranking period of 6 months and a holding period of 6 months ($J = 6/K = 6$), an equally weighted loser portfolio returns –1.87 percent per month, 2.19 percent less than the winner portfolio which returns 0.32 percent. Finally, a ranking period of 12 months and a holding period of 12 months ($J = 12/K = 12$) leads to a return of 0.27 percent.

In this case, an equally weighted portfolio formed from the stocks in the bottom percent of previous three-month performance returns –0.91 percent per month, while the top percent portfolio returns –0.61 percent. Average overall returns are highest for the medium-term strategy. This supports the approach in the literature to mainly focus on this strategy based on 6-month ranking and holding periods (e.g., Jegadeesh and Titman, 1993; Rouwenhorst, 1998; Hong, Lim, and Stein, 2000). The winners of the short-term strategy have much higher returns than the losers. For both the short-term and the medium-term strategy, returns are significant at the 1 percent level. For the long-term strategy, both winner and loser returns are negative, very close to each other, and not significant.

Compared with previous findings in the literature, the negative returns of the loser portfolios are relatively high. Jegadeesh and Titman (1993), Jegadeesh and Titman (2001), Rouwenhorst (1998), and Hong, Lim, and Stein (2000), for example, do not find negative returns for their loser portfolios at all. However, these authors report considerably higher average returns of their winners' portfolios. As for our data the difference between winner and loser portfolios is still greater, we find a higher overall performance of our momentum portfolios. Besides the effect of a potential survivorship bias due to the omission of delisted stocks, a reason for the higher returns we find is likely to be that we chose smaller and more extreme portfolios and through this exchanged higher returns for higher risk by foregoing diversification benefits. As Rouwenhorst (1998) aptly states, stocks with higher standard deviations, all else equal, are more likely to show unusual performance.

Looking at the risk of the three momentum portfolios, we find that the standard deviations decrease with the time horizon of the strategies. While the short-term portfolio has a monthly standard deviation of 6.06 percent, the medium-term portfolio's standard deviation is 4.33 percent, and the long-term portfolio's standard deviation is 3.02 percent. Interestingly, the medium-term strategy has a higher return and simultaneously a lower standard deviation than the short-term strategy. Although the lower standard deviation of the long-term strategy comes along with a lower return, as expected, the relationship between risk and return is worst in this case. Compared with Rouwenhorst (1998) who reports monthly standard deviations of 5.62 percent for his loser (decile) portfolio, and of 5.27 percent for his winner (decile) portfolio for the momentum strategy based on 6-month

ranking and holding periods, our standard deviations, which result from portfolios that contain only the top and bottom 1 percent of available stocks, do not seem overly high. A further reason for the high returns of the strategy may be the particular characteristics of the time period from 1994 to 2009 that we are looking at. With the dot-com bubble at the beginning of the twentieth century as well as with the financial crisis the market faced two strong as well as prolonged declines which should at least partly be responsible for the highly negative returns of the loser portfolios and the only slightly positive returns of the winner portfolios.

Table 4.2 presents the average monthly abnormal returns of the momentum portfolios using the average monthly NYSE return as the market proxy. The returns have been obtained based on the methodology discussed in section two. Panel A shows the returns of the market proxy as adjusted to the respective strategy, the raw return of the momentum portfolios, and the abnormal returns resulting from subtracting market from momentum returns. As expected based on the results of Table 4.1, the average monthly abnormal return is highest for the medium-term strategy with 2.08 percent. The abnormal return of the short-term strategy is also considerably high with 1.83 percent. Both returns are significant at the 1 percent level. The long-term strategy produces the lowest and nonsignificant abnormal return of 0.01 percent.

Assessing the profitability of momentum trading strategies requires an assessment of the trading costs. Panel B therefore shows average monthly returns that have been adjusted for a 0.2 percent transaction costs rate. While the short-term strategy's average monthly abnormal return is 1.56 percent, the medium-term strategy returns 1.95 percent, and the long-term strategy 0.03 percent. Again, both returns of the short-term as well as the medium-term strategies are significant at the 1 percent level. Panel C shows average monthly abnormal returns that have been adjusted for a 0.5 percent transaction costs rate. In this case, the short-term strategy's average monthly abnormal return is 1.40 percent and it is significant at the 1 percent level. The medium-term strategy returns 2.10 percent in excess of the market. The return is significant at the 1 percent level. The long-term strategy is characterized by an insignificant abnormal return of 0.02 percent.

In Panel D, transaction costs are increased to 1 percent. Although the short-term strategy still returns 0.45 percent in excess of the market, this return is no longer significant. The long-term strategy now underperforms

Table 4.2 Abnormal Montly Returns of Momentum Portfolios Using the Average NYSE Return as the Market Proxy over the Time Period from 1994 until 2009

This table presents average monthly abnormal returns in percentages for price momentum portfolio strategies involving NYSE stocks from December 1994 to May 2009. P represents the return of the momentum portfolio, i.e., the zero-cost, winner minus loser portfolio, for a given J/K-strategy. J represents ranking periods, where $J = 3$, 6, or 12 months, and K represents holding periods where $K = 3$, 6, or 12 months. M represents the average NYSE return which is used as the market proxy. The abnormal return of the momentum portfolios using the average NYSE return as the market proxy $(P - M)$ is calculated by subtracting market return from momentum return. In Panel A, raw returns are presented without considering transaction costs. In Panel B, transaction costs of 0.2 percent are considered in calculating the return of the momentum portfolio. In Panel C, transaction costs of 0.5 percent are considered in calculating the return of the momentum portfolio. In Panel D, transaction costs of 1 percent are considered in calculating the return of the momentum portfolio. For monthly return differences, t statistics are shown in parentheses.

Ranking Period (J)		Panel A Holding Period (K)			Panel B Holding Period (K)			Panel C Holding Period (K)			Panel D Holding Period (K)		
		3	6	12	3	6	12	3	6	12	3	6	12
3	Market Return (M)	0.0026			0.0026			0.0026			0.0026		
	Momentum Return (P)	0.0209			0.0181			0.0140			0.0071		
	Abnormal Return (P - M)	0.0183			0.0156			0.0114			0.0045		
	(t-stat)	(-3.31)			(-2.82)			(-2.08)			(-0.82)		
6	Market Return (M)		0.0015			0.0015			0.0015			0.0015	
	Momentum Return (P)		0.0223			0.0210			0.0189			0.0154	
	Abnormal Return (P - M)		0.0208			0.0195			0.0174			0.0139	
	(t-stat)		(-5.10)			(-4.77)			(-4.27)			(-3.41)	
12	Market Return (M)			0.0021			0.0021			0.0021			0.0021
	Momentum Return (P)			0.0030			0.0023			0.0013			−0.0004
	Abnormal Return (P - M)			0.0009			0.0002			−0.0008			−0.0025
	(t-stat)			(-0.30)			(-0.07)			(0.28)			(0.87)

the market by 0.25 percent. Only the medium-term strategy significantly outperforms the market at the 1 percent level with an abnormal return of 1.39 percent. In general, these returns show that the momentum effect not only existed in the period we observed, but also that it could have been profitably exploited even after considering transaction costs. This at least applies to the investor who is willing to bear the considerable risk of using this strategy based on the very extremes of the considered stocks' return distribution.

This table presents average monthly abnormal returns in percentages for price momentum portfolio strategies involving NYSE stocks from December 1994 to May 2009. *P* represents the return of the momentum portfolio, i.e., the zero-cost, winner minus loser portfolio, for a given *J/K*-strategy. *J* represents ranking periods, where *J* = 3, 6, or 12 months, and *K* represents holding periods where *K* = 3, 6, or 12 months. *M* represents the average NYSE return which is used as the market proxy. The abnormal return of the momentum portfolios using the average NYSE return as the market proxy (*P − M*) is calculated by subtracting market return from momentum return. In Panel A, raw returns are presented without considering transaction costs. In Panel B, transaction costs of 0.2 percent are considered in calculating the return of the momentum portfolio. In Panel C, transaction costs of 0.5 percent are considered in calculating the return of the momentum portfolio. In Panel D, transaction costs of 1 percent are considered in calculating the return of the momentum portfolio. For monthly return differences, t statistics are shown in parentheses.

CONCLUSION

Using NYSE data from December 1994 to May 2009, we analyze whether momentum trading strategies can generate significant positive returns even in a turbulent market phase. Our findings suggest that even after years of academic analysis and considerable awareness of momentum effects investors can still generate superior returns using momentum portfolio strategies. We find significant positive abnormal market-adjusted returns for short- and medium-term momentum strategies based on equally long ranking and formation periods of 3 and 6 months, respectively. A long-term strategy based on equally long ranking and formation periods of 12 months, however, cannot significantly outperform the market. Even after considering transaction

costs of 0.2, 0.5, and 1 percent, respectively, there are significant results. Only the medium-term strategy based on 6-month ranking and holding periods, however, significantly outperforms the market if transaction costs are set to 1 percent. Interestingly, the strategy based on 6-month ranking and holding periods offers the highest return while simultaneously having the lowest risk in terms of standard deviation.

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NOTES

1. For an explanation of the gradual distribution of new information in the market, see Oehler (2002).

2. For an overview of the components of trading costs, see Korajczyk and Sadka (2004).

3. These assumptions can be considered conservative as transaction costs have decreased since these articles were published due to factors such as technological change and increased competition.

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THE FINANCIAL FUTURES MOMENTUM

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ABSTRACT

The momentum strategy is the most famous anomaly arguing against the hypothesis of financial market efficiency. In this chapter, the momentum strategy produces a significant abnormal return for holding periods of six months and one year using financial futures (stock indexes, currencies, and fixed income). Furthermore, this study characterizes those futures contracts that contribute to the momentum strategy return. When the sample is split in two groups, depending on the level of volatility, a significantly higher return is obtained in the high volatility group. Moreover, when the sample of futures is split in four groups, depending on the trading volume and open interest levels, those contracts with high trading volume and low open interest report the best *momentum* performance.

INTRODUCTION

In recent years a large number of studies have analyzed several investing strategies that produce abnormal returns in financial markets. As a result, the efficiency of these markets has been again questioned, especially after many hedge funds put these strategies into practice. The momentum effect is one of the most important phenomena studied in the literature. This effect is based on the hypothesis that those assets with the best (worst) return performance in the past will continue to perform similarly (best or worst) in the future. The trading rule to exploit this return pattern is very

simple: take long positions in those assets with the best performance in the past and short positions in those assets with the worst past performances. The momentum effect has been found to be significant for investment horizons of between nine months and a year. There is no agreement about an explanation for the momentum effect. The most important line of work tries to relate the momentum effect strategy return with macroeconomic variables. This line of work produces quite successful results, and some authors assert that this phenomenon is compatible with the efficiency hypothesis—when returns are properly adjusted by risk.

In this chapter, we will study the momentum effect on financial futures markets. This work will contribute to the literature by relating the momentum strategy return with liquidity linked variables (trading volume and open interest) and volatility.

LITERATURE REVIEW

The most important studies covering the momentum effect in stock markets are those of Jegadeesh and Titman (1993, 2001). These authors find significant abnormal returns for intermediate investment horizons of up to one year. Recently, Shen, Szakmary, and Sharma (2007), Miffre and Rallis (2007), and Pirrong (2005) found abnormal returns in futures markets for the momentum strategy. Shen et al. (2007) and Miffre and Rallis (2007) studied the momentum effect in commodity futures markets. Miffre and Rallis (2007) concluded that momentum strategies buy backwardated contracts and sell contangoed contracts.

The momentum effect survives as the most famous anomaly that argues against the hypothesis of financial market efficiency. There is consensus in the literature that the profitability of momentum-based trading strategies cannot be fully accounted for in the context of market factor models[1]. An outstanding contribution in this field is made by Karolyi and Kho (2004). These authors propose a very complete bootstrap procedure to test the return abnormality in momentum-based strategies. Specifically, they compute time-varying expected returns with market-wide and macroeconomic instrumental variables—and they are able to explain almost 80 percent of the profits.

There are few studies relating the momentum effect in futures markets with open interest, traded volume, and volatility. Bessembinder and Seguin

(1993) make an important contribution in this field. They find a positive relationship between volatility and traded volume and a negative relationship between volatility and open interest. Lee and Swaminathan (2000) use past traded volume to predict the persistence of the momentum effect in stock markets.

DATA

The database used is extracted from a CD published by the Commodity Research Bureau (CRB). Specifically, we have collected closing prices, traded volumes, and open interest. Futures return time-series have been computed while carefully avoiding mixing futures contracts with differing maturities. The contracts are rolled over two weeks before the futures maturity.

The sample includes a set of 18 contracts representing the most important markets in the world.[2] The list includes seven currency futures (Euro/USD, Yen/USD, Canadian dollar/USD, British pound/USD, Australian dollar/USD, Swiss franc/USD, and U.S. dollar index); six stock index futures (CAC 40, FTSE 100, Nikkei 225, S&P 500, Swiss market index, Dow Jones EURO STOXX 50); and five fixed income futures (Euro bund 10-Y, Canadian government bond 10-Y, U.S. Treasury note 2-Y, U.S. Treasury note 5-Y, and U.S. Treasury note 10-Y). We have excluded commodity futures contracts because commodity price time-series have specific special features and have been already studied in Shen et al. (2007) and Mifre and Rallis (2007). The period for the returns time-series runs from May 1991 to December 2007. The time-series of volume and open interest covers the period January 2001 to December 2007. On average, the transaction costs of the 18 contracts have been estimated at 0.096 percent over the average nominal contract values for the studied period. This cost includes the bid-ask spread, and an estimation of the intermediation commission for opening and closing futures positions.

METHODOLOGY AND RESULTS

Following the methodology in previous studies such as Shen et al. (2007) and Jegadeesh and Titman (1993, 2001), we have tested the existence of the momentum effect in a sample of futures contracts. We have constructed basic momentum tests as follows. Firstly, we define five *formation* periods

(*F*) and five *holding* periods (*H*). We have chosen the following period lengths for *F* and *H*: 1, 3, 6, 12, and 24 months. The reported tables will display results only for *F* = *H*, the remaining combinations of *F* and *H* periods are omitted to save space. Based on each futures return in the *F* period, we then group the periods into one of three portfolios (P1, P2, and P3), where P1 contains the six futures with highest past returns (winners); and P3 contains the six futures with lowest past returns (losers). The remaining six futures are included in the P2 portfolio. We then compute portfolio returns for each holding period. Finally, the momentum portfolio return is calculated: P1 – P3. That is, the momentum portfolio contains long positions in the past winning contracts and short positions in the past losing contracts.

A momentum effect will exist if the average return of this portfolio is positive and significantly different from zero. To test the significance of momentum profits in each portfolio, we use t statistics that are asymptotically distributed such as N(0,1) under the null hypothesis that the true profits are zero. Because we generally use overlapping data, we have corrected our standard errors for heteroscedasticity and autocorrelation using the Newey and West adjustment.

Momentum Strategy Profits

Table 5.1 presents the results for the whole sample and *F* = *E* periods. All the returns are annualized to facilitate comparison. Two market indicators are reported in each row to complete the analysis. The first indicator, termed *reference*, is an equally weighted portfolio with a long position in each of the 18 contracts in the sample. The second indicator is the S&P 500 index. Results in Table 5.1 show that all the momentum strategies obtain positive returns: but only for the 6- and 12-month periods are the mean returns significantly different to zero at the 5 percent of significance level.[3] Furthermore, the mean return of momentum strategies for 6 and 12 months is more than 500 basic points higher than the *reference* portfolio and the S&P 500 annual returns. These results are similar to Jagadeesh and Titman (1993 and 2001) for 6- and 12-month periods. Nevertheless, we found no overreaction evidence in the way De Bondt and Thaler (1985, 1987) and Conrad and Kaul (1998) found for the 24-month period in the U.S. stock markets.

Table 5.1 Average Momentum Profits

F/H	P1	P2	P3	P1 – P3	Reference	S&P 500
1 mo	4.000%	3.443%	2.105%	1.895%	2.087%	2.139%
	1.845	2.046	0.902	0.650		
3 mo	2.823%	3.325%	2.782%	0.042%	1.268%	1.188%
	1.342	1.898	1.343	0.017		
6 mo	5.972%	3.100%	−0.516%	6.488%	0.821%	0.698%
	3.450	2.930	−0.241	2.932		
12 mo	7.373%	1.686%	−0.473%	7.847%	0.485%	0.363%
	2.613	1.251	−0.162	2.094		
24 mo	5.213%	1.879%	1.029%	4.184%	0.287%	0.217%
	1.352	1.394	0.246	0.874		

This table provides annualized means of holding period (H) returns for various portfolios. The P1, P2, and P3 columns contain the portfolio returns for the winning, intermediate, and losing contracts for each formation period (F). Below the means are t statistics and based on Newey and West standard errors. The reference column reports the annualized average return of an equally weighted portfolio composed of long positions in the 18 futures contracts. In the last column, the annualized average return of the S&P 500 is provided as a benchmark.

Momentum and Volatility

Pirrong (2005) suggests that differences in volatility across futures can mask the momentum effect because highly volatile contracts will be winners or losers more frequently than less volatile contracts. Nevertheless, his analysis shows that the momentum effect persists after futures returns are standardized by their own volatility. We will study this point further. We have split the 18 contracts in two groups of nine contracts, according to their daily volatility during the sample period. Table 5.2 reports the results for the nine most volatile (Panel A), and the nine least volatile (Panel B) contracts. Most volatile contracts show positive returns higher than the corresponding returns appearing in Table 5.1. On the contrary, less volatile contracts show returns significantly below the corresponding returns appearing in Table 5.1. The only momentum strategy in Table 5.2 with an average return significantly different to zero at the 5 percent significance level is the six-month momentum strategy in Panel A; and it is significantly higher than the corresponding return in Table 5.1 using the z test (z = 3.365).[4] Therefore, we can conclude that the momentum effect is more persistent in highly volatile futures contract portfolios.

Table 5.2 Average Momentum Profits and Volatility

F/H	Panel A: Most Volatile Contracts				Panel B: Least Volatile Contracts			
	P1	P2	P3	P1 – P3	P1	P2	P3	P1 – P3
1 mo	6.124%	4.766%	2.188%	3.936%	2.68%	2.68%	0.66%	2.02%
	1.999	1.563	0.649	1.086	1.821	2.087	0.516	1.006
3 mo	5.612%	3.342%	2.528%	3.843%	1.43%	2.28%	1.92%	−0.49%
	2.080	1.117	0.881	1.186	0.902	1.993	1.41	−0.224
6 mo	8.307%	4.312%	−0.496%	8.803%	2.94%	2.58%	−0.53%	3.47%
	3.017	1.668	−0.153	2.501	2.137	2.904	−0.415	1.669
12 mo	7.444%	5.156%	−0.687%	8.131%	2.75%	1.77%	0.74%	2.01%
	1.924	1.457	−0.154	1.363	2.027	1.076	0.788	1.213
24 mo	4.836%	5.318%	−0.542%	5.377%	2.18%	4.16%	0.29%	1.89%
	0.757	1.196	−0.108	0.791	1.28	2.874	0.129	0.696

This table reports the momentum strategy average return for the two groups of nine contracts based on daily volatility during the sample period. See the notes at the foot of Table 5.1 for more comments.

Momentum, Trading Volume and Open Interest

Using a similar approach to Wan and Yu (2004), we analyzed the influence of traded volume on momentum strategy returns. The trading volumes and open interest used are not specific to the nearest contract, as this information is not reported on the CRB CD. Rather, these figures are in terms of the notional dollar value of contracts for all maturity months, defined as the total number of contracts traded multiplied by the nearby futures price— multiplied by the contract multiplier. For those futures whose prices are not in dollars, the corresponding exchange rate is used. To measure the traded volume influence on momentum strategies we follow a two-step procedure. First, in each formation period, we divide the 18 contracts in two groups, depending on the relative increases in traded volume with regard to the previous formation period. In a second stage, we build the P1, P2, and P3 portfolios within each group in the usual way; and then calculate the momentum strategy return.

Panel A and Panel B in Table 5.3 provide momentum strategy returns for those futures with high and low relative increases in traded volume, respectively. Results in Panel A and Panel B show that the only significant average momentum strategy return corresponds to 12 months, with average return of 11.642 percent and 15.284 percent and Newey and West t

Table 5.3 Average Momentum Profits and Relative Increase in Traded Volume

F/H	P1	P2	P3	P1 – P3	Reference	S&P 500
	Panel A. High Relative Increase in Traded Volume					
1 mo	7.739%	10.688%	10.487%	−2.749%	3.341%	3.138%
	2.293	3.101	2.942	−0.621		
3 mo	6.384%	5.236%	7.685%	−1.301%	1.669%	0.480%
	1.347	1.525	2.103	−0.255		
6 mo	8.163%	3.489%	2.355%	5.808%	1.019%	−0.155%
	2.026	1.455	1.065	1.011		
12 mo	18.707%	−1.086%	7.065%	11.642%	0.581%	−0.110%
	4.664	−1.945	12.056	2.925		
	Panel B. Low Relative Increase in Traded Volume					
1 mo	6.902%	6.182%	4.163%	2.739%	3.341%	3.138%
	1.801	1.346	0.933	0.684		
3 mo	4.004%	5.882%	7.943%	−3.939%	1.669%	0.480%
	0.825	1.608	2.220	−0.861		
6 mo	6.542%	2.418%	1.536%	5.006%	1.019%	−0.155%
	1.319	0.926	0.362	1.858		
12 mo	14.283%	12.090%	−1.001%	15.284%	0.581%	−0.110%
	2.018	33.870	−0.173	11.727		

Panel A and Panel B provide annualized mean returns of momentum strategies for those contracts with high and low relative increases in traded volumes in comparison with the previous formation period, respectively. See notes at the foot of Table 5.1 for more comments.

statistics of 2.925 and 11.727, respectively. Furthermore, the 12-month, low-volume, momentum average return is significantly higher than the 12-month, high-volume return using the z test (z = 5.63). Therefore, we can deduce that the momentum effect is more persistent in futures port-folios with low relative increases in traded volume. Lee and Swaminathan (2000) found that momentum is stronger among high-volume stocks. This result seems contrary to our results in futures markets; nevertheless, all futures contracts included in the sample can be considered as liquid assets and, in addition, the liquidity measures used in both studies are not comparable.

Another important variable in futures market microstructure analysis is open interest. In Bessembinder and Seguin (1993), open interest is

taken as a measure of market depth. Therefore, the influence of trading activity in momentum strategies will be more complete if we analyze their sensitivity to different levels of open interest. To measure the influence of open interest on momentum strategies we follow a similar procedure to that used above for traded volume. First, for each formation period, we divide the 18 contracts in two groups, depending on their relative increase in open interest with regard to the previous formation period. In a second stage, we build the P1, P2, and P3 portfolios within each group in the usual way and calculate the momentum strategy return. Panel A and Panel B in Table 5.4 provide momentum strategy returns for those futures with high and low relative increases in open interest, respectively.

Results in Table 5.4 show that the only significant average momentum strategy return corresponds to the 12-month period in Panel A, with an average return of 11.02 percent and a Newey and West t statistic of 2.91. Furthermore, the 6- and 12-month momentum returns in Panel A are significantly above the corresponding returns in Panel B. Therefore, we can deduce that the momentum effect is more persistent in futures portfolios with high relative increases in open interest.

From the previous analysis of the influence of trading activity on momentum strategy returns an investor would choose those contracts with low relative increases in traded volume and high relative increases in open

Table 5.4 Average Momentum Profits and Relative Increase in Open Interest

F/H	Panel A. High Relative Increase				Panel B. Low Relative Increase			
	P1	P2	P3	P1 – P3	P1	P2	P3	P1 – P3
1 mo	9.63%	7.66%	10.65%	−1.02%	3.39%	3.69%	6.87%	−3.49%
	2.50	2.05	2.95	−0.23	0.88	0.89	1.81	−0.84
3 mo	6.66%	5.81%	7.03%	−0.37%	8.53%	6.65%	8.06%	0.47%
	1.57	1.37	2.15	−0.08	1.69	1.66	2.06	0.08
6 mo	8.32%	2.09%	1.59%	6.73%	9.11%	1.31%	4.90%	4.98%
	1.80	1.80	0.55	1.13	2.56	0.53	1.39	1.44
12 mo	10.63%	−1.05%	−0.38%	11.02%	14.74%	6.14%	8.43%	6.30%
	2.92	−2.01	−0.05	2.91	3.29	6.10	2.30	0.77

Panel A and Panel B provide annualized mean returns of momentum strategies for those contracts with high and low relative increases in open interest in comparison with the previous formation period, respectively. See notes at the foot of Table 5.1 for more comments.

interest. However, an investor might be unable to apply both criteria simultaneously. On this point, we need to study how both activity measures interact in order to obtain feasible trading rules. In a similar way to the above cases, we have followed a three-step procedure. First, for each formation period we divide all the sample contracts into two groups, depending on the relative increases in traded volume. In each of these two groups we then divide the contracts in two more subgroups, according to the relative increase in open interest. In a third stage, we build the P1, P2, and P3 portfolios within each subgroup in the usual way and calculate the momentum strategy return.

Panels A, B, C, and D in Table 5.5 provide momentum strategy returns for each subgroup. Results in Table 5.5 show that the only significant

Table 5.5 Momentum and Relative Increase in Open Interest (OI) and Traded Volume (V)

F/E	P1	P2	P3	P1 – P3	P1	P2	P3	P1 – P3
	Panel A. High OI and High V				**Panel B. High OI and Low V**			
1 mo	11.154%	8.077%	10.686%	0.468%	5.934%	6.153%	9.204%	−3.270%
	1.460	1.861	2.785	0.088	1.295	1.118	2.008	−0.753
3 mo	6.673%	−0.620%	6.576%	0.096%	3.184%	8.155%	10.042%	−6.857%
	2.611	−0.121	2.150	0.024	0.588	1.717	2.182	−1.160
6 mo	5.896%	3.842%	2.781%	3.115%	10.170%	11.927%	3.166%	7.004%
	1.412	0.914	1.029	0.610	2.136	2.777	1.260	1.268
12 mo	−1.168%	2.007%	−1.647%	1.416%	10.229%	19.408%	−2.166%	8.063%
	−0.749	0.260	−0.326	0.216	0.963	6.533	−0.521	1.848
	Panel C. Low OI and High V				**Panel D. Low OI and Low V**			
1 mo	5.064%	11.531%	11.263%	−6.199%	6.054%	5.218%	3.560%	2.494%
	1.291	2.849	3.090	−1.355	1.600	0.971	0.805	0.653
3 mo	8.781%	5.492%	7.573%	1.209%	4.009%	7.149%	7.293%	−3.284%
	1.460	0.981	1.867	0.186	1.008	1.453	1.598	−0.697
6 mo	10.200%	3.038%	0.094%	10.017%	8.489%	1.574%	3.990%	4.499%
	3.253	0.414	0.083	3.805	2.278	0.534	1.232	1.210
12 mo	16.472%	10.312%	8.218%	8.254%	8.356%	18.153%	−2.048%	−4.609%
	2.932	29.010	0.892	2.298	3.482	3.117	−0.423	−0.574

Panels A, B, C, and D report momentum strategy returns in four groups after dividing all the sample contracts in two groups, depending on their relative increases in traded volume. The contracts in both of these groups are then divided into two subgroups, depending on the relative increases in open interest. See notes at the foot of Table 5.1 for more comments.

momentums are for 6 and 12 months in Panel C with average returns of 10.017 percent and 8.254 percent; and Newey and West t statistics of 3.805 and 2.298, respectively. Therefore, when we let open interest and traded volume interact, we can see that the momentum effect is more persistent in futures portfolios with high relative increases in traded volume and low relative increases in open interest.

This conclusion agrees with Bessembinder and Seguin (1993) in relation to volatility, trading volume, and open interest. Bessembinder and Seguin (1993) found that unexpected volume shocks have an asymmetric effect on volatility: the impact of high unexpected volume shocks on volatility being larger than the impact of negative shocks. Nevertheless, an unexpected level of open interest mitigates the volume effect on volatility because it is inversely related. We have found a similar result for the momentum strategy. Momentum strategies are more persistent for highly volatile futures, high relative increases in trading volume, and low relative increases in open interest (see Tables 5.2 and 5.5). This is a sensible result as it would be expected that high return investment strategies are associated with high volatility; and this is consistent with the efficiency hypothesis. Furthermore, futures contracts with high trading volumes and low open interest are probably futures with a higher speculative component (see Wan and Yu, 2004).

Efficiency Tests and Risk Evaluation

One important point in an analysis of momentum strategies is to test if returns are abnormally high. That is, if the strategy returns reflect only a reward for risk. Following Jegadeesh and Titman (1993), we first computed risk-adjusted returns using the CAPM and the Fama and French (1993) three-factor model (not reported because of space restrictions). Both tests showed that risk-adjusted momentum returns were positive, but smaller, and significantly different to zero for 6 and 12 month periods at the 5 percent and 10 percent significance level, respectively. Therefore, the traditional tests can only partially explain momentum strategy returns (about 50 percent).

Following Shen et al. (2007), we also analyzed the distributional properties of momentum returns. The test proposed by Shen et al. (2007) is based on a control strategy. In this control strategy, for each month, futures are

randomly assigned to the P1, P2, and P3 portfolios in the formation period, and the P1 – P3 return is computed for each holding period. This procedure continues until the sample period is complete and this enables us to obtain a return average similar to the momentum strategy. This simulation is repeated 1,000 times for each pair of *F/H* periods in order to obtain the control strategy distribution.

It can be seen in Table 5.6 that when comparing momentum returns in Panel A against control strategy distribution in Panel B, that the momentum return means for 6- and 12-month periods remain extremely high. The average momentum returns for these periods are 6.488 percent and 7.847 percent, respectively. These average returns are above the 99.5 percentile of the empirical distribution of the 1,000 simulated control strategies (4.584 percent and 5.005 percent, respectively). Therefore, it seems that taking long positions in past winners and short positions in past losers offers extremely high returns. However, are these returns abnormally high? To answer this question we compute the Sharpe ratio for each momentum strategy period and the control strategy pair computed after 1,000 simulations. Again, by comparing momentum Sharpe ratios in Panel A against control strategy Sharpe ratios in Panel B, we can see that momentum Sharpe ratios are above the 99.5 percent percentile of the empirical distribution for 6 and 12 month periods.

CONCLUSION

The momentum strategy is the most famous anomaly arguing against the hypothesis of financial market efficiency. The momentum strategy produces a significant abnormal return for holding periods of six months and one year using financial futures (stock indexes, currencies, and fixed income). Furthermore, this study characterizes those futures contracts that contribute to the momentum strategy return. When the sample is split in two groups depending on the level of volatility, a significantly higher return is obtained in the high volatility group. Moreover, when the sample of futures is split into four groups, depending on the trading volume and open interest levels, those contracts with high trading volume and low open interest report the best *momentum* performance. Finally, we have tested if those momentum strategies with average returns that are significantly different to zero continue being positive and significantly different to zero after a

Table 5.6 Descriptive Statistics and Bootstrap Tests for the Momentum Strategy Returns

F/H		1 Mo	3 Mo	6 Mo	12 Mon	24 Mo
Panel A. Descriptive Statistics						
Mean		1.895%	0.042%	6.488%	7.847%	4.184%
Volatility		8.818%	8.458%	6.789%	10.533%	13.361%
Skewness		−0.125	−0.395	0.158	−0.051	0.073
Kurtosis		5.008	3.250	2.234	2.584	1.850
Minimum		−10.587%	−14.448%	−6.310%	−16.410%	−24.278%
Maximum		12.140%	9.960%	15.474%	31.537%	39.089%
Sharpe ratio		0.215	0.005	0.956	0.745	0.313
Panel B. Bootstrap Tests						
Mean	P=0.005	−3.705%	−3.960%	−4.390%	−4.987%	−5.707%
	P=0.025	−3.162%	−3.007%	−3.304%	−3.875%	−4.728%
	P=0.50	−0.205%	−0.039%	−0.019%	0.004%	−0.032%
	P=0.975	3.097%	3.221%	3.281%	3.800%	5.292%
	P=0.995	4.150%	3.955%	4.584%	5.055%	6.600%
Volatility	P=0.005	5.575%	4.850%	4.135%	3.905%	2.029%
	P=0.025	5.706%	5.057%	4.595%	4.458%	3.218%
	P=0.50	6.373%	6.188%	6.228%	7.120%	7.875%
	P=0.975	7.089%	7.490%	8.079%	10.646%	13.432%
	P=0.995	7.322%	7.913%	8.787%	11.808%	15.457%
Skewness	P=0.005	−0.885	−1.469	−1.484	−1.771	−1.560
	P=0.025	−0.660	−0.951	−1.253	−1.216	−1.291
	P=0.50	−0.036	−0.027	0.005	0.013	0.012
	P=0.975	0.625	1.015	1.320	1.213	1.283
	P=0.995	0.846	1.525	2.003	1.699	1.580
Kurtosis	P=0.005	2.725	2.142	1.949	1.441	1.114
	P=0.025	2.939	2.414	2.117	1.628	1.297
	P=0.50	3.958	3.479	3.339	2.642	2.079
	P=0.975	6.549	7.192	7.368	4.985	3.672
	P=0.995	7.657	9.652	10.038	6.900	3.950
Sharpe ratio	P=0.005	−0.604	−0.689	−0.737	−0.829	−1.100
	P=0.025	−0.511	−0.489	−0.566	−0.559	−0.662
	P=0.50	−0.031	−0.006	−0.003	0.000	−0.005
	P=0.975	0.513	0.527	0.569	0.540	0.787
	P=0.995	0.657	0.653	0.782	0.707	1.290

Panel A reports descriptive statistics for P1–P3 momentum portfolio returns with formation (F) period equal to the holding (H) period. Panel B provides key distribution points for each descriptive statistic across 1,000 bootstrapped replications in which futures are assigned to the P1, P2, and P3 portfolios randomly. P = percentiles of the empirical distributions. The reported means, volatilities (standard deviations), minimums, maximums, and Sharpe ratios are annualized.

risk-adjustment is introduced. A one-factor CAPM correction and the Fama and French (1993) three-factor model (not reported due to space restrictions) showed that risk-adjusted momentum returns were positive, but smaller, and significantly different to zero for 6- and 12-month periods. Therefore, the traditional tests can only partially explain momentum strategy returns. Furthermore, we have randomly simulated the momentum return average 1,000 times in order to obtain the distributional properties of this strategy. Results are very positive for 6- and 12-month periods as the mean and Sharpe ratios are above the 99.5 percentile of the empirical distribution. This result adds more evidence for considering momentum returns as abnormally high.

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NOTES

1. See, for example, Fama and French (1996), and Shen et al. (2007).
2. The EURO STOXX 50 and the Eurodollar futures contract time-series have been completed using the spot prices in the periods March 1991 to December 1998 and March 1991 to April 1998, respectively.

3. Significant positive returns are also obtained for the following pairs of F/H months: 6/3, 12/3, and 12/6.

4. The statistic is computed as the difference between both averages divided by the square root of the sum of the squared standard errors. The statistic has a standard normal distribution (under the null hypothesis of equality of means).

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ORDER PLACEMENT STRATEGIES IN DIFFERENT MARKET STRUCTURES
A Primer

Giovanni Petrella

ABSTRACT

This chapter studies how the optimal trading strategy differs across market structures. An important component of the order placement strategy is the choice between limit orders and market orders. Our analysis has several specific implications for trading strategies in continuous order-driven markets and call auctions. First, in continuous order-driven markets, high volatility days, or high volatility stocks make it convenient to use limit orders. Second, in continuous order-driven markets, relatively patient (eager) traders place limit (market) orders. Third, in call auctions, executed orders receive price improvement. Fourth, in call auctions, traders are more aggressive since they will not pay the aggressive price, but they will benefit from it in terms of higher probability of execution.

INTRODUCTION

The basic choices that a trader has to make refers to the type (i.e., to trade via limit orders, market orders, or a combination of both), size, and timing of the orders that he or she is going to use to trade. This set of choices is

called order placement strategy. In this chapter, we study how the optimal trader's order placement strategy differs across market structures.

Markets use trading rules to arrange trades. As Harris (2003) points out, order precedence rules (OPRs) serve to match buyers and sellers, and trade pricing rules (TPRs) set the execution price. OPRs rank all buy and sell orders in order of increasing precedence and determine who will trade. Most markets use the price priority rule as primary OPR and the time precedence rule as secondary OPR. The trade pricing rules (TPRs) depend on the type of market. Call auctions use the uniform pricing rule and all trades take place at the same market clearing price. By contrast, continuous order-driven markets use the discriminatory pricing rule and trades take place at different prices. Trading strategies that are successful in one market may work poorly in a market with different trading rules. This implies that traders need to design their trading strategies conditioned upon the rules of the market where they trade. In this chapter we present several implications for trading strategies developed on the basis of the trading rules that govern continuous order-driven markets and call auctions.

COSTS AND BENEFITS OF LIMIT ORDER TRADING

The order placement strategy depends on the relative merits and costs of limit orders and market orders (Harris, 1998). Let us first consider the costs and benefits from placing limit orders.

Limit order traders bear two types of risks and costs (Handa and Schwartz, 1996). First, the risk of adverse informational change is known as ex-post regret or winner's curse. This risk materializes when the market price moves against the limit order trader. Bearish news may cause the price of the stock to fall and the trader's buy limit order to execute or, equivalently, bullish news may cause the price of the stock to rise and the trader's sell limit order to execute. In both cases the trader will regret the execution. Second, the risk of limit order not executing (i.e., nonexecution risk) is a potential cost for limit order traders. This risk also depends on the price dynamics. Bullish news may cause the price of the stock to rise and the trader's buy limit order not to execute. Bearish news may cause the price of the stock to fall and the trader's sell limit order not to execute. From this discussion it seems that the limit order trader faces a situation like "Heads you win . . . tails I lose," since

he or she gets the execution but regrets it or he or she correctly forecasts the price movement but does not get the execution.

Therefore, why should a trader place a limit order? Let us consider the benefits associated with limit order trading. The main advantage of using limit orders is the better price that results from limit order execution. Buyers who submit limit orders hope to buy at the bid. If they had submitted a buy market order instead, they would have paid the ask price (which is strictly higher than the bid). Sellers who submit limit orders hope to sell at the ask price. If they had submitted a sell market order instead, they would have received the bid price (which is strictly lower than the ask price). However, limit order traders do not always realize their expectations. Limit order traders receive better prices only if their order actually trades. If the market moves away from their limit price, they may never trade. If they still want to trade, they will have to "chase the price" by raising their bid or lowering their offer. For example, if the market price goes up and a buy limit order is not executed, the trader will have to raise the limit order's bid or to use a market order. This would make the final purchase price actually worse than the price that the trader would have obtained had he or she used market orders at the time of the first limit order submission.

Limit order execution depends on price dynamics as well and, specifically, limit orders get executed when a liquidity event occurs (Anolli and Petrella, 2007). A liquidity event is the arrival of a trader on the other side of the market who is buying liquidity (and is not an informed trader). In other words, the trader posted a buy limit order and an impatient seller arrived or the trader posted a sell limit order and an impatient buyer arrived. Alternatively, one can look at the same event as "mean reversion" in the pricing process: the trader posted a buy limit order and the price first went down and then up or the trader posted a sell limit order and the price first went up and then down. Based on this result, if we reconsider the question "Why should a trader place a limit order?", the answer might be stated in an alternative way: because the trader expects that sufficient mean reversion would offset the costs that might result from an informational change. This implies that the gain from limit order trading depends on the intraday volatility level. Mean reversion is usually associated with accentuated intraday transitory volatility. To measure the extent of this characteristic it is necessary to estimate the stock return autocorrelation (or serial correlation), that is the correlation of the return of stock i at time

t with the return of stock i at time $t - 1$. Positive autocorrelation means that positive returns tend to be followed by positive returns and negative returns tend to be followed by negative returns (i.e., neighboring returns tend to have the same sign). Negative autocorrelation means that positive returns tend to be followed by negative returns and negative returns tend to be followed by positive returns (i.e., neighboring returns tend to have different signs). Negative short-run serial correlation is evidence of accentuated intraday mean reversion and creates ideal market conditions to submit limit orders (since the risk of nonexecution drops). In fact, intraday volatility is a natural property of order-driven markets (Handa, Schwartz, and Tiwari, 1998). Without intraday volatility, traders would not find profitable to submit limit orders.

The cost-benefit ratio of trading via limit orders depends on the type of volatility that the market exhibits (Foucault, 1999). Stock return volatility can either be permanent or transitory. Permanent volatility refers to the change in price motivated by the arrival of new information. A new piece of information makes the change in the stock value "permanent" and is known as efficient volatility because if the market is informationally efficient, the price must reflect the information as soon as it is available. This is the type of volatility that limit order traders would like to avoid. By contrast, transitory volatility refers to price movements that will be quickly reverted. Transitory volatility is generated by traders demanding liquidity and the price bouncing back and forth between bid and ask quotes which is also called inefficient volatility since such price movements do not improve to the price discovery process. This is the volatility that limit order traders would like to find. Trading by liquidity traders creates transitory volatility and trading by momentum traders reinforces it. By contrast, trading by informed traders creates permanent volatility since they move the price to the new equilibrium level.

TRADING IN A CONTINUOUS ORDER-DRIVEN MARKET

Trading in a limit order book takes place when a standing limit order (i.e., a limit order waiting for execution) matches a market order or a marketable limit order from the opposite side of the market. Any trader needs to choose whether to place a limit order or to submit a market order.

Additionally, if the trader uses a limit order, he also needs to set the limit price. The decision whether to submit a market or a limit order in a continuous order-driven market is made with respect to the gains from trading and the probability of limit order execution (Horrigan and Wald, 2005). Limit order trading involves the risk of nonexecution but also offers the promise of lower execution costs (i.e., superior returns). If executed, a buy (sell) limit order would pay (receive) a lower (higher) price. However, limit order execution is uncertain, whereas a market order would be executed with certainty. The certainty of market order execution comes with increased transaction costs: a buy (sell) market order would pay (receive) a higher (lower) price. A trader chooses between limit and market orders based on the expected pay-offs of each trading strategy. A trading strategy based on market orders consumes liquidity and pays the bid-ask spread, whereas one based on limit orders provides liquidity and earns the bid-ask spread. The trade price associated with a limit order strategy is superior to that associated with a market order strategy. In fact, limit orders—provided that they get execution—buy at the bid and sell at the ask price, whereas market orders buy at the ask and sell at the bid.

More formally, the pay-off of a trading strategy depends on the trader's reservation price or target price (rp), the trade execution price (tp), and the probability of order execution (p). Given that the execution is certain, the expected gain for a market order strategy ($E[\pi_{MO}]$) is

$$E\left[\pi_{MO}\right] = \begin{cases} \left(rp - tp\right) & \text{if} \quad \textit{buy order} \\ \left(tp - rp\right) & \text{if} \quad \textit{sell order} \end{cases} \qquad (6.1)$$

Since market orders execute against the best quotes on the opposite side of the market, the previous equation becomes

$$E\left[\pi_{LO}\right] = \begin{cases} p\left(rp - b\right) & \text{if} \quad \textit{buy order} \\ p\left(a - rp\right) & \text{if} \quad \textit{sell order} \end{cases} \qquad (6.2)$$

where a indicates the best ask quote and b the best bid quote.

For the limit order strategy, the pay-off is computed as for the market order route, with two important differences. First, to compute the *expected* gain it is necessary to take into account the probability of limit order execution.

Second, the execution price associated with a limit order strategy is strictly better than that associated with the market order strategy. The expected gain for a limit order strategy ($E[\pi_{LO}]$) is

$$E[\pi_{LO}] = \begin{cases} p(rp - b) & if \quad buy\ order \\ p(a - rp) & if \quad sell\ order \end{cases} \tag{6.3}$$

The break-even conditions for buy and sell orders between market order and limit order strategies can be stated as follows

$$(rp - a) = p(rp - b)\ if \quad buy\ order$$
$$(b - rp) = p(a - rp)\ if \quad sell\ order \tag{6.4}$$

Based on Equation 6.4—which in turn is based on Equation 6.1, Equation 6.2, and Equation 6.3—it is possible to derive a break-even probability as the probability value that equates the expected gains associated with limit order placement and market order submission. The break-even probability (p_{BE}) for a buy order is

$$p_{BE} = \frac{rp - a}{rp - b} = \frac{rp - b - s}{rp - b} = 1 - \frac{s}{rp - b} \tag{6.5}$$

where *s* indicates the bid-ask spread.

Equation 6.5 can be used to decide the best trading strategy by comparing the break-even probability of limit order execution with the actual probability of limit order execution. If the break-even probability is higher than the actual, it is preferable to submit a market order, otherwise a limit order would be preferable. Equation 6.5 also implies that the higher the reservation price is, the higher the break-even probability, and the more appropriate is to place a market order. In fact, as the reservation price increases, the differential gain between limit order and market order vanishes. Additionally, Equation 6.5 implies that the higher is the bid-ask spread, the lower is the break-even probability, and the less suitable is to use a market order since it would imply a largely inferior execution price with respect to a limit order strategy.

The probability of limit order execution strongly affects the expected gain from limit order trading and, consequently, the choice between limit and market orders. Five factors affect the probability of limit order execution (Hollifield, Miller, and Sandas, 2004): the aggressiveness of the limit

price, the depth of the book, the rate of market orders, the duration of the order, and the volatility of stock returns. First, for buy orders, the higher the limit price, the higher the probability of execution; for sell orders, the lower the limit price, the higher the probability of execution. Second, the larger the size of depth on the buy (sell) side, the lower the probability of execution for a buy (sell) limit order. Third, the larger the arrival rate of a market order on the opposite side of the market, the higher the probability of execution for a limit order. Fourth, the longer the duration of the limit order, the higher the probability of execution. Fifth, the larger the price volatility, the higher the probability of execution for a limit order, which does not imply that order execution will be profitable; it simply implies that higher volatility entails higher probability of execution. Execution is profitable for a limit order trader if the volatility that triggered the limit order execution is temporary. Execution is unprofitable for a limit order trader if the volatility that triggered the limit order execution is permanent.

Three implications arise from the previous discussion. First, high volatility days or high volatility stocks make convenient to use limit orders. Traders might even place limit orders on both sides of the market, acting as market makers, to benefit from accentuated intraday volatility (Petrella, 2006). Second, relatively patient traders place limit orders. This strategy is usually called passive trading strategy (PTS). Large investors may prefer PTS because this strategy does not cause market prices to change (due to market impact) as the orders are naturally absorbed by the market. Third, relatively eager traders place market orders. In a dynamic setting, a trader might define an order placement strategy where he first uses limit orders (as a patient trader) and then switches to market orders (that is, he becomes impatient) to trade the quantity associated with unexecuted limit orders.

TRADING IN A CALL AUCTION

In a call auction, multiple orders are batched together periodically for a simultaneous execution (Economides and Schwartz, 1995). At the time of the call, a market clearing price that maximizes the tradable quantity is determined and applied to execute all matchable orders. In a continuous order-driven market, trades are made whenever matchable buy and sell orders happen to cross. By contrast, in a call auction, trades are made at specific points in time when the market clearings are held (e.g., at the open, at the close, and/or at specific times during the trading day).

Call auctions differ from continuous order-driven markets along three dimensions. First, in terms of immediacy, waiting time (execution speed) is lower (higher) in continuous markets. Second, in terms of price discovery, prices in call markets are better than in continuous markets. Prices are highly volatile in continuous markets because of news (efficient volatility) and order imbalance (inefficient volatility). Traders get their orders executed depending on the current market conditions at the time of the submission. By contrast, in a call auction, the terms of the trade depends on the cumulative market conditions at the end of the preopening phase. This implies that a transitory order imbalance might be easily wiped out in a call auction by orders arriving from the opposite side of the market and thus reducing inefficient volatility (i.e., temporary price swings). Third, in terms of trading volume, volume is higher in continuous markets. Some traders that do not get execution in a call market, may execute their trades in a continuous market (with zero surplus) if, on the opposite side of the market, there are impatient traders demanding liquidity. In short, continuous markets sacrifice surplus (i.e., expected profits) for immediacy, whereas call auctions sacrifice immediacy for a better price discovery process.

Trading in a call auction is only apparently equivalent to trading in a continuous market. Orders entered in a call auction are executed according to the standard price priority rule followed by the time priority rule, just as in continuous order-driven markets. However, limit and market orders are handled differently in call and continuous trading and, consequently, they should be submitted differently.

The operation of a call auction has two main implications for the design of trading strategies. First, executed orders receive price improvement in a call auction (Schwartz, Francioni, and Weber, 2006). In fact, there is no bid-ask spread in a call auction because all executed orders clear at the same price. Almost all executed orders receive price improvement (or positive surplus or positive expected profits). Precisely, buy orders priced above the single clearing price and sell orders priced below it receive price improvement. Only orders priced exactly at the clearing price do not receive price improvement. Second, traders are more aggressive in a call auction. In a continuous market, limit orders provide immediacy and set the prices, whereas market orders demand immediacy and accept limit orders prices. The limit price affects the probability of execution and sets the price. In a call market, all participants wait until the market will be "called" and all orders executed simultaneously. Both limit order and market order traders

supply liquidity to each other. The market clearing price will be determined by the equilibrium between the overall demand and the overall supply. The limit price affects the probability of execution, but it does not set the price (although it does affect the market clearing price). Precisely, the impact of an order on the clearing price depends on the size of the order with respect to the rest of the market. If such order is small in size, it will not affect the clearing price. The previous discussion implies that, in a call auction, a trader has a strong incentive to place an aggressively priced order since he will not pay the aggressive price for the stock, because the clearing price will be set by the overall demand and supply, but he will benefit from such a price that will be used to set the orders that will be executed in the call auction according to the price priority rule.

CONCLUSION

In this chapter, we study how the optimal trader's strategy differs across market structures. The choice between limit orders and market orders is an important component of the order placement strategy. Limit orders supply liquidity to the markets because they provide other traders an opportunity to trade at specified conditions (i.e., the limit price). By placing a limit order, a trader enters in a position that is comparable to a short option position. A buy limit order, e.g., is equal to a short position in an American-style put option as the trader extends to anyone in the market the right to sell a certain number of shares (equal to the size of the order) at a certain price (equal to the limit price of the order). By contrast, market orders demand liquidity because they consume the liquidity offered by limit orders. The choice between limit orders and market orders depends on the gains from trading and the probability of execution.

Our analysis highlights several implications for trading strategies in continuous order-driven markets and call auctions. In a continuous order-driven market, the gains from trading by limit orders depend on the size of the bid-ask spread. The larger is the bid-ask spread, the larger is the benefit for a limit order trader, if the limit order executes. In a call auction, there is no bid-ask spread and almost all executed orders receive price improvement.

As for the probability of execution, in a continuous order-driven market, the probability of limit order execution depends on the limit price and market conditions. A more aggressive price increases the probability of

execution, but it lowers the benefit of limit order trading. As for the market conditions, if prices are moving to a new level (permanent volatility), the trader should use a market order and settle for the current price; whereas, if prices are fluctuating around and will revert back to a previous level (transitory volatility), the trader should be patient and use a limit order. In a call auction, limit prices determine the precedence and (may) affect the market clearing price, but they are not execution prices. Consequently, limit order traders are more aggressive in call auctions since they will not pay the aggressive price, but they will benefit from it in terms of higher probability of execution.

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TECHNICAL TRADING

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PROFITABILITY OF TECHNICAL TRADING RULES IN AN EMERGING MARKET

Dimitris Kenourgios and Spyros Papathanasiou

ABSTRACT

This chapter investigates the profitability of technical trading rules in the Athens Stock Exchange (ASE), utilizing the FTSE/ASE 20 index during the period 1995 to 2008. We focus on a less developed and efficient stock market, given the existing scarcity of research in such markets. The technical rules that will be explored are simple moving averages. We compare technical trading strategies in the spirit of Brock, Lakonishok, and LeBaron (1992), employing traditional t test and bootstrap methodology under the generalized autoregressive conditional heteroskedasticity model. The results provide strong evidence on the profitability of the technical trading rules against the "buy and hold" strategy and contradict the efficient market hypothesis.

INTRODUCTION

This chapter explores the profitability of simple technical rules in the Athens Exchange Market (ASE) and particularly for the FTSE/ASE 20 index. The FTSE/ASE 20 is the most important index of the ASE and represents the 20 companies with the largest capitalization. The technical trading rules that we use to evaluate the profitability of technical analysis against the buy and hold strategy (benchmark) are variations of the simple moving average rule.

Technical analysis forecasts the future direction of prices through the study of past market data, primarily price, and volume. In its simplest form, technical analysis considers only the actual price and volume behavior of the market. Moving averages help traders to track the trends of financial assets by smoothing out the day-to-day price fluctuations, or noise. Although the majority of the professional traders and investors use technical analysis, most academics, until recently, had not recognized the validity of these methods.

Technical anomalies are observed in most developed and developing markets, leading traders and investors to earn significant abnormal returns. This chapter investigates these anomalies which appear to be in contrast with the efficient market hypothesis (EMH). A financial market can be considered as efficient if prices fully reflect all available information and no profit opportunities are left unexploited (Fama, 1965, 1970; Fama and French, 1988). The agents form their expectations rationally and rapidly arbitrage away any deviations of the expected returns consistent with supernormal profits. Therefore, it is the EMH and the random walk theory versus practice.

The methodology that is employed for the analysis of the data is the traditional t test, which has been used in many prior studies for the investigation of technical anomalies (e.g., Brown and Jennings, 1989; Neftci, 1991; Gençay, 1998). In addition, we compare the t test results with those obtained by bootstrap methodology. Bootstrapping, introduced by Efron (1979), is a method for estimating properties of an estimator (such as its variance) by measuring those properties when sampling from an approximating distribution. One standard choice for an approximating distribution is the empirical distribution of the observed data. In the case where a set of observations can be assumed to be from an independent and identically

distributed population, this can be implemented by constructing a number of resamples of the observed dataset (and of equal size to the observed dataset), each of which is obtained by random sampling with replacement from the original dataset. Following bootstrap methodology, we use the returns generated from the pseudo ASE series and we apply the trading rules to the series. Therefore, comparisons are then made between returns from these simulated series and the original ASE series.

Among the international studies examining the technical anomalies, Brock, Lakonishok, and LeBaron (1992), hereafter BLL (1992), investigate two popular trading rules (moving average and trading range break rule), utilizing the Dow Jones Index from 1897 to 1986. Overall, their results provide strong support for the technical strategies. Kwon and Kish (2002) provide an empirical analysis on technical trading rules (the simple moving average, the momentum, and trading volume), utilizing the NYSE value-weighted index over the period 1962 to 1996. Their results indicate that the technical trading rules can capture profit opportunities over a buy-hold strategy. In addition, Wong, Manzur, and Chew (2003) examine the role of technical analysis in signaling the timing of stock market entry and exit for the Singapore stock market. They test the performance of moving average and the relative strength index and find that the applications of technical indicators provide substantial profits. Further, Atmeh and Dobbs (2006) investigate the performance of various moving average rules in the Jordanian stock market. Their results show that technical trading rules can help to predict market movements, and there is some evidence that (short) rules may be profitable after allowing for transactions costs.

The research on technical anomalies for the Athens Stock Exchange is still very limited. Vasiliou, Eriotis, and Papathanasiou (2008a) examine the performance of various types of technical trading rules in the Athens Stock Exchange, during the period 1995 to 2005. In particular, this study examines the predictability of daily returns using various moving averages rules for the Athens General Index. Their results provide strong support for the examined technical strategies. Vasiliou, Eriotis, and Papathanasiou (2008b) apply technical analysis methodology into the behavior theory for the large capitalization firms of the ASE from 1995 to 2005. Using standard and more complicated tests, they provide evidence of a strong increase in trading rules performance over time.

This study is significant for three reasons. First, it focuses on a less developed and efficient stock market, given the existing paucity of research in such markets. Second, in contrast to prior relevant studies, it examines the profitability of technical trading rules after considering transaction costs imposed to the participants in the ASE. Finally, traders would benefit from this research, as they will find that these technical rules work in the ASE and are definitely profitable, since they have been tested with statistical and more advanced econometric methods.

The structure of this chapter is organized as follows: The second section of this chapter analyzes methodological issues. The third section presents the data and the empirical findings of the research. The final section contains the concluding remarks.

METHODOLOGY

In order to evaluate the performance of simple moving averages, we compare the returns given by the buy signals of the moving average with the returns of the buy and hold strategy. In addition, we compare the returns given by the buy signals of the moving average minus the returns of the sell signals of the moving average with the returns of the buy and hold position. We then calculate the returns after transaction costs. All transactions assume commission as entry and exit fees (0.2 percent of the investing capital).

First, we examine whether moving averages produce better results than the buy and hold strategy using the standard t test. Moving averages give buy signal when the short-term moving average crossover the long-term one. On the other side, we have a sell signal when the long-term moving average crossover the short-term one. Historically, moving average crossovers tend to lag the current market action.

We use t test in order to assess if the means of two data groups are statistically different from each other in order to compare these means. We calculate the t statistic using the following formulas:

$$\frac{\mu_{buys(sells)} - \mu_{buy\&hold}}{\sqrt{\left(\dfrac{\sigma^2}{N_{observ.}} + \dfrac{\sigma^2}{N_{buys(sells)}}\right)}} \tag{7.1}$$

$$\frac{\mu_{buys} - \mu_{sells}}{\sqrt{(\frac{\sigma^2}{N_{buys}} + \frac{\sigma^2}{N_{sells}})}} \tag{7.2}$$

where σ^2 is the square root of the standard deviation of the returns, μ is the mean return for the buys, sells, and buy and hold position, and N is the number of signals for the buys, sells, and observations.

Using t tests, we compare the mean returns of the unconditional buy methodology with the returns of the buy signals given by the moving averages and the returns of the unconditional buy methodology with the returns of the buy signals minus the returns of the sell signals given by the moving averages. The results provided by the t test will help to either accept the null hypothesis (there is no actual difference between mean returns) or reject it (there is an actual difference between the mean returns).

It is well known that the results obtained by t test assume independent, stationary, and asymptotically normal distributions. However, it is quite common that financial time series exhibit non-normality based on excessive skewness, kurtosis, and heteroskedasticity. Following BLL (1992), we overcome these statistical problems adopting the bootstrap technique. Bootstrap is a computer-based resampling procedure introduced by Efron (1979), which has been discussed in the statistics and econometrics literature over the past 20 years (e.g., Efron, 1987; Freedman and Peters, 1984a, 1984b; Veall, 1992). This method requires no analytical calculations and the procedure uses only the original data for resampling to access the unobservable sampling distribution and to provide a measure of sampling variability, bias, and confidence intervals. Efron and Tibshirani (1986) propose that the use of the bootstrap enlarges the type of statistical problem that can be analyzed, reduces the assumptions required to validate the analyses, and eliminates the tedious theoretical calculations associated with the assessment of accuracy.

The idea behind the bootstrap is to use resampling to estimate an empirical distribution for the statistic. The procedure of the bootstrap methodology is the following: First, we create Z bootstrap samples, each consisting of N observations by sampling with replacement from the original return series. Second, we calculate the corresponding price series for each bootstrap sample, apply the moving average rule to each of the Z artificial price-series and calculate the performance statistic of interest

for each of the pseudo price series. Finally, we determine the p value by calculating the number of times the statistic from the pseudo series exceed the statistic from the original price series. In order to use the bootstrap method, a data generating process for market prices or returns must be specified a priori. The bootstrap method can be used to generate many different return series by sampling with replacement from the original return series. The bootstrap samples created are pseudo return-series that retain all the distributional properties of the original series, but are purged of any serial dependence.

Financial time series usually exhibit a characteristic known as volatility clustering, in which large changes tend to follow large changes, and small changes tend to follow small changes. In either case, the changes from one period to the next are typically of unpredictable sign. Volatility clustering, or persistence, suggests a time-series model in which successive disturbances, although uncorrelated, are nonetheless serially dependent.

To account for the phenomenon of volatility clustering, which is very common in financial time series, the model we use is the generalized autoregressive conditional heteroskedasticity, or GARCH (1,1), model, proposed initially by Engle (1982) and further developed by Bollerslev (1986). The specification of the GARCH (1,1) model is the following:

$$r_t = \gamma + \delta r_{t-1} + \varepsilon_t$$
$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{7.3}$$

where r is the return of the stock index, σ^2 is the variance, the residuals ε_t are conditionally normally distributed with zero mean and conditional variance (σ^2), and the standardized residuals are independent and identically distributed N(0,1). The variance equation is a function of three terms: the mean ω, news about volatility from the previous period, measured as the lag of the squared residual from the mean ε_{t-1}^2 equation (α is the ARCH term), and last period's forecast variance σ_{t-1}^2 (β is the GARCH term). The sum of ARCH and GARCH coefficients ($\alpha + \beta$) indicates the degree of persistence in volatility. Values of ($\alpha + \beta$) close to unity imply that the persistence in volatility is high.

In order to use bootstrap under GARCH (1,1), we first estimate the GARCH (1,1) by using maximum likelihood and apply the bootstrap method on the standardized residuals. Then produce GARCH series by using the estimated parameters and the crumbled residuals. In this chapter,

each of the simulations is based on 500 replications of the null model, which should provide a good approximation of the return distribution under the null model.

To test the significance of the trading rule excess returns, the following hypothesis can be stated:

$$H_0 : XR \leq \overline{XR}^*$$
$$H_1 : XR \succ \overline{XR}^*$$

(7.4)

Under the null hypothesis (H_0), the trading rule excess return (XR) calculated from the original series is less than or equal to the average trading rule return for the pseudo data samples ($\overline{X}R^*$). The p values from the bootstrap procedure are then used to determine whether the trading rule excess returns are significantly greater than the average trading rule return given that the true data-generating process is GARCH (1,1).

DATA AND EMPIRICAL RESULTS

In this study, we use daily closing prices of the FTSE/ASE 20 index from 1/1/1995 to 31/12/2008. The database used is composed of 3,249 observations. The FTSE/ASE 20 index is one of the most famous indexes of the ASE and includes the 20 companies with the largest capitalization. The requirements for the firms to participate in this index are the capitalization, marketability, and the free-float. The index of the Athens Stock Exchange was designed with the cooperation of the London Stock Exchange and FTSE International Limited.

We evaluate the performance of the following moving average rules against the buy and hold strategy: (1,9), (1,15), (1,30), (1,60), (1,90), (1,120), and (1,150). The first number in each pair indicates the days in the short period and the second number shows the days in the long period.

Standard Statistical Results

Table 7.1 reports some summary descriptive statistics for the daily returns of the FTSE/ASE 20 index. We calculate the returns as log differences of the FTSE/ASE 20 level. We observe that the returns exhibit excessive (lepto) kurtosis and non-normality.

Table 7.1 Descriptive Statistics

Num	3,249
Maximum	0.0877
Minimum	−0.0973
Mean	0.000531183
Median	0.000174311
Range	0.1922
Standard Deviation	0.0178
Skewness	0.0759
Kurtosis	6.7123
JB statistic	0.000151223
JB p value	0.0000
Buy-hold mean return	0.00020439
	(after fees)

The JB statistic is Jarque and Bera's (1987) test for normality, being distributed as x^2 with 2 degrees of freedom under the null of normal distribution.

Table 7.2 presents the results using simple moving average trading strategies. The rules differ by the length of the short and long period. For example, (1,60) indicates that the short period is one day and the long period is 60 days. We report the number of buy "N(Buy)" and sell "N(Sell)" signals generated during the period in columns 3 and 4. The mean buy and sell daily returns are reported separately in columns 5 and 6, while column 7 lists the differences between the mean buy and sell daily returns ("Buy/Sell"). These tests are computed using the BLL (1992) method.

We observe in column 7 that the buy/sell differences are significantly positive for all rules. This leads to the rejection of the null hypothesis (equality with zero). The mean buy/sell returns are all positive with an average daily return of 0.0987 percent. This is 24.675 percent on a year basis (250 trading days × 0.0987 percent).

The mean buy returns are all positive with an average daily return of 0.0669 percent. This is 16.725 percent on a year basis (250 trading days × 0.0669 percent). The t statistics reject the null hypothesis since the mean return of the buy and hold position is 0.020439 percent (see Table 7.1). Six of the seven tests reject the null hypothesis that the returns equal the unconditional returns at the 5 percent significance level using a two-tailed test. About the sells, the daily average return is 0.00318 percent. This is 7.95 percent on a year basis. All the tests also reject the null hypothesis at the 5 percent significance level.

Table 7.2 Standard Results for the Simple Moving Average Rules

Period (1)	Test (2)	N(Buy) (Long Strategy) (3)	N(Sell) (Short Strategy) (4)	Buy (Long Strategy) (5)	Sell (Short Strategy) (6)	Buy/Sell (7)
1/1/1995 to 12/31/2008	(1,9)	336	336	0.000938 (2.1504)	-0.000275 (-4.3182)	0.001213 (3.5765)
	(1,15)	238	238	0.000911 (2.0271)	-0.000240 (-4.1216)	0.001151 (3.3562)
	(1,30)	140	139	0.000856 (2.5425)	-0.001084 (-3.04105)	0.00194 (5.31961)
	(1,60)	97	97	0.000762 (2.33062)	-0.000648 (-3.00431)	0.00141 (5.20577)
	(1,90)	67	68	0.000625 (2.01446)	-0.000383 (-2.48048)	0.001008 (3.88020)
	(1,120)	58	59	0.000577 (1.98212)	-0.00279 (-2.38126)	0.000856 (3.18968)
	(1,150)	44	45	0.000571 (1.95453)	-0.000039 (-2.11723)	0.000010 (3.21245)
	Average			0.000669	0.000318	0.000987

N(Buy) and N(Sell) are the number of buy and sells signals generated by the rule.

In columns 5, 6, and 7, the number in parentheses are standard t statistics, testing the difference between the mean buy return and the unconditional mean return, the mean sell return and the unconditional mean return, and buy/sell and zero, respectively.

The last row reports averages across all seven rules.

The upper (lower) critical values of the t test values are ± 1.96 at 5% level.

If technical analysis does not have any power to forecast price movements, then we should observe that returns on days when the rules emit buy signals do not differ appreciably from returns on days when the rules emit sell signals. In this chapter, we provide evidence that the technical strategies used win the buy and hold strategy (FTSE/ASE 20). Overall, the buy and hold strategy (see Table 7.1) gives 5.10975 percent annual return (0.020439 × 250 days), while the strategy of simple moving averages 24.675 percent.

Bootstrap Results

Following BLL (1992) methodology, we create 500 bootstrap samples, each consisting of 3,249 observations by resampling with replacement the

standardized residuals of the GARCH (1,1) model. Then, we generate GARCH price-series by using the estimated parameters and the crumbled residuals. After that, we apply the moving averages to each of the 500 pseudo price-series. Then, we determine the *p* value by calculating the number of times the statistic from the artificial series exceeds the statistic from the original price series (FTSE/ASE 20 index).

Table 7.3 presents the estimates of the GARCH (1,1) model. Based on the Akaike Information Criterion, the Schwarz Criterion, and Dickey-Fuller and Phillips-Perron unit root tests, we find that the GARCH (1,1) model is well specified.[1] Values of $\alpha + \beta$ close to unity imply that the persistence in volatility is high. In our case, the sum of the ARCH and GARCH coefficients ($\alpha + \beta$) is very close to one indicating that volatility shocks are very persistent.

Table 7.4 displays the results of GARCH (1,1) simulations using simple moving average trading strategies via bootstrapping. We present results for the seven moving average rules that we examine. All the numbers presented in columns 4, 5, and 6 are the fractions of the simulated result which are larger than the results for the original FTSE/ASE 20 index. We report the mean buy and sell returns separately in columns 4 and 5. The results presented in columns 4, 5, and 6 are *p* values. The *p* values from the bootstrap procedure are then used to determine whether the trading rule excess returns (simple moving averages) are significantly greater than the average trading rule return given from original series. The numbers in parentheses in columns 4, 5, and 6 show how many series from 500 replications are greater than the original returns.

Table 7.3 Estimates of GARCH (1,1) Model

γ	δ	ω	α	β
0.00040308	0.18353	0.000434	0.12836	0.86487
(1.7439)	(9.2178)	(5.5613)	(14.4956)	(108.6476)

We estimate the following GARCH (1,1) model:

$r_t = \gamma + \delta r_{t-1} + \varepsilon_t$

$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$

where *r* is the return of the stock index, σ^2 is the variance, the residuals ε_t are conditionally normally distributed with zero mean and conditional variance (σ^2), the standardized residuals are independent and identically distributed N(0,1), α is the ARCH term, and β is the GARCH term.

Estimated on daily returns series of the FTSE/ASE 20 index for the period 1/1/1995 to 12/31/2008.

Numbers in parentheses are t ratios.

Table 7.4 Results of Simulation Tests under GARCH (1,1) Using Bootstrapping (500 replications)

Period (1)	Test (2)	Results (3)	Buy (4)	Sell (5)	Buy/Sell (6)
1/1/1995 to 12/31/08	(1,9)	Fraction > FTSE/ASE 20	0.81	0.20	0.72
			(405)	(99)	(361)
	(1,15)	Fraction > FTSE/ASE 20	0.80	0.21	0.68
			(399)	(107)	(342)
	(1,30)	Fraction > FTSE/ASE 20	0.82	0.24	0.63
			(410)	(119)	(317)
	(1,60)	Fraction > FTSE/ASE 20	0.79	0.20	0.62
			(397)	(102)	(311)
	(1,90)	Fraction > FTSE/ASE 20	0.83	0.19	0.60
			(415)	(95)	(302)
	(1,120)	Fraction > FTSE/ASE 20	0.82	0.26	0.61
			(407)	(129)	(305)
	(1,150)	Fraction > FTSE/ASE 20	0.81	0.23	0.59
			(402)	(115)	(297)
	Average		0.81	0.22	0.63

We create 500 bootstrap samples, each consisting of 3,249 observations by resampling with replacement the standardized residuals of the GARCH (1,1) model.

The numbers presented in columns 4, 5, and 6 are the fractions of the simulated result which are larger than the results for the original FTSE/ASE 20 index.

Results presented in the columns 4, 5, and 6 are p values.

The numbers in parentheses in columns 4, 5, and 6 show how many series from 500 replications are greater than the original returns.

From Table 7.4 (columns 4, 5, and 6), we observe that most of the simulated GARCH (1,1) series are greater than those from the original FTSE/ASE 20 index of ASE series. For example, using the moving average (1,9) rule, buy/sell position (column 6), 361 (from 500) of the simulated GARCH series generate a mean return larger than that from the original FTSE/ASE 20 index, which is 72 percent of the simulations. All the results for buy, sell, and buy/sell positions are highly significant, resulting in the acceptance of the null hypothesis. This means that the trading rule excess return (XR) calculated from the original series is less than or equal to the average trading rule return for the pseudo data samples ($\bar{X}R^*$). Finally, our results are consistent with BLL (1992) and in line with the existing

evidence on the profitability of technical trading strategies in emerging and less developed stock markets.

CONCLUSION

This chapter investigates the profitability of technical trading rules in an emerging market such as the Athens Stock Exchange. Particularly, we use variations of simple moving averages for the FTSE/ASE 20 index, using daily data for the period 1995 to 2008. Following the BLL (1992) methodology, we evaluate the performance of seven moving averages rules (1,9), (1,15), (1,30), (1,60), (1,90), (1,120), and (1,150) against the buy and hold strategy, using both standard tests and bootstrap methodology.

Using t tests, we compare the mean returns of the unconditional buy methodology with the returns of the buy signals given by the moving averages and the returns of the unconditional buy methodology with the returns of the buy signals minus the returns of the sell signals given by the moving averages. In this setup, we test the null hypothesis (there is no actual difference between mean returns) against the alternative (there is an actual difference between the mean returns). Using bootstrap methodology, we compare the returns conditional on buy (or sell) signals from the actual FTSE/ASE 20 data with the returns from simulated comparison series generated by a model from the null hypothesis class being tested. The null model tested is the GARCH (1,1).

About the simple moving averages trading strategies, we find that all the buy/sell differences are positive. Also, all the t tests for the differences are highly significant rejecting the null hypothesis (equality with zero). In addition, the mean buy/sell returns are all positive with a daily return of 0.0987 percent in average (24.675 percent annual return). Overall, the results indicate that making trading decisions based on moving average rules lead to significantly higher returns than the buy and hold strategy, even after transaction costs. In addition, the results show that technical rules produce useful signals and can help to predict market movements. More specific, the profitability of technical strategies such as moving averages on large capitalization stocks is better than the profitability we get by simply following the market (buy and hold). In particular, the buy and hold strategy gives 5.10975 percent annual

return, while simple moving averages 24.675 percent (buy/sell) on an annual basis. Using bootstrapping, the results are quite similar. Most of the simulated GARCH (1,1) series are greater than those from the original FTSE/ASE 20 index of ASE series. Our results are in line with the existing literature on the performance of technical trading rules in emerging and less developed stock markets.

Our findings contradict to the efficient market hypothesis as traders and investors can gain abnormal returns using moving average trading strategies. Furthermore, our results (after transactions costs) are consistent with the simple technical rules having predictive power. Finally, the profitability of the applied technical strategies in this chapter is verified by using econometrical and statistical methods. Our research indicates that the benefits of technical trading strategies, such as the prediction of price movements and the identification of trends and patterns, can be exploited by traders to earn significant returns on the ASE.

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NOTES

1. Results, not presented here, are available upon request.

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TESTING TECHNICAL TRADING RULES AS PORTFOLIO SELECTION STRATEGIES

Vlad Pavlov and Stan Hurn

INTRODUCTION

Technical analysis refers to the practice of using algorithms based solely on current and historical stock returns or prices to generate buy and sell signals. In other words, all information relating to perceived fundamental variables driving stock prices, such as dividend payments, for example, is ignored. As this approach to portfolio selection violates the market efficiency hypothesis even in its weakest form (Jensen, 1978), it is controversial, although it remains in common use by market practitioners.

Brock, Lakonishok, and LeBaron (1992), hereafter BLL (1992), provide a formal statistical framework for evaluating the performance of technical analysis based investing strategies. BLL (1992) applied a number of moving average and trading range rules to the Dow Jones Industrial Average over a very long sample period. They constructed bootstrapped distributions of trading profits generated from a variety of data-generating processes and found that the rules generated profits in excess of what would be expected if the return generating processes followed the assumptions of popular statistical models. The BLL (1992) findings were particularly remarkable because every one of the 26 trading rules they considered was found to be capable of outperforming the buy and hold benchmark. A large number of

subsequent studies have shown similar results (see, inter alia, Levich and Thomas, 1993; Osler and Chang, 1995; Hudson, Dempsey, and Keasey, 1996; Gençay, 1998; Lo, Mamaysky, and Wang, 2000).

In a significant paper, Sullivan, Timmermann, and White (1999) identify a subtle source of data-snooping bias in the BLL (1992) results. They point out that the BLL universe of investment rules itself is an outcome of a prior extensive specification search by the investment community. They apply the "reality check" due to White (2000) that takes into account the uncertainty about the nature of profitable trading rules and the parameters of these rules. They examine nearly 8,000 parameterizations of trading rules using the same data as BLL. Under White's test the in-sample evidence in favor of superior performance of technical trading rules appears much weaker. Importantly, the analysis of an extended sample which includes post 1989 data, not available to BLL, shows no evidence of superior performance. While certain trading rules do outperform the benchmark using the original BLL sample (1897–1986), the rules were not found to be profitable in a further 10 years' out-of-sample data (1987–1996). Moreover, when short-sale constraints and transaction costs were accounted for in the application of the trading rules to contracts on the S&P 500 futures index, no evidence of superior performance could be found.

This chapter proposes to examine the profitability of trading rules on a much larger set of data than a single stock market or currency index. The idea is to apply technical trading rules to individual stocks and then form portfolios based on the signals produced by the rules. In order to avoid the data snooping bias, the entire distribution of returns over all trading rules will be examined rather than trying to pick a particular set of trading rule parameters. A bootstrapping exercise is then undertaken to examine if the distribution of returns to technical rules is consistent with the distribution of returns generated by drawing a portfolio randomly from the universe of stocks (a "darts" portfolio).

The rest of the chapter is structured as follows. The second section of this chapter describes the dataset employed, and the third section deals with various methodological points related to the construction of portfolios based on buy and sell signals generated by moving average rules. The performance of these portfolios is also illustrated. In this chapter's fourth section, the results obtained from implementing this investment strategy are examined in more detail in terms of a bootstrapping exercise. Conclusions are contained in the fifth and final section of this chapter.

DATA

The data are taken from the Centre for Research in Finance (CRIF) database containing monthly observations on prices, returns, dividends and capital reconstructions for all corporate securities listed on the Australian Stock Exchange (ASX). The analysis is performed on monthly returns defined as the sum of the capital gain and dividend yield, taking into account any capital reconstructions.

The sample of returns covers the period from December 1973 to December 2008. As a baseline for comparative purposes, Table 8.1 reports the means and standard deviations of returns for equally weighted stocks in different size cohorts. Returns statistics in Table 8.1 are calculated under two different sets of assumptions about returns during the periods of nontrading. In the first set of statistics, the return for a size cohort in each period is calculated as the average of only the stocks traded during the current month. This effectively means that all nontraded stocks are inferred with the average return based on all traded stocks in the cohort.

In the second approach, the common treatment of missing observations, especially when calculating an index return, namely that of setting the capital gains on a nontraded stock to zero (effectively valuing the stock at the last available market price) is adopted. Return statistics calculated using this assumption are in columns 4 and 5 of Table 8.1.

As expected, inferring missing returns with zeros biases the estimate of the mean return downward (a random stock is expected to provide a positive return). It also implies zero volatility for the periods of nontrading, so the effect on the standard deviation estimates is intuitive. On the other hand estimating the returns based on traded stocks only ignores exits and de-listings which tend to be associated with distress (although stocks can also exit the database due to mergers). For smaller stocks, in particular, an exit from the database is often preceded by a period of low liquidity and depressed returns. It is reasonable to expect that the mean return estimates in the second column are biased upward and provide an upper bound of the estimates of the underlying expected return.

Both sets of mean return and standard deviation estimates are close (within 10 basis points) for stocks up to the 400 to 500 cohort and begin diverging rather rapidly afterward. We conclude that the mean returns estimates become very sensitive to the treatment of missing returns and exits

Table 8.1 Monthly Returns (%) by Size*

Filter	Traded Securities Only		All Listed, Missing return = 0	
CAP	Mean	Standard Deviation	Mean	Standard Deviation
Top 100	1.19	4.97	1.15	4.82
100–200	1.20	4.84	1.18	4.74
200–300	1.07	4.77	1.03	4.63
300–400	0.95	5.08	0.91	4.87
400–500	0.95	5.53	0.87	5.21
500–600	0.94	5.98	0.83	5.46
600–700	1.09	6.65	0.91	6.03
700–800	1.33	7.41	0.99	6.34
800–900	2.66	9.13	1.67	6.84
900–1000	3.54	10.47	1.49	6.53
Top 500				
Equally weighted	1.07	4.75	1.03	4.57
Value weighted	1.12	4.90	0.91	4.44

* Size is defined according to the relative ranking based on the price of the last observed trade.

for very small stocks (with ranks >500). The rest of the analysis in this chapter therefore concentrates on the top 500 stocks.

PORTFOLIO FORMATION

One of the most popular technical trading rules is the moving average or momentum rule.[1] To implement the rule, two moving averages $MA_t(h_1)$ and $MA_t(h_2)$ are constructed using averaging windows with lengths h_1 and h_2. Trading signals are generated by crossovers; the moving average $MA_t(h_1)$ crossing the moving average from $MA_t(h_2)$ below is interpreted as a signal to take a long position in the stock, crossing from above triggers the taking of a short position or the liquidation of a long position. Buy if: $MA_t(h_1) > MA_t(h_2)$, $MA_{t-1}(h_1) < MA_{t-1}(h_2)$. Sell if: $MA_t(h_1) < MA_t(h_2)$; $MA_{t-1}(h_1) > MA_{t-1}(h_2)$.

In the traditional (or momentum) interpretation of the rules $h_1 < h_2$, so that $MA_t(h_1)$ involves a shorter averaging window and a more volatile moving average than $MA_t(h_2)$. When this inequality is reversed ($h_1 < h_2$), the

rule will be referred to as contrarian. In this chapter, two types of moving averages may be used in rule construction:

1. Simple moving average: $MA_t(b) = \dfrac{1}{b} \sum\limits_{j=b-1}^{0} p_{t-j}$;

2. Exponentially weighted moving average: $MA_t(b) = b\, MA_{t-1}(b) + (1-b)p_t$

Rules based on simple averaging appear more common in industry and especially academic practice. The motivation for considering exponentially weighted moving average (EWMA) rules is to allow the averaging parameters to be continuously variable. This makes for dramatically different results as will be demonstrated shortly. Figure 8.1 illustrates the operation of the exponentially weighted momentum trading rule for a selected Australian stock.

Figure 8.1 Moving Average Rules and Signals for Australian Foundation Investment Company Limited (Parameters of the Moving Average are h_s = .3 and h_l = .8; Signals are Reversed for a Corresponding Contrarian Rule)
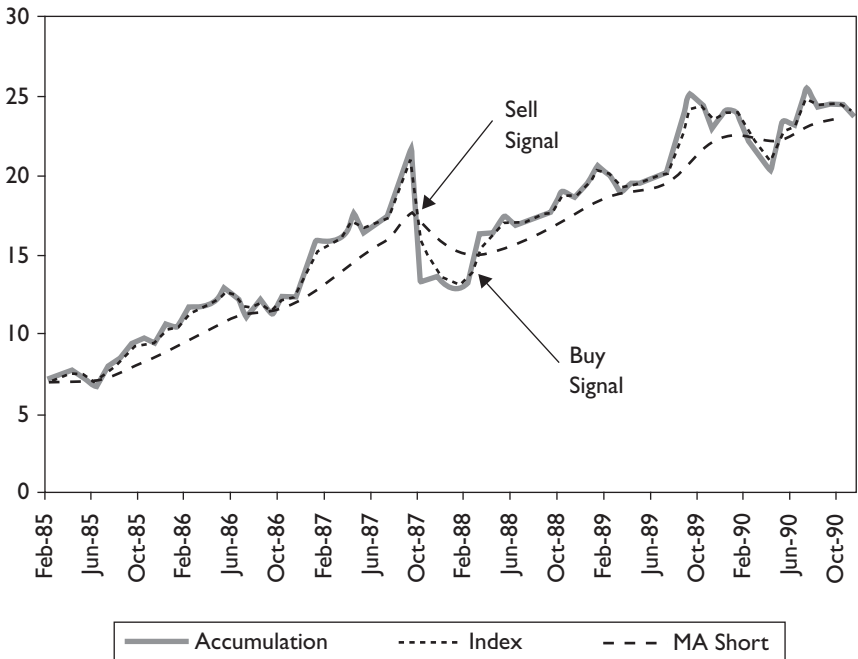
For a fixed combination of parameters momentum portfolios are formed using the following procedure. Trading signals are generated for every month and each stock in the CRIF database over the available sample period. Buy and sell signals are used to form arbitrage (or zero cost) portfolios by purchasing all stocks which generate "buy" signals in a particular month financing this purchase by shorting the stocks for which "sell" signals have been generated. If no buy or sell signals are generated in a particular month the portfolio reverts to a neutral position (zero holdings of all stocks). If $S_{t,i}$ and $B_{t,i}$ are defined as the indicator functions for buy and sell signals respectively (i.e., $S_{t,i} = 1$ if a sell signal is generated for the stock i at time t and zero otherwise) and is the total number of stocks available for investment at time t, then the arbitrage portfolio return is calculated as:

$$R_{t+1} = \frac{\sum_{i=1}^{N_t} B_{t,i} * R_{t+1,i}}{\sum_{i=1}^{N_t} B_{t,i}} - \frac{\sum_{i=1}^{N_t} S_{t,i} * R_{t+1,i}}{\sum_{i=1}^{N_t} S_{t,i}}$$

This arbitrage portfolio is held for one month and then sold, so the portfolio is turned over completely at the end of each month. An information coefficient (IC) is defined as the ratio of the mean return to standard deviation and is a popular performance measure for standalone portfolios.

Two additional criteria are applied to stock selection to weed out thinly traded securities. To be included in the long/short portfolio at time t, the security must have no missing observations over the three years prior to portfolio formation. In addition, it is assumed that investors can anticipate short term de-listings, so that any stocks that exit the database in period $t + 1$ because they have been dropped from the ASX register are not included in the portfolio. Since we concentrate on large stocks, this assumption makes no material difference to the results as exits are relatively rare. The number of securities that pass the liquidity criteria each month ranges between 273 and 411 with the average of 342 securities.

Figure 8.2 illustrates information coefficients using one-month holding returns on the arbitrage portfolio constructed using weighted moving averages for different combinations of h_1 and h_2. It is important to note that no further optimizations have been applied and in particular the same moving average parameters are used for all stocks. For comparison, Figure 8.3

Figure 8.2 Information Coefficients for One-Month Holding Period Returns on the Contrarian (Left Triangle) and Conventional (Right Triangle) Portfolios Constructed Using the EWMA Rules with Parameters h_1 and h_2, Respectively (Sample Period, January 1973–December 2008)
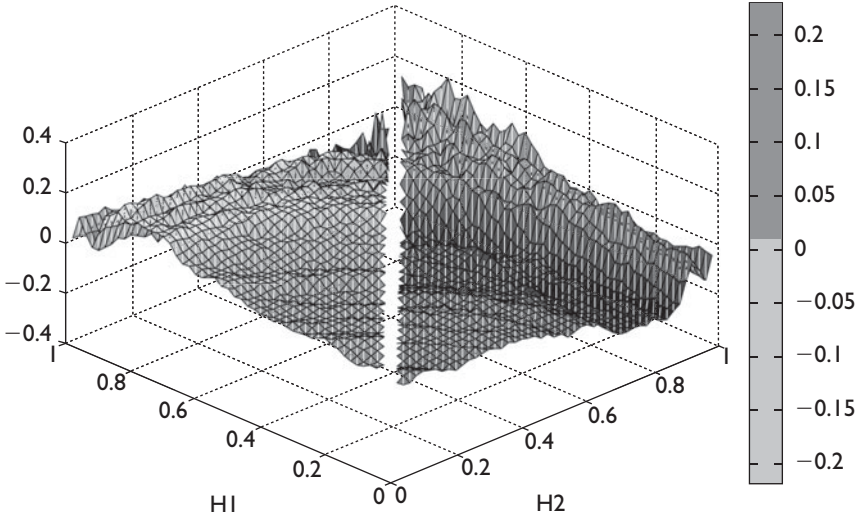
Figure 8.3 Information Coefficients for One-Month Holding Period Returns on the Contrarian (Left Triangle) and Conventional (Right Triangle) Portfolios Constructed Using the Simple MA Rules with Parameters h_1 and h_2, Respectively (Sample Period, January 1973–December 2008)
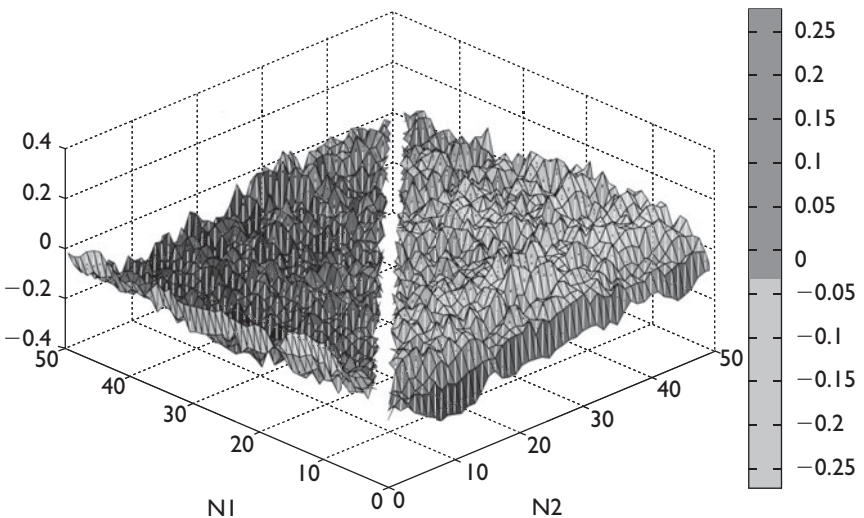
shows the graph of information coefficients for an arbitrage portfolio and the parameters the rule for simple moving averages.

The difference is dramatic; profits from rules constructed using weighted averages display an almost deterministic dependence on parameters. The corresponding graph constructed using simple rules contains much more noise. Another notable difference is that contrarian profits dominate the surface of the ICs constructed using EWMA rules; the IC surface constructed using simple averaging show positive returns to the traditional momentum rule (i.e., long on downside up crossovers). This apparent contradiction is now examined in a little more detail.

In turns out that the resolution to this conundrum is to be found in the provision of a more appropriate comparison between rules based on different types of averaging. In particular, the parameters of simple MA rules may be mapped onto the parameters of weighted MA rules by matching the corresponding return volatilities. Specifically, consider two moving averages: an EWMA with the parameter h and a simple moving average with the averaging window N. For a given window N, pick an EWMA parameter so that the volatility of the weighted average is the same as the volatility of the simple average. Using geometric returns and assuming stationarity in variance this means choosing h to match

$$\text{Var}\left((1-h)\sum_{j=0}^{\infty}h^{j}r_{t-j}\right)=\text{Var}\left(\frac{1}{N}\sum_{j=0}^{N-1}r_{t-j}\right).$$

It can be shown after some manipulation that this means that h has to satisfy the following quadratic equation:

$$\left(1+\frac{1}{N}\right)h^{2}-2h+1-\frac{1}{N}=0.$$

What this quadratic relationship actually means is that the EWMA rules magnify a small area in the southwest corner of the IC surface of the simple returns plotted in Figure 8.3. For example, the simple MA with $N=12$ corresponds to the EWMA $h=0.85$. So the usable EWMA rules effectively correspond to simple MA rules with up to one-year averaging window.

The surface plot of the information coefficients for one-month holding returns on arbitrage portfolios based on simple MA signals for different combinations of volatility matched combinations of h_1 and h_2 is shown on Figure 8.4. It is clear that the underlying relationship is very similar to the one observed for the EWMA rules. The plot also identifies the constrast between the different forms of averaging. In particular, simple averaging lacks resolutions at low values of the averaging parameters and hence for more volatile trading rules. On the other hand, in the Australian dataset, momentum rules appear to produce profits at relatively large values of the smoothing parameters of the long MA. With a fixed grid, the EWMA rules resolve this area relatively poorly.

A more fundamental problem with examining rules at large h values is the very small number of trading signals that they produce. For example, for $h_{1,2} > 0.9$, the average number of signals per period is less than 1, which complicates statistical evaluation of the results. For this reason and also because it appears to us that the contrarian profits that we identify at short averaging horizons have not been covered in the literature, we concentrate on the exponentially weighted moving average rules.

Figure 8.4 Information Coefficients for One-Month Holding Period Returns on the Contrarian (Left Triangle) and Conventional (Right Triangle) Portfolios Constructed Using the Simple MA Rules with Parameters h_1 and h_2. The Axes Have Been Rescaled to Match the Volatility of EWMA Rules (Sample period, January 1973–December 2008)
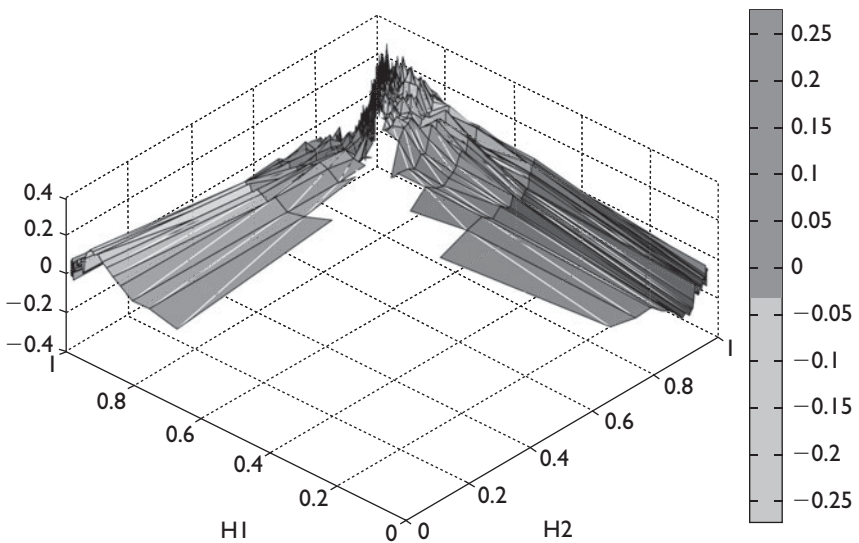
BOOTSTRAP EXPERIMENT

No attempt is made to describe statistical tests of the parameters of the momentum return distributions in this chapter. Instead we conduct a simple bootstrapping exercise in the spirit of one of the classic finance experiments by comparing the distribution of the arbitrage profits from investing in a momentum portfolio with the distribution of profits from an arbitrage (or zero cost) darts portfolio selected randomly from the available securities. The random portfolio is constructed as follows. For each month (t) we note the number of securities included in the long ($N_{L,t}$) and short ($N_{S,t}$) legs of the momentum portfolio. We then select $N_{L,t}$ and $N_{S,t}$ stocks at random from the population of all securities that in period t pass the liquidity criterion (i.e., have an uninterrupted three-year trading history). Just as in the momentum portfolio random securites in each leg are equally weighted. For each combination of h_1 and h_2, we draw 10 such random portfolios conditional on the size of the momentum portfolio for 49,500 random draws in total. We then save the mean and standard deviation of the return for each random portfolio.

Figure 8.5 shows the histograms of the distribution for information coefficients for the combinations of (h_1, h_2) such that $h_2 < h_1$ (i.e., the contrarian interpretation of the rule) and the histogram of the information coefficients for random portfolios. The histogram based on the momentum rule returns can be interpreted as a scaled estimate of the profit distribution for an investor with a uniform prior over the parameters of the momentum rule. While it may have been possible to think of a more fine-tuned prior or refine the prior through a recursive learning algorithm, the objective in this chapter is merely descriptive. We are trying to identify if the sample of securities selected by the full collection of momentum rules is in some sense unusual or differs in a systematic way from a random sample.

The distribution of information coefficients for the momentum rules is clearly bimodal. It also has a considerable overlap with the histogram of information coefficients for random portfolios. The reason for the overlap is very simple. When the smoothing parameters of both moving averages are small ($h < 0.3$), the trading rule generates a very large number of signals. This means that both legs of the momentum portfolio include large numbers of securities, most of the signals pick up noise in

Figure 8.5 Bootstrapped Distribution of Information Coefficients for Darts Portfolios versus the Distribution of Information Coefficients for Contrarian Rules
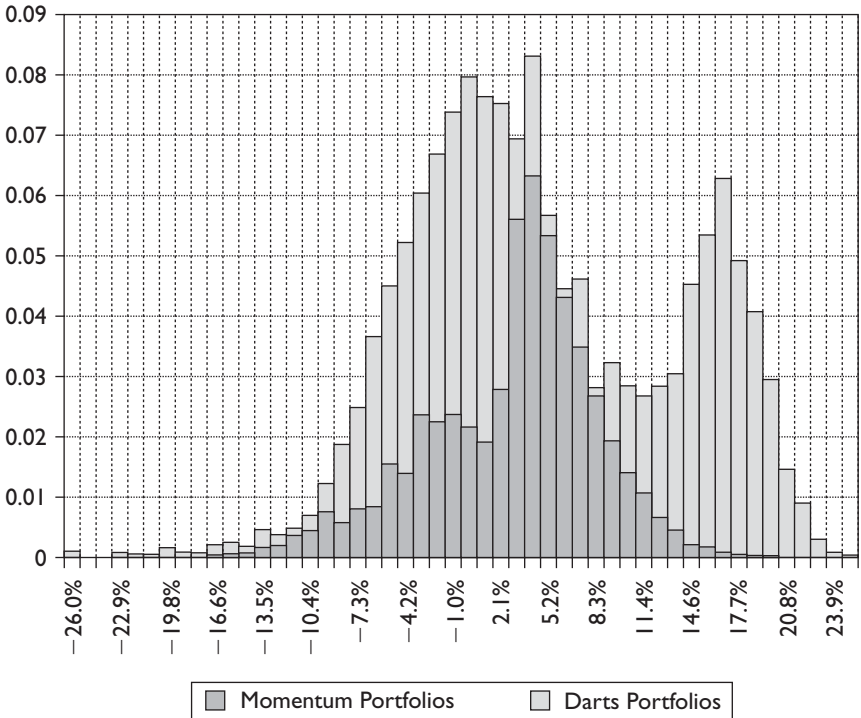
the data and the rules provide very little selectivity. For these parameter combinations, the arbitrage portfolio looks very much like a random selection of securities. It is possible to rule out such combinations either by manipulating the prior or imposing some restrictions on the portfolio turnover, but as discussed previously, our a priori preference is to avoid excessive manipulations of atheoretical parameters to avoid accusations of data snooping.

The larger of the two modes is much more interesting. It clearly lies well outside of the IC distribution for the darts portfolio. The 99 percentile of the darts distribution is 0.12 which compares to 0.16 for the more extreme mode of the momentum distribution (the exact percentile of the empirical darts distribution corresponding to the mode is 0.16 percent). Momentum portfolios could generate an appearance of profits by

creating unusual exposures to systematic movements in stock returns. To check this possibility we evaluted the exposures of the portfolio based on the contrarian rule producing the extreme mode of the IC distribution (the rule with the parameters $h_1 = 0.67$, $h_2 = 0.16$) using the conventional three-factor model. The factors were constructed by first sorting stocks into portfolios based on 40 size cohorts and then using the principal components analysis on the unconditional correlation matrix to extract the components. The justification for this selection of factors is provided in Hurn and Pavlov (2003).

Factor exposures were then evaluated by a series of rolling regressions. To estimate the exposures the arbitrage portfolio is frozen based on buy/sell signals at time t, then the return on this fixed portfolio over three years prior to portfolio formation were regressed on the realizations of the factors. Figure 8.6 shows the time-series of rolling beta estimates. There appears to be no obvious exposures to the factors or extreme observations. The average risk exposures in particualar are not significantly different from zero. It is clear therefore that the profits generated by the momentum portfolios are not due to the trading rules introducing unusual exposures to small or growth stocks.

CONCLUSION

The aggregate distribution of information coefficients of momentum or moving average trading rules across a wide range of parameter combinations with the corresponding distribution of randomly selected portfolios has been compared. The moving average rules used here are appealing because of their analytical simplicity; they are also still among the most popular with technical analysis practitioners. This analysis identified two main points. First, it appears that at least in the Australian data over the period from 1973 to 2008 the returns on the momentum rules are strongly contrarian over a one-month investment horizon. Second, there is an obvious mode of the return distribution which is very difficult to explain by alluding to pure chance selection. On its own, the analysis in this chapter does not immediately lead to any specific trading rules or investment strategies based on moving average crossover rules. Rather, it suggests that at least in some parameter subset these momentum rules appear to pick a systematic factor in returns which is not part of the "usual suspects" (e.g., market growth or size).

Figure 8.6 Rolling Estimates of the Factor Exposures of the Contrarian Rule with $h_1 = 0.67$ and $h_2 = 0.16$

ACKNOWLEDGMENTS

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NOTES

1. This interpretation of "momentum" in technical analysis differs from the academic interpretation of the term which follows from the analysis by Jegadeesh and Titman (1993). In this chapter we will use the term momentum rules as interchangeable with moving average rules.

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DO TECHNICAL TRADING RULES INCREASE THE PROBABILITY OF WINNING? EMPIRICAL EVIDENCE FROM THE FOREIGN EXCHANGE MARKET

Alexandre Repkine

ABSTRACT

In this chapter we test whether technical analysis increases one's chances of beating the foreign exchange market. We apply pattern recognition techniques in order to identify points of market entry based on past history, and consider a range of strategies represented by various combinations of stop-loss and stop-limit orders using eight years of the daily foreign exchange data for the world's 10 major currency pairs. While we are unable to identify a universally winning strategy, our analysis supports the claim that, on average, the application of technical trading rules results in the increased probability of winning.

INTRODUCTION

Technical analysis is commonly understood as a set of rules used to predict the future market movement based on the information on its past history. In this chapter, we test whether two specific technical analysis trading rules can increase the probability of beating the foreign exchange market.

While the subject has received substantial attention in the literature, the focus appears to have been on challenging the weak form of the efficient market hypothesis (EMH), suggesting that all information about the market's past behavior is already incorporated in the current price, to use the former for gaining any excess returns (Fama, 1970). As a recent review of the literature on technical analysis in the foreign exchange markets by Menkhoff and Taylor (2007) argues, technical analysis rules have been enjoying a "widespread and continuous use" even if there is as yet no consensus among academics on its practical value. The generalized stylized fact derived in this review on the basis of the received literature is that technical analysis rules are normally used in conjunction with the fundamental analysis, performing better in the short run and with volatile currencies, but in rather unstable a manner. Unstable performance here is understood in the sense that it is impossible to identify a technical trading rule that would result in consistent excess returns for all currency pairs and time periods. Excess returns are computed after adjustments have been made for the foregone interest rate, the extent of risk, and transaction costs (Menkhoff and Taylor, 2007, Table 4).

In this chapter, we approach the issue of the performance of technical analysis rules by asking ourselves a question: *Does the application of technical trading rules in the foreign exchange market increase the probability of one's beating the market?* We attempt to answer this question by estimating the empirical probabilities of enjoying positive and of suffering negative returns for a large number of trading strategies based on the technical analysis charting patterns and incorporating the fact that traders tend to limit their losses and run their profits by placing stop-loss and stop-limit orders (see, e.g., Bae, Jang, and Park, 2003 on the stop-limit orders; Osler, 2005 on the stop-loss orders). A stop-loss order is specified in terms of the number of points by which the market has to move in the loss-making direction so that the position will be closed at a loss. Alternatively, a stop-limit order would specify at what profit in terms of the market points the position shall be closed. A point is defined as the minimum possible movement of an exchange rate, and

is always normalized to one. For example, suppose the current exchange rate of euro versus U.S. dollar is 1.3200 (i.e., 1 euro buys 1.3200 U.S. dollars). A one-point deviation would result in the exchange rate becoming either 1.3201 or 1.3199. With the stop-loss value equal to 100 and the stop-limit value equal to 300 points, the position will be closed at a loss if the exchange rate at some point in time reaches the level of 1.3100, and profits will be made if the euro appreciates up to the level of 1.3500. We test for a large number of strategies specified in terms of the technical analysis rules used to identify points of entry as well as in terms of specific combinations of stop-loss and stop-limit orders, and find that on average such strategies do result in positive returns, as opposed to the zero returns suggested by EMH. However, we are unable to identify a set of strategies that would uniformly result in positive profits for all currency pairs.

This chapter is organized as follows. In the next section we introduce the empirical methodology employed in this study. We then discuss our dataset and empirical results. The final section summarizes and concludes.

EMPIRICAL METHODOLOGY

We use daily closing exchange rates provided by the Forex Capital Markets (FXCM, www.fxcm.com), for the period of January 1, 1999 to January 3, 2007. Since the global foreign exchange market operates round the clock, the FXCM defines the closing exchange rate to be the one fixed at 23:59:59, New York (Eastern Standard) time.

We assume that a technical analysis rule is used as a decision rule to enter the market. We employ pattern recognition techniques in order to identify the entry points (i.e., we apply the "chartist" approach). We then assume that a trader opens a position (e.g., buys euros for U.S. dollars) simultaneously with placing a *stop-loss* and a *stop-limit* order. The stop-loss order specifies a loss-limiting value, the stop-limit order specifies a profit-taking value b. Once the exchange rate deviates from its value at the time of market entry in the profit-making direction by b points or more, the position is closed, and the realized profit is b. However, if it moves first in the loss-making direction by a points, the position is closed at a loss equal to a.

As mentioned in this chapter's first section, the probability of the exchange rate moving by b points in the profit-making direction before moving by a points in the loss-making one, is $\dfrac{a}{(a+b)}$, making it impossible

to achieve any positive returns since the expected return in that case will be

$E[R] = S \times \left[b \times \dfrac{a}{a+b} - a \times \left(1 - \dfrac{a}{a+b} \right) \right] = 0$, where S is the size of the open

position, and $E[R]$ is the expected return.

In this chapter, we test whether entering the market as indicated by the technical analysis rules increases the probability of the market moving in the profit-making direction, rendering $E[R] > 0$. In other words, we test whether entering the market by the technical trading rules changes the formula for expected return to $E[R] = S \times [b \times p - a \times (1 - P)] > 0$ where

$p > \dfrac{a}{a+b}$.

We use two charting rules of technical analysis, namely, the *bull* and the *double bottom* patterns, to enter the market. These two patterns are used for opening a long position in the currency pair, i.e., indicating an upward market movement in the future. These charting patterns are relatively simple compared with the other ones representing two major groups of technical patterns, namely, the trend continuation and trend reversal patterns (Luca, 2000.) For example, the bull flag is simpler to define and recognize compared with the head-and-shoulders or a triangle pattern. In the same way, the double-top pattern is simpler than the triple-top or a diamond formation. In other words, we limit our analysis to the two characteristic representative patterns of the two major groups, also ignoring their "bearish" counterparts.

In order to identify these charting patterns, we use the template-matching technique (Duda and Hart, 1973) used for the recognition of digital images. The key to implementing this technique is the template onto which the currency pair's past exchange rates are superimposed in order to see whether these past currency pair movements fit a particular pattern. The extent to which such a fit occurs is measured by a statistic called fitting value, whose high values would indicate the chart pattern is strongly present, recommending entry into the market. Figure 9.1 represents a template for the double-bottom and bull patterns signaling entry into the market.

Gray cells in the template represent the matched pattern (in our case, the double-bottom in the left pane and bull in the right pane). We divide the historical time window during which the pattern fit is tested into 10 subperiods, each one corresponding to a specific column in the template. Ten percent of the earliest observations in our historical window are

Figure 9.1 The Double-Bottom and the Bull Patterns

–	1	2	3	4	5	6	7	8	9	10
1	0.5	−1	−1	−1	0.5	0.5	−1	−1	−1	0.5
2	1	0	−1	0	1	1	0	−1	0	1
3	0.5	0	−1	0	0.5	0.5	0	−1	0	0.5
4	0	0.5	−1	0.5	0	0	0.5	−1	0.5	0
5	0	1	−1	1	0	0	1	−1	1	0
6	−1	1	0	1	−1	−1	1	0	1	−1
7	−1	0.5	0	0.5	−1	−1	0.5	0	0.5	−1
8	−1	0	0.5	0	−1	−1	0	0.5	0	−1
9	−1	0	1	0	−1	−1	0	1	0	−1
10	−1	−1	0.5	−1	−1	−1	−1	0.5	−1	−1

–	1	2	3	4	5	6	7	8	9	10
1	0.5	0	−1	−1	−1	−1	−1	−1	−1	0
2	1	0.5	0	−1	−1	−1	−1	−1	−1	0
3	1	1	0.5	0	−1	−1	−1	−1	0	0.5
4	0.5	1	1	0.5	0	−1	−1	−1	0	1
5	0	0.5	1	1	0.5	0	0	0	0.5	1
6	0	0	0.5	1	1	0.5	0	0	1	1
7	−1	0	0	0.5	1	1	0.5	0.5	1	1
8	−1	−1	0	0	0.5	1	1	1	1	0
9	−1	−1	−1	−1	0	0.5	1	1	0	−2
10	−1	−1	−1	−1	−1	0	0.5	0.5	−2	−3

Note: The left pane represents the double bottom pattern. The right pane represents the bull pattern.

mapped onto the first column of our template; the next 10 percent observations are mapped onto the second column; while the last 10 percent are mapped onto the tenth column of the template. The highest exchange rate that occurred during the historical window corresponds to the top of the template, while the lowest one corresponds to the bottom of the template so that the vertical dimension of the template grid corresponds to the set of 10 exchange rate subranges. For each trading day we thus have a different sample of exchange rates in the historical window and consequently the different values of maximum and minimum historical exchange rates corresponding to the top and the bottom of the template; but the number of days corresponding to each column of the template remains the same, as well as the length of the historical window itself.

As explained in the pages that follow, the fitting statistic is a weighted sum of the observations that fit into specific exchange rate ranges within the trading window. Each cell in the template represents a weight for a combination of time period and an exchange rate range. An ideally fitting observation would fall into the gray cells with weight 1, while the observations that do not fit so well would receive smaller weights. Since the seminal work of Duda and Hart (1973), no particular rule has been devised for the weights, except for the requirement that the more remote the cells are from the ones representing the desired pattern (the gray cells), the smaller the weights should be relative to 1 (the gray cell weight), possibly becoming negative. This requirement is satisfied in all the template patterns we use.

We compute the total fitting value for the historical window as a sum of the individual fits for the subperiods represented by our template's columns. The individual fit for the subperiod is computed by performing three steps.

1. Compute the percentage of observations that falls into each one of the 10 subranges covered by the historical window.
2. Multiply these percentages by weights in the corresponding cells.
3. Sum the resulting 10 products to get the value of the fit for the particular subperiod.

For example, if today we choose the historical trading window to be 100 days and the exchange rate fluctuation range between 1 and 2 during the past 100 days, each column in our template would correspond to a subperiod of 10 days with the first row of the template corresponding to the range of [1.9;2], the second one to [1.8;1.9] and the tenth row (which is the bottom row) corresponding to the range of [1;1.1]. If, for example, for the past 100 days the exchange rate were fluctuating in the range of [1.9;2], then for each 10-day subperiod 100 percent of the observations would map into the upper row cell so that the value of the fit for each subperiod would be simply equal to the template weight value, and the total fit for the historical window would be equal to the sum of the weights in the first row of the template.

In this study we apply the trading window of 40 days, which is the length used by the authors of studies that apply similar pattern recognition techniques (Leigh et al., 2002, and references therein). Regarding the fitting statistic, for each currency pair and the technical analysis pattern, we round the highest estimated fitting value down to the nearest integer.

Suppose we examine the performance of the bull trading rule in the case of a EUR/USD currency pair. We determine the entry points by applying the pattern recognition techniques to the technical analysis patterns as described above. We then proceed by setting the stop-limit and stop-loss values. Let b be the stop-limit value, while a is the stop-loss value. We proceed with the estimation of empirical probabilities of profitable entries as follows.

1. Given the sample of the observed exchange rates for EUR/USD (January 1, 1999 to January 31, 2007), identify points of entry based on the bull pattern template from Figure 9.1 and the fitting statistic level (say, 7).
2. Compute the number of profitable entries, i.e., the ones that result in the exchange rate deviating by points in the profit-making direction *before* deviating by a points in the loss-making direction. Call the

share of such profitable entries N_p. This will be our empirical probability of a profitable entry.

3. As follows from the weak-form EMH, the foreign exchange movements are described by a simple random walk process, so that the share of profitable entries should approach $N_{EMH} = \frac{a}{a+b}$. The latter follows from the fact that a simple random walk is a martingale process (Williams, 1991). By computing $N_p - s$ and $N_{EHM} - s$ for a large number of combinations of a and b, we can test whether the former is statistically greater than the latter.

4. In case we find $N_p > N_{EHM} = \frac{a}{a+b}$ for a particular trading rule and currency pair, the average expected empirical return on this rule is statistically positive for this currency pair, since $E[R_p] = S \times [N_p \times b$

$$- (1 - N_p) \times a] > S \times \left[b \times \frac{a}{a+b} - \left(1 - \frac{a}{a+b}\right) \times a \right] = 0.\ R_p \text{ is the empirical}$$

return on a particular trading rule and a combination of stop-limit and stop-loss values.

We let a and b vary between 1 and 1,000 points with the increment of 1 point, which supplys us with one million strategies for each currency pair and the technical analysis pattern (bull flag or double-bottom). The next section presents and discusses our empirical results.

EMPIRICAL RESULTS

In what follows, we use the following codenames for the currencies in our sample: EUR is euro, USD is the U.S. dollar, GBP is the British pound, NZD is the New Zealand dollar, CAD is the Canadian dollar, AUD is the Australian dollar, CHF is the Swiss franc, and JPY is the Japanese yen. When a technical analysis rule signals entry into the market, a *currency pair is being bought*. For example, if a trader analyses the performance of euros versus U.S. dollars and deems euro is going to appreciate, she or he buys the *EURUSD* currency pair in the sense that the trader is buying euros for U.S. dollars. Below we present the differences between the empirical probabilities of realizing positive returns by using technical analysis signals and the theoretical ones. We interpret positive differences as evidence of the technical analysis rules being able to increase the probability of realizing a positive return.

Since both *a* and *b* vary within the limits of 1 to 1,000, we have one million strategies for each currency pair and one of the two technical trading patterns. We tested the extent to which the set of empirical probabilities of winning N_p exceed their theoretical counterparts N_{EHM} in the statistical sense by employing a two-sample, one-tailed heteroscedastic t test. In all 20 cases, the estimated differences between empirical and theoretical probabilities proved to be statistically significant from zero, meaning the two technical rules we have been using are indeed causing a change in the probability to win or to lose.

As evidenced by Table 9.1, in all but four cases, entering the market according to one of the two technical trading rules does increase the probability of winning. As mentioned in the Empirical Methodology section, this is tantamount to realizing a positive return on a technical trading strategy. It is important to notice, however, that figures in Table 9.1 are not profits per se, they are namely differences between empirical and theoretical probabilities of winning.

An interesting question is whether the results reported in Table 9.1 can be of value to a practicing trader. In fact, the apparent ability of the two technical trading rules to increase the probability of beating the market does not necessarily mean that one can identify a strategy that would uniformly result in statistically positive returns.

In order to see whether one can identify such a strategy, we partition the range of stop-limit values *b* and stop-loss values *a* into 10 subranges each, and see whether we can find a particular *range* of these values that uniformly results in a higher probability of winning relative to its theoretical counterpart. Table 9.2 below represents such a partition for the case of EURUSD and the bull charting pattern. Sets of strategies resulting in positive differences

Table 9.1 Differences Between Empirical and Theoretical Probabilities of Realizing Positive Returns Due to Technical Analysis Application

	EURUSD	GBPUSD	NZDUSD	USDCAD	AUDUSD
Bull	−1.54%	−21.78%	25.38%	11.41%	13.93%
Double-Bottom	38.93%	31.24%	−14.96%	11.08%	1.07%
	USDCHF	USDJPY	GBPJPY	GBPUSD	EURCHF
Bull	23.90%	25.00%	10.00%	17.62%	−49.47%
Double-Bottom	26.15%	50.00%	25.00%	24.73%	25.38%

Table 9.2 Average Differences Between Empirical and Theoretical Probabilities of Winning for EURUSD, Bull Pattern

Limit (*b*) Stop (*a*)	100	200	300	400	500	600	700	800	900	1,000
100	−50.00%	−23.98%	−16.14%	−12.20%	−9.81%	−8.21%	−7.06%	−6.19%	−5.51%	−4.97%
200	−37.30%	−50.00%	−37.40%	−29.91%	−24.93%	−21.37%	−18.71%	−16.63%	−14.98%	−13.62%
300	−39.86%	−62.60%	−50.00%	−41.64%	−35.69%	−31.22%	−27.76%	−24.98%	−22.71%	−20.82%
400	−43.80%	−70.09%	−58.36%	−50.00%	−43.74%	−38.88%	−34.99%	−31.81%	−29.16%	−26.92%
500	−46.19%	−75.07%	−64.31%	−56.26%	−50.00%	−45.00%	−40.90%	−37.50%	−34.61%	−32.14%
600	−10.83%	−12.63%	−2.78%	4.88%	11.00%	16.00%	20.17%	23.69%	26.72%	29.33%
700	7.06%	18.71%	27.76%	34.99%	40.90%	45.83%	50.00%	53.57%	56.67%	59.38%
800	6.19%	16.63%	24.98%	31.81%	37.50%	42.31%	46.43%	50.00%	53.13%	55.88%
900	5.51%	14.98%	22.71%	29.16%	34.61%	39.28%	43.33%	46.87%	50.00%	52.78%
1,000	4.97%	13.62%	20.82%	26.92%	32.14%	36.67%	40.62%	44.12%	47.22%	50.00%

Limit (*b*) and Stop (*a*) are the values of stop-limit and stop-loss orders. Bold figures represent ranges of these values.

between empirical and theoretical probabilities are shaded. Recall that, as evidenced by Table 9.1, the average difference between the empirical and theoretical probabilities of winning is statistically negative for this case (i.e., for the bull pattern in the case of the EURUSD currency pair).

We observe that in not an insignificant number of cases it is possible to realize a positive return by following a technical analysis strategy, for example, by buying euros with U.S. dollars on the bull charting signal in Figure 9.1, and setting the stop-limit and stop-loss values to be 400 and 600 points, respectively. However, after having inspected similar tables for all rules and currency pairs, we failed to discover any empirical regularity in the placement of positive numbered cells in those tables. In other words, we were unable to find a particular range or set of ranges of the stop-limit and stop-loss values that would result in a statistically positive increase in the probability of winning for all currencies and both charting patterns.

Table 9.3 presents the cross-currency pair analysis of our strategies' performance for the bull trading pattern. We look at the 10 subranges of both stop-limit and stop-loss values and compute the average share of *the number of cases* across the 10 currency pairs when the difference between empirical and theoretical probabilities of winning is positive.

In 86 percent of the cells in Table 9.3 the values are above 50 percent, implying that the average return across currencies of the double-bottom

Table 9.3 Share of Technical Trading Strategies Resulting in Positive Empirical Returns Across Currencies, Bull Pattern

Limit (b) Stop (a)	100	200	300	400	500	600	700	800	900	1,000
100	60%	60%	60%	60%	60%	60%	60%	50%	40%	40%
200	30%	60%	60%	60%	60%	60%	60%	50%	50%	40%
300	30%	50%	60%	60%	70%	70%	70%	60%	60%	50%
400	50%	60%	70%	70%	70%	70%	70%	60%	60%	50%
500	50%	50%	60%	70%	70%	70%	70%	60%	60%	60%
600	50%	50%	60%	70%	80%	80%	80%	70%	70%	70%
700	60%	60%	70%	70%	80%	80%	80%	70%	70%	70%
800	60%	60%	60%	70%	70%	80%	70%	70%	70%	60%
900	60%	60%	60%	70%	70%	60%	70%	70%	60%	60%
1,000	60%	60%	60%	70%	70%	60%	60%	70%	60%	40%

Limit (*b*) and Stop (*a*) are the values of stop-limit and stop-loss orders. Bold figures represent ranges of these values.

trading rule for the corresponding range of stop-limit and stop-loss values is predominantly statistically positive. We computed a similar table for the bull flag trading rule and observed the same predominance of the money-making strategies over the loss-making ones (90 percent of the cells).

Finally, the regression analysis (results available immediately upon request) for the individual currency pairs did not reveal any robust relationship between winning probability increases and stop-limit and stop-loss values for neither trading rule and the currency pairs either, leading us to believe that it is indeed hard to find a universally working strategy even if the technical rules appear to be working on average across currency pairs and the stop-limit and stop-loss parameters.

CONCLUSION

In this study we examined the ability of two technical analysis rules, namely, the bull and double-bottom pattern, to increase the probability of winning in the foreign exchange market relative to the theoretical probability. The latter was computed on the basis of the efficient market hypothesis, implying, among other things, that foreign exchange rates follow a simple random walk.

In the course of our analysis we tested one million strategies for the world's 10 major currency pairs on the dataset covering eight years, which allows us to formulate two stylized facts that simultaneously demonstrate the technical analysis' potential for profitability, and the difficulty of its practical application:

1. The bull and double-bottom technical analysis rules increase on average the probability of winning compared to what is stipulated by the efficient market hypothesis.
2. It is hardly possible to indicate a strategy in terms of the trading rule and a combination of stop-loss and stop-limit values, which would consistently result in statistically positive profits in the case of all currency pairs.

The two stylized facts above help explain the persistent popularity of technical analysis rules among popular traders on the one hand and lack of the "sure-fire" trading strategies on the other hand (otherwise, everyone would be a millionaire!). Indeed, while technical analysis appears to be

increasing the probability of winning, the lack of systemic pattern in the winning strategies' parameters and underlying technical trading rules makes it difficult, if not impossible, to use technical analysis for reaping consistent positive returns.

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TECHNICAL ANALYSIS IN TURBULENT FINANCIAL MARKETS
Does Nonlinearity Assist?

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ABSTRACT

Along with the existence of financial markets, financial practitioners and academic researchers are always concerned by the question of whether we can forecast the future path of stock returns. In theory, if financial markets are not fully efficient under the weak-form as defined by Fama (1970), investors can generate abnormal profits by performing technical analysis based on past price and trading volume data. A comparison of the predictive power between competitive models shows that technical trading tools commonly used might not be valid and effective in turbulent times such as extreme events and financial crisis due explicitly to the assumption of linear dependences in stock returns. At the empirical level, we first apply commonly used chartist tools to empirically study and forecast stock returns from actual data. These models are then extended to nonlinear framework and employed to test for the contribution of nonlinearity in modeling stock returns. Using intraday data from two developed markets (France and Germany), we point out the superiority of nonlinear models and the contribution of nonlinearity-enhanced technical models over the linear tools, especially when stock returns are subject to structural changes.

INTRODUCTION

As long as financial markets exist, investors and portfolio managers attempt to make forecasts about the future asset prices based on the latter's past patterns. The hope is then to establish trading rules that render their investments profitable. For many peoples, the question in financial practice is not whether it is possible to forecast the future path of asset prices, but how to efficiently forecast it. Of the techniques used to recommend "buy" or "sell" signals based on an investigation of the predictability of price changes, the technical analysis has received less academic attention albeit it is widely employed by practitioners.[1]

In theory, the use of technical analysis will have no value if financial markets are at least weak-form efficient since in this case future price movements cannot be predicted using past price movements (Fama, 1970, 1991). Empirical research is, however, not conclusive on the usefulness of such trading rules. On the one hand, a number of studies find that technical analysis is unable to reliably predict future returns (Fama and Blume, 1966; Jensen and Bennington, 1970; Marshall and Cahan, 2005; Marshall, Cahan, and Cahan, 2008). For example, the study of Marshall et al. (2008) shows no evidence that technical trading rules are profitable using 5-minute raw and squared return series in the U.S. equity markets after the bootstrap methodology is employed to correct for the potential of data snooping bias.[2] Using the similar approach, Marshall and Cahan (2005) reject the validity of technical analysis for the stock market in New Zealand even though the latter displays symptoms of an inefficient market such as small nature, short-selling constraints, and lack of insider trading regulation. Other studies also report that technical analysis is not profitable once transaction costs are considered (e.g., Allen and Karjalainen, 1999; Olson, 2004).

There is, on the other hand, a considerable amount of evidence to suggest that stock returns display short-term momentum profits and as a result the use of technical trading rules may lead to economically significant excess returns in financial markets (e.g., Brock, Lakonishok, and LeBaron, 1992; Corrado and Lee, 1992; Bessembinder and Chan, 1995; Hudson, Dempsey, and Keasey, 1996; Detry and Gregoire, 2001; Lee et al., 2003). More precisely, Brock et al. (1992) provide evidence that a relatively simple set of technical trading rules has predictive power for changes in the Dow Jones Industrial Average, while empirical results of subsequent studies are consistent with profitable technical analysis in European and Asian equity

markets. Overall, past price movements and price trends may still have the merits in forecasting the future price changes, and technical trading rules such as moving averages, standard filter rules, and trading range break have become standard technical indicators in financial practice.

This chapter joins the previous studies by reinvestigating the effectiveness of technical trading rules in two major developed markets, Germany and France, using intraday data. We contribute to the related literature in that we introduce nonlinearities into traditional linear technical models to capture any nonlinear dependence and adjustment in the past price changes. At the same time, our approach permits to examine the usefulness of technical analysis in financial market turbulences, which has rarely been the focus of previous work. Our motivations come essentially from the fact that the presence of numerous market distortions during crisis times may lead to nonlinear forms of price dependence. The obtained results from estimating nonlinearity-enhanced models confirm effectively our basic intuition that nonlinearities do improve the effectiveness of technical analysis, especially during episodes of widespread market panics.

The remainder of the chapter is organized as follows: the second section of this chapter outlines the reasons for which nonlinearities are introduced into technical trading rules to test for the effectiveness of technical analysis against market efficiency. This chapter's third section describes data used and discusses empirical results. Summary conclusions are provided in this chapter's final section.

NONLINEAR MODELING FOR TECHNICAL ANALYSIS

The succession of financial crises over the past two decades such as the stock crash in 1987, the Asian financial crisis in 1997, the Internet bubble collapse in 2000, and more recently the current global financial crisis in 2007 to 2009 has generated widespread market panics and pointed out the weakness of the usual financial analysis and modeling techniques in forecasting the dynamic of financial markets. For example, technical analysis seems to be relevant only in the short term and may not yield good predictions when markets pass through financial turbulences and crises. After briefly discussing the economic justifications of nonlinearity for financial markets, we discuss the appropriate nonlinear models to further test the effectiveness of technical trading rules in turbulent financial markets.

Nonlinearity and Stock Market Dynamics

The financial literature has advanced several microeconomic and macroeconomic justifications for the introduction of nonlinearity in modeling financial market dynamics. Regarding microeconomic explanations, one should note transaction costs (Dumas, 1992; Anderson, 1997), information asymmetry (Artus, 1995), behavioral heterogeneity (De Grauwe and Grimaldi, 2005; Boswijk, Hommes, and Manzan, 2007), and mimetic behavior (Orléan, 1990) that are suggested to be the main sources of nonlinearity, structural breaks, and changes in asset price dynamics. From a macroeconomic view, Artus (1995) show that the naissance and withdraw of speculative bubbles may induce asymmetric and nonlinear dynamics in financial price dynamics.

Empirically, Gouriéroux, Scaillet, and Szafarz (1997) suggest that beside the fact that financial markets are naturally and theoretically characterized by nonlinear dynamics, the tools used to model stock price dynamics should capture nonlinearity. The authors identify five types of nonlinearity. First, nonlinearity may take root in predicted variables. For example, to evaluate the risk of a financial asset, we forecast its squared return which is a nonlinear variable. Second, nonlinearity is directly incorporated into forecasting tools used to predict future dynamics of price. Third, nonlinearity is present in the model parameters and is apprehended through the rejection of the normality for almost all financial series. Fourth, nonlinearity characterizing the price dynamics may be due to the presence of nonlinear relationships between past and present realizations of financial series (e.g., series of stock returns). This type of nonlinearity can be present either in the mean or in the variance of the series under consideration or both. Finally, the last type of nonlinearity is inherent to financial strategies adopted by investors in order to optimize the risk-return tradeoff.

Nonlinear Models

Several nonlinear models have been used in recent years to reproduce the dynamics of financial markets. Indeed, financial return dynamics are often modeled by using the so-called regime-switching models while generalized autoregressive conditional heteroscedasticity class models are rather applied to conditionally evaluate return volatility. Among these nonlinear models, we focus on nonlinear models in mean and particularly on bilinear (BL) and nonlinear moving average (NMA) models that will be applied to intraday

stock data at the empirical stage. Compared to previous studies on nonlinear stock price dynamics, our empirical investigation has two advantages. On the one hand, the use of these nonlinear models enables to appropriately extend the usual models of technical analysis (e.g., moving average model and smoothing model) to a nonlinear context. On the other hand, their applications to intraday data would enhance the predictive power of the models used since this analysis appears to be particularly accurate in the short term.

Bilinear Models (BL)

The BL models were introduced by Granger and Anderson (1978). Their modeling techniques and different specifications such as stochastic BL and determinist BL are rigorously presented in Guégan (1994). BL models constitute an extension for autoregressive moving average (ARMA) models by adding both compounded AR and MA terms to a traditional ARMA model. The nonlinearity of BL models is then introduced through these compounded terms. It is worth noting that BL models are generally recommended for reproducing the dynamics of financial series with periods of high volatility followed by phases of lower volatility. Such dynamics characterize financial markets particularly when they pass through turbulent phases.

Let Y_t be described by a BL process of (p, q, P, Q) orders, then its dynamics can be defined as follows:

$$Y_t = \sum_{i=1}^{p}\alpha_i Y_{t-i} + \sum_{j=1}^{q}\beta_j \varepsilon_{t-j} + \sum_{k=1}^{P}\sum_{l=1}^{Q}\delta_{kl}Y_{t-k}\varepsilon_{t-l} + \varepsilon_t \qquad (10.1)$$

where ε_t is an error term, and α_i, β_j, and δ_{kl} belong to $\mathfrak{R}^3$. If $P < Q$, the BL model is said to be upper-diagonal, under-diagonal for $P > Q$, and diagonal for $P = Q$. Assuming that $\varepsilon_t \rightarrow N(0, \sigma_\varepsilon^2)$ and Y_t is inversible, i.e., we can write $\varepsilon_t = f(Y_t, Y_{t-1}, \ldots)$, BL models can be estimated using a procedure similar to that of Box and Jenkins (1970).[3] It means that modeling steps that we usually employ for dealing with ARMA models (i.e., specification and determination of lag number, estimation, validation, and prediction) are also applicable to BL models. However, it is commonly advised to test the null hypothesis of linearity against its alternative of nonlinearity in order to correctly specify the BL models. The Saikkonen and Luukkonen (1991) test, which contains three main steps below, can be used to test for the robustness of BL models.

- Step 1: We estimate a usual AR(p) model, retain the estimated residual $\hat{\varepsilon}_t$ and compute the sum of squared residuals (SSR) under the null hypothesis $SSR_0 = \sum_{i=1}^{T} \hat{\varepsilon}_t^2$

- Step 2: We estimate the following regression $\hat{\varepsilon}_t = \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}$

  $+ \sum_{k=1}^{P} \sum_{l=1}^{Q} \delta_{kl} Y_{t-k} \varepsilon_{t-l} + v_t$ and we compute $SSR_1 = \sum_{i=1}^{T} \hat{v}_t^2$

- Step 3: We compute the statistics $BL = T \dfrac{SSR_0 - SSR_1}{SSR_0}$, where T

  denotes the observation number associated with the regression of the second step. Under the null hypothesis of linearity, the statistic BL is distributed as a χ^2 with (P $\times$ Q) degrees of freedom.

BL models were used only in some studies such as Subba Rao and Gabr (1984), Chan and Tong (1986).[4]

Nonlinear Moving Average (NMA) Models

NMA models were introduced by Robinson (1977). These models are based on Volterra developments and are defined as[5]

$$Y_t = \sum_{i=0}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=0}^{q} \sum_{j=0}^{q} \theta_{ij} \varepsilon_{t-i} \varepsilon_{t-j} + \sum_{i=0}^{q} \sum_{j=0}^{q} \sum_{k=0}^{q} \theta_{ijk} \varepsilon_{t-i} \varepsilon_{t-j} \varepsilon_{t-k} + \cdots \quad (10.2)$$

where ε_t is a white noise and θ_0 is equal to 1. NMA models are estimated by the method of moments, but their practical application in economics and finance is somewhat limited. In practice, Robinson (1977) has recommended a NLM model of order one as in Equation 10.3 to capture the asymmetry characterizing business cycles with gradual expansion and abrupt recession. The NLM model is accordingly suitable for modeling the dynamics of financial markets whose evolution also displays high degree of asymmetric patterns.

$$Y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-1} \varepsilon_{t-2} \quad (10.3)$$

The asymmetry is captured through the term, $\varepsilon_{t-1}\,\varepsilon_{t-2}$, while the forecasting of positive and negative phases is reproduced depending on the

sign of ε_t and through the observations $\{\varepsilon_t,\ \varepsilon_{t-1}\ \varepsilon_{t-2},\ \ldots\}$ and $\{-\varepsilon_t,\ -\ \varepsilon_{t-1}$ $-\ \varepsilon_{t-2},\ \ldots\}$, respectively.

DATA AND EMPIRICAL RESULTS

Data and Preliminary Results

Previous studies that focus on technical trading rules show that the analysis is particularly appropriate in the short term using high frequency data. For comparative purpose, we employ, in our empirical application, intraday stock price data of two developed countries: France (CAC 40) and Germany (DAX 30). The use of intraday data permits to test the instantaneous adjustment dynamics of stock markets. Our data, consisting of five-minute prices obtained from Euronext database, cover the period from January 2, 2007 to April 22, 2009 in order to test the effectiveness of technical analysis during the financial crisis.

To start, we check the stationarity of our variables using Dickey-Fuller, Philips-Perron, and KPSS unit root tests. The hypothesis of unit root is rejected only for the series in the first difference, indicating that both indexes are integrated of order one, $I(1)$.[6] We then focus on stock returns defined as the first difference of stock prices expressed in logarithm.

The investigation of descriptive statistics of French and German stock market intraday returns, reported in Table 10.1, provides evidence of strong rejection of the symmetry and normality hypotheses. It also shows some volatility excess and autoregressive conditional heteroscedasticity effects in French and German stock returns. These findings indicate a priori some evidence of nonlinearity and asymmetry characterizing stock price dynamics.

To check the validity of technical analysis, we will first estimate usual linear models, and then we examine whether the introduction of nonlinearity contributes to improve the forecasting power of technical analysis.

Table 10.1 Descriptive Statistics

	Mean	SD	Skewness	Kurtosis	Jarque–Bera	ARCH (q)	No. of obs.
RF	−1.31E−05	0.0015	0.161	19.51	65,5373.0	6762.7 (15)	57,710
RG	−4.74E−06	0.0015	0.184	24.53	111,4553.0	8600.9 (16)	57,710

RF, French stock returns; RG, German stock returns; SD, standard deviation; ARCH, autoregressive conditional heteroscedasticity.

The Linear Modeling

We tested several linear specifications and finally retained the two follow-ing linear models that provide the best fit to the data: AR(2) and MA(2) for both market indexes. We report estimation results in Table 10.2. Our find-ings indicate some linear temporal dependencies in both index dynamics, which is typically coherent with the chartist principle. It appears, however, from squared coefficient as well as information criteria and statistical prop-erties of the estimated residuals that linear models fail to capture the whole of stock price dynamics, perhaps because of structural breaks caused by the 2007 to 2008 financial crisis. The low level of R^2 confirms effec-tively this result. The latter also induces some asymmetry in price dynam-ics, which usually calls for the application of a nonlinear rather than linear framework.

Table 10.2 Linear Estimation

Variable	Coefficient	Standard Error	t Statistic	p Value
France: MA(2) specification				
Constant	$-1.31E-05$	$6.24E-06$	-2.093676	0.0363
MA(1)	-0.001719	0.004163	-0.413063	0.6796
MA(2)	-0.011290	0.004163	-2.712170	0.0067
R^2	0.000132			
France: AR(2) specification				
C	$-1.31E-05$	$6.24E-06$	-2.095230	0.0362
AR(1)	-0.001791	0.004163	-0.430345	0.6669
AR(2)	-0.011415	0.004163	-2.742301	0.0061
R^2	0.000133			
Germany: MA(2) specification				
Constant	$-4.74E-06$	$6.17E-06$	-0.768243	0.4423
MA(1)	-0.012380	0.004163	-2.974176	0.0029
MA(2)	-0.011376	0.004163	-2.732832	0.0063
R^2	0.000285			
Germany: AR(2) specification				
Constant	$-4.73E-06$	$6.17E-06$	-0.766629	0.4433
AR(1)	-0.012368	0.004163	-2.971223	0.0030
AR(2)	-0.011715	0.004163	-2.814160	0.0049
R^2	0.000287			

Nonlinear Modeling for Technical Analysis

First of all, the linearity is tested using Saikkonen and Luukkonen (1991) test. Then BL and NMA models are estimated. The most important findings are reported in Table 10.3 and Table 10.4. The linearity is rejected for

Table 10.3 Linearity Test of Saikkonen and Luukkonen (1991)

	France	Germany
BL	10.3	7.72
(*p* value)	(0.03)	(0.10)

Table 10.4 Nonlinear Estimation Results

	France	Germany
	BL model	
α_1	0.21	0.87
	[0.21]	[0.49]
α_2	0.06	0.36
	[2.3]	[1.81]
β_1	−0.24	−0.91
	[−0.20]	[−0.52]
β_2	−0.08	0.39
	[−1.67]	[1.75]
δ_{11}	5.4	0.35
	[1.93]	[1.13]
δ_{22}	0.65	[2.58]
	[2.3]	0.70
$\bar{R}^2$	0.11	0.07
DW	2.0	2.01
NRNL (*p* value)	0.04	0.03
	NMA model	
θ_1	−0.03	−0.05
	[−2.35]	[−4.16]
θ_{11}	−0.37	−0.08
	[−4.57]	[−2.76]
$\bar{R}^2$	0.55	0.45
DW	2.1	1.86
NRNL (*p* value)	0.38	0.23

NRNL designates the *p* value for no-remaining nonlinearity. Values between [.] denote the t statistics.

the French market index at the statistical level of 5 percent, while it is rejected for German market index only at the 10 percent level.

For both indexes, the specification tests lead to choose a BL(2,2,2,2) and NMA of one order that we estimate by the maximum likelihood method. According to our findings, BL models seem not to capture the whole non-linearity characterizing our data (NRNL test), even though nonlinear terms are statistically significant. NMA models seem however to be more appropriate to capture the asymmetry inherent to French and German stock market dynamics. Indeed, their estimators are statistically significant and they seem to have apprehended all nonlinearity inherent to stock returns under consideration. In addition, the negativity of their coefficients indicates that French and German indexes are still undervalued and that markets are in phase of correction.

Otherwise, the validation of a NMA model to reproduce these stock return dynamics indicates a nonlinear time-varying dependency in stock returns. This is consistent with profitable technical analysis, but suggests an extension of the usual tools to a nonlinear framework to improve the forecasting accuracy.

CONCLUSION

In this chapter, we have examined the effectiveness of technical trading rules in two major developed markets, the German and French stock markets, using intraday data. We have used both linear and nonlinear technical analysis models. The usefulness of nonlinear models is justified by many factors, in particular, the presence of numerous market distortions such as information and transaction costs, asymmetries, investor's heterogeneity, and structural changes during financial crisis. Our empirical findings confirm effectively our basic intuition that nonlinearities do improve the effectiveness of technical analysis, especially during episodes of widespread market panics.

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NOTES

1. Marshall, Cahan, and Cahan (2008) note that market participants and journalists consistently attach, according to the results obtained from surveys, more emphasis on technical analysis than on fundamental analysis as far as the short-term forecast horizon is concerned. In particular, the respondents give approximately twice as much weight on technical analysis for intraday horizons as they do for one-year horizons.

2. The bootstrap methodology was introduced to finance literature by Brock, Lakonishok, and LeBaron (1992) and has become popular for assessing the statistical significance of technical trading rule profitability. It consists of comparing conditional buy or sell signal using the original return series with conditional buy or sell signal generated from the corresponding simulated series using specified technical analysis models such as moving average, random walk, AR(1), GARCH-M, and EGARCH. Note that, to obtain the bootstrap results, the initial sample is simulated n times (n sufficiently large, i.e., n is usually higher than 1,000) by resampling with replacement so that the usual normal distribution needs not to be assumed for the model residuals.

3. See Guégan (1994) for more details concerning other estimation methods for BL models such as the method of moments.

4. See Chan, Moeanaddin, and Tong (1988) for more details regarding the problems and limitations associated with BL modeling.

5. See Wiener (1958) and Brillinger (1970) for more details about Volterra developments and their statistical properties.

6. Results of unit root tests are available upon request to the corresponding author.

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PROFITING FROM THE DUAL-MOVING AVERAGE CROSSOVER WITH EXPONENTIAL SMOOTHING

Camillo Lento

ABSTRACT

This chapter reexamines the profitability of the dual-moving average crossover trading rule by analyzing the incremental profit contribution of utilizing an exponential smoothing technique to calculate the moving averages. The analysis is conducted on the S&P 500, NASDAQ, and Dow Jones Industrial Average from January 1999 to April 2009 (N = 2,596). The results suggest that the profitability of the moving average cross-over rule is significantly enhanced by using an exponential smoothing technique that reduces the weight of the most recent price observation. The additional profits are not the result of increased risk. Rather, exponentially smoothing prices to calculate the moving averages results in a fewer number of signals that are more informative. Bootstrapping simulations were used to test for significance.

INTRODUCTION

The dual-moving average crossover (DMACO) trading strategy is one of the simplest, yet most popular trading rules among practitioners (Taylor and Allen, 1992; Lui and Mole, 1998). It is one of the few trading rules that is statistically well defined (Neftci, 1991). The DMACO is calculated with two moving averages of a security price. Relative to each other, one moving average is short term (STMA), while the other long term (LTMA). The LTMA will move in the same direction as the STMA, but will have a lower variance and move at a slower rate. The different rate of direction creates situations where the values of the two moving averages may equal or crossover one another. These crossover points generate buy and sell signals under the DMACO. A buy signals occurs when the STMA rises above the LTMA, whereas a sell signal occurs when the STMA breaks below the LTMA (Murphy, 2000).

Various studies have tested the profitability of technical trading rules (e.g., Bessembinder and Chan, 1998; Lo, Mamaysky, and Wang, 2000; Lento, 2008). This chapter provides new insights on the profitability and sign prediction ability of the DMACO by utilizing an exponential smoothing technique to calculate the STMA and LTMA. Traditionally, the latest prices are of the most value to an exponentially smoothed average. However, this study utilizes a smoothing technique that places more weight on the older values.

The trading rules are tested on the S&P 500, NASDAQ, and Dow Jones Industrial Average (DJIA) for the period January 1999 to April 2009 (N = 2,596). The results suggest that the profitability of DMACO is significantly enhanced when the STMA and LTMA are calculated with the exponential smoothing technique. The increased profitability is significant, in many cases in excess of 5.0 percent per annum, and consistent across each moving average combination and index. Profitability is defined as returns in excess of the naïve buy-and-hold trading strategy.

The additional profits are not the result of increased risk. Rather, exponentially smoothing prices to calculate the moving averages results in a fewer number of signals that are more informative. The results from the sign prediction tests are consistent with the profitability tests as large, positive returns followed the buy signal of the exponentially smoothed DMACO

The remainder of this chapter is organized as follows: the next section describes the DMACO. The third section of this chapter describes the

data, while the fourth section explains the methodology. This chapter's fifth section presents the results, and a conclusion is provided in the final section.

BACKGROUND ON THE MOVING AVERAGES

The Dual-Moving Average Crossover Trading Rule

The DMACO produces a buy (sell) signal when the STMA cuts the LTMA from below (above). The simple rule has a large variety of forms based on the timeframe selected for each average (Neely, Weller, and Dittmar, 1997). The intuition behind the DMACO can be explained in terms of momentum. When SMTA is greater than the LTMA, the security's value in the recent past exceeds its value in the more distant past, which in moving average models signals that an upward trend is developing (Levich, 2001). When the STMA moves below the LTMA, this provides a lagged indicator that the price is moving downward relative to the historical price.

There are two variants of the DMACO trading rule: variable length moving average (VMA), and the fixed-length moving average (FMA). The VMA generates a buy (sell) signal whenever the STMA is above (below) the LTMA. After a buy (sell) signal, the investor will be long (out of) the market until a sell (buy) signal is generated. Conversely, the FMA focuses solely on the crossing of the moving averages. This method stresses that the returns should be different for a few days following a crossover (Brock, Lakonishok, and LeBaron, 1992).

Empirical Tests of DMACO Trading Rule[1]

There are many studies on moving average rules. Brock et al. (1992) was one of the most influential, and found that returns generated from the signals of a DMACO rule outperformed three popular models (AR(1), GARCH-M, and the exponential GARCH). Buy signals resulted in higher returns than sell signals, and displayed less volatility than the sell signal returns.

Levich and Thomas (1993) also tested moving average rules to evaluate the potential for abnormal profits. Their study suggests that the DMACO generated excess returns that would have been highly unlikely to have been observed by chance.

Gençay and Stengos (1998) tested a 50-day and a 200-day DMACO. Linear and nonlinear models were used to assess the predictability the signals on the daily DJIA from 1897 to 1988. The results provide evidence of a 10 percent (or better) forecasting improvement during the Great Depression years and in the years 1980 to1988. The technical trading rules provided more moderate returns during the period 1939 to 1950. Gençay (1999) corroborated the significance of moving average rules as a tool to predict foreign exchange rates. He concluded that simple moving average rules provide significant correct signals and returns.

However, the literature does not provide consensus support for the profitability of the DMACO. For example, Kho (1996) presents a contrary viewpoint by supporting the ineffectiveness of technical trading rules by suggesting that time-varying risk premiums can explain a substantial amount of the profitability of DMACO in foreign currency markets.

Recent research reveals that DMACO is profitable in certain Asian equity markets (Lento, 2007). The DMACO trading rule was profitable in 22 of the 24 (91.7 percent) tests. The 1-day, 50-day DMACO performed the best as all nine variants tested outperformed the buy-and-hold trading strategy as it earned annual excess returns in the range of 1.8 percent to 32.6 percent. The 1-day, 200-day DMACO also earned annual excess returns in the range of 1.5 percent to 10.9 percent.

Exponential Smoothing and Moving Averages

A moving average relies equally on past observations (i.e., the weight assigned to the observations are the same and equal to 1/N). Exponential smoothing assigns *exponentially decreasing weights* to older observations. In other words, *recent observations are given relatively more weight in forecasting than older observations*. There is one or more smoothing parameter to be determined (or estimated) in exponential smoothing and these choices determine the weights assigned to the observations (Hyndman et al., 2008).

Exponential smoothing has been used in technical trading rules. For example, the triple exponential smoothing oscillator (TRIX) was developed by John Hutson, while Gerald Appel developed the moving average convergence/divergence (MACD). Although exponential smoothing is used in practice to develop trading rules, little academic research exists that tests the profitability of exponential smoothing techniques. Specifically, there is

no known research that tests whether exponential smoothing can increase the profitability and sign prediction ability of the DMACO. This chapter helps to fill this gap in the literature.

METHODOLOGY

Calculating the Dual-Moving Average Crossover Trading Signals

As discussed, the DMACO generates a buy (sell) signal whenever the STMA is above (below) the LTMA as follows:

Buy Signal Equation

$$\frac{\sum_{s=1}^{S} R_{i,t}}{S} > \frac{\sum_{l=1}^{L} R_{i,t-1}}{L} = Buy \qquad (11.1)$$

Sell Signal Equation

$$\frac{\sum_{s=1}^{S} R_{i,t}}{S} < \frac{\sum_{l=1}^{L} R_{i,t-1}}{L} = Sell \qquad (11.2)$$

where $R_{i,t}$ is the average security price given the number of days that defines the STMA, and is $R_{i,t-1}$ the average price over the number of days the defines the LTMA.

Traditionally, the STMA and LTMA are calculated with the security price time-series. The moving averages in this study are calculated with an exponentially smoothed security price-time series. The smoothing scheme employs the single exponential smoothing methodology and begins by defining S_2 to y_1, where S_i stands for smoothed observation, and y stands for the original security price. The subscripts refer to the time periods, 1, 2, …, n. For the third period, $S_3 = \alpha y_2 + (1 - \alpha) S_2$. The smoothed series starts with the smoothed version of the second observation (i.e., there is no S_1). For any time period t, the smoothed value St is found by computing:

$$S_t = \alpha y_{t-1} + (1-\alpha)S_{t-1} \qquad 0 < \alpha \leq 1 \qquad t \geq 3 \qquad (11.3)$$

where parameter α is the *smoothing constant*. Normally, α is set to greater than 50 percent to allow for more weight on the more recent observation. However, this study utilizes an α of 10 percent, thereby placing significantly

less weight on the recent observation. More weight is placed on the past observations to eliminate any excess volatility or noise created by a single observation. The STMA and LTMA will be calculated on the exponentially smoothed time-series (*exponentially smoothed DMACO*), as opposed to the raw prices (*traditional DMACO*). The following STMA,LTMA combinations will be used: (1,50), (10,50), and (1,200).

Calculating the Profits

Profitability is determined by comparing the returns generated by the DMACO to the buy-and-hold return. The buy-and-hold returns are calculated by investing at t_1 and holding the security until the end of the data set. This test does not rely on short sales. Rather, after a sell signal, the returns are calculated by assuming that the capital will be placed in savings account. An average, nominal interest rate of 3 percent per annum will be earned while out of the market.

The methodology relies on this simple technique because of the possible problems related to nonlinear models such as computational expensiveness, over-fitting, data snooping, and difficulties interpreting the results (see White, 2005 for a thorough discussion of these issues).

The profit generated from the DMACO are adjusted for both the bid-ask spread and brokerage costs (similar to Gençay, 1998). The bid-ask spread for the S&P 500, NASDAQ, and DJIA exchange traded funds are used as a proxies for the actual index.

Bootstrapping to Estimate Statistical Significance

The significance of the results is tested by using the bootstrap approach developed by Levich and Thomas (1993). This approach, first, observes the data set of closing prices, with the sample size denoted by $N + 1$, that corresponds to a set of N returns. The mth ($m = 1, ..., M$) permutation of these N returns ($M = N!$) is related to a unique profit measure ($X[m, r]$) for the rth trading rule variant ($r = 1, ..., R$) used in this study. Thus, for each variable, a new series can be generated by randomly reshuffling the returns of the original series.

To maintain the distributional properties of the original data, the starting and ending points of the randomly generated time-series are fixed at their original values for each sequence of M returns. However, the time-series

properties are random. Various notional paths that the returns could have taken from time t (starting day) to time $t + n$ (ending day) can be generated. An empirical distribution of profits $X[m, r]$ is generated by applying the DMACO to the notional paths. A simulated p value is produced by computing the proportion of returns generated from the simulated series that is greater than the return computed with the actual series.

Sign Prediction Ability of the DMACO

In addition to profits, the effectiveness of DMACO's ability to predict future price movements will be evaluated. A buy (sell) signal is correct if the holding period return following the signal is positive (negative). A 1-day and 10-day lag will be utilized to evaluate the signals (Brock et al., 1992). The predictive value (PV) is calculated as follows:

$$(CS_t) / (CS_t + IS_t) \tag{11.4}$$

where CS_t denotes the number of correct buy signals given the time lag t, and IS_t denotes the number of incorrect buy signals given the time lag t.

Analyzing the aggregate daily returns that follow a signal will provide insight into the sign prediction ability. A large, positive (negative) return would be expected to follow a buy (sell) signal. The significance of the returns will be determined by testing for a difference between returns following the buy and sell (buy-sell) signals. The trading rules can forecast future movements of security returns if the difference between the buy-sell returns is positive and significant. The t statistic will be calculated as follows (Brock et al., 1992):[2]

$$\frac{\mu_b - \mu_s}{\sqrt{(\sigma_b^2 / \eta_b) + (\sigma_s^2 / \eta_s)}} \tag{11.5}$$

DATA

The technical trading rules are tested on daily data from the S&P 500, NAS-DAQ, and DJIA for the period January 1999 to April 2009 (N = 2,596). The 10-year period provides a sufficient number of observations to test the

DMACO trading rule. The daily returns are calculated as the holding period return of each day as follows:

$$r_t = \log(p_t) - \log(p_{t-1}) \qquad (11.6)$$

where p_t denotes the market price.

TRADING WITH THE EXPONENTIALLY SMOOTHED DMACO

The following section describes the empirical results of the exponentially smoothed DMACO by assessing the trading rule's profitability and sign prediction ability. The results suggest that the exponentially smoothed DMACO is able to generate significant profits by producing fewer, more powerful, trading signals than the traditional DMACO.

Profits from the Exponentially Smoothed DMACO

The results on the profitability of the exponentially smoothed DMACO are very impressive. The results are presented in Table 11.1. Both the buy-and-hold trading strategy and the traditional DMACO experienced negative returns, while the exponentially smoothed DMACO was profitable in all settings. The exponentially smoothed DMACO outperformed the traditional DMACO trading rule in all nine tests. The excess profits were large, and significant, ranging from 3.5 percent to 8.6 percent. The excess returns over the buy-and-hold trading strategy are even larger.

A possible explanation for the excess profits could be that the exponentially smoothed DMACO takes on additional risks (i.e., the profits are more volatile). To test this possible explanation, the Sharpe ratio has been calculated for the returns from both DMACO calculations. The Sharpe ratio is presented in Table 11.1 and reveals that the exponentially smoothed DMACO does not take on additional risk. Conversely, six of the nine tests reveal that the returns from the exponentially smoothed DMACO are less risky than the traditional model.

The DMACO earned the excess profits on less trading signals than the traditional model. Aside from the obvious fact that the reduced number of trading signals resulted in less transaction costs, the results appear to suggest that the exponentially smoothed DMACO generates trading signals

Table 11.1 Profitability of the Exponentially Smoothed DMACO

	DMACO Traditional Calculation STMA,LTMA			DMACO Exponentially Smoothed STMA,LTMA			Excess Profitability of Exponentially Smoothed DMACO		
Market	**1,50**	**10,50**	**1,200**	**1,50**	**10,50**	**1,200**	**1,50**	**10,50**	**1,200**
S&P 500 (N = 2,596)									
Annual Return	(7.1%)	(9.3%)	(0.1%)	0.9%	(0.7%)	5.9%			
Buy-and-Hold Return	(5.7%)	(5.7%)	(5.8%)	(5.7%)	(5.7%)	(5.8%)			
Over/(Under) Performance	(1.4%)	(3.6%)	5.7%	6.6%	5.0%	11.7%	8.0%	8.6%	6.0%
Sharpe Ratio	(0.015)	(0.019)	(0.000)	0.004	(0.003)	0.025	(0.011)	(0.016)	0.025
p value	0.12	0.34	0.15	0.06	0.11	0.02			
No. of Trades	180	10	86	42	42	16			
Dow Jones (N = 2,596)									
Annual Return	(6.3%)	(5.1%)	(4.5%)	0.7%	(1.7%)	(0.3%)			
Buy-and-Hold Return	(2.9%)	(2.9%)	(3.6%)	(2.9%)	(2.9%)	(3.6%)			
Over/(Under) Performance	(3.5%)	(2.3%)	(0.9%)	3.6%	1.2%	3.3%	7.1%	3.5%	4.2%
Sharpe Ratio	(0.014)	(0.011)	(0.010)	0.003	(0.007)	(0.001)	(0.011)	(0.004)	(0.009)
p value	0.12	0.16	0.09	0.04	0.09	0.06			
No. of Trades	198	10	122	48	44	26			
NASDAQ (N = 2,596)									
Annual Return	3.7%	8.1%	4.3%	12.1%	10.2%	7.3%			
Buy-and-Hold Return	(4.8%)	(4.8%)	(6.6%)	(4.8%)	(4.8%)	(6.6%)			
Over/(Under) Performance	8.5%	12.9%	10.9%	16.9%	15.1%	13.9%	8.4%	2.2%	3.9%
Sharpe Ratio	0.005	0.011	0.006	0.029	0.024	0.019	0.024	0.013	0.013
p value	0.04	0.03	0.05	0.02	0.03	0.01			
No. of Trades	160	18	76	38	38	18			

that are more predictive than the traditional DMACO. This assertion is further tested and corroborated through section Sign Prediction Ability testing.

Sensitivity of Profits to the Smoothing Factor

As discussed in the methodology, an exponential smoothing factor (α) of 10 percent was utilized in this study, thereby placing significantly less weight on the more recent observation. It is important to investigate the sensitivity of the smoothing factor on the profits generated by exponentially smoothed DMACO model.

Figure 11.1 Sensitivity of Excess Return to Smoothing Factor on the NASDAQ
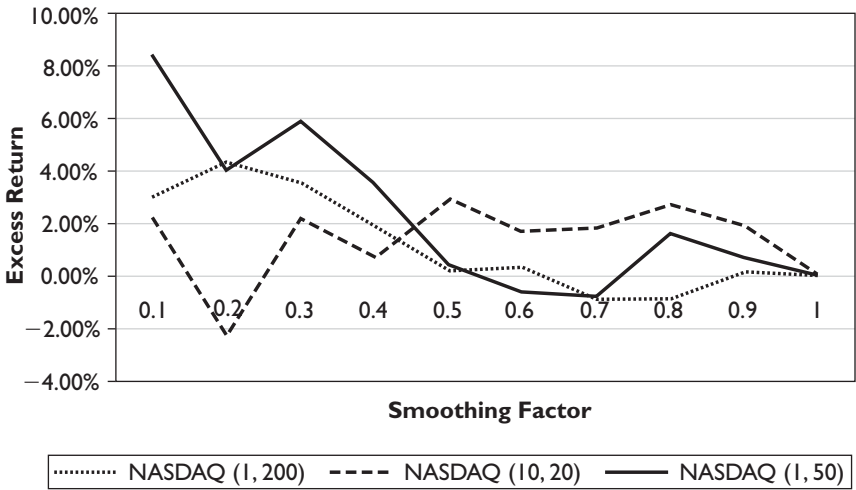
Figure 11.1 presents a chart of the excess profits generated on the NAS-DAQ by the three exponentially smoothed DMACO variants (over the traditional model) with various smoothing factors. Figure 11.1 reveals that the excess profits from the exponentially smoothed DMACO diminish as the smoothing factor (α) shifts from 10 percent to 100 percent, or stated differently, as more weight is placed on the most recent daily observation. This observation is most clearly evident with the DMACO (1,200) and DMACO (1,50). Interestingly, the DMACO (10,20) generated excess returns for most of the α, with a steep decline from 80 percent to 100 percent.

Figure 11.1 presents the results from only the NASDAQ. The same test on the S&P 500 and DJIA reveals similar results (data not presented).

Sign Prediction Ability of the Exponentially Smoothed DMACO

The PV of each trading signal given a 1-day and 10-day lag is presented in Table 11.2. Note that Table 11.1 presents the results of the VMA from a profitability standpoint, while the sign prediction ability tests the FMA perspective as defined by Brock et al. (1992). The binomial probability distribution was used to calculate the probability of the PV occurring by chance, and can be interpreted similar to a *p* value.

Table 11.2 Predictive Value (PV) of Buy and Sell Signals

	Panel A. Lag 1					
	DMACO Traditional Calculation STMA,LTMA			DMACO Exponentially Smoothed STMA,LTMA		
Market Index	1,50	10,50	1,200	1,50	10,50	1,200
S&P 500 (N = 2,596)						
Buy Signal, PV	56.7%	40.0%	48.8%	61.9%	33.3%	62.5%
BPD Probability	0.03	0.82	0.71	0.19	0.95	0.19
Sell Signal, PV	38.9%	0.0%	34.9%	42.9%	52.4%	50.0%
BPD Probability	0.99	NA	0.99	0.80	0.50	0.50
Dow Jones (N = 2,596)						
Buy Signal, PV	48.5%	60.0%	54.1%	50.0%	54.5%	50.0%
BPD Probability	0.69	0.37	0.26	0.50	0.41	0.50
Sell Signal, PV	49.5%	60.0%	50.8%	45.8%	59.1%	46.2%
BPD Probability	0.70	0.37	0.53	0.73	0.42	0.50
NASDAQ (N = 2,596)						
Buy Signal, PV	47.5%	22.2%	55.3%	52.6%	63.2%	62.5%
BPD Probability	0.81	0.99	0.21	0.50	0.17	0.17
Sell Signal, PV	48.8%	44.4%	47.4%	42.1%	52.6%	44.4%
BPD Probability	0.83	0.98	0.71	0.67	0.49	0.69

	Panel B. Lag 10					
	DMACO Traditional Calculation STMA,LTMA			DMACO Exponentially Smoothed STMA,LTMA		
Market Index	1,50	10,50	1,200	1,50	10,50	1,200
S&P 500 (N = 2,596)						
Buy Signal, PV	55.6%	60.0%	58.1%	57.1%	61.9%	87.5%
BPD Probability	0.17	0.19	0.18	0.33	0.19	0.03
Sell Signal, PV	43.3%	40.0%	23.2%	52.4%	61.9%	12.5%
BPD Probability	0.91	0.93	0.99	0.50	0.19	0.99
Dow Jones (N = 2,596)						
Buy Signal, PV	53.5%	80.0%	44.3%	54.2%	63.6%	50.0%
BPD Probability	0.27	0.03	0.84	0.42	0.14	0.50
Sell Signal, PV	44.4%	20.0%	62.3%	54.2%	45.%	53.8%
BPD Probability	0.88	0.95	0.03	0.42	0.73	0.5
NASDAQ (N = 2,596)						
Buy Signal, PV	57.5%	55.6%	55.3%	63.2%	68.4%	75.0%
BPD Probability	0.11	0.20	0.42	0.17	0.08	0.05
Sell Signal, PV	37.5%	55.6%	50.0%	63.2%	47.4%	55.6%
BPD Probability	0.99	0.20	0.50	0.17	0.67	0.33

Overall, the buy signals were correct more often than the sell signals. At both the 1-day and 10-day lag, 14 of the 18 tests of the exponentially smoothed DMACO had PVs of greater than 50 percent, whereas the traditional DMACO resulted in 12 of 18 positive PVs. At the 10-day lag, six of the nine exponentially smoothed DMACO sell signals had PVs greater than 50 percent.

The aggregate daily returns that follow the buy and sell signals and the buy-sell t statistics are presented in Table 11.3. The daily returns following the signals should provide the same conclusion regarding the informational content of trading rule signals as the predictive value analysis.

Table 11.3 Daily Average Percentage Return After Signal

Market Index	DMACO Traditional Calculation STMA,LTMA			DMACO Exponentially Smoothed STMA,LTMA		
	1,50	10,50	1,200	1,50	10,50	1,200
Lag 1						
S&P 500 (N = 2,596)						
Buy Signal	−0.0004	−0.0049	0.0015	0.0025	−0.0029	0.0018
Sell Signal	0.0009	0.0420	0.0047	0.0029	−0.0018	−0.0022
Buy-Sell, t statistic	−1.339	−0.899	0.789	0.698	−0.451	1.225
Dow Jones (N = 2,596)						
Buy Signal	−0.0006	0.0164	0.0003	0.0013	−0.0006	0.0014
Sell Signal	−0.0006	−0.0022	−0.0011	0.0011	−0.0009	0.0006
Buy-Sell, t statistic	0.199	0.985	0.559	1.052	−0.765	0.921
NASDAQ (N = 2,596)						
Buy Signal	−0.0004	−0.0220	0.0037	0.0011	0.0040	−0.0005
Sell Signal	−0.0004	0.0134	0.0012	0.0019	0.0003	0.0050
Buy-Sell, t statistic	−0.701	−0.653	0.088	0.879	0.678	−0.076
Lag 10						
S&P 500 (N = 2,596)						
Buy Signal	−0.0018	0.0208	0.0065	0.0073	0.0060	0.0152
Sell Signal	0.0025	0.0262	0.0161	−0.0030	−0.0091	0.0227
Buy-Sell, t statistic	−1.223	0.886	0.349	1.253	1.102	0.726
Dow Jones (N = 2,596)						
Buy Signal	0.0000	0.0351	−0.0061	0.0020	0.0117	0.0012
Sell Signal	0.0022	0.0096	−0.0041	−0.0028	−0.0036	−0.0055
Buy-Sell, t statistic	0.055	0.987	−0.765	1.092	2.083*	1.365
NASDAQ (N = 2,596)						
Buy Signal	0.0032	0.0064	0.0027	0.0192	0.0264	0.0136
Sell Signal	0.0031	−0.0172	0.0090	−0.0073	−0.0028	0.0139
Buy-Sell, t statistic	0.446	1.650	0.754	2.065*	1.981*	1.256

*Significant p values at the 5% level. The t statistic critical values are as follows: 1.645 at 0.10 α, 1.96 at the 0.05 α, and 2.576 at the α.

The return analysis is consistent with the profitability and predictive value tests. At the 1-day lag, the returns following a buy signal were positive in four of nine for the traditional DMACO, while the exponentially smoothed DMACO buy signals were followed by positive returns in six of the nine tests. At the 10-day lag, all nine tests of the exponentially smoothed DMACO's buy signal generated positive returns. The sell signals do not appear to be as predictive. At the 1-day lag, negative returns following a sell signal in four of nine for the traditional DMACO, while the exponentially smoothed DMACO's sell signals were followed by negative returns in only three of the nine tests. However, at the 10-day lag, the exponentially smoothed DMACO's sell signal was followed by negative returns in seven of the nine tests. These results are similar to prior studies (Brock et al.,1992; Lento & Gradojevic, 2007).

The results from the sign prediction tests (predictive value and return analysis) are consistent with the profitability tests, and corroborate the proposition that the exponentially smoothed DMACO results in fewer, more powerful signals than the traditional DMACO model.

CONCLUSION

This chapter provides new insights into the profitability of technical analysis by developing and testing a trading model that is shown to earn abnormal profits, and predict future price movements. The exponentially smoothed DMACO was tested on the S&P 500, NASDAQ, and DJIA for the period January 1999 to April 2009. The results suggest that the profitability of DMACO is significantly enhanced when the STMA and LTMA are calculated with the exponential smoothing technique. The increased profitability is significant, in many cases in excess of 5.0 percent per annum, and consistent across each moving average combination and data set.

The additional profits are not the result of increased risk. Rather, exponentially smoothing prices results in a fewer number of signals that are more informative. The results from the sign prediction tests are consistent with the profitability tests as large, positive returns follow the buy signal of the exponentially smoothed DMACO.

This study also investigated the sensitivity of the profits to the smoothing factor, and reveals that the profits decline as the smoothing factor increases (i.e., as more weight is placed on the most recent observation). Researchers are encouraged to further explore the profitability of the

DMACO by utilizing different smoothing technique. For example, the STMA and LTMA can be calculated on a time-series that has been smoothed with a double or triple exponential smoothing technique as opposed to the single exponential smoothing technique.

The traditional DMACO trading rules have been shown to be profitable as inputs into the combined signal approach (Lento, 2008). Investors can also explore the profitability of the exponentially smoothed DMACO by jointly employing the individual DMACO trading rules into the combined signal approach (Lento, 2008; Lento, 2009).

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NOTES

1. This section is not intended to be a comprehensive review of the literature on moving average trading rules. Readers interested in a literature review are encouraged to read Pring (2002).

2. Note that this test statistic does not always conform to the student distribution. However, an approximation for the degrees of freedom was developed by Satterthwaite (1946). If the number of observations is sufficiently large, this test statistic will converge to a standard normal distribution and the t-table critical values can be used.

SHAREHOLDER DEMANDS AND THE DELAWARE DERIVATIVE ACTION

Edward Pekarek

ABSTRACT

Among the most "interesting and ingenious" corporate "accountability mechanisms" is the shareholder derivative action. An aggrieved investor may demand the independent directors of a corporate issuer to litigate on behalf of the corporation, for harm(s) allegedly committed upon the corporation. This chapter explores who is eligible to sue derivatively and identifies some of the basic requirements to initiate derivative litigation.

INTRODUCTION

The efficient market hypothesis (EMH) presumes that existing stock prices always reflect the entire universe of information that is relevant to a given security. The EMH posits that the so-called "free" market functions as a pure pricing mechanism and equities will always trade at their relative "fair value" in a liquid and transparent market, leaving investors facing the impossible, at least in theory, to outperform the overall market through expert portfolio strategies, stock selection or market timing.

Various studies, including a number of those analyzed in the preceding chapters of this section, have revealed the possibility that technical trading

rules may produce investment results which are superior to traditional "buy and hold" portfolio selection strategies. While the application of technical trading rules may result in an increased probability of investment success, no amount of portfolio selection modeling, no matter how prescient, can prevent, or predict precisely, the presence of concealed corporate wrongdoing.

While some trading models utilize historical data such as moving averages, and still others seek to extrapolate future results through the use of nonlinearity-enhanced technical models or pattern recognition techniques, corporate insiders can, and do, go to great lengths to prevent transgressions such as self-dealing from being discovered by the market. Of course, one need only look to the headlines in the financial media during the macro decline of 2008 and 2009 for ample evidence that corporate wrongdoing is just as prevalent today as it was during the cynical era of Enron, or the "wild west" environment which made Jesse Livermore infamous.

This necessarily begs the question of how statistical modeling has consistently failed to detect this sort of undisclosed insider activity, and if the EMH pricing mechanism does properly discount all relevant information at any given moment, insider misconduct such as that which occurred in the Enron, Tyco, Worldcom, HealthSouth, or Adelphia scandals, should simply never have the chance to fester into enterprise-destroying frauds without being discovered. Nonetheless, sage fund managers, such as James Chanos, profit from a fraud scheme's imminent collapse through short-sale strategies. *See* Chanos (2002).

Some pundits maintain technical analysis and trading acumen can be confounded by market manipulation. *See* Degraaf (2009). Still others view chart interpretation and analysis as something akin to a "methodology for interpreting . . . the behavior of [humans] and markets" through a record of "inerasable fingerprints of human nature made graphic in the greatest struggle, next to war, in human experience" Edwards, Magee, and Bassetti (2007). The question of whether technical analysis can reveal such manipulation, as well as other forms of wrongdoing involving the managers of publicly held issuers, the corporate board of directors, is not the topic of this chapter. *See* 8 Del. C. § 141. This chapter contemplates some of the remedies available to shareholders of Delaware corporations where such wrongdoing has occurred.

Among the more "interesting and ingenious" corporate "accountability mechanisms" devised by common law to address such wrongdoing, is the

shareholder derivative action. *Kramer*, 546 A.2d at 351; *see also* Block, Barton, and Radin (1987). Derivative litigation has been instituted by shareholders of Delaware corporations in federal courts throughout the United States. *See In re CNET Networks, Inc.*, 483 F. Supp. 2d 947; *In re Bristol-Myers Squibb*, 2007 WL 959081; *Prince*, 148 Fed. Appx. 249. The necessary initial step a shareholder must take in pursuit of derivative relief is to communicate a demand to the corporation's "independent" directors, in which it must articulate the specific relief she or he seeks. If the "independent" director(s) refuse to take the action(s) demanded by the shareholder, or, if a lawful basis exists for the shareholder to be excused from the demand requirement, derivative litigation may proceed, provided certain other requirements are first satisfied.

Unlike claims for breach of duty, securities fraud, and the like, where the plaintiff(s) typically seeks relief related to alleged harms *committed upon them as individuals* by corporate fiduciaries, and perhaps by others, derivative litigation is reportedly "popular" because stock losses are not required to bring an action, as is the case with securities fraud litigation (Koppel, 2009). A typical shareholder derivative action involves the pursuit of civil and/or equitable relief on behalf of a corporation in which an investor owns an equity stake, often in the form of common stock. *Blasband*, 971 F.2d at 1040. The derivative shareholder litigates as a nominal plaintiff only, acting on behalf of the corporation in which she or he owns equity, for harm(s) allegedly *committed upon the corporation*, and as the term suggests, one who sues derivatively, "seeks redress on behalf of the corporation." *Kramer*, 546 A.2d at 351; *see also* Block, Barton, and Radin (1987); *Ryan*, 918 A.2d at 349. Pre-suit requirements established by Delaware law contain subtle nuances, some of which can result in the dismissal of a derivative action if performed improperly or ignored.

POLICY PURPOSES FOR DERIVATIVE ACTIONS

Delaware law developed the derivative action as a mechanism to enforce various rights of the corporation, and indirectly, its stakeholders, through the assertion of civil (and/or equitable) claims on behalf of that corporation, which, it has itself refused, *Kramer*, 546 A.2d at 351; *see also* Block, Barton, and Radin (1987), or "failed to enforce [rights] which may properly be asserted." *Aronson*, 473 A.2d at 808 *n.*1; *Maldonado*, 413 A.2d at 1255; *Harff*, 324 A.2d at 218; *Cantor*, 18 Del. Ch. 359. A shareholder suing derivatively is

a nominal litigant, acting on behalf of and for the benefit of the corporation, which is named, nominally, as a defendant that is concurrently the indispensable, *Agostino*, 845 A.2d at 1116–17 *n*.15, "real party in interest to which any recovery usually belongs." *Schuster*, 127 Cal. App. 4th at 312; *see also In re Tyson Foods, Inc.*, 919 A.2d 563; *Maldonado*, 413 A.2d at 1255; *Levine*, 219 A.2d at 145; *Slutzker*, 28 A.2d at 528; *Solimine*, 19 A.2d at 344. Corporate policy reforms and relief of other ilk may result from a successful derivative action, but the shareholder(s) recover(s) no money damages. At least one court has recently treated the shareholder of a corporation as a fiduciary for the purposes of derivative litigation. *Egelhof*, 2008 WL 352668. Directors and the nominal defendant corporation typically retain separate counsel due to the inherent tension unique to derivative litigation. *Kolbe*, 1988 WL 110511, at *1.

A nominal corporate defendant's state of incorporation is generally the source of the substantive (and certain procedural) law applied, including the specific derivative demand requirements, *compare* Fed. R. Civ. P. R. 23.1 *with* Del. Ch. R. 23.1, as well as any related demand(s) for books and records. *See* 8 Del. C. § 220. According to New York law, "issues related to the 'internal affairs' of a corporation are decided under the law of the state of incorporation because that state has an interest superior to that of other states in regulating the internal affairs of its corporation." *Potter*, 11 Misc. 3d at 965–66. Notwithstanding the above, a shareholder's first obstacle is often navigating the demand requirements of Delaware law, because of its influence as the "preeminent . . . place for businesses to incorporate since the early 1900s," and accordingly, due to the significant number of publicly held concerns which are Delaware corporations (Black, 2007).

DEMAND REQUIREMENTS

Because derivative litigation "impinges on the managerial freedom of directors," a shareholder can only initiate a derivative suit subsequent to the assertion of a written demand upon the independent directors that articulated actions be pursued on behalf of the corporation. *Stone*, 911 A.2d at 366. Both the Federal Rules of Civil Procedure and the Delaware Chancery Court Rules, with limited exceptions, require that a demand be made and served upon a corporation's directors. *Compare* Del. Ch. Court R. 23.1 *with* Fed. R. Civ. P. 23.1. Rule 23.1 of the Federal Rules of Civil Procedure codified a long-standing common law requirement that a

shareholder must first make a demand upon directors before initiating derivative litigation. *See* Fed. R. Civ. P. 23.1; *Mullins*, 45 F.Supp. 871; *Findley*, 240 P.2d 421. In a so-called "double" derivative suit, in which a shareholder of a parent corporation alleges injury(ies) to a subsidiary, any demand(s) must also be made on the subsidiary directors, unless the demand is excused by law, for example, by what is known as "futility," a factual condition which must first be demonstrated as to the directors of both the subsidiary and the parent. *Rales*, 634 A.2d at 934.

A shareholder demand should "alert the [b]oard of [d]irectors so that it can take such corrective action, if any, as it feels is merited." *Allison*, 604 F.Supp. at 1117. The derivative demand is also a mechanism designed "to curb a myriad of individual shareholders from bringing potentially frivolous lawsuits on behalf of the corporation, which may tie up the corporation's governors in constant litigation and diminish the board's authority to govern the affairs of the corporation." *Ryan*, 918 A.2d at 352; *see also* Fed. R. Civ. P. 23.1; Del Ch. Court R. 23.1. One district court recently criticized "scandalous" derivative litigation, and opined that it typified "[t]he very abuses that led to the reform embodied by the PSLRA permeate the world of derivative litigation." *In re JPMorgan Chase & Co.*, 2008 WL 4298588, at *10; *id*.

Delaware and federal rules offer little guidance regarding what must actually appear within a shareholder demand. Neither rule provides specific detail as to other mechanical and procedural aspects of a proper demand. Rule 23.1 does clearly mandate, however, that a valid shareholder demand must be made upon directors of the corporation, or upon a "comparable authority." If such a demand is not communicated to the corporation's directors, the shareholder's pleadings must articulate in detail the reason(s) for failure to assert a demand. *See Simon*, 775 N.Y.S.2d at 317; *id*. Delaware courts have detailed technical requirements for shareholder demands. *See Allison*, 604 F.Supp. at 1117; *id*.

All "Reasonably Available" Information Should Be Gathered for a Demand

A prudent shareholder will expend all reasonable efforts and exhaust all reasonable means to gather relevant facts prior to bringing derivative litigation, and the due diligence performed prior to crafting a demand should be no exception. *Beam I*, 845 A.2d at 1056; *id*. Potential sources of relevant

information for an investigating shareholder include: SEC filings, local tax authority records, county property records, state and federal court dockets, secretaries of state corporation filings; as well as a variety of non-government sources, including media reports, press releases, investor relations representatives, corporate Web sites and business data sources such as Bloomberg, Dun & Bradstreet, Hoovers, Westlaw, and Lexis; and self-regulatory organizations such as stock exchanges and the Financial Industry Regulatory Authority ("FINRA"). *Rales*, 634 A.2d at 935 *n*.10.

Shareholders contemplating derivative litigation are encouraged by courts to employ Delaware's Section 220 demand to inspect corporate books and records as a fact-finding tool *prior* to initiating a derivative action. *See, e.g., id*. If a tribunal determines that a failure to employ a Section 220 demand before initiating derivative litigation was unreasonable, under the circumstances of the case, the risk of dismissal is substantial. *Id*. If a shareholder seeks to be excused from the demand requirement, it is virtually *expected* that the shareholder will have first "used a Section 220 books and records inspection to uncover such facts," before seeking relief from the Delaware Chancery Court. *Id.; Beam II*, 833 A.2d at 983–84; *see In re Walt Disney Co.*, 825 A.2d at 279; *see also Beam I*, 845 A.2d at 1056 *n*.51.

Many legitimate uses exist for the information that results from corporate books and records inspections, such as "bring[ing] a derivative suit in the case of corporate waste or mismanagement, or to bring a suit attaching some aspect of a company's public disclosures," or to evaluate the propriety of the refusal by directors to satisfy the terms of a shareholder demand. *See, e.g., Disney*, 2005 WL 1538336, at *5; *see also Grimes*, 724 A.2d at 564. A Delaware court recently noted that directors are afforded an opportunity to "exculpate themselves" in the face of a Section 220 demand. *In re Tyson Foods, Inc.*, 919 A.2d at 578.

The Section 220 inspection provisions function, *inter alia*, to: (i) investigate a company's suspected wrongdoing; (ii) ensure that it can prepare a thorough shareholder demand; and (iii) form the basis of a particularized pleading; and (iv) "can serve as a 'tool at hand' [for directors] to defend against unfounded charges of wrongdoing." *Id*. at 578 *n*.20. The unique opportunity for directors to inform aggrieved shareholders, and to demonstrate the directors exercised good faith business judgment in the disputed managerial decisions, including responses to shareholder demands, serves as a valuable by-product of the requirement that a shareholder must conduct a duly diligent investigation of all reasonably available information prior to

asserting a demand. The liberal use of Section 220 inspections *before* filing a derivative action supports the ideal of judicial economy pragmatically, because it may deter some meritless litigation. *Id*.

At least one Delaware jurist has noted, with apparent disappointment, "surprisingly, little use has been made of section 220," he speculated the books and records demand remains fallow, in the derivative context, due to "an unseemly race to the court house, chiefly generated by the 'first to file' custom seemingly permitting the winner of the race to be named lead counsel." *Rales*, 634 A.2d at 935 *n*.10. Considering the depth of factual detail often required to assert a shareholder demand properly, and mindful of the Delaware courts' criticism of litigants who have not utilized the tools made available to them, a Section 220 demand to inspect corporate books and records is likely part of a prudent course of conduct *prior* to the assertion of a derivative demand upon a corporation's independent directors.

Demand Deadlines: When Must Directors Respond?

Delaware law affords directors broad discretion to determine whether to bring a lawsuit on behalf of the corporation they manage in response to a shareholder demand. 8 Del. C. § 141(a); *see also In re IAC/InterActiveCorp. Sec. Litig.*, 478 F. Supp. 2d. at 598. Directors of Delaware corporations are generally protected from liability for refusing a shareholder demand, provided the decision was not "wrongful," meaning that the refusal was: (i) a legitimate exercise of the directors' good faith business judgment; and (ii) a sound exercise of lawful discretion. *Aronson*, 473 A.2d at 813; *id*. The amount of time directors are permitted to render decisions regarding shareholder demands varies widely, with "no precise rule as to how much time a [b]oard must be given to respond to a demand." *Allison*, 604 F.Supp. at 1117–18. Procedural rules do not specify how long recipient directors have to respond to a shareholder demand.

Delaware courts consider complexities of contended issues and the directors' actions in response to a proper shareholder demand. Where directors do not respond to a shareholder demand, jurists employ fact-intensive analysis, guided by a rule of reason, in order to determine whether the time between the assertion of a shareholder demand, and the filing of a derivative action, is appropriate or premature. One such court held a derivative suit initiated one month after asserting a shareholder demand was appropriate, *Rubin*, 701 F. Supp. at 1046, while another found

the filing of a derivative complaint roughly 10 weeks after serving a demand was premature, reasoning the "magnitude and complexity" of contested issues warranted affording the directors additional time to decide, *see Allison*, 604 F.Supp. at 1118, while yet another tribunal found an eight-month interval to be insufficient, due to the particular complexities of that case. *Mozes*, 638 F. Supp. at 221.

Juridical determination of whether the initiation of derivative litigation is premature is guided by a case-by-case consideration which utilizes highly fact-intensive findings to scrutinize whether directors have informed themselves "of all material information essential to an objective and meaningful evaluation of the demand." *Allison*, 604 F.Supp. at 1117–18; *Abramowitz*, 513 F.Supp. at 132–33. This standard suggests the degree of detail provided by a shareholder derivative demand might directly influence what is perceived to be a reasonable amount of time for directors to respond. Perhaps an inversely correlative relationship exists between: (i) the amount of time directors are afforded to render a decision regarding a shareholder demand; and (ii) the depth of detail within the factual information provided in such a demand, relative to the factual complexity of the disputed issue(s).

STANDING TO SUE DERIVATIVELY

A timely, duly diligent, and otherwise proper demand that directors initiate suit on behalf of the corporation is a condition precedent to the commencement of Delaware derivative litigation. Del. Ch. Court R. 23.1; Fed. R. Civ. P. 23; *see also In re eBay, Inc. Shareholders Litig.*, 2004 WL 253521, at *2; *see also In re J.P. Morgan Chase & Co.*, 2005 WL 1076069, at *8. Absent a legal excuse, it is a "threshold question of standing as to whether the shareholder has made a demand on the board of directors." *In re IAC/InterActiveCorp Sec. Litig.*, 478 F. Supp. 2d at 597. The viability of a derivative suit can turn on the initial inquiry of whether the shareholder has competently pleaded standing relative to an allegedly wrongful refusal of a properly asserted demand, or of the futility of asserting such a demand, which, if established, would obviate the demand requirement. *Miller*, 1992 WL 329313, at *5; *see also* Futility discussion, *infra*. A shareholder who contends she or he has standing to sue derivatively, as a function of legal excuse due to demand futility, must adhere to alternative pleading requirements set forth in Delaware Chancery Rule 23.1. *Id.*; *see also id*. at *5 n.10.

Continued Shareholder Status

In order to impose a derivative demand upon a Delaware corporation, a prospective nominal plaintiff "must have been a shareholder at the time of the challenged transaction[s] to have standing to maintain a shareholder derivative suit." *Blasband*, 971 F.2d at 1040. That putative plaintiff must have been a genuine stakeholder in the corporation, concurrent with any alleged wrongdoing, and she or he must retain shareholder status throughout the course of derivative litigation. *See id.* at 1041; *Lewis*, 477 A.2d at 1046; *see also* 8 Del. C. § 327.

The "sole purpose" of this continuing ownership requirement is to prevent the "evil" of opportunistic plaintiffs from purchasing stock in a Delaware corporation simply "in order to maintain a derivative action designed to attack a transaction which occurred prior to the purchase of the stock." *Id*. at 1040–41. The requirement that a derivative plaintiff retains shareholder status throughout the case "ensures that the plaintiff has sufficient incentive to represent adequately the corporation's interests during litigation." *Id.* at 1041. The presumptive legislative intent of these statutory provisions is to prevent abuse of the derivative action mechanism. *Id*. Delaware law apparently does not, however, require the plaintiff to hold the entire position in the stock of the corporation being sued derivatively throughout the pendency of such litigation. This may be especially relevant where a shareholder also contemplates a separate action for securities fraud and might face somewhat competing issues, such as those which involve loss causation. *See*, *e.g.*, *Dura Pharmaceuticals*, 544 U.S. 336.

FUTILITY EXCUSES THE DEMAND REQUIREMENT

If a shareholder demand asserted on a corporation's directors would be pointless, or "futile," the requirement of a demand letter is excused as a matter of law, and a derivative action may proceed, provided futility is "well-pleaded." *See* Fed. R. Civ. P. 23.1; *see also In re IAC/InterActive Corp Sec. Litig.*, 478 F. Supp. 2d at 598. The primary purpose of the demand requirement is to afford directors the "opportunity to examine the alleged grievance and related facts and to determine whether pursuing the action is in the best interest of the corporation." *Ryan*, 918 A.2d at 352 *n*.20; *see also* Fed. R. Civ. P. 23.1; Del. Ch. Ct. R. 23.1. However, directors might not

always be inclined to act in the best interest of a corporation in which a putative shareholder-plaintiff holds a stake. One such example where a shareholder might be excused due to demand futility is where "directors are incapable of making an impartial decision regarding whether to institute such litigation." *Stone*, 911 A.2d at 366. Delaware courts have recognized where "a question is rightfully raised over whether the board will pursue these claims with 100% allegiance to the corporation, since doing so may require that the board sue *itself* on behalf of the corporation," a demand may be excused due to futility. *Ryan*, 918 A.2d at 354.

FUTILITY, DIRECTOR INDEPENDENCE, AND BUSINESS JUDGMENT

The director of a Delaware corporation is presumed to be incapable of acting objectively in the context of a shareholder demand if she or he is "interested in the outcome of the litigation." *Grimes*, 673 A.2d 1207; *see also In re eBay*, *Inc.*, 2004 WL 253521. Delaware courts consider a "classic example[ ]" of director self-interest to be "a business transaction involv[ing] either a director appearing on both sides of a transaction or [ ] receiving a [ ] benefit from a transaction not received by the shareholders generally." *Berger*, 2005 WL 2807415, at *6. Delaware law provides at least "two instances where a plaintiff is excused from making demand." *Ryan*, 918 A.2d at 352. A shareholder can first raise reasons that cast doubt regarding the independence, or disinterest, of a majority of the corporation's directors. *Id.*; *Zimmerman*, 2002 WL 31926608, at *7. For example, where "three directors of a six person board are not independent and three directors are independent, there is not a majority of independent directors and demand would be futile." *Beam I*, 845 A.2d at 1046 *n*.8; *cf. In re Oracle Corp.*, 824 A.2d 917.

A second manner in which a shareholder may be excused from the required demand is to plead particularized reasons which raise reasonable doubts that the corporate acts connected to the alleged wrongdoing were not a product of the board's valid exercise of business judgment. *Ryan*, 918 A.2d at 352; *see also* Del. Ch. Ct. R. 23.1. Courts generally respect the decisions made by corporate directors, unless a shareholder alleges a majority of the directors lacked independence in relation to a contested decision, or that certain directors are actually interested in the transaction(s) at issue, and did "not act in good faith, act[ed] in a manner that cannot be attributed

to a rational business purpose, or reach[ed] their decision by a grossly neg-
ligent process that include[d] the failure to consider all material facts rea-
sonably available." *Berger*, 2005 WL 2807415, at *6.

A recent Delaware decision found a shareholder established demand
futility with pleading allegations that detailed wrongdoing committed by a
compensation committee of the nominal defendant corporation's board of
directors, and where members of that compensation committee also consti-
tuted the board's majority; the shareholder also raised sufficient doubts
challenging whether the disputed transactions were actually the result of a
valid exercise of business judgment. *Ryan*, 918 A.2d at 354. Similarly, if
a board's majority includes familial or material financial interest(s); or if the
directors are for some other reason unable to act independently, such as
control or domination; or if it is otherwise established the "underlying
transaction is not the product of a valid exercise of business judgment," the
putative plaintiff would be excused from the required pre-suit derivative
demand. *Beam I*, 845 A.2d at 1049.

A director is considered to be "interested," in the derivative context, if it
can be demonstrated that she or he will incur a potential personal benefit,
or avoid a detriment, that is not equally shared by the stockholder(s), as a
result of the outcome of a decision detailed in the derivative demand. *Id.*
Whether a director can exercise independent and good faith business judg-
ment is often answered by analyzing the "personal consequences resulting
from the decision." *Id.* The "primary basis" for measurement of the extent
(or lack) of a director's independence is "whether the director's decision is
based on the corporate merits of the subject before the board, rather than
extraneous considerations or influences." *Id.* When a shareholder can show
that the majority of a board's directors lack independence, no demand is
required and the shareholder may proceed with the litigation derivatively.

CONCLUSION

The corporate accountability mechanism of a Delaware derivative action
requires a shareholder to thoroughly investigate the facts related to alleged
wrongdoing and be duly diligent in obtaining all reasonably available infor-
mation, utilizing various government and non-government sources, as well
as a Section 220 corporate books and records inspection demand. A Dela-
ware corporation's directors must discharge the duty to be fully informed
when making the decision of whether to refuse a shareholder demand, or to

initiate an action on behalf of the corporation, and must make that decision as a good faith exercise of valid business judgment in order to withstand subsequent challenges by the shareholder. A demand must be asserted for what has been described as a "proper purpose."

Directors who are "interested," or who cannot be considered "independent," need not be served with a shareholder demand, and if the majority of a Delaware corporation's board of directors cannot be construed as disinterested or independent, a shareholder can proceed directly to litigation, with reliance on the doctrine of futility, excused of the condition precedent to serve a derivative demand. However, judicial evaluations have differed greatly regarding the question of the disinterest and/or independence of directors.

A shareholder must carry the burden of establishing reasonable doubt as to director interest or dependence when seeking to be excused from the demand requirement. A shareholder might be able to reduce the time that is reasonable for a board to decide whether to accept or refuse a demand by providing as much relevant factual detail as is reasonably possible about the contested transactions and/or activities. Delaware courts undertake exacting reviews of the factual complexities of a shareholder demand in order to determine whether an action was initiated prematurely, and the outcome of those evaluations can vary greatly, but the analysis is typically governed by a rule of reason. The overall rigor required of shareholders also extends to the degree of particularity that is expected of a derivative pleading, which supports a policy of judicial economy by preventing meritless lawsuits that might otherwise encumber the limited managerial resources of Delaware corporations, to the potential detriment of its other shareholders.

The derivative action truly is an ingenious corporate accountability mechanism. When a shareholder discovers facts that indicate potential harm has been brought upon the corporate form, it is unlike any other legal measure designed to empower shareholders. However, the many nuances of derivative litigation, and its particular pre-litigation requirements, are sometimes steep obstacles aggrieved shareholders must navigate adroitly if they expect that their derivative claim will ever see the interior of a courtroom.

ACKNOWLEDGMENTS

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EXCHANGE- TRADED FUND STRATEGIES

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LEVERAGED EXCHANGE-TRADED FUNDS AND THEIR TRADING STRATEGIES

Narat Charupat

ABSTRACT

Leveraged and leveraged inverse exchange-traded funds (ETFs) are designed to generate *daily* returns that are in multiples or negative multiples of the daily returns on some benchmarks. Although these products are relatively recent, they have been the fastest-growing segment of the U.S. ETF market. Due to the daily rebalancing of leverage employed, the returns on these ETFs over any holding period longer than one day will deviate from the stated multiples. This chapter examines the risk and return patterns of several trading strategies.

INTRODUCTION

Leveraged and leveraged inverse exchange-traded funds (hereafter referred to collectively as leveraged ETFs) are publicly traded mutual funds that aim to generate *daily* returns that are in multiples or negative multiples of the daily returns on some benchmarks. They were first introduced in the United States in 2006.[1] Since then, this segment of the U.S. ETF market has grown very quickly in terms of assets under management and trading activity.

Currently (July 2009), there are over 100 leveraged ETFs traded on U.S. exchanges, with assets totaling approximately $31 billion. The majority of them (over 60 leveraged ETFs) are managed by ProShares and are listed on the American Stock Exchange (AMEX). Other providers include Direxion Funds and Rydex Investments. Typically, these ETFs offer returns that are 2×, 3×, −2×, or −3× the benchmark returns.[2] The benchmarks include bond indexes, equity indexes and subindexes, commodities and their indexes, currencies, and real estate indexes.

Although leveraged ETFs currently account for only 5.35 percent of the total ETFs market in terms of assets under management (i.e., $31 billion out of $578 billion), their trading volume is disproportionately large at 37.18 percent of the total ETFs trading volume. One reason for this disproportion is that speculators (e.g., day traders), whose trading is typically short-term in nature, are attracted by the embedded leverage. Another reason is that leveraged ETFs are designed to provide the specified leveraged returns only on a *daily* basis. This is achieved by daily rebalancing the dollar amount of leverage that they use.[3] The daily rebalancing causes the returns compounded over any holding period longer than one day to differ from the promised ratios. As a result, any investors who want to hold these ETFs for a long period will have to adjust their positions in the funds regularly to counter the effect of the funds' rebalancing. This leads to more trading activity in the funds.

In this chapter, I examine the risk-return patterns of leveraged and leveraged inverse ETFs. I also discuss a few trading strategies for these funds.

TRADING STRATEGIES

Directional Trades

The most straightforward use of leveraged ETFs is for traders to express their views on the directions of the movements of the underlying benchmarks. Individuals who believe that the prices of the underlying benchmarks are moving up, can buy bull (e.g., 2× or 3×) and/or short bear (e.g., −2× or −3×) leveraged ETFs. Individuals who have the opposite opinions can buy bear and/or short bull leveraged ETFs.

There are two related issues to keep in mind when using leveraged ETFs in directional trades. First, as alluded to above, the compounded return from holding these ETFs over a long horizon will be different from the stated leverage ratio. Second, the compounded return from buying a bull

(bear) leveraged ETF will be different from shorting a bear (bull) leveraged ETF on the same benchmark.

To see the reason why these two issues arise, note that a leveraged ETF is designed to maintain its stated leverage ratios (such as $3\times$ or $-2\times$ the benchmark return) on a daily basis. This is so that traders can buy or sell it on any day and get the promised ratio. To achieve this, the fund's *dollar* amount of leverage is adjusted daily to reflect the changes in the value of the benchmark, so that the *percentage* of leverage is maintained.

For example, suppose a $2\times$ leveraged ETF is started today where the benchmark index is at 100. The fund would borrow 100 in order for its total exposure to be 200. Then, if the benchmark goes up to 110 tomorrow (i.e., a 10 percent increase), the value of the fund will now be 220, of which 120 belongs to the fund's holders and 100 is owed to the lender.[4] As a result, to maintain the $2\times$ leveraged ratio going forward, the fund will need to increase their borrowing to 120 to match the holders' equity in the fund. Vice versa, if instead of going up by 10 percent, the benchmark declines by 10 percent tomorrow, the value of the fund will now be 180, of which 80 belongs to the fund's holders and 100 is owed to the lender. Therefore, to maintain the $2\times$ leveraged ratio going forward, the fund will need to reduce their borrowing to 80 to match the holders' equity in the fund.

The daily rebalancing of the fund's exposure causes its compounded return to deviate from its stated ratio. To illustrate this fact, Table 13.1 presents a simple two-day example of a $2\times$ bull leveraged ETF under four different return paths. Consider return path 1, where on day 1, the benchmark index increases by 10 percent, and the next day it declines by 5 percent. Over two days, the benchmark return is $(1.1 \times 0.95) - 1 = 4.50$ percent, causing holders of this $2\times$ ETF to think that they would get a 9 percent return on the ETF. However, the actual returns are $+20$ percent for day 1 and -10 percent

Table 13.1 Examples of Returns on a $2\times$ ETF Under Various Return Paths

| Path | Benchmark Return | | Benchmark Compounded | ETF Return | | ETF Compounded |
	Day 1	Day 2	Return	Day 1	Day 2	Return
1	+10%	−5%	+4.50%	+20%	−10%	+8.00%
2	+2.2252%	+2.2252%	+4.50%	+4.4504%	+4.4504%	+9.10%
3	−10%	+5%	−5.50%	−20%	+10%	−12.00%
4	−2.7889%	−2.7889%	−5.50%	−5.7778%	−5.7778%	−10.84%

for day 2, resulting in a two-day return of $(1.2 \times 0.9) - 1 = 8$ percent, which is less than twice the benchmark return.[5]

The less volatile the underlying benchmark's daily returns *over the return path*, the higher the compounded returns will be. Consider return path 2, where the benchmark return on each of the two days were 2.2252 percent (i.e., zero volatility with the same two-day benchmark return as in path 1), the compounded return of the 2× ETF would be 9.10 percent, which exceeds twice the benchmark return.

The same conclusion obtains for the case where the benchmark declines over the two days. Consider return paths 3 and 4. Under both paths, the benchmark's two-day return is −5.50 percent. However, under path 3 (where there is volatility), the 2× ETF's return is −12 percent, which is less than twice the benchmark return. On the other hand, under path 4 (where there is zero volatility), the 2× ETF's return is −10.84 percent, which is higher than twice the benchmark return.

Volatility has the same effects on bear leveraged ETFs. To see this, the same calculations as in Table 13.1 are repeated for a −2× ETF. The results are in Table 13.2. Here again, volatility causes ETF returns to be lower. For example, under return path 3 (which is volatile), the benchmark's two-day return is −5.50 percent, while the return on this bear ETF is +8 percent, which is less than twice the negative of the benchmark return (i.e., +11 percent). On the other hand, for return path 4, there is no volatility and the ETF return is higher at 11.89 percent (which exceeds twice the negative of the benchmark return).

Formally, define the compounded return over N days from holding a leveraged ETF whose leveraged ratio is β as

$$r_{t,t+N} = \prod_{j=1}^{N}(1 + \beta\, i_{t+j-1,t+j}) - 1 \tag{13.1}$$

Table 13.2 Examples of Returns on a −2× ETF Under Various Return Paths

Path	Benchmark Return		Benchmark Compounded Return	ETF Return		ETF Compounded Return
	Day 1	Day 2		Day 1	Day 2	
1	+10%	−5%	+4.50%	−20%	+10%	−12.00%
2	+2.2252%	+2.2252%	+4.50%	−4.4504%	−4.4504%	−8.70%
3	−10%	+5%	−5.50%	+20%	−10%	+8.00%
4	−2.7889%	−2.7889%	−5.50%	+5.7778%	+5.7778%	+11.89%

where $i_{t+j-1,t+j}$ is the daily rate of return on the benchmark.[6]

It then follows that the payoff from investing \$1 in a leveraged ETF over N days is

$$1 + r_{t,t+N} = \prod_{j=1}^{N}(1 + \beta\, i_{t+j-1,t+j}) \tag{13.2}$$

which can be rewritten as

$$1 + r_{t,t+N} = \prod_{j=1}^{N}(1 + \beta\, i_{t+j-1,t+j}) = \exp\left[\sum_{j=1}^{N}\ln(1 + \beta\, i_{t+j-1,t+j})\right] \tag{13.3}$$

Taking a second-order Taylor expansion of the right-hand side of Equation (13.3) yields the following approximation[7]

$$1 + r_{t,t+N} \approx (1 + \beta\, \bar{i})^{N} \exp\left[-\frac{1}{2}\frac{\beta^2}{(1 + \beta\, \bar{i})^2} N s^2\right] \tag{13.4}$$

where $\bar{i}$ is the average of the benchmark's daily return *during the period*, and $s^2 = \frac{1}{N}\sum_{j=1}^{N}(i_{t+j-1,t+j} - \bar{i})^2$, is the sample variance of the daily returns.

Equation (13.4) states that the N-day compounded return on a leveraged ETF, $r_{t,t+N}$, is equal to the compounded return based on the *average* benchmark return over the period multiplied by an exponential term. If there is no volatility in the return path (i.e., $s^2 = 0$), the exponential term is equal to one, and $r_{t,t+N}$ exceeds β times the benchmark's compounded return. This implies that in a steadily rising or steadily declining market, the N-day return from a leveraged ETF will be greater than promised by the ratio.

On the other hand, when there is volatility in the return path, the exponential term is less than 1. The higher the volatility of the return path, the lower will be the exponential term. Therefore, leveraged ETFs will perform poorly in a sideways market where the benchmark fluctuates but does not change by much over a given period. In addition, the higher the absolute value of the multiple, the greater will be the impact of volatility.

Finally, it is clear from Tables 13.1 and 13.2 that the returns on bull and bear leveraged ETFs are not the exact opposite of each other. For example, suppose a trader buys both a 2× and a −2× ETF. Then, if return path 1

occurs, the combined two-day return will be −4 percent, rather than zero. This is due to the fact that *daily* returns on one ETF are the negative of daily returns on the other. When these returns are compounded, the resulting *N*-day returns are no longer the negative of one another.

One implication of this difference in returns is that a long position in a bull (bear) ETF is not the same as a short position in a bear (bull) ETF over any holding period longer than one day. Which position to use depends on the trader's belief regarding the direction and the volatility of the benchmark.

Consider first the case where volatility is expected to be low. If a trader believes that the benchmark is going to rise, he or she could either long the bull-leveraged ETF or short the bear-leveraged ETF. However, it can be shown that a long position in the bull ETF will perform better. This can be seen from Equation (13.4). Consider an extreme case where volatility is zero (i.e., $S^2 = 0$). Then, the *N*-day return on a long position in a bull-leveraged ETF with a leverage ratio of β, where $\beta > 0$, is

$$r_{t,t+N} = \left(1 + \beta\,\bar{i}\right)^N - 1 \tag{13.5}$$

while the *N*-day return on a short position in a bear-leveraged ETF with a leverage ratio of $-\beta$ is

$$r_{t,t+N} = -\left[\left(1 - \beta\,\bar{i}\right)^N - 1\right] \tag{13.6}$$

It is straightforward to show that in a rising market (i.e., $\bar{i} > 0$), the return in Equation (13.5) will be higher than the return in Equation (13.6).

Next, if the trader believes that the benchmark is going to decline, he or she could either short the bull-leveraged ETF or long the bear-leveraged ETF. If volatility is expected to be low, then a long position in the bear ETF will perform better. Again, this can be shown by comparing the negative of the returns in Equations (13.5) and (13.6).

On the other hand, consider the case where volatility is expected to be high. In this case, it is less clear-cut which strategy will be more profitable. For example, if the trader believes that the benchmark is going to rise, he or she could buy a bull ETF or short a bear ETF. The *N*-day return on a long position in a bull leveraged ETF with a leverage ratio of β is

$$r_{t,t+N} \approx \left(1 + \beta\,\bar{i}\right)^N \exp\left[-\frac{1}{2}\frac{\beta^2}{\left(1 + \beta\,\bar{i}\right)^2}\,Ns^2\right] - 1 \tag{13.7}$$

while the N-day return on a short position in a bear-leveraged ETF with a leverage ratio of $-\beta$ is

$$r_{t,t+N} \approx - \left\{ \left(1 - \beta\,\bar{i}\right)^N \exp\left[-\frac{1}{2} \frac{\beta^2}{\left(1 - \beta\,\bar{i}\right)^2} N s^2 \right] - 1 \right\} \qquad (13.8)$$

Given the leverage ratio β and the length of holding period N, the returns in Equations (13.7) and (13.8) will depend on the magnitude of expected return $\bar{i}$ and volatility s.

Theoretically, it can be shown that there are combinations of $\bar{i}$ and s such that the return in Equation (13.7) exceeds the return in Equation (13.8), and vice versa. However, for a realistically high volatility (say, between 30 percent and 60 percent per annum) and a reasonable expected rate of return (say, below 40 percent per annum), the return in Equation (13.8) will always be higher (and thus shorting a bear ETF is better than buying a bull ETF).

To see this, note that the returns in Equations (13.7) and (13.8) depend on the product between compounded return based on $\bar{i}$ and an exponential term. When, $\bar{i} > 0$, the compounded return in Equation (13.7) (i.e., $(1 + \beta\,\bar{i})^N$) is greater than the compounded return in Equation (13.8) (i.e., $(1 - \beta\,\bar{i})^N$). The higher the $\bar{i}$, the greater is the difference. At the same time, the value of the exponential term in Equation (13.8) is less than the value of the exponential term in Equation (13.7) for any $\bar{i} > 0$ and any non-zero volatility, s^2. The larger the volatility, the lower is the exponential term in Equation (13.8). Therefore, positive expected return and high volatility affect the product of the two terms in opposite directions. For reasonable values of $\bar{i}$ and s, the effect of volatility is greater than the effect of expected return. As a result, the return in Equation (13.8) is greater than in Equation (13.7).

Finally, if it is expected that the benchmark is going to drop and volatility will be high, then the same line of reasoning as above can be used to show that shorting a bull ETF is a better strategy than buying a bear ETF.

Straddles

In option trading, a long (short) straddle involves buying (writing) a call and a put options with the same exercise price and maturity date. A long straddle will be profitable if the underlying stock price becomes more volatile than expected by the market and the price moves sufficiently far from the exercise

price. A short straddle will be profitable if the stock price moves in a narrow range and ends up close to the exercise price. In other words, a straddle is a trading strategy that traders use to express their beliefs about the volatility and the size (but not the direction) of the underlying price movement.

In the context of leveraged ETFs, it has been suggested in several print and Web media that a trader who wants to express his or her opinions on a benchmark's future volatility can use a long straddle—buying both a bull and a bear-leveraged ETF on the benchmark, or a short straddle—shorting both a bull and a bear ETFs.

Consider first the case where a trader expects a period of low volatility. If he or she buy a long straddles, the N-day return from this straddle in the extreme case of zero volatility is $[(1 + \beta \bar{\imath})^N - 1] + [(1 - \beta \bar{\imath})^N - 1]$, which can be shown to be positive regardless of the direction and the size of the underlying benchmark movement. The bigger the movement (in either direction) and the longer the holding period, the higher is the return. Note, however, that this strategy is very risky. If the benchmark is not expected to change by much and/or volatility does not stay low, then the return from this strategy may not be worth the risk of the investment. Therefore, this strategy might be used only if the trader believes that the benchmarks will steadily and significantly move upward or downward.

Consider next the case where the benchmark's volatility is expected to be high. In this case, a short straddle will be profitable if the benchmark fluctuates but ends up close to where it begins. Recall from the discussion in the previous section that leveraged ETFs perform poorly in a sideways market. Hence, in such a market (e.g., $\bar{\imath} = 0$), the return from a short straddle will definitely be positive. The higher the volatility, the more positive is the return.

In contrast, if the benchmark moves up or down significantly, the return from a short straddle will be low. The wider the move (in either direction), the lower is the return. Indeed, the return from a short straddle can theoretically be negative. However, for realistic values of $\bar{\imath}$ and s, the return will be positive, but may not be worth the risk of the investment.

In summary, a long straddle might be used if the benchmark is expected to steadily and significantly increase or decline. On the other hand, a short straddle can be used if the benchmark is expected to be volatile but to not move far from its original value. The risk of these two straddles is substantial and may not be merited by their payoffs.

CONCLUSION

In this short chapter, I discuss the risk and return patterns of investments in leveraged ETFs. These ETFs attempt to provide daily returns that are in multiples or negative multiples of the daily returns on some underlying benchmarks. Due to the funds' daily rebalancing of the amounts of leverage, the returns on these ETFs over a long holding period will deviate from the promised ratio. Holding-period returns from a long position in a leveraged ETF will not be the same as the negative of the return from a short position. This implies that buying (shorting) a bull ETF is not the same as shorting (buying) a bear ETF. As a result, depending on traders' expectation regarding the benchmark's expected return and volatility, certain trading strategies will perform better than others over a long holding period even if they are the same on a daily basis.

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NOTES

1. Leveraged mutual funds had been in existence long before 2006. However, they were not publicly traded.

2. ETFs with greater leverage (such as 4× or −4×) are currently being considered.

3. Hence, the percentage (not the dollar amount) of leverage is constant from day to day.

4. For simplicity, the borrowing rate is assumed to be zero. The logic does not change if a non-zero rate is used.

5. It is obvious that the order of the daily returns in the path does not matter.

6. Here, two assumptions are made. First, it is assumed that leveraged ETFs have no tracking errors, which can be justified by the fact that these funds typically use derivatives such as forward contracts or total return swaps to achieve their desired returns. Second, their market prices are assumed to match closely their NAVs. Empirical tests done on *traditional* (i.e., non-leveraged) ETFs in the U.S. market show that while deviations existed, they were generally small and highly transient, especially when the underlying benchmarks are domestic indexes. See, for example, Ackert and Tian (2008), Chu and Hsieh (2002), and Engle and Sarkar (2006)

7. This approximation is taken from Co (2009).

ON THE IMPACT OF EXCHANGE-TRADED FUNDS OVER NOISE TRADING
Evidence from European Stock Exchanges

Vasileios Kallinterakis and Sarvinjit Kaur

ABSTRACT

Exchange-traded funds bear properties that render them appealing to rational investors in terms of trading and cost-effectiveness, thus raising the possibility of their introduction bearing an adverse effect over the significance of noise trading. We test for this hypothesis for the first time in the literature on the premises of the three largest European markets (France, Germany, and the United Kingdom). Our results reveal that noise trading is found to be insignificant in all three markets both before as well as after the introduction of ETFs, with its insignificance manifesting itself also in their ETF segments.

INTRODUCTION

Exchange-traded funds (ETFs) have constituted perhaps the most dynamically permeating innovation in capital markets during the last decade. In strictly conceptual terms, their underlying investments aim at mimicking

the composition of a predetermined benchmark (e.g., an index) whose performance they track; as these funds are publicly traded in stock exchanges like normal equity, this endows investors with the unique opportunity of trading an index through a single stock—the ETF. ETFs rose in prominence first in the United States and Canada during the 1990s and later experienced a phenomenal expansion since the years of the dot-com bubble internationally. According to the U.S. Investment Company Institute,[1] the total value of managed ETF assets in the United States amounted to almost half a trillion ($482,018 billion) U.S. dollars in March 2009 with the industry witnessing a prolific expansion in European and Asian capital markets since 2000. In view of the above developments, research in finance has recently begun to exhibit a surging interest in the area with an increasing number of studies focusing on the examination of ETF return-properties (see Deville, 2008 for an excellent review).

An issue bearing interesting policymaking implications with regards to ETFs relates to whether their introduction has born any effect over noise trading in the underlying spot markets. ETFs aim at improving informational efficiency by fostering investor participation (Deville, 2008) through their simplicity (they allow an index to be traded as a stock), cost-effectiveness (very low management fees), risk-diversification (one ETF share provides exposure to all the stocks included in an index), and high liquidity (they are traded by various investors as hedging instruments). If ETFs as a product succeed in attracting rational investors, then this is expected to translate in enhanced efficiency coupled with a reduction of noise trading at the spot level, since ETF trades on their underlying benchmark stocks will be motivated by a fundamentals-driven clientele. However, it is possible that noise investors might be tempted to shift from the spot market to the ETF one in order to take advantage of the ease and low cost of ETF transactions.[2] If so, this would raise the potential for irrational trading in the ETF market with large deviations of prices there from fundamentals (De Long et al., 1990), thus implying that the anticipated benefits from ETFs over securities pricing at the spot level would fail to be realized.

Despite the obvious importance of the above from an investor's as well as a regulatory perspective, it is worth noting that the issue of the impact of ETF introduction over noise trading has not been explored in the literature. We aim at covering this gap here by addressing this issue in a comparative context in order to obtain an improved insight; more specifically, our investigation is undertaken on the premises of a sample comprised of the

French, German, and U.K. stock exchanges which constitute the largest equity markets in Europe and which also maintain the longest standing and most heavily traded ETF segments on the continent. Using an ad hoc heterogeneous traders' empirical design, we examine the presence of noise trading in those three markets' spot segments prior to and after the introduction of ETFs, as well as its presence in their respective ETF segments. The next sections will thus be devoted to the delineation of the methodological approach (and data) employed here; in the following section, we shall embark on the presentation and discussion of our results.

DATA

Our data includes the daily closing prices of both the main spot market indexes as well as their corresponding ETFs of the French, German, and UK markets; the indexes involved here are the CAC 40, the DAX 30 and the FTSE 100, respectively. The choice of these three markets relates to the fact that they constitute the pioneers in the introduction of ETFs in Europe and bear the most developed ETF markets on the continent. Since there usually exists more than one ETF linked to a particular index in each market (Deville, 2008), the ETF series used here are those of the first ETFs linked to that index. More specifically, our ETF sample includes the series (launch-date in brackets) of the iSHARES FTSE 100 (April 28, 2000), the DAXEX (January 3, 2001), and the Lyxor ETF CAC 40 (January 22, 2001). The sample-window of each market assumes a period prior to the introduction of the ETF equal in length to the period following its introduction (with the post-introduction period ending on June 30, 2008 for all markets) to ensure comparability between the two periods for each market.[3] The pre- and post-ETF periods for each market therefore are: UK (April 10, 1992 to April 27, 2000; April 28, 2000 to June 30, 2008), France (August 13, 1993 to January 21, 2001; January 22, 2001 to June 30, 2008) and Germany (July 8, 1993 to January 2, 2001; January 3, 2001 to June 30, 2008). All data on spot indexes and ETF closing prices were obtained from DataStream.

METHODOLOGY

To investigate the impact of the introduction of ETFs on noise trading, we shall rely on the empirical framework introduced by Sentana and Wadhwani (1992), which assumes two types of traders in the market, namely "rational

speculators" and "feedback traders." The demand function of the rational speculators is as follows

$$Q_t = \frac{E_{t-1}(r_t) - \alpha}{\theta\, \sigma_t^2} \qquad (14.1)$$

where Q_t represents the fraction of the shares outstanding of the ETF (or, alternatively, the fraction of the market portfolio) held by those traders, $E_{t-1}(r_t)$ is the expected return of period t given the information of period $t - 1$, α is the risk-free rate (or else, the expected return such that $Q_t = 0$), θ is a coefficient measuring the degree of risk-aversion, and σ_t^2 is the conditional variance (risk) at time t. On the other hand, the demand function of the feedback traders is

$$Y_t = \gamma r_{t-1} \qquad (14.2)$$

where γ is the feedback coefficient and r_{t-1} is the return of the previous period $(t - 1)$ expressed as the difference of the natural logarithms of prices at periods $t - 1$ and $t - 2$, respectively. A positive value of γ implies the presence of positive feedback trading ("trend-chasing"), while a negative value indicates the presence of negative feedback trading ("contrarianism"). As all shares must be held in equilibrium, we have

$$Q_t + Y_t = 1 \qquad (14.3)$$

Substituting the corresponding demand functions in Equation (14.3), we have

$$E_{t-1}(r_t) = \alpha - \gamma r_{t-1}\theta\, \sigma_t^2 + \theta\, \sigma_t^2 \qquad (14.4)$$

To transform Equation (14.4) into a regression equation, we set $r_t = E_{t-1}(r_t) + \varepsilon_t$, where ε_t is a stochastic error term and by substituting into Equation (14.4), the latter becomes

$$r_t = \alpha - \gamma r_{t-1}\theta\, \sigma_t^2 + \theta\, \sigma_t^2 + \varepsilon_t \qquad (14.5)$$

where r_t represents the actual return at period t and ε_t is the error term. To allow for autocorrelation due to nonsynchronous trading or market frictions, Sentana and Wadhwani (1992) develop the following empirical version of Equation (14.5)

$$r_t = \alpha + (\phi_0 + \phi_1 \, \sigma_t^2) r_{t-1} + \theta \, \sigma_t^2 + \varepsilon_t \tag{14.6}$$

where ϕ_0 is designed to capture possible nonsynchronous trading effects and $\phi_1 = -\theta\gamma$. Thus, a positive (negative) ϕ_1 would indicate the presence of negative (positive) feedback trading. As Equation (14.5) shows, return autocorrelation in this model rises with the risk in the market (σ_t^2) as indicated by the inclusion of the term $\gamma r_{t-1} \, \theta \, \sigma_t^2$. If positive (negative) feedback traders prevail, then the autocorrelation will be negative (positive). To control for possible asymmetric behavior of feedback trading contingent on the market's direction, Sentana and Wadhwani (1992) extend Equation (14.6) as follows

$$r_t = \alpha + (\phi_0 + \phi_1 \, \sigma_t^2) r_{t-1} + \theta \, \sigma_t^2 + \varepsilon_t \tag{14.7}$$

As the Equation (14.7) suggests, positive values of ϕ_2 ($\phi_2 > 0$) indicate that positive feedback trading grows more significant following market declines as opposed to market upswings. Thus, the coefficient on r_{t-1} now becomes

$$\phi_0 + \phi_1\sigma_t^2 + \phi_2 \quad if \quad r_{t-1} \geq 0$$
$$\phi_0 + \phi_1\sigma_t^2 - \phi_2 \quad if \quad r_{t-1} < 0$$

In order to test for feedback trading with the Sentana and Wadhwani (1992) model, we have to specify the conditional variance (indicated by the σ_t^2) in Equation (14.7). The conditional variance σ_t^2 is modeled here as an asymmetric generalized autoregressive conditional heteroscedasticity process (Glosten, Jagannathan, and Runkle, 1993)

$$\sigma_t^2 = \omega + \beta \, \varepsilon_{t-1}^2 + \gamma \, \sigma_{t-1}^2 + \delta S_{t-1} \, \varepsilon_{t-1}^2 \tag{14.8}$$

Here δ captures the asymmetric responses of volatility following positive versus negative innovations. S_{t-1} is a binary variable equaling one if the innovation at time $t - 1$ is negative and zero otherwise. If δ is positive and statistically significant, then negative innovations increase volatility more that positive innovations. The aim here is to use a conditional variance model capable of capturing the well-documented asymmetric effects of volatility (Bollerslev, Engle, and Nelson, 1994) and allow us to examine any link between those effects and the asymmetric behavior of feedback trading tested through Equation (14.7).

DESCRIPTIVE STATISTICS

Descriptive statistics for the daily log-difference returns of the three market indexes and their corresponding ETFs are provided in Table 14.1. The statistics reported are the mean, the standard deviation, measures for skewness and kurtosis, the normality test, and the Ljung–Box (LB) test statistic for five lags. The skewness and kurtosis measures indicate departures from normality (returns-series appear significantly negatively skewed and highly leptokurtic), something further confirmed by the Jarque-Bera test. Rejection of normality can be partially attributed to temporal dependencies in the moments of the series. The LB statistic is significant,[4] thus providing evidence of temporal dependencies in the first moment of the distribution of returns, due to, for example, market inefficiencies. However, the LB statistic is incapable of detecting any sign reversals in the autocorrelations due to positive/negative feedback trading. It simply provides an indication that first-moment dependencies are present. Evidence on higher order temporal dependencies is provided by the LB statistic when applied to squared returns. The latter is significant and higher than the LB statistic calculated for the returns, suggesting that higher moment temporal dependencies are pronounced.

RESULTS; CONCLUSION

We begin the presentation of our results by estimating the set of Equation (14.6) and Equation (14.8) for the spot market indexes prior to and after the introduction of ETFs. It is interesting to note here the complete absence of significant feedback trading both before as well as after the introduction of ETFs; more specifically, as Table 14.2 indicates, the feedback coefficient

Table 14.1 Descriptive Statistics

	Spot Market Indexes Daily Returns			ETF Daily Returns		
	CAC 40 (8/13/1993–6/30/2008)	**DAX 30** (7/8/1993–6/30/2008)	**FTSE 100** (4/10/1992–6/30/2008)	**Lyxor ETF 40** (1/22/2001–6/30/2008)	**DAX^{EX}** (1/3/2001–6/30/2008)	**iSHARES FTSE 100** (4/28/2000–6/30/2008)
μ	0.0185	0.0328	0.0185	−0.0133	−0.0011	−0.0032
σ	1.32	1.42	1.03	1.38	1.48	1.22
S	−0.1215*	−0.28111*	−0.1831*	−0.0089	−0.1397*	−1.2855*
K	2.9453*	3.6778*	3.2295*	3.413*	5.5375*	21.9750*
Jarque–Bera	1412.3195*	2253.3520*	1862.3610*	941.8184*	2501.6097*	43158.58*
LB(5)	18.1084*	7.0093	29.9359*	15.5127*	5.770	32.3469*
LB²(5)	828.9228*	1,224.1033*	903.3027*	590.0530*	385.9894*	349.9365*

Asterisk (*) denotes significance at the 1 percent level. μ, mean; σ, standard deviation; S, skewness; K, excess kurtosis; LB(5) and LB²(5) are the Ljung−Box statistics for returns and squared returns, respectively, distributed as chi-square with 5 degrees of freedom.

Table 14.2 Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Pre- versus Post-ETF Spot Market Indexes Daily Returns

Conditional mean equation: $r_t + \alpha + (\phi_0 + \phi_1\,\sigma_t^2)r_{t-1} + \theta\,\sigma_t^2 + \varepsilon_t$

Conditional variance specification: $\sigma_t^2 = \omega + \beta\,\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 + \delta S_{t-1}\,\varepsilon_{t-1}^2$

	Pre-ETF			Post-ETF		
	CAC 40	DAX 30	FTSE 100	CAC 40	DAX 30	FTSE 100
α	−0.0319	0.0314	0.0050	−0.0218	0.0150	−0.0141
	(0.0605)	(0.0452)	(0.0298)	(0.0265)	(0.0289)	(0.0231)
θ	0.0531	0.0271	0.0440	0.0238	0.0055	0.0160
	(0.0434)	(0.0329)	(0.0403)	(0.0181)	(0.0172)	(0.0248)
ϕ_0	0.0551	0.0180	0.0762	−0.0520	−0.0196	−0.0478
	(0.0464)	(0.0381)	(0.0401)	(0.0335)	(0.0337)	(0.0308)
ϕ_1	−0.1095	−0.0058	−0.0067	−0.0017	−0.0056	−0.0126
	(0.0224)	(0.0142)	(0.0331)	(0.0109)	(0.0085)	(0.0144)
ω	0.0228	0.0279	0.0053	0.0247	0.0268	0.0160
	(0.0065)*	(0.0054)*	(0.0015)*	(0.0042)*	(0.0045)*	(0.0027)*
β	0.0161	0.0580	0.0164	−0.0299	−0.0170	−0.0183
	(0.0078)	(0.0120)*	(0.0080)	(0.0067)*	(0.0105)	(0.0088)
γ	0.9432	0.9036	0.9544	0.9222	0.9149	0.9214
	(0.0073)*	(0.0111)*	(0.05700)*	(0.0094)*	(0.0116)*	(0.0103)*
δ	0.0500	0.0418	0.0459	0.1731	0.1670	0.1520
	(0.0101)*	(0.0131)*	(0.0115)*	(0.0159)*	(0.0152)*	(0.0119)*
$(\beta + \delta)/\beta$	4.1056	1.7190	3.7988	−4.7893	−8.8235	−7.3060
Half-life	43.8020	39.0358	110.5566	32.4251	36.9183	32.8171

(ϕ_1) is indicative of statistically insignificant positive feedback trading for all tests, thus implying that noise investors do not bear a decisive presence in our sample markets. Moreover, the ϕ_0 coefficient is reflective of insignificant first-order autocorrelation (whose sign switches from positive to negative in the aftermath of the introduction of ETFs), suggesting that the spot markets in the UK, France, and Germany are characterized by enhanced efficiency. Moving to the conditional variance process, we notice that δ remains consistently positive and significant throughout our tests, thus suggesting that negative innovations tend to increase volatility more than positive ones, something further confirmed when calculating the asymmetric ratio $(\beta + \delta)/\beta$.[5] This volatility asymmetry appears more pronounced during the post-ETF period as indicated by the higher values of

the δ coefficient (and the higher absolute values of the asymmetric ratio).[6] What is more, volatility exhibits high persistence, as reflected through the statistically significant γ coefficient, thus denoting the significant impact of lagged volatility over contemporaneous volatility. To illustrate this persistence, we calculate the volatility half-life as $HL = \ln(0.5)/\ln(\beta + \gamma + \delta/2)$, in line with Harris and Pisedtasalasai (2006). Our results indicate that volatility is highly persistent, with its persistence, however. exhibiting signs of decline in the post-ETF period for all markets.

Repeating the above analysis using the set of Equation (14.7) and Equation (14.8) to control for possible asymmetries in feedback trading contingent on market direction, we notice (Table 14.3) a consistently negative (and insignificant) ϕ_2 coefficient which reveals the absence of any such asymmetries. As the rest of the estimates reported in Table 14.3 are similar

Table 14.3 Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Pre- versus Post-ETF Spot Market Indexes Daily Returns

Conditional mean equation: $r_t = \alpha + (\phi_0 + \phi_1 \sigma_t^2)r_{t-1} + \theta\sigma_t^2 + \phi_2 |r_{t-1}| + \varepsilon_t$
Conditional variance specification: $\sigma_t^2 = \omega + \beta \varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 + \delta S_{t-1} \varepsilon_{t-1}^2$

	Pre-ETF			Post-ETF		
	CAC 40	**DAX 30**	**FTSE 100**	**CAC 40**	**DAX 30**	**FTSE 100**
α	−0.0178	0.0250	0.0103	−0.0303	0.0121	−0.0170
	(0.0562)	(0.0378)	(0.0268)	(0.0371)	(0.0348)	(0.0260)
θ	0.0691	0.0192	0.0541	0.0195	0.0039	0.0119
	(0.0400)	(0.0336)	(0.0389)	(0.0255)	(0.0167)	(0.0256)
ϕ_0	0.0616	0.0158	0.0786	−0.0542	−0.0204	−0.0488
	(0.0478)	(0.0340)	(0.0335)*	(0.0290)	(0.0252)	(0.0290)
ϕ_1	−0.0134	−0.0050	−0.0080	−0.0014	−0.0054	−0.0125
	(0.0217)	(0.0140)	(0.0280)	(0.0077)	(0.0048)	(0.0012)
ϕ_2	−0.0426	0.0214	−0.0206	0.0182	0.0065	0.0096
	(0.0370)	(0.0469)	(0.0311)	(0.0355)	(0.0294)	(0.0353)
ω	0.0235	0.0275	0.0054	0.0249	0.0269	0.0159
	(0.0169)	(0.0130)	(0.0026)	(0.0071)*	(0.0063)*	(0.0045)*
β	0.0162	0.0577	0.0167	−0.0307	−0.0171	−0.0182
	(0.0090)	(0.0001)*	(0.0075)	(0.0122)	(0.0086)	(0.0060)*
γ	0.9419	0.9045	0.9539	0.9227	0.9149	0.9218
	(0.0201)*	(0.0224)*	(0.0101)*	(0.0126)*	(0.0107)*	(0.0141)*

Asterisk (*) denotes significance at the 1% level. Parentheses include the standard errors of the estimates.

to those reported previously in Table 14.2, this further confirms the absence of significant feedback trading pre- and post-ETF and also shows that the documented volatility asymmetries cannot be associated with asymmetries in the behavior of feedback traders.

To assess the significance of the difference in feedback trading between the two periods, we run the specification proposed by Antoniou, Koutmos, and Pericli (2005)

$$R_t = \alpha + \theta\, \sigma_t^2 + [\phi_{0,1}D_t + \phi_{0,2}(1 - D_t)]R_{t-1} + [\phi_{1,1}D_t + \phi_{1,2}(1 - D_t)]\sigma^2 R_{t-1} + \varepsilon_t \quad (14.9)$$

$$\sigma_t^2 = \beta_{0,1}\, D_t + \beta_{0,2}(1 - D_t) + \beta_1\, \sigma_{t-1}^2 + \beta_2\, \varepsilon_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2 \qquad (14.10)$$

where $D_t = 1$ for the pre-ETF period and $D_t = 0$ for the post-ETF period. As the β_0 estimates in Table 14.4 reveal, the average level of volatility appears to have significantly (insignificantly, in the case of Germany) declined post-ETF, a fact in line with the reduction in volatility persistence illustrated in Tables 14.2 and 14.3. What is more, feedback trading is found to be insignificant prior to and after the launch of the ETF segment in all three markets with its presence being insignificantly different between the two periods. The ϕ_0 coefficient furnishes us with the same sign-switch reported in the previous tests (positive pre-, negative post-ETF), and appears significant only in the case of the German market post-ETF; results from the t statistics support its significant period-to-period difference in the case of the UK and France.

We finally turn our attention to the ETF level and repeat our tests for the ETF series of our sample. According to Table 14.5, there is no evidence of significance surrounding feedback trading here either. Much like in Tables 14.2−14.4, results here confirm the presence of highly persistent and asymmetric volatility while all ETFs are characterized by insignificantly negative first-order autocorrelation, similar to the post-ETF estimates reported for spot indexes.

As the previous results indicate, Europe's three largest capital markets appear to accommodate largely insignificant feedback trading during the last couple of decades. The introduction of ETFs did little to change this, more so since feedback traders are found to be insignificant in that market segment as well. Although the advent of ETFs has coincided with structural

Table 14.4 Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: Test for Parameter Changes in the Spot Market Indexes Daily Returns Pre- versus Post-ETF

Conditional mean equation: $R_t = \alpha + \theta\sigma_t^2 + [\phi_{0,1} D_t + \phi_{0,2} (1 - D_t)] R_{t-1} + [\phi_{1,1}D_t + \phi_{1,2} (1 - D_t)]\sigma^2 R_{t-1} + \varepsilon_t$

Conditional variance specification: $\sigma_t^2 = \omega + \beta\,\varepsilon_{t-1}^2 + \gamma\,\sigma_{t-1}^2 + \delta\,S_{t-1}\,\varepsilon_{t-1}^2$

	CAC40	DAX	FTSE100
α	−0.0086	0.0303	0.0025
	(0.0253)	(0.0290)	(0.0181)
θ	0.0215	0.0074	0.0197
	(0.0179)	(0.0163)	(0.0218)
$\phi_{0,1}$	0.0896	0.0087	0.0866
	(0.0420)	(0.0330)	(0.0396)
$\phi_{0,2}$	−0.0520	−0.0520	−0.0501
	(0.0346)	(0.0000)*	(0.0310)
$\phi_{1,1}$	−0.0197	0.0014	−0.0057
	(0.0193)	(0.0088)	(0.0325)
$\phi_{1,2}$	−0.0037	−0.0105	−0.0151
	(0.0110)	(0.0064)	(0.0145)
$\beta_{0,1}$	0.0387	0.0347	0.0139
	(0.0055)*	(0.0046)*	(0.0021)*
$\beta_{0,2}$	0.0211	0.0262	0.0103
	(0.0031)*	(0.0037)*	(0.0018)*
β	−0.0026	0.0278	0.0071
	(0.0026)	(0.0075)*	(0.0072)
γ	0.9242	0.8997	0.9280
	(0.9242)*	(0.0079)*	(0.0064)*
δ	0.1132	0.1049	0.0994
	(0.1132)*	(0.0096)*	(0.0090)*
Wald Test t statistics			
$\phi_{0,1} = \phi_{0,2}$	6.8081*	3.3799	7.4167*
$\phi_{1,1} = \phi_{1,2}$	0.5333	1.2259	0.0711
$\phi_{0,1} = \phi_{0,2}$	21.4075*	5.687	6.7111*

Asterisk (*) denotes significance at the 1% level. Parentheses include the standard errors of the estimates.

Table 14.5 Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: ETF Daily Returns

Conditional mean equation: $r_t + \alpha + (\phi_0 + \phi_1 \, \sigma_t^2)r_{t-1} + \theta\sigma_t^2 + \varepsilon_t$

Conditional variance specification: $\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \gamma\sigma_{t-1}^2 + \delta S_{t-1} \, \varepsilon_{t-1}^2$

	Lyxor ETF CAC 40	DAX^{EX}	iSHARES FTSE 100
α	−0.1272	−0.0106	−0.0032
	(0.0271)	(0.0298)	(0.0240)
θ	0.0184	0.0235	0.0035
	(0.0187)	(0.0170)	(0.0252)
ϕ_0	−0.0521	−0.0251	−0.0717
	(0.0338)	(0.0325)	(0.0283)*
ϕ_1	−0.0016	0.0115	−0.0101
	(0.0109)	(0.0078)	(0.0082)
ω	0.0253	0.0301	0.0155
	(0.0044)*	0.0042)	(0.0027)*
β	−0.0275	−0.0190	−0.0035
	(0.0075)*	(0.0401)*	(0.0081)
γ	0.9519	0.9200	0.9183
	(0.0099)*	(0.0117)*	(0.0087)*
δ	0.1811	0.1536	0.1331
	(0.0169)*	(0.0134)*	(0.0113)*

Asterisk (*) denotes significance at the 1% level. Parentheses include the standard errors of the estimates.

changes in spot volatility dynamics (decline of average volatility levels, increase in volatility asymmetries, and decrease in its persistence), the fact remains that the spot markets in Europe's major stock exchanges exhibit signs of enhanced efficiency and are dominated by rational investors both before and after the ETF launch. The fact that this appears to be the case in the ETF segments as well is particularly encouraging from a regulatory viewpoint, as it suggests that ETFs have thus far managed to serve their original purpose, namely, contribute towards the completeness and efficiency of these markets. In view of the above results—and given that the ETF industry has already begun to take off in emerging markets in recent years—it would be worth extending the present study by investigating in the future (as more data becomes available with time) how the introduction of ETFs impacts on noise trading in these markets as well, more so given the differential conditions typifying their institutional frameworks compared to their developed counterparts.

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NOTES

1. Available at: http://www.ici.org/stats/etf/etfs_03_09.html

2. This "migration-hypothesis" was formally tested (Antoniou, Koutmos, and Pericli, 2005) in the case of index futures' introduction with results largely refuting it.

3. Since the market indexes mentioned here have been with us at least since the 1970s, the pre-ETF introduction period would have been disproportionately large compared with the post ETF one.

4. With the exception of the DAX index and its corresponding ETF.

5. As Antoniou, Koutmos, and Pericli (2005) show, the contribution of a positive innovation is reflected in β while the contribution of a negative

innovation by the sum of $\beta + \delta$. An asymmetric ratio value greater than unity (in absolute terms) would thus suggest that negative innovations contribute more to market volatility than positive ones.

6. The switch in the sign of the asymmetric ratio post-ETF is due to the directional change of volatility autocorrelation between the two subperiods; more specifically, contemporaneous volatility is found to increase with lagged squared innovations pre-ETF, yet the inverse occurs post-ETF as the switch in the sign of the volatility autocorrelation coefficient (β) in Table 14.2 indicates.

PENETRATING FIXED-INCOME EXCHANGE-TRADED FUNDS

Gerasimos G. Rompotis

ABSTRACT

This chapter investigates various issues concerning the performance, the trading premium, and trading activity of fixed-income exchange-traded funds (ETFs). Findings first indicate that ETFs slightly underperform their tracking indexes. Moreover, the results indicate that ETFs trade daily, on average, at a premium to their net asset value. Regression analysis reveals that the premium is strongly persistent on a daily basis. Further regression analysis demonstrates that the premium is meaningful in determining future returns. In particular, return is found to be positively and negatively affected by the contemporaneous and lagged premium, respectively. Finally, evidence on the positive relationship between trading volume and lagged intraday volatility and premium are revealed.

INTRODUCTION

Apart from the equity-linked exchange-traded funds (ETFs), new types of ETFs allocating funds in nonequity investments are now available. One significant category of these new ETFs is the fixed-income ETFs. Fixed-income ETFs track the performance of fixed-income securities. In a stock ETF, the fund is generally composed of all the stocks in the index. However,

this is not the case in most bond ETFs. The fund holds a fraction of the bonds that make up the underlying index. Bond prices are relatively straightforward being a function of the risk-free rate, the coupon, the quality of the bond, and the years to maturity.

Fixed-income ETFs may track broad bond market indexes containing a broad mix of both government and corporate bonds at different maturities. Furthermore, fixed-income ETFs may invest in treasury bonds based on different maturities along the yield curve. Moreover, there are the treasury inflation protected securities ETFs (TIPS) which pay interest equal to the Consumer Price Index (CPI) plus a premium. They provide a hedge against inflation and are designed to outperform regular bonds when inflation expectation rises. Another type of fixed-income ETFs relates to those that invest in different asset classes allowing investors to get a fully diversified portfolio by just buying an ETF. Finally, there is the target date or lifecycle ETFs that target the defined contribution pension plan market. Target date funds are similar to balanced asset allocation funds having one additional feature, namely, they become more conservative as they approach the target date. Funds reduce risk by selling stocks and buying bonds as the target date approaches.

Bond ETFs can be as liquid and transparent as stock ETFs, offering investors the flexibility of trading stocks along with the benefits on investing in bonds. Fixed-income ETFs moves just like stocks, they can be intraday traded and can be sold short at any time throughout the trading day. In contrast, bond mutual funds only trade at the end of the trading day, making the bond ETF more liquid than a bond mutual fund.

The main similarities between bonds and fixed-income ETFs are that they are affected by the same factors such as the fluctuations in interest rates, variations in yield spreads, and changes in yield curves. The effects of interest rates on bond prices are especially severe during the periods of financial and banking crisis. As a matter of fact, the current crisis has resulted in increases in the "spreads" or the premium which large corporations pay to borrow money by issuing bonds to investors. On the other hand, the basic differences between fixed-income ETFs and bonds are that the ETFs usually distribute dividends on a monthly basis, while bonds usually pay interest twice a year. Furthermore, bond ETFs have no maturity date while bonds do. In addition, the income received by ETFs on the bonds included in their portfolio are reinvested in new bonds rather than returned to investors. Moreover, ETFs trade on stock exchanges, whereas

bonds are generally bought and sold through dealer firms. Finally, individual investors can execute active trading strategies with ETFs that may be difficult to apply by using bonds themselves. Short selling is such an example. The same patterns apply when comparing bond ETFs with open-ended fixed-income mutual funds.

Going further, there are differences between ETFs and open-ended fixed-income mutual funds. Apart from the trading on stock exchanges and the execution of active investing strategies and intraday trading orders mentioned above, ETF investors pay transaction fees to brokerage firms while mutual fund investors do not. In addition, with mutual funds investors pay purchase and redemption fees when they enter or exit the fund, while ETF investors do not have to pay such fees. Moreover, the majority of open-ended mutual funds are actively managed and, as a result, they tend to impose higher management fees than the passively managed ETFs. Apart from their unique advantages, the fixed-income ETFs are also subject to some significant weaknesses (described in Mazzilli, Maister, and Perlman (2008)). One disadvantage is that the bond ETFs do not mature, which means that when an investor decides to redeem their ETF shares, it may be at a price that is lower than the initial investment. In addition, the determination of the exact yield for fixed-income ETFs can be difficult. Tracking failure is another potential disadvantage of bond ETFs, while noncurrent trading hours may also occur between the bond ETFs and their holdings.

In this chapter, we examine various issues concerning the performance of fixed-income ETFs, the replication efficiency, the premium, the relationship between premium and return, and the determinative factors of trading activity. At first, the results show that fixed-income ETFs underperform their benchmarks. Going further, the findings demonstrate that fixed-income ETFs trade, on average, at a persistent premium to their net asset value (NAV). Regression analysis reveals that the premium is indicative of future returns. Finally, evidence of the positive relationship between trading volume and lagged intraday volatility and premium is found.

METHODOLOGY

Performance and Risk

Returns of ETFs are calculated using both their NAV and the trading prices. Daily returns are estimated in percentage terms, while the risk is the standard deviation of daily returns. A second performance measure we

apply is tracking error, which indicates the return difference between ETFs and indexes. Two tracking error measures are employed. The first one (TE1) concerns the difference in returns between ETFs and indexes and the second one (TE2) estimates tracking error as the standard deviation in return differences between ETFs and indexes (found in Frino and Gallagher, 2001).

Premium and Persistence of Premium

We first estimate premium as the dollar difference between the closing price and NAV and then as the percentage deviation between ETF closing prices and NAVs. In general, one key feature of ETFs is the chances they offer institutional investors to execute profitable arbitrage strategies, which in turn contribute to the sharp elimination of premiums or discounts in trading prices. To verify this argument, we search for persistence patterns in fixed-income ETF premiums. We follow the approach of Elton et al. (2002) and regress the premium (either the dollar or the percentage) of iShares on day t against the premium on day $t - 1$. The model we apply is represented in Equation (15.1).

$$\text{Premium}_t = \alpha + \beta \, \text{Premium}_{t-1} + \varepsilon \qquad (15.1)$$

Explaining Return

According to Jares and Lavin (2004), there is a significant connection between return and premium for Japan and Hong Kong iShares. More specifically, the authors find a strong and significantly negative relationship between return and contemporaneous premium and a significantly positive relation between return and lagged premium. On the contrary, Cherry (2004) finds that ETF return is negatively related to lagged premium. The findings of these studies suggest that premiums are meaningful for the determination of future returns of ETFs.

We investigate the relation between the premium and return of fixed-income ETFs, applying a time-series regression of each ETF return on the contemporaneous and lagged premium (premium on day t and day $t - 1$, respectively). The model we estimate is shown in Equation (15.2).

$$\text{Return}_t = \alpha + \beta_1 \, \text{Premium}_t + \beta_2 \, \text{Premium}_{t-1} + \varepsilon \qquad (15.2)$$

Explaining Volume

Elton et al. (2002) demonstrate that the trading volume of *Standard & Poor's Depositary Receipts* (SPDRs), which track the S&P 500 Index, is significantly affected by the lagged premium and lagged intraday volatility estimated as the fraction of the intraday highest price minus the intraday lowest price of the tracking index divided by the closing price of index. Lagged values of volatility and premium are considered since the difference between the price and NAV is calculated at the end of the day and, therefore, the difference signals (if any) arbitrage opportunities the next day.

We search whether Elton et al. (2002) regression analysis of volume applies to fixed-income ETFs by using the intraday volatility of ETFs themselves and not the intraday price volatility of indexes. The model we apply is represented by Equation (15.3).

$$\text{LnVolume}_t = \alpha + \beta_1\,\text{Volatility}_{t-1} + \beta_2\,\text{Premium}_{t-1} + \varepsilon \qquad (15.3)$$

DATA AND STATISTICS

In this chapter we use ETF trading data that cover the period July 29, 2002 to February 27, 2009. Our data consists of the closing prices, which are the 4 p.m. bid/ask midpoint, and the NAVs of a sample of 35 fixed-income Barclay's iShares. The 22 ETFs of the sample are bond funds tracking various broad market, treasury, government credit, credit, municipal, mortgage, and international bond indexes; and 13 are specialty ETFs which track various asset allocation, target date (pension market), and preferred stock indexes. The closing prices of iShares were gathered from Nasdaq.com. Nasdaq.com also provided us with the daily volumes of ETFs. The daily NAVs were found on the Website of iShares (www.us.ishares.com).

Table 15.1 reports information concerning the symbol of the sample's ETFs, name, type, inception date, expense ratio, intraday volatility, and average daily volume. The average expense ratio of ETFs is equal to 24 bps reflecting the low managerial expenses charged by ETFs as a result of their passive investing character. Furthermore, the average intraday volatility is equal to 1.281 percent, while the average daily volume approximates the 116,000 shares. However, it should be noted that there are significant variations among the individual average volumes. Indicatively, the maximum average daily volume of the sample amounts to 1.3 million shares while the minimum volume is equal to 383 shares.

Table 15.1 Profiles of ETFs

The following exhibit presents the profiles of ETFs which, are the symbol, name, investing style (type), inception date, expense ratio, intraday volatility estimated (as the fraction of the ETFs' intraday highest trading price minus the intraday lowest trading price divided by the closing price), and the average daily volume in number of shares.

Symbol	Name	Type	Inception Date	Expense Ratio (%)	Intraday Volatility (%)	Volume
AGG	Barclays Aggregate Bond Fund	Broad Market	09/22/2003	0.24	0.446	298,903
SHY	Barclays 1–3 Year Treasury BF	Treasury	07/22/2002	0.15	0.152	528,736
IEI	Barclays 3–7 Year Treasury BF	Treasury	01/05/2007	0.15	0.381	70,527
IEF	Barclays 7–10 Year Treasury BF	Treasury	07/22/2002	0.15	0.463	246,674
TLH	Barclays 10–20 Year Treasury BF	Treasury	01/05/2007	0.15	0.640	17,674
TLT	Barclays 20+ Year Treasury BF	Treasury	07/22/2002	0.15	0.799	1,332,332
AGZ	Barclays Agency Bond Fund	Treasury	11/05/2008	0.20	0.574	9,461
SHV	Barclays Short Treasury Bond Fund	Treasury	01/05/2007	0.15	0.087	156,532
TIP	Barclays TIPS Bond Fund	Treasury	12/04/2003	0.20	0.512	273,241
GBF	Barclays Government/Credit BF	Government Cred	01/05/2007	0.20	0.384	11,894
GVI	Barclays Intermediate Gov/Cred BF	Government Cred	01/05/2007	0.20	0.457	13,124
HYG	iBoxx $ High Yield Corporate BF	Credit	04/04/2007	0.50	1.390	189,243
LQD	iBoxx $ Investment Grade Corp BF	Credit	07/22/2002	0.15	0.682	239,435
CSJ	Barclays 1–3 Year Credit BF	Credit	01/05/2007	0.20	0.500	44,727
CFT	Barclays Credit Bond Fund	Credit	01/05/2007	0.20	0.692	12,247
CIU	Barclays Intermediate Credit BF	Credit	01/05/2007	0.20	0.570	24,694
CMF	S&P California Municipal BF	Municipal Bond	10/04/2007	0.25	0.838	8,073

MUB	S&P National Municipal BF	Municipal Bond	09/07/2007	0.25	0.963	71,118
NYF	S&P New York Municipal BF	Municipal Bond	10/04/2007	0.25	0.653	2,765
SUB	S&P Short Term National Mun BF	Municipal Bond	11/05/2008	0.25	0.667	8,063
MBB	Barclays MBS Bond Fund	Mortgage	03/13/2007	0.36	0.498	60,660
EMB	JPMorgan USD Emerg Markets BF	International	12/17/2007	0.60	1.371	16,117
AOA	S&P Aggressive Allocation Fund	Allocation	11/04/2008	0.34	4.523	30,024
AOK	S&P Conservative Allocation Fund	Allocation	11/04/2008	0.31	2.256	6,880
AOR	S&P Growth Allocation Fund	Allocation	11/04/2008	0.33	3.558	26,458
AOM	S&P Moderate Allocation Fund	Allocation	11/04/2008	0.32	3.472	9,305
TZD	S&P Target Date 2010 Index Fund	Target Date	11/04/2008	0.31	5.266	383
TZE	S&P Target Date 2015 Index Fund	Target Date	11/04/2008	0.31	0.262	411
TZG	S&P Target Date 2020 Index Fund	Target Date	11/04/2008	0.31	0.273	505
TZI	S&P Target Date 2025 Index Fund	Target Date	11/04/2008	0.31	0.874	8,402
TZL	S&P Target Date 2030 Index Fund	Target Date	11/04/2008	0.30	0.237	1,595
TZO	S&P Target Date 2035 Index Fund	Target Date	11/04/2008	0.30	1.596	556
TZV	S&P Target Date 2040 Index Fund	Target Date	11/04/2008	0.29	1.528	500
TGR	S&P Target Date Retir Income IF	Target Date	11/04/2008	0.31	4.554	952
PFF	S&P U.S. Preferred Stock IF	Preferred Stock	03/26/2007	0.48	2.703	332,473
Average				**0.24**	**1.281**	**115,848**

EMPIRICAL RESULTS

Performance and Risk

Table 15.2 presents the average returns and risks of ETFs and indexes. The average NAV return is negative and equal to minus 5.2 bps. The corresponding average return of indexes is equal to minus 3.8 bps. Comparing average returns, we infer that the ETFs slightly underperform their benchmarks. The underperformance of fixed-income ETFs revealed by our findings is consistent with the respective underperformance reported by Svetina and Wahal (2008). When it comes to risk, results show that there is no significant difference between the volatility of ETFs and indexes. Considering the price returns, the results indicate that the ETFs still underperform the indexes. More specifically, the average return of ETFs is equal to -4.3 bps. With regard to risk, the average standard deviation of price returns is equal to 1.174, being higher than the corresponding risk estimation of indexes, which is equal to 0.944.

The next exhibit presents the return and risk calculations of ETFs and the tracking indexes. Return is the average daily return and risk is the standard deviation of daily return. Calculations are presented in two vertical panels. Panel A presents returns and risks when NAVs are used, while Panel B presets returns and risks in trading prices terms. N represents the number of daily observations.

Tracking errors are displayed in Table 15.3. The average TE1 of ETFs is equal to -1.4 bps. Considering the statistical significance of tracking error estimates, the applied t tests indicate that the estimates are significant for 17 out of 35. The TE2 of ETFs in NAV terms is equal to 11.5 bps. With respect to price returns, the average TE1 is essentially equal to zero while only 8 out of the 35 individual tracking error estimates are statistically indifferent from zero. However, the average TE2 of ETFs is considerable being equal to 1.215 showing that the difference between the price returns of ETFs and indexes are more volatile relative to the corresponding relationship in NAV terms.

Premium and Persistence of Premium

Table 15.4 presents the average daily premiums of ETFs. The standard deviation in daily premiums is also reported in the exhibit. Results demonstrate that, on average, the fixed-income ETFs trade at a premium to their NAV.

Table 15.2 Return and Risk

Symbol	N	Panel A. NAV Terms				Panel B. Price Terms			
		Return		Risk		Return		Risk	
		ETF	Index	ETF	Index	ETF	Index	ETF	Index
AGG	1,364	−0.001	0.017	0.272	0.253	0.000	0.017	0.408	0.253
SHY	1,659	0.002	0.014	0.123	0.111	0.002	0.014	0.129	0.111
IEI	536	0.024	0.037	0.349	0.351	0.024	0.037	0.371	0.351
IEF	1,659	0.008	0.024	0.434	0.425	0.008	0.024	0.447	0.425
TLH	536	0.023	0.040	0.675	0.674	0.023	0.040	0.691	0.674
TLT	1,659	0.015	0.035	0.761	0.756	0.016	0.035	0.761	0.756
AGZ	75	0.062	0.061	0.343	0.334	0.069	0.061	0.840	0.334
SHV	536	0.003	0.015	0.064	0.078	0.003	0.015	0.071	0.078
TIP	1,315	−0.003	0.016	0.435	0.425	−0.003	0.016	0.465	0.425
GBF	536	0.003	0.020	0.353	0.348	0.003	0.020	0.410	0.348
GVI	536	0.006	0.021	0.279	0.274	0.007	0.021	0.394	0.274
HYG	475	−0.085	−0.053	0.605	0.594	−0.083	−0.053	1.375	0.594
LQD	1,659	−0.004	0.017	0.371	0.359	−0.003	0.017	0.629	0.359
CSJ	536	−0.005	0.013	0.182	0.177	0.000	0.013	0.563	0.177
FT	536	−0.019	0.001	0.412	0.403	−0.013	0.001	0.839	0.403
CIU	536	−0.013	0.005	0.332	0.323	−0.008	0.005	0.509	0.323
CMF	351	−0.001	0.007	0.452	0.454	−0.001	0.007	0.669	0.454
MUB	370	−0.004	0.006	0.423	0.417	−0.003	0.006	0.609	0.417

(Continued)

Table 15.2 (Continued)

| Symbol | N | Panel A. NAV Terms | | | | Panel B. Price Terms | | | |
| | | Return | | Risk | | Return | | Risk | |
		ETF	Index	ETF	Index	ETF	Index	ETF	Index
NYF	351	−0.003	0.010	0.446	0.493	0.004	0.010	0.764	0.493
SUB	75	0.028	0.032	0.103	0.359	0.042	0.032	1.232	0.359
MBB	492	0.008	0.029	0.322	0.309	0.009	0.029	0.374	0.309
EMB	299	−0.063	−0.038	0.983	0.920	−0.059	−0.038	1.547	0.920
AOA	75	−0.198	−0.189	2.802	2.809	−0.204	−0.189	2.764	2.809
AOK	75	−0.050	−0.043	0.693	0.692	−0.027	−0.043	2.034	0.692
AOR	73	−0.115	−0.106	1.873	1.878	−0.064	−0.106	3.466	1.878
AOM	75	−0.098	−0.090	1.187	1.189	−0.066	−0.090	2.730	1.189
TZD	75	−0.090	−0.080	1.221	1.220	−0.061	−0.080	0.908	1.220
TZE	75	−0.116	−0.105	1.495	1.499	−0.088	−0.105	1.302	1.499
TZG	75	−0.141	−0.130	1.773	1.774	−0.115	−0.130	1.241	1.774
TZI	75	−0.164	−0.153	2.029	2.035	−0.135	−0.153	1.786	2.035
TZL	75	−0.188	−0.175	2.295	2.298	−0.193	−0.175	1.785	2.298
TZO	75	−0.205	−0.194	2.511	2.512	−0.209	−0.194	1.938	2.512
TZV	75	−0.217	−0.205	2.639	2.641	−0.183	−0.205	2.269	2.641
TGR	75	−0.064	−0.053	0.947	0.951	−0.042	−0.053	2.100	0.951
PFF	482	−0.159	−0.135	2.715	2.690	−0.164	−0.135	2.677	2.690
Average	**499**	**−0.052**	**−0.038**	**0.940**	**0.944**	**−0.043**	**−0.038**	**1.174**	**0.944**

Table 15.3 Tracking Error of ETFs

The following exhibit presents the calculations of ETF tracking error, which represents the difference in performance between ETFs and tracking indexes. Two alternative tracking error estimations are used. The first one (TE1) concerns the average raw return difference between ETFs and indexes and the second one (TE2) estimates tracking error as the standard deviations in daily return differences between ETFs and indexes. In addition, t test values on the statistical significance of raw returns' difference are presented. Calculations are presented in two vertical panels. Panel A presents tracking error when NAV returns are used in estimating ETF returns, while Panel B shows tracking error when ETF returns are calculated in trading price terms.

	Panel A. NAV Terms				Panel B. Price Terms		
Symbol	TE1	t Test	TE2		TE1	T-test	TE2
AGG	−0.018*	−6.262	0.104		−0.017‡	−1.856	0.339
SHY	−0.012*	−8.531	0.057		−0.012*	−6.078	0.081
IEI	−0.014*	−4.516	0.070		−0.014‡	−1.749	0.180
IEF	−0.016*	−7.788	0.083		−0.016*	−3.876	0.166
TLH	−0.018*	−3.739	0.109		−0.017	−1.509	0.269
TLT	−0.019*	−7.648	0.103		−0.019*	−3.159	0.247
AGZ	0.001	0.093	0.101		0.008	0.087	0.785
SHV	−0.012*	−2.943	0.093		−0.012*	−2.708	0.102
TIP	−0.019*	−7.046	0.099		−0.019*	−2.970	0.229
GBF	−0.017*	−4.086	0.095		−0.016	−1.111	0.339
GVI	−0.015*	−4.217	0.084		−0.013	−0.971	0.320
HYG	−0.032*	−4.723	0.148		−0.030	−0.502	1.326
LQD	−0.021*	−8.147	0.105		−0.020	−1.575	0.519
CSJ	−0.018*	−4.493	0.093		−0.013	−0.536	0.575
CFT	−0.020*	−3.747	0.123		−0.013	−0.394	0.786
CIU	−0.018*	−3.857	0.109		−0.013	−0.656	0.454
CMF	−0.008	−1.114	0.137		−0.008	−0.260	0.586
MUB	−0.010	−1.352	0.140		−0.009	−0.332	0.513
NYF	−0.013	−1.093	0.223		−0.006	−0.126	0.854
SUB	−0.004	−0.092	0.344		0.011	0.070	1.302
MBB	−0.021*	−4.805	0.095		−0.020‡	−1.762	0.252
EMB	−0.025	−2.631	0.163		−0.020	−0.253	1.395
AOA	−0.009	−0.935	0.086		−0.015	−0.052	2.447
AOK	−0.007	−1.087	0.054		0.015	0.067	2.005
AOR	−0.009	−0.910	0.085		0.042	0.113	3.167
AOM	−0.008	−0.911	0.074		0.024	0.080	2.578
TZD	−0.010	−1.016	0.087		0.018	0.108	1.448
TZE	−0.011	−1.033	0.092		0.018	0.078	1.973
TZG	−0.011	−1.032	0.092		0.015	0.712	1.830
TZI	−0.011	−0.990	0.098		0.018	0.057	2.689
TZL	−0.012	−1.049	0.102		−0.017	−0.056	2.681
TZO	−0.012	−0.969	0.105		−0.016	−0.039	3.482
TZV	−0.012	−0.955	0.107		0.021	0.055	3.381
TGR	−0.011	−1.114	0.084		0.011	0.044	2.219
PFF	−0.024‡	−1.949	0.274		−0.029	−0.638	0.999
Average	**−0.014**	**−3.048**	**0.115**		**−0.005**	**−0.906**	**1.215**

* Significant at the 1% level. †Significant at the 5% level. ‡Significant at the 10% level.

Table 15.4 Premium in Prices of ETFs

This next exhibit presents the calculations of ETF average daily premium along with the standard deviation of daily premium. Premium is estimated both in dollar terms, by subtracting the closing NAV of ETFs on day t from the closing trading price on the same day, and in percentage terms, by dividing the difference between the closing trading price and closing NAV by the closing NAV. Calculations are presented in two vertical panels. Panel A presents the pecuniary premium and Panel B presents the percentage premium.

Symbol	Panel A. Pecuniary Premium		Panel B. Percentage Premium	
	Average	Standard Deviation	Average	Standard Deviation
AGG	0.309	0.469	0.305	0.476
SHY	0.042	0.038	0.052	0.046
IEI	0.064	0.135	0.061	0.125
IEF	0.040	0.096	0.048	0.110
TLH	0.077	0.215	0.072	0.199
TLT	0.043	0.161	0.048	0.169
AGZ	0.390	0.668	0.370	0.650
SHV	0.069	0.039	0.063	0.035
TIP	0.203	0.314	0.201	0.325
GBF	0.395	0.569	0.386	0.562
GVI	0.445	0.609	0.433	0.594
HYG	1.510	1.609	1.754	2.185
LQD	0.488	0.738	0.470	0.776
CSJ	0.869	1.078	0.880	1.114
CFT	0.927	0.948	0.972	1.056
CIU	0.922	1.072	0.957	1.155
CMF	0.793	1.134	0.793	1.175
MUB	0.627	0.840	0.646	0.896
NYF	0.987	1.504	1.018	1.630
SUB	0.689	1.014	0.670	0.978
MBB	0.157	0.218	0.154	0.212
EMB	1.194	1.761	1.316	2.175
AOA	0.108	0.403	0.472	1.800
AOK	0.101	0.320	0.402	1.292
AOR	0.209	0.631	0.889	2.682
AOM	0.153	0.446	0.629	1.843
TZD	0.263	0.498	1.106	2.087
TZE	0.289	0.506	1.225	2.144
TZG	0.186	0.422	0.803	1.805
TZI	−0.010	0.560	−0.020	2.392
TZL	−0.061	0.793	−0.209	3.387
TZO	0.151	0.691	0.733	3.064
TZV	0.206	0.662	0.955	2.914
TGR	−0.019	0.719	−0.048	2.856
PFF	0.192	0.325	0.590	1.065
Average	**0.372**	**0.634**	**0.548**	**1.314**

The average dollar premium is equal to 37.2 cent while the respective per-centage premium is equal to 0.548 percent. The respective premium's volatilities are equal to 0.634 and 1.314. Earlier findings of the literature on equity ETFs also reveal that ETFs trade at prices that are different from their NAV. In particular, Hughen (2003) reports that Malaysia iShares trade at a premium to its net value. Jares and Lavin (2004) find similar results for the Japan and Hong Kong iShares. On the contrary, Elton et al. (2002) report that SPDRs trade at a discount to its NAV.

The results of the regression analysis are reported in Table 15.5. The average slope coefficient for the dollar premium is positive and equal to 0.486. The majority of individual betas (27 out of 35 beta estimates) are positive and significant. The same pattern applies to the percentage pre-mium. The average beta estimate is equal to 0.489 while 26 single beta coefficients are positive and significant at the 10 percent level or better. Overall, our results contrast those of Elton et al. (2002) and indicate that the premium of fixed-income ETFs is sufficiently persistent on a daily basis, implying limitations to the execution of arbitrage.

Explaining Return

Table 15.6 provides the results of Equation (15.2) on the relationship between return and premium. Results provide sound evidence on the posi-tive relationship between return and contemporaneous premium and the negative impact of lagged premium on return. The average estimate of con-temporaneous premium is equal to 0.781, while all the single estimations are positive and statistically significant. The positive average estimation implies that an increase in contemporaneous premium by 1 unit results in an increase in ETF return by 0.781 percent on the same day.

With respect to the relationship between the lagged premium and return, the results provide strong evidence on the negative correlation between these two factors. The relevant average coefficient of the model is equal to −0.664. In addition, the majority of the single estimates are negative (only one is positive but insignificant) while 31 out of the 34 negative estimations are significant. Our findings are in line with the ones reported by Cherry (2004) about equity ETFs (he estimates an average beta of −0.680). Overall, our results make us reject the efficient market hypothesis for fixed-income ETFs and reveal possible opportunities for investors to exploit the premium in ETF trading prices and execute profitable arbitrage strategies.

Table 15.5 Persistence in Premium

The following exhibit presents the results of a time-series regression model which searches for persistence patterns in iShares' premium. Specifically, the premium of ETFs on day $t + 1$ is regressed on the premium on day t. Model is applied to the pecuniary premium (Panel A) and the percentage premium (Panel B).

	Panel A. Pecuniary Premium					Panel B. Percentage Premium				
Symbol	Alpha	t Test	Beta	t Test	R–sq	Alpha	t Test	Beta	t Test	R^2
AGG	0.029	1.404	0.907*	16.468	0.603	0.028	1.386	0.907*	16.284	0.603
SHY	0.033*	19.403	0.217*	5.963	0.047	0.040*	19.719	0.219*	6.191	0.048
IEI	0.055*	8.632	0.139*	3.235	0.019	0.053*	8.835	0.134*	3.133	0.018
IEF	0.038*	10.501	0.074	1.207	0.005	0.044*	10.717	0.073	1.203	0.005
TLH	0.070*	7.056	0.089	1.307	0.008	0.066*	7.172	0.081	1.211	0.007
TLT	0.042*	10.381	0.034	0.808	0.001	0.047*	10.736	0.024	0.619	0.001
AGZ	0.316*	3.558	0.204‡	1.776	0.042	0.298*	3.473	0.208‡	1.808	0.043
SHV	0.053*	8.164	0.236†	2.430	0.056	0.048*	8.208	0.236†	2.434	0.056
TIP	0.044*	3.561	0.784*	13.477	0.614	0.041*	3.337	0.796*	13.623	0.633
GBF	0.068†	2.609	0.829*	15.988	0.687	0.068†	2.545	0.825*	15.348	0.681
GVI	0.062†	2.672	0.863*	20.544	0.744	0.062†	2.627	0.860*	19.889	0.739
HYG	0.312†	2.290	0.791*	10.641	0.622	0.312†	2.141	0.820*	12.014	0.668
LQD	0.099†	2.235	0.797*	10.236	0.636	0.096†	2.091	0.795*	9.547	0.633
CSJ	0.119†	2.579	0.867*	18.454	0.751	0.119†	2.587	0.868*	18.784	0.753
CFT	0.253*	2.732	0.730*	8.840	0.531	0.268†	2.584	0.728*	8.344	0.528
CIU	0.074†	2.179	0.924*	25.946	0.851	0.077†	2.143	0.924*	25.549	0.850

CMF	0.107†	2.538	0.863*	17.708	0.744	0.105†	2.393	0.866*	16.808	0.750
MUB	0.103*	3.113	0.837*	19.082	0.700	0.105*	3.018	0.839*	18.612	0.704
NYF	0.152*	3.192	0.852*	14.761	0.725	0.148*	2.984	0.860*	14.413	0.740
SUB	0.583*	4.088	0.162	1.394	0.026	0.568*	4.119	0.160	1.372	0.025
MBB	0.100*	5.392	0.367*	3.597	0.135	0.100*	5.456	0.350*	3.366	0.123
EMB	0.276†	2.428	0.768*	7.075	0.589	0.299†	2.440	0.772*	7.460	0.595
AOA	0.094†	2.033	0.097	0.430	0.009	0.432†	2.045	0.057	0.243	0.003
AOK	0.122*	3.495	−0.211	−0.751	0.044	0.492*	3.452	−0.219	−0.769	0.048
AOR	0.133‡	1.861	0.230†	2.133	0.061	0.567‡	1.865	0.229†	2.133	0.061
AOM	0.150†	2.692	0.016	0.137	0.000	0.616*	2.684	0.015	0.129	0.000
TZD	0.071	1.603	0.744*	9.383	0.550	0.295	1.597	0.749*	9.532	0.558
TZE	0.134†	2.362	0.547*	4.068	0.298	0.553†	2.298	0.559*	5.702	0.311
TZG	0.101‡	1.993	0.464*	3.077	0.213	0.441†	2.074	0.461*	3.100	0.209
TZI	−0.007	−0.123	0.364‡	1.739	0.131	−0.015	−0.058	0.363‡	1.744	0.130
TZL	−0.022	−0.336	0.694*	4.662	0.483	−0.077	−0.275	0.688*	4.660	0.474
TZO	0.102	1.465	0.310‡	1.821	0.096	0.496	1.637	0.314‡	1.859	0.099
TZV	0.149†	2.183	0.279	1.509	0.078	0.693†	2.313	0.280	1.523	0.077
TGR	−0.008	−0.125	0.693*	8.163	0.481	−0.022	−0.090	0.683*	7.935	0.467
PFF	0.103*	4.514	0.462*	3.825	0.212	0.248*	4.309	0.576*	5.583	0.329
Average	**0.117**	**3.838**	**0.486**	**7.461**	**0.337**	**0.220**	**3.845**	**0.489**	**7.468**	**0.342**

* Significant at the 1% level. †Significant at the 5% level. ‡Significant at the 10% level.

Table 15.6 Regression Analysis of Performance

Table 15.6 presents the results of a time-series regression which seeks to explain the relation between the return and premium of ETFs. Specifically, the return of ETFs is regressed on the contemporaneous and the lagged premium of ETFs. Model is applied using the price returns.

Symbol	Intercept	t Test	CP	t Test	LP	t Test	R^2
AGG	−0.006	−0.376	0.934*	13.757	−0.916*	−15.475	0.560
SHY	−0.015†	−2.345	0.901*	10.703	−0.565*	−4.965	0.116
IEI	−0.028‡	−1.628	1.215*	10.269	−0.357*	−3.020	0.169
IEF	−0.042*	−2.975	1.274*	8.754	−0.200	−1.567	0.098
TLH	−0.066†	−2.123	1.266*	6.105	−0.022	−0.120	0.132
TLT	−0.049†	−2.372	1.181*	6.380	0.188	1.229	0.071
AGZ	0.094‡	1.884	0.898*	14.222	−0.981*	−15.557	0.838
SHV	−0.001	−0.171	0.796*	10.072	−0.736*	−9.320	0.223
TIP	−0.032‡	−1.908	0.878*	7.897	−0.734*	−6.497	0.139
GBF	−0.024	−1.211	0.731*	11.815	−0.659*	−11.713	0.327
GVI	−0.016	−0.940	0.917*	13.391	−0.866*	−14.141	0.510
HYG	−0.295*	−7.177	0.996*	19.016	−0.872*	−16.615	0.839
LQD	−0.029†	−2.097	1.052*	20.225	−0.994*	−19.175	0.656
CSJ	−0.018†	−1.669	0.939*	38.399	−0.922*	−38.281	0.899
CFT	−0.060	−1.547	0.960*	17.631	−0.915*	−17.770	0.763
CIU	−0.063*	−2.955	0.882*	17.535	−0.828*	−17.205	0.601
CMF	−0.062†	−2.178	0.866*	12.366	−0.788*	−11.012	0.583
MUB	−0.097*	−3.260	0.942*	13.556	−0.795*	−10.548	0.570
NYF	0.042‡	1.849	0.728*	15.846	−0.769*	−15.690	0.721
SUB	0.013	0.689	0.985*	45.451	−0.951*	−33.876	0.992
MBB	−0.037‡	−1.951	0.959*	13.382	−0.665*	−9.274	0.294
EMB	0.078	1.187	0.769*	19.287	−0.871*	−21.835	0.625
AOA	−0.155	−0.437	0.428‡	1.877	−0.515†	−2.188	0.179
AOK	0.081	1.062	0.816*	9.393	−1.077*	−22.586	0.892
AOR	0.011	0.054	0.881*	8.288	−0.937*	−6.620	0.730
AOM	0.007	0.045	0.899*	11.872	−1.003*	−13.245	0.814
TZD	−0.021	−0.203	0.312*	4.814	−0.356*	−5.482	0.305
TZE	0.054	0.400	0.360*	4.393	−0.484*	−3.994	0.457
TZG	0.022	0.148	0.169†	2.058	−0.351*	−4.257	0.203
TZI	−0.159	−1.086	0.305*	4.662	−0.575*	−8.719	0.526
TZL	−0.229	−1.324	0.281*	4.029	−0.445*	−4.687	0.377
TZO	−0.096	−0.662	0.308*	4.166	−0.464*	−4.789	0.550
TZV	0.007	0.041	0.305*	3.329	−0.524*	−4.097	0.456
TGR	−0.041	−0.398	0.819*	16.538	−0.860*	−17.365	0.828
PFF	−0.147	−0.953	0.402	1.405	−0.430	−1.283	0.023
Average	**−0.039**	**−1.045**	**0.781**	**12.082**	**−0.664**	**−11.193**	**0.488**

* Significant at the 1% level. †Significant at the 5% level. ‡Significant at the 10% level.

CP, contemporaneous premium; LP, lagged premium.

Explaining Volume

Regression results of Equation (15.3) on the explanatory variables of ETF volume are presented in Table 15.7. According to the results, the average volatility's coefficient is positive and equal to 0.509 and the average premium's estimate is also positive and equal to 0.305. With respect to the single estimates of the control variables, there are three negative volatility's estimates, of which only one is significant. Moreover, there are 21 (out of 33) positive volatility's coefficients that are significant. Considering the relevant figures of premium, there are 8 negative estimates (4 statistically significant) and 27 positive estimations (27 significant). A last significant finding concerns the intercept of the model, whose estimates are positive and strongly significant.

Overall, our results about the impact of lagged trading volatility and premium on volume are in line with those of Elton et al. (2002). With respect to the constant, Elton et al. (2002) report a negative estimate which is close to zero, while we estimate sizeable constant coefficients. Big intercepts indicate that there is a significant proportion of shares that are constantly traded regardless of the influence of lagged volatility and premium. This investing interest is probably related to the trading convenience, the flexibility in executing intraday orders, the tax efficiency, and the liquidity of ETFs.

CONCLUSION

This chapter sheds light on various issues surrounding the performance of fixed-income ETFs, the premium in trading prices, and their trading activity. These issues are examined employing a sample of 35 fixed-income iShares available on Nasdaq.com. Results indicate that, on average, fixed-income ETFs underperform their tracking indexes. Underperformance applies both to NAV and trading price returns, driving to significant tracking error calculations.

Going further, the findings of the chapter demonstrate that the fixed-income ETFs trade, on average, at a premium to their NAV which amounts to \$0.372 or 54.8 bps. Time-series regression analysis demonstrates that premium is strongly persistent on a day-by-day basis, which reflects restrictions to the execution of arbitrage strategies that could sharply make the premium vanish.

Table 15.7 Regression Analysis of Volume

The following exhibit presents the results of a time-series regression model which seeks to explain the impact of lagged intraday volatility and premium on ETF trading activity. Specifically, the volume of ETFs on day t is regressed on the intraday volatility and percentage premium on day $t − 1$.

Symbol	Intercept	t Test	LV	t Test	LP	t Test	R^2
AGG	11.699*	204.742	0.860*	10.919	0.194*	2.807	0.093
SHY	12.045*	196.642	3.073*	9.341	2.950*	5.836	0.123
IEI	9.573*	58.249	2.272*	5.390	−0.774‡	−1.961	0.250
IEF	11.858*	333.627	0.568*	8.798	−0.217	−1.128	0.042
TLH	8.678*	93.947	0.798*	7.003	0.332‡	1.693	0.133
TLT	13.316*	329.351	0.473*	10.565	0.055	0.385	0.048
AGZ	8.134*	29.356	0.897†	2.181	−1.043†	−2.629	0.095
SHV	11.105*	108.362	0.135	0.824	3.624†	2.573	0.014
TIP	11.737*	160.411	0.612*	3.439	0.639*	5.637	0.245
GBF	7.754*	60.497	0.619*	4.167	0.203†	2.335	0.023
GVI	8.477*	122.676	0.584*	6.836	0.346*	4.414	0.112
HYG	10.253*	105.990	0.355*	7.842	0.226*	8.739	0.287
LQD	11.179*	281.025	0.520*	10.542	0.515*	14.291	0.238
CSJ	9.353*	118.437	0.533*	4.585	0.510*	13.276	0.372
CFT	7.690*	71.447	0.600*	7.982	0.458*	7.340	0.160
CIU	8.238*	83.525	0.599*	5.528	0.610*	12.921	0.323
CMF	8.295*	85.669	0.051	0.760	0.124†	2.057	0.016
MUB	10.794*	260.685	0.087*	3.812	0.196*	6.202	0.124
NYF	7.036*	63.289	0.051	0.498	0.113‡	1.902	0.016
SUB	8.305*	37.577	0.322	1.440	−0.361	−1.240	0.029
MBB	9.464*	50.652	0.748†	2.531	1.488*	4.773	0.151
EMB	8.633*	97.390	0.246*	7.708	0.084*	2.784	0.186
AOA	8.604*	25.832	0.080	1.588	−0.382*	−3.015	0.155
AOK	6.721*	17.132	0.045	0.469	0.248	1.042	0.017
AOR	7.874*	22.300	0.130†	2.021	−0.112	−1.145	0.067
AOM	7.744*	22.604	0.006	0.131	0.168	1.080	0.016
TZD	2.574*	5.689	−0.109†	−2.246	0.045	0.246	0.078
TZE	2.377*	5.690	0.163	0.599	−0.181	−1.154	0.022
TZG	3.551*	8.010	0.309	0.543	−0.521†	−2.479	0.087
TZI	4.220*	7.952	−0.293	−0.893	0.196	1.044	0.024
TZL	1.677*	4.400	2.036*	3.320	0.157	1.503	0.152
TZO	1.993*	5.093	0.070	0.832	0.035	0.280	0.013
TZV	2.510*	5.796	0.136	1.216	0.062	0.461	0.025
TGR	4.340*	9.337	−0.038	−0.652	0.342†	2.557	0.095
PFF	10.205*	104.849	0.279*	8.915	0.356†	2.509	0.387
Average	**7.943**	**91.378**	**0.509**	**3.958**	**0.305**	**2.741**	**0.121**

* Significant at the 1% level. †Significant at the 5% level. ‡Significant at the 10% level.

LV, lagged volatility; LP, lagged premium.

Moreover, the chapter reveals that the premium is indicative for future returns. More specifically, findings indicate that return is positively related to the contemporaneous premium while it is negatively affected by the one lagged premium. These findings imply that the fixed-income ETF market is not totally efficient and may offer investors opportunities to gain abnormal returns.

Finally, sound evidence on the positive relationship between trading volume and lagged intraday volatility and premium are revealed. The majority of individual volatility and premium estimates are positive and significant, indicating that investors make their trading decisions in response, among other factors, to the price volatility and premium on the previous trading day.

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SMOOTH TRANSITION AUTOREGRESSIVE MODELS FOR THE DAY-OF-THE-WEEK EFFECT

An Application to the S&P 500 Index

Eleftherios Giovanis

ABSTRACT

This chapter examines the day-of-the-week effect for the S&P 500 index. More specifically, OLS, GARCH (1,1), and EGARCH (1,1) estimations with and without bootstrapping simulations provide that there is the day-of-the-week effect. On the contrary, we examine the S&P index for linearities against nonlinearities. We accept that there are nonlinearities and we choose the ESTAR model based on a specific test and we find that, with ESTAR-GARCH (1,1) estimation, with and without bootstraping simulation, there is the day-of-the-week effect in the middle regime, while there is none in the outer regime, where higher average returns are presented on Mondays.

INTRODUCTION

In this chapter, we examine the well-known day-of-the-week effect. The first method we use is ordinary least squares (OLS); the second is the generalized autoregressive conditional heteroscedasticity (GARCH) method, in

order to solve for autocorrelation and ARCH effect; and the third method is the exponential GARCH, or EGARCH, model allowing for leverage effects. The latter two models are able to capture volatility and ARCH effects, but the disadvantage is that they are unable to estimate nonlinearities for different regimes. The three most popular models that have been proposed for nonlinear estimation are the threshold autoregressive (TAR) model (Tong, 1990), the smooth transition autoregressive (STAR) models (Chan and Tong, 1986), and Markov-switching regime autoregressive (MS-AR) model (Hamilton, 1989). TAR and MS-AR models assume a sharp switch between regimes, while STAR models assume a smooth switching. The reasons why we prefer the STAR models is that they allow for smooth transition and switching between regimes because this fact might be more realistic as it might be highly impossible that all agents act and react simultaneously to a given economic and trading signal.

LITERATURE REVIEW

Many research papers have been written testing the day-of-the-week effect. Among them is the paper of Aggarwal and Tandon (1994), who test the day-of-the week effect and find that Monday returns are negative in 13 countries, but are significant only in seven of them. Lakonishok and Smidt (1988) find persistently negative and significantly different from zero Monday average returns, while Mills et al. (2000) observe a Tuesday effect, rather than a Monday effect on the Athens Stock Exchange (ASE). Draper and Paudyal (2002) examine the FTSE All-Share and FTSE 100 indexes and they find that Monday average returns are negative and generally the returns of the other four days of the week are significantly higher.

The first studies in the day-of-the week effect report significant negative average returns on Mondays. But more recent studies find a shift in the weekday pattern, where average returns on Mondays were no longer negative, but researchers discovered positive and significantly different average returns on Monday than the other weekday returns (Mehdian and Perry, 2001; Pettengill, 2003). Furthermore, Alagidede and Panagiotidis (2009) examine the Ghana Stock Exchange and the day-of-the-week effect hypothesis is rejected. Furthermore, Friday's returns are the most significant when asymmetric GARCH is estimated, but this seasonal anomaly seems to disappear when the time-varying asymmetric GARCH is employed. In a recent study, Onyuma (2009) examines the NSE 20 Share

Index of the Kenyan Stock Market using regression analysis and finds that Mondays and Fridays present the lowest negative and highest positive returns, respectively. In addition, Alagidede (2008) rejects the day-of-the-week effect in Egypt, Kenya, Morocco, and Tunisia, but finds higher positive returns on Friday in Zimbabwe. Kenourgios and Samitas (2008) examine the day-of-the-week effect for the ASE indexes and uncover that this anomaly is presented in the period 1995 to 2000, but it decreases in strength after Greece's entry into the Eurozone.

A few papers study smooth transition autoregressive models in stock returns. In an older study Aslanidis (2002) examines smooth transition regressive models using financial and macroeconomic time-series, allowing the transition variable to be either a past value of the dependent variable or of an exogenous variable and he finds that in-sample movements are explained and described in a more efficient way by smooth transition models rather than by linear models. Moreover, McMillan (2003) examines FTSE All-Share index returns using financial and macroeconomic series and suggests that nonlinear STAR models more efficiently describe the dynamic behavior of the market.

METHODOLOGY

Definition of Ordinary Least Squares Model for the Day-of-the-Week Effect

The stock returns are given by Equation (16.1).

$$R_t = \log(P_t - P_{t-1}) \qquad (16.1)$$

For the day-of-the week effect, we apply the following model estimated with OLS:

$$R_t = \beta_1 D_{MON} + \beta_2 D_{TUE} + \beta_3 D_{WED} + \beta_4 D_{THU} + \beta_5 D_{FRI} + \gamma R_{t-1} + \varepsilon_t \qquad (16.2)$$

where R_t is defined as in Equation (16.1), dummy variable D_{MON} takes a value of 1 if returns are on Mondays and 0 otherwise, and so on; and ε_t is the disturbance term. We obtain the autoregressive term R_{t-1} in Equation (16.2) to correct for possible nonsynchronous trading.

Definition of GARCH (1,1) Model for the Day-of-the-Week Effect

We test in Equation (16.2) if there are ARCH effects, applying ARCH-LM test (Engle, 1982). If there are ARCH effects we apply the symmetric GARCH (1,1) model proposed by Bollerslev (1986), whereby the variance equation is defined as

$$\sigma_t^2 = \omega + a_1\, u_{t-1}^2 + a_2 \sigma_{t-1}^2 \qquad (16.3)$$

The mean equation remains the same as in Equation (16.2). The standard GARCH model is symmetric in its response to past innovations. Since good news and bad news may have different effects on the volatility, we consider an alternative GARCH model in an attempt to capture the asymmetric nature of volatility responses.

Definition of EGARCH (1,1) Model for the Day-of-the-Week Effect

The asymmetric GARCH model we estimate is the EGARCH model, which was proposed by Nelson (1991) and has the following form:

$$\log(\sigma_t^2) = \omega + \log a_1\,(\sigma_{t-1}^2) + a_2 \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \delta \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \qquad (16.4)$$

We expect for the asymmetries allowed finding a negative value for coefficient γ if the relationship between volatility and returns is negative. More specifically, it is expected $\gamma < 0$, so "good news" generates less volatility than "bad news," where γ reflects the leverage effect.

Definition of STAR Models for the Day-of-the-Week Effect

Smooth transition autoregressive models were introduced and developed by Chan and Tong (1986) and is defined as

$$R_t = \pi_{10} + \pi_1{'} w_t + (\pi_{20} + \pi_2{'} w_t) F(R_{t-d}; \gamma, c) + u_t \qquad (16.5)$$

where $u_t \sim (0, \sigma^2)$, π_{10} and π_{20} are the intercepts in the middle and outer regime respectively, $w_t = (R_{t-1} \ldots R_{t-j})$ is the vector of the explanatory variables consisting of the dependent variable with $j = 1 \ldots p$ lags, R_{t-d} is the transition variable, parameter c is the threshold giving the location of the transition function, and parameter γ is the slope of the transition function. We shall consider two transition functions (Teräsvirta and Anderson, 1992), the logistic and the exponential, as defined by Equation (16.6) and Equation (16.7), respectively. Parameter d indicates the delay and we divide parameter γ with $\sigma(r)$, which is the standard deviation of R_t. First we apply a test to examine if R_t is linear or not, proposed by Teräsvirta, Lin, and Granger (1993). The STAR models estimation consists of three steps (Teräsvirta, 1994).

$$F(R_{t-d}) = (1 + \exp[-\gamma(1/\sigma(r))(R_{t-d} - c)])^{-1}, \gamma > 0 \qquad (16.6)$$

$$F(R_{t-d}) = 1 - \exp(-\gamma(1/\sigma^2(r))(R_{t-d} - c)^2), \gamma > 0 \qquad (16.7)$$

The first step is the specification of the autoregressive process of $j = 1 \ldots p$. In order to find j value, we estimate the auxiliary regression in Equation (16.8) for various values of $j = 1 \ldots p$, and we select that value for which the p value is the minimum. Also the maximum value for p is set up at 5. The second step is testing linearity for different values of delay parameter d. We then estimate the following auxiliary regression:

$$R_t = \beta_o + \beta_1 w_t + \ldots + \sum_{j=1}^{p} \beta_{2j} R_{t-j} R_{t-d} + \sum_{j=1}^{p} \beta_{3j} R_{t-j} R_{t-d}^2 + \sum_{j=1}^{p} \beta_{4j} R_{t-j} R_{t-d}^3 + \varepsilon_t \quad (16.8)$$

The null hypothesis of linearity is $H_0: \beta_{2j} = \beta_{3j} = \beta_{4j} = 0$. In order to specify the parameter d the estimation of Equation (16.8) is carried out for a wide range of values $1 \leq d \leq D$ and we choose $d = 1, \ldots 9$ in a similar process as we follow with the computation of value j. The third and last step is the specification of STAR model. We test the following hypotheses (Teräsvirta and Anderson, 1992):

$$H_{04} : \beta_{4j} = 0, j = 1, \ldots, p \qquad (16.9)$$

$$H_{03} : \beta_{3j} = 0 \mid \beta_{4j} = 0, j = 1, \ldots, p \qquad (16.10)$$

$$H_{02} : \beta_{2j} = 0 \mid \beta_{3j} = \beta_{4j} = 0, j = 1, \ldots, p \qquad (16.11)$$

If we reject the hypothesis made in Equation (16.9), then we choose the logistic STAR (LSTAR) model. If Equation (16.9) is accepted and Equation (16.10) is rejected, then the exponential STAR (ESTAR) model is selected. Finally, accepting Equation (16.9) and Equation (16.10) and rejecting Equation (16.11), we choose the LSTAR model. Thereafter, when we have found the order of d from Equation (16.8) and j values and the specification of STAR model, we estimate the corresponding smooth transition autoregressive model for the day-of-the-week effect. Equation (16.5) becomes

$$
\begin{aligned}
R_t = {}& \pi_1{}' w_t + \beta_1 D_{MON} + \beta_2 D_{TUE} + \beta_3 D_{WED} + \beta_4 D_{THU} \\
& + \beta_5 D_{FRI} + (\pi_2\, w_t + \gamma_1 D_{MON} + \gamma_2 D_{WED} + \gamma_3 D_{WED} \\
& + \gamma_4 D_{THU} + \gamma_5 D_{FRI})\, F\, (R_t - d;\, \gamma,\, \mathrm{c}) + u_t \qquad (16.12)
\end{aligned}
$$

where u_t follows GARCH (1,1) processes as we noted in a previous section. We exclude π_{10} and π_{20} intercepts to avoid multicollinearity problem. In order to compute the values of parameters c and γ, we apply a grid search in relation to Equation (16.6) or Equation (16.7) with nonlinear least squares and Levenberg-Marquardt algorithm. The model Equation (16.12), we propose, has the flexibility that dummy variables in the outer regime no longer take values of zero and unit. It is very close to a fuzzy logic approach, where there is a different weighting in each observation and so in each point of time.

Bootstrapping Regressions

We estimate the above models with and without bootstrapping simulation. In all cases the steps for the bootstrapping simulated regression are the same and we follow the process described in Davidson and MacKinnon (2004). The bootstrapping replications have been set up at 1,000.

DATA

The data are daily and cover the period January 4, 1950 to March 31, 2009. The subperiod January 4, 1950 to December 31, 2008 is selected for

estimating purpose and therefore is used for in-sample forecasting. The remaining period January 2 through March 31, 2009 is used as the out-of-sample forecasting period.

EMPIRICAL RESULTS

Ordinary Least Squares Results

In Table 16.1, the regression results for the day-of-the-week effect with the OLS method are reported. We observe that average returns on Monday are negative, while the average returns on the other days of the week are positive. All estimated coefficients are statistically significant except from the coefficient indicating Thursday returns. Furthermore, the higher average returns are not presented on Fridays, as expected, but they are reported on Wednesdays with no bootstrapping simulations, while higher returns are presented on Fridays with bootstrapping regression. The main problem with OLS estimation is that autocorrelation and ARCH effects are not eliminated, according to p values of the respective tests, LBQ^2 and ARCH-LM, while in bootstrapping regression these problems are solved. In both estimations we reject the null hypothesis of regression coefficients equality, according to F statistic.

Generalized Autoregressive Conditional Heteroscedasticity—GARCH Results

In Table 16.2, the situation is quite different with GARCH (1,1) estimation: while there are negative returns on Mondays, the highest returns are reported on Fridays and not on Wednesdays, as we found with OLS. According to the log-likelihood statistic, the Akaike information criteria, and the Schwarz information criteria, GARCH (1,1) has greater estimating performance. Furthermore, autocorrelation and ARCH effects are eliminated in both estimations. According to F statistic, we reject the hypothesis that the estimated coefficients are equal in both estimations. With this procedure, the day-of-the-week effect exists, as negative average returns and the highest positive average returns are reported on Mondays and Fridays, respectively.

Table 16.1 Ordinary Least Squares Results for the Day-of-the-Week Effect

			Panel A. Parameters			
Models	β_{MON}	β_{TUE}	β_{WED}	β_{THU}	β_{FRI}	γ
	−0.00083	0.00034	0.00073	0.00026	0.00067	0.04053
	[−4.628]*	[1.990]†	[4.228]*	[1.487]	[3.799]*	[4.950]*
OLS	$R^2_{adjusted}$	AIC	SBC	LL	LBQ^2 (12)	ARCH-LM (5)	F statistic
	0.004945	−6.516	−6.513	48366.60	2995.4	284.169	28.327
					(0.000)	(0.000)	(0.000)

			Panel B. Parameters			
	β_{MON}	β_{TUE}	β_{WED}	β_{THU}	β_{FRI}	γ
	−0.00051	0.00032	0.00083	0.00043	0.00098	0.0373
	[−2.935]*	[1.916]‡	[4.915]*	[2.523]†	[5.769]*	[4.458]*
OLS with bootstrap ping simulation	$R^2_{adjusted}$	AIC	SBC	LL	LBQ^2 (12)	ARCH-LM (5)	F statistic
	0.004070	−6.523	−6.520	48417.17	8.215	0.372	14.682
					(0.768)	(0.8681)	(0.000)

AIC=Akaike information criteria; SBC=Schwarz information criteria; LL=log likelihood; LBQ^2 (12)=Ljung-box test on squared standardized residuals with 12 lags; ARCH-LM (5)=Lagrange multiplier test for ARCH effects with 5 lags.

*Significance at 0.01 level. †Significance at 0.05 level. ‡Significance at 0.10 level.

p values in parentheses; t statistics in brackets.

Table 16.2 GARCH (1,1) Results for the Day-of-the-Week Effect

		Panel A. Parameters					
Models	Mean Equation	β_{MON}	β_{TUE}	β_{WED}	β_{THU}	β_{FRI}	γ
		−0.00049	0.00036	0.00085	0.00052	0.00101	0.1058
		[−4.266]*	[3.184]*	[7.278]*	[4.446]*	[8.305]*	[12.760]*
GARCH (1,1)	Variance Equation	ω	α_1	α_2			
		5.29e−07	0.0736	0.922			
		[6.485]*	[17.209]*	[219.25]*			

	Panel B. Diagnostics					
$R^2_{adjusted}$	AIC	SBC	LL	LBQ^2 (12)	ARCH-LM (5)	F statistic
0.000410	−6.920	−6.915	51371.24	13.778	1.588	12.591
				(0.315)	(0.1594)	(0.000)

		Panel A. Parameters					
	Mean Equation	β_{MON}	β_{TUE}	β_{WED}	β_{THU}	β_{FRI}	γ
		−0.00040	0.00039	0.00075	0.00051	0.00080	0.1030
		[−4.353]*	[3.049]*	[5.632]*	[3.766]*	[5.980]*	[17.001]*

(Continued)

Table 16.2 (Continued)

	Panel A. Parameters			
Variance Equation	ω	α_1	α_2	
GARCH (1,1) with bootstrapping simulation	4.58e−05	0.0201	0.8859	
	[2.683]*	[2.372]†	[1.873]‡	

	Panel B. Diagnostics					
$R^2_{adjusted}$	AIC	SBC	LL	LBQ^2 (12)	ARCH-LM (5)	F statistic
0.003287	−6.740	−6.735	50037.111	4.457 (0.974)	0.518 (0.7628)	8.975 (0.000)

AIC=Akaike information criteria; SBC=Schwarz information criteria; LL=log likelihood; LBQ^2 (12)=Ljung-box test on squared standardized residuals with 12 lags; ARCH-LM (5)=Lagrange multiplier test for ARCH effects with 5 lags.

*Significance at 0.01 level. †Significance at 0.05 level. ‡Significance at 0.10 level.

p values in parentheses; t statistics in brackets.

Exponential Generalized Autoregressive Conditional Heteroscedasticity—EGARCH Results

With EGARCH (1,1) estimation we obtain quite similar results and conclusions with those of GARCH (1,1), where negative average returns are reported only on Mondays, and Fridays presents the highest average returns (Table 16.3). Furthermore, bootstrapping regression presents lower values for the information criteria and the log-likelihood statistic, which means that based on these values, the EGARCH (1,1) model without bootstrapping simulation is preferred. Also the coefficient δ, indicating the leverage effects, has negative and correct sign and it is statistically significant in EGARCH (1,1) without bootstrapping simulation, while with bootstrapping regression, coefficient δ has the correct sign but is statistically insignificant.

Linearity Tests and Specification of STAR Model

In this section, we provide the results of the linearity tests and STAR model specification. According to the Akaike information criteria and the statistical significance of AR(p) process, the value of j which is chosen is equal to 2. The value for delay d is chosen based on the minimum p value for which the linearity hypothesis is rejected. Because we have four values for the delay parameter for which the minimum p value is obtained, we

AQ1 choose the higher F statistic, that is, $d = 4$, as we observe in Table 16.4, indicating rather a slow response. In Table 16.5, we present the F statistics for the STAR model specification. We observe that we accept the hypothesis of Equation (16.9) and reject the hypothesis of Equation (16.10), thus we choose the ESTAR model.

ESTAR-GARCH (1,1) Estimation

In Table 16.6, the results of the ESTAR model with GARCH (1,1) process are presented. As initial values for parameters c and γ, we used, respectively, the sample mean and 1, whose values were found equal with -0.0053 and 4.489, respectively. From the results of Table 16.6, we observe that in the middle regime of ESTAR without bootstrapping estimation negative average returns are reported on Monday, while the highest positive average returns are presented on Fridays. All the parameters in the linear middle regime are statistically significant. On the other hand, in the outer regime

Table 16.3 EGARCH (1,1) Results for the Day-of-the-Week Effect

		Panel A. Parameters					

Models	Mean Equation	β_{MON}	β_{TUE}	β_{WED}	β_{THU}	β_{FRI}	γ
		−0.00057	0.00017	0.00065	0.00037	0.00890	0.1062
		[−5.048]*	[1.584]	[5.688]*	[3.216]*	[7.433]*	[13.121]*
EGARCH (1,1)	Variance Equation	ω	α_1	α_2	δ		
		−0.2061	0.1273	0.9888	−0.0725		
		[−13.97]*	[17.871]*	[781.48]*	[−15.38]*		

	Panel B. Diagnostics					

$R^2_{adjusted}$	AIC	SBC	LL	LBQ^2 (12)	ARCH-LM (5)	F statistic
0.000670	−6.937	−6.931	51497.25	30.788	5.609	11.554
				(0.002)	(0.000)	(0.000)

		Panel A. Parameters					

EGARCH (1,1) with bootstrapping simulation	Mean Equation	β_{MON}	β_{TUE}	β_{WED}	β_{THU}	β_{FRI}	γ
		−0.00049	0.00015	0.00077	0.00032	0.000880	0.1042
		[−3.196]*	[3.424]*	[5.832]*	[2.335] [†]	[6.345]*	[17.468]*

Variance Equation	ω	α_1	α_2	δ			
	−0.219	0.0152	0.9751	−0.0125			
	[−2.37] †	[2.204] †	[95.287]*	[0.609]			

Panel B. Diagnostics

$R^2_{adjusted}$	AIC	SBC	LL	LBQ^2 (12)	ARCH-LM (5)	F statistic
0.016065	−6.761	−6.755	50188.57	9.085	0.960	6.238
				(0.696)	(0.4407)	(0.000)

AIC=Akaike information criteria; SBC=Schwarz information criteria; LL=log likelihood; LBQ^2 (12)=Ljung-box test on squared standardized residuals with 12 lags; ARCH-LM (5)=Lagrange multiplier test for ARCH effects with 5 lags.

*Significance at 0.01 level. †Significance at 0.05 level.

p values in parentheses; t statistics in brackets.

Table 16.4 Linearity Tests for S&P 500 Index

Delay (d)	1	2	3	4	5	6	7	8	9
F statistic	3.475	1.714	0.246	20.623	4.521	16.137	0.065	0.001	12.481
	(0.002)	(0.113)	(0.960)	(0.000)	(0.000)	(0.000)	(0.998)	(1.000)	(0.000)

p values in parenthesis.

Table 16.5 STAR Model Specification for S&P 500 Index

Delay (d)	F statistic H_{04}: $\beta_4 = 0$	F statistic H_{03}: $\beta_3 = 0 / \beta_4 = 0$	F statistic H_{02}: $\beta_2 = 0 / \beta_3 = \beta_4 = 0$	Type of Model
4	0.0006	30.278	18.068	
	(0.9994)	(0.000)	(0.000)	ESTAR

p values in parentheses

with ESTAR estimation, significant positive average returns are presented only on Mondays, while negative returns are reported on Tuesdays. The returns of the other days of the trading week are statistically insignificant. The model corrects for autocorrelation and ARCH effects in all significance levels. Based on the F statistic, we reject the null hypothesis that the regression coefficients are equal.

In bootstrapping ESTAR estimation and the middle regime, we conclude that there is the day-of-the-week effect, while the highest returns are presented on Fridays and negative returns on Mondays. All the coefficients in the middle regime are statistically significant. In the outer regime and the bootstrapping regression only, coefficients π_{21}, β_{MON}, and β_{WED} are significant, and we observe that there is a reverse Monday effect, while the average returns on Mondays are positive and the average returns are negative on Wednesdays. The remaining weekday average returns are statistically insignificant. The bootstrapping ESTAR corrects for both autocorrelation and ARCH effects. According to F statistic, the null hypothesis of the coefficients equality is rejected. We observe that based on the information criteria and log-likelihood statistic, ESTAR outperforms the previous models, except from EGARCH, but the comparison might not be the most appropriate as the formulation of the last model is different.

Table 16.6 ESTAR-GARCH (1,1) Results for the Day-of-the-Week Effect

		π_{11}	π_{12}	β_{MON}	β_{TUE}	β_{WED}	β_{THU}	β_{FRI}
ESTAR-GARCH (1,1)	Coefficients in the Middle Regime	0.11968	−0.02440	−0.00029	0.00027	0.00768	0.00055	0.00105
		[13.348]*	[−2.756]*	[−2.242] †	[2.121] †	[5.434]*	[3.779]*	[6.562]*
	Coefficients in the Outer Regime	π_{21}	π_{22}	γ_{MON}	γ_{TUE}	γ_{WED}	γ_{THU}	γ_{FRI}
		12.0400	9.10608	0.06126	−0.04860	−0.2823	0.08464	0.01376
		[2.292] †	[2.036]†	[3.225]*	[−2.203] †	[−1.221]	[0.348]	[0.079]
	Variance Equation	ω	α_1	α_2				
		6.08E−07	0.0714	0.9233				
		[10.778]*	[29.233]*	[367.458]*				
	Diagnostics	$R^2_{adjusted}$	AIC	SBC	LL	LBQ^2 (12)	ARCH-LM (5)	F statistic
		0.009411	−6.922	−6.916	51385.27	15.160	1.623	9.824
						(0.233)	(0.1499)	(0.000)
ESTAR-GARCH (1,1) with Bootstrapping Simulation	Coefficients in the Middle Regime	π_{11}	π_{12}	β_{MON}	β_{TUE}	β_{WED}	β_{THU}	β_{FRI}
		0.11302	−0.02108	−0.00070	0.00046	0.00059	0.00035	0.00091
		[16.804]*	[−6.201]*	[−4.768]*	[3.247]*	[4.225]*	[2.381] †	[6.181]*

(Continued)

Table 16.6 (Continued)

Coefficients in the Outer Regime	π_{21}	π_{22}	$\gamma_{\mathbf{MON}}$	$\gamma_{\mathbf{TUE}}$	$\gamma_{\mathbf{WED}}$	$\gamma_{\mathbf{THU}}$	$\gamma_{\mathbf{FRI}}$
	7.39233	−0.05273	0.01017	0.0137	−0.0223	0.01715	−0.12192
	[1.785] ‡	[−0.008]	[1.803] ‡	[0.153]	[−2.77]*	[0.127]	[−1.247]
Variance Equation	ω	α_1	α_2				
	2.83e−05	0.0052	0.6758				
	[2.047]†	[2.647]*	[4.233]*				
Diagnostics	R^2_{adjusted}	AIC	SBC	LL	LBQ^2 (12)	ARCH-LM (5)	F statistic
	0.015165	−6.755	−6.746	50148.48	11.064	0.601	14.332
					(0.523)	(0.4369)	(0.000)

AIC = Akaike information criteria; SBC = Schwarz information criteria; LL= log likelihood; LBQ^2 (12) = Ljung-box test on squared standardized residuals with 12 lags; ARCH-LM (5) = Lagrange multiplier test for ARCH effects with 5 lags.

*Significance at 0.01 level. †Significance at 0.05 level. ‡Significance at 0.10 level.

p values in parentheses; t statistics in brackets.

Table 16.7 Forecasting Criteria for the Estimated Models

Models	In-Sample		Out-of-Sample		Percentage of Correct Signal in Out-of-Sample Period
	RMSE	MAE	RMSE	MAE	
OLS	0.009316	0.006374	0.026476	0.020524	56.7%
GARCH (1,1)	0.009316	0.006376	0.026465	0.020493	55.0%
EGARCH (1,1)	0.009316	0.006375	0.026495	0.020552	56.7%
ESTAR-GARCH (1,1)	0.008729	0.006165	0.026248	0.020330	63.4%

Forecasting Results and Performance

In Table 16.7, we report the forecasting performance measures. The mean absolute error (MAE) is very close and the root mean square error (RMSE) is identical with all models, except in the ESTAR model, for in-sample period, which the latter model presents the best performance. In out-of-sample period, RMSE and MAE are lower in GARCH (1,1), followed by OLS, and then by EGARCH (1,1). ESTAR-GARCH (1,1) presents lower RMSE and MAE and so better forecasts performance. In the percentage of the correct signal criteria, OLS and EGARCH (1,1) model outperform GARCH (1,1), where the first two models capture the correct signal at 56.7 percent (34 of 60) trading days, while GARCH (1,1) captures correctly at 55.0 percent (33 of 60) trading days. ESTAR-GARCH (1,1) outperforms all models, capturing the correct signal in 38 of 60 trading days or a percentage order of 63.4 percent. Specifically in the short horizon of 10 ahead periods, ESTAR-GARCH (1,1) predicts correctly at 70 percent, while OLS predicts correctly at 60 percent and GARCH models capture the correct signal only at 30 percent. In particular, many investors and traders are interested in the forecasting of the correct signal over a five-day trading week. For this purpose, ESTAR-GARCH model outperforms significantly the simple GARCH models.

CONCLUSION

In this chapter we examine the day-of-the-week effect on the S&P 500 index. We find that this calendar anomaly exists according to all estimations, except in ESTAR-GARCH (1,1), where the Monday effect exists in

the linear middle regime and the reverse Monday effect is reported in the nonlinear outer regime. We propose the STAR models for the day-of-the-week effect; however, this is only a proposed model, which was examined for only one calendar anomaly and using only one index, while further research can be applied in other calendar effects. Furthermore, the forecasting performance of ESTAR model outperforms the forecasting ability of the other estimated models, especially regarding the correct signal, which is the most important and realistic tool in real-world trading environments.

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FOREIGN EXCHANGE MARKETS, ALGORITHMIC TRADING, AND RISK

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DISPARITY OF USD INTERBANK INTEREST RATES IN HONG KONG AND SINGAPORE
Is There Any Arbitrage Opportunity?

Michael C. S. Wongand Wilson F. Chan

ABSTRACT

This chapter compares USD interest rates in two interbank markets, namely, Hong Kong Interbank Best Offer Rate (HIBOR) and Singapore Interbank Best Offer Rate (SIBOR). Both Hong Kong and Singapore are global currency trading centers located in the same time zone, in which there are many global banks, fund houses, and hedge funds. However, we find a consistent disparity between HIBOR and SIBOR in 2008, which even reaches 90 basis points after June 2008. This obviously contradicts the well-known efficient market hypothesis. This chapter attempts to explain why bank dealers would be reluctant to do arbitrage.

INTRODUCTION

USD is an international currency for international transactions. Many international activities on lending and borrowing are based on USD, undergone in New York, London, Zurich, Singapore, Hong Kong, or Tokyo. The

interbank markets for USD funds should be very efficient because of the presence of dealers from global banks. Disparity in the USD interest rate in these markets should be extremely narrow and directionless, especially when the markets operate in the same time zone. This chapter compares the USD interbank fixing rate in Hong Kong and Singapore, denoted by HIBOR and SIBOR. We find that HIBOR is consistently higher than SIBOR in 2008. The disparity becomes much wider after June 2008 and reaches to 80 basis points. This seems to be inconsistent with the well-known efficient market hypothesis (EMH) and to provide traders arbitrage opportunities.

Previous studies on interest rate and interest spreads document that credit risk, liquidity risk, and tax can affect interest rate (see, for instance, Elton et al. 2001; Eom Helwege, and Uno, 2003; and Longstaff, 2004). These studies focus mainly on the corporate bond market in the United States. Few studies explore the interest spreads in the interbank money market. It is generally assumed that borrowers in interbank markets are credible participants, spreads in interbank markets could be negligible, and traders do not have any arbitrage opportunity. However, our evidence shows a contradictory picture.

This chapter will proceed as follows: the second section of this chapter introduces the HIBOR and SIBOR markets. This chapter's third section describes our data and findings. The fourth section of this chapter provides explanations on the disparity between HIBOR and SIBOR, and the fifth section concludes the chapter.

HIBOR AND SIBOR

Interbank markets are very active in major international banking centers, such as New York, London, Singapore, and Hong Kong. Bank dealers bring global supply and demand to these markets in order to exchange for funds. They may also actively look for arbitrage opportunities. It would be very hard to find any evidence of market inefficiency in interbank markets for those actively traded products.

A USD fund is an actively traded product in interbank markets of different regions. Interest rate calculation for floating rate assets and liabilities denominated in USD are mostly based on USD interbank rate plus a spread. Outside the United States, the interbank USD interest rate generally refers to London Interbank Bank Offer Rate (LIBOR), Singapore

Interbank Offer Rate (SIBOR), and Hong Kong Interbank Offer Rate (HIBOR), respectively. Interbank dealers will collectively fix the interest rate in both the AM and PM. These are so-called AM and PM fixings. AM fixing is commonly used as a basis for interest rate calculation. In New York there is no New York interbank offer rate, although New York is an active money market. Both LIBOR and SIBOR have had a long history in the market. The Hong Kong banking community formally launched the USD fixing rate on December 18, 2006. This is also the start of the sample period of this study.

DATA AND FINDINGS

This chapter selects 1-month, 3-month, and 6-month USD interest rates in the period between December 18, 2006 and November 28, 2008 for analysis. The interest rates are interbank fixing rates (AM) in Hong Kong and Singapore (i.e., HIBOR and SIBOR). Figure 17.1 shows 3-month HIBOR and SIBOR in the sample period. The two USD interest rates move closely and HIBOR tends to move higher than SIBOR in 2008. Figures 17.2 to 17.4 show the disparity between HIBOR and SIBOR for

Figure I7.I Three-Month USD HIBOR and SIBOR (in %): December I8, 2006 to November 28, 2008
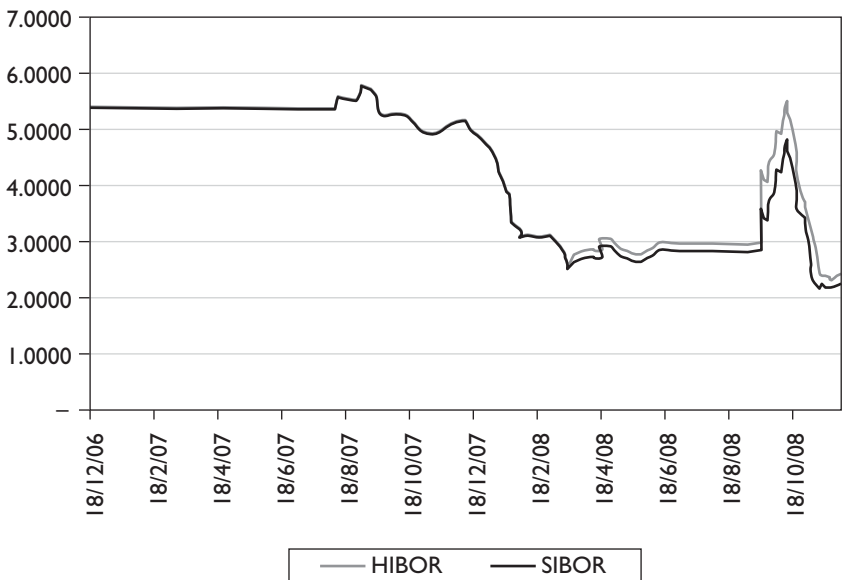
Figure 17.2 Difference between HIBOR and SIBOR: 1-Month Tenor

HIBOR-SIBOR(1m)

Figure 17.3 Difference between HIBOR and SIBOR: 3-Month Tenor

HIBOR-SIBOR(3m)
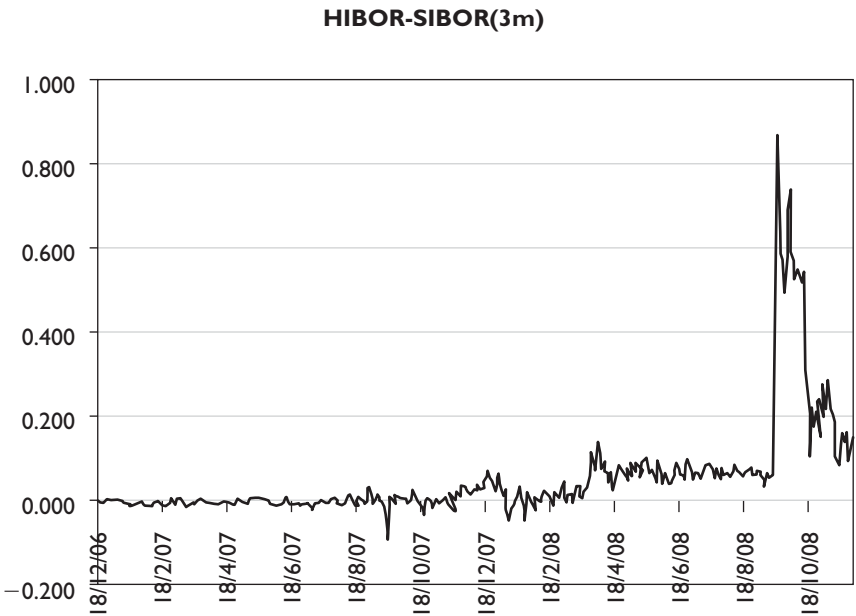
Figure 17.4 Difference between HIBOR and SIBOR: 6-Month Tenor

HIBOR-SIBOR(6m)
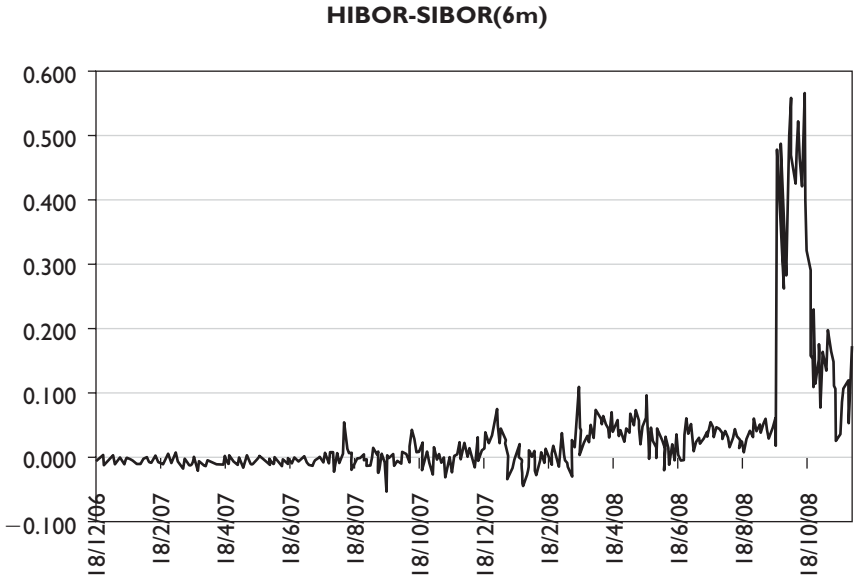
1-month, 3-month, and 6-month tenors, respectively. In Figure 17.2, 1-month HIBOR is consistently higher than 1-month SIBOR in 2008. The average difference is around 15 basis points in the period between January 2008 and June 2008. The difference finally reaches 80 basis points in September and October of 2008. A similar phenomenon also happens to 3-month and 6-month HIBOR and SIBOR.

EXPLANATIONS FOR THE HIBOR-SIBOR DISPARITY

According to logic of EMH, the disparity between HIBOR and SIBOR should be corrected quickly because both markets are trading the same product and in the same time zone. One important assumption of EMH is the presence of professional traders who are able to do arbitrage. Their collective efforts should effectively correct any mispricing. In the interbank money market, bank dealers take the role of the "professional traders" and are assumed to actively look for arbitrage opportunities. In practices, bank dealers have some constraints in their arbitrage decisions, including:

- **Capital requirement:** Basel II, the global banking regulation, requires capital requirements on credit exposures to other banks.

Many banks have internal guidelines that bank dealers are not allowed to take unnecessary funds and credit positions. This restricts bank dealers from taking the benefit of arbitrage. Nonbank institutions do not have such constraints, but they cannot easily access the HIBOR and SIBOR markets. If they want to make gains from arbitrage between HIBOR and SIBOR, they will require a wider gap between HIBOR and SIBOR to compensate their transactions costs paid to bank dealers.

- **Counterparty risk:** In 2008, counterparty risk was a big issue in interbank transactions. The financial troubles of Bear Stearns in March 2008 triggered off concerns over the financial soundness of global institutions. Bank dealers became more sensitive to credit quality in lending via the interbank markets. The financial crisis that happened in July to October in 2008 made bank dealers to be extremely cautious in allocating their credit exposures. The higher HIBOR against SIBOR might indicate higher credit risk involved in the Hong Kong interbank market. This can be true as there is higher number of small-sized banks in Hong Kong than in Singapore.

- **Liquidity risk:** In 2008 liquidity was a big issue for many banks. Financial markets became volatile and marketable assets suddenly turned to be less marketable. To assure liquidity, banks would prefer loans of much shorter maturity, such as overnight loans. This weakened the incentives of bank dealers to do arbitrage in the 1-month, 3-month, and 6-month interbank market.

CONCLUSION

The previous finding shows evidence of disparity between HIBOR and SIBOR, which are USD interbank fixing rates in Hong Kong and Singapore, respectively. The disparity stays at around 15 basis points in the first-half of 2008 and even reaches 90 basis points in the crisis period of 2008. Even though the disparity provided bank dealers arbitrage opportunities, they might find hard it to do arbitrage because of consideration on capital requirements, counterparty risk, and liquidity risk. Efficient market hypothesis might have overstated the power of professional traders. In volatile market environments, arbitrage opportunities may exist but professional traders could become reluctant to arbitrage.

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FOREX TRADING OPPORTUNITIES THROUGH PRICES UNDER CLIMATE CHANGE

Jack Penm and R. D. Terrell

ABSTRACT

We have undertaken this research in forex trade assessment and investment decisions under climate change, using new and important zero-non-zero patterned time-series approaches. Our results indicate that Granger feedback relations exist in the system, involving exchange rates and price indexes. This is valuable not only in predicting price changes but also in capturing forex trading opportunities.

INTRODUCTION

Powerful computing equipment has had a dramatic impact on forex modeling and simulations, and has motivated development of innovative computing-intensive time-series approaches to forex trade assessment for capturing trading opportunities. New zero-non-zero (ZNZ) patterned time-series methodology has specified models in a more sophisticated manner. This has

enabled the use of data in highly adaptive ways and facilitated major innovations in development of management and evaluation of forex modeling and trading strategy. Against that background, we undertake research in forex movement modeling and data analysis using new and important patterned time-series approaches. While trade and environmental investment decisions still have to operate in an uncertain market, and human judgment can never be fully replaced, quantitative time-series analysis has an important role to play in guiding effective trade decisions and setting trade strategy.

This chapter investigates a very important issue, namely, causal links between exchange rates and price indexes, and undertakes an assessment of the causal positioning of the significant relevant economic variables involved in the interactions. Perhaps the simplest of many contending hypotheses is that there is a short-term causal link, in which international capital flows lead movements in the exchange rate. The absence of stable long-term relationships would indicate that, over a long period, the levels of exchange rates are less dependent on the levels of prices. If stable long-term relationships exist among exchange rates and price indexes, then, after temporary deviations in the short term, the levels of exchange rates would revert to their traditional long-term relationships with price indexes. Identification of such long-term relationships, if they exist, would be essential in forecasting exchange rate movements, which affects buying and selling trade behavior and thereby identifies future trading opportunities.

We test this hypothesis using recent developments in cointegration theory. The tests are undertaken within the framework of ZNZ patterned vector error-correction modeling (VECM) and associated cointegrating vectors, with allowance for possible zero entries proposed in Penm and Terrell (2003). This approach is particularly useful for analyzing cointegrating relationships between prices and exchange rates in forex trade markets. Its special attraction is that, by permitting zero coefficients in the VECM, it allows for a highly insightful economic interpretation of the cointegrating relationships and their re-adjustment following deviations from equilibrium. New error-correction technologies for linear and nonlinear modeling are helpful in explaining and interpreting certain aspects of causal links between prices and exchange rates. The patterned cointegrating vectors in the VECM are valuable not only in taking trading opportunities but also in forecasting price changes.

There are also several other issues that must be addressed before we set out the full complexity of the pattern of linkages we are to investigate.

The relevant price variables may differ from country to country and at different points in the sequence of events. We therefore examine consumer prices, wholesale prices, and export and import prices, in order to fully understand the strength and direction of certain causal links. We also consider whether such links are short term or long term in nature and whether it is possible in a complex sequential process to detect feedback loops. We construct a system model to investigate the following two causal chains.
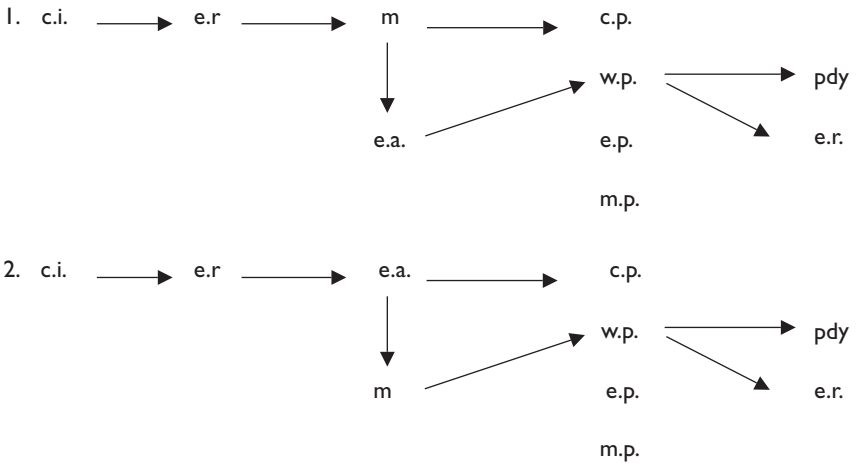
c.i. = capital flows: e.r. = exchange rates: m = money supply movements; e.a. = economic activities; c.p. = consumer prices; w.p. = whole prices: e.p. = export prices: m.p. = import prices: pdy = productivity changes.

We also propose to include a forgetting factor in the estimation of the patterned VECMs. The forgetting factor technique is a data-weighting process that allows the estimation to place greater weight on more recent observations and less weight on earlier data. In such estimation, the effects on the underlying relationships of evolution generated by the causal linkage process will be accounted for.

As to why a subset time-series model is used, subset modeling includes full-order models, and researchers use this approach whenever measurements exhibit some periodicity. If the underlying true time-series process has a subset structure, the suboptimal full-order specification can give rise to inefficient estimates and inferior projections. Our forgetting factor approaches improve estimated parameter profile, model structure, and performance reliability for assessing complex relationships involving

slowly evolving long-term effects, such as climate change. These qualities are not found in conventional time-series approaches involving only full-order models. Subset modeling is superior to full-order modeling for discovering complex relationships, as has been clearly indicated in Penm and Terrell (2003).

In order to illustrate the practical use of the proposed forex modeling and trade forecast approach, we investigate the causal relationships among exchange rates, price indexes, other macroeconomic variables, and the exchange rate forecasting in Taiwan using the monthly data over the period 1982 to 2008. Researchers have recognized the potential hazards that climate change and environmental change may present for small island developing states such as Taiwan. Changes are expected to be negatively impacted, and thus directly threaten the Taiwanese population. Those changes include: a general rise in surface temperature and in sea level; changes in seasonal temperature variation and rainfall patterns; variations in soil moisture and water resources; and increases in the incidence of severe weather events such as typhoons and floods.

Climate change in Taiwan has both environmental and socioeconomic outcomes for agriculture: changes in the availability and quality of land, soil, and water resources, for example, may later be reflected in poorer crop performance, which causes prices to rise. Climate-related changes in agricultural conditions will likely only increase Taiwan's dependence on imported food. The price indexes track changes in the prices consumers pay for products and services. Those price indexes will therefore track changes over time in the long-term effects of climate changes and their impacts on the production, use, and disposal of items purchased each year by consumers.

This chapter is organized as follows: the second section of this chapter outlines the construction of patterned vector error-correction modeling, which demonstrates the "presence and absence" restrictions on the coefficients of subset time-series systems, including full-order systems. Also, brief descriptions are given of the forgetting factor techniques used for estimation. In this chapter's third section we assess the causal link between exchange rates and price indexes in Taiwan. We also present the forex forecasting results indicating significant movements in exchange rates, in which the MAE criterion is used to examine prediction performance. A brief summary is provided in the final section of this chapter.

METHODOLOGY

The Forgetting Factor

The use of forgetting factor in time-series analysis has attracted considerable interest in recent years. For example, Penm and Terrell (2003) utilize a forgetting factor in subset autoregressive modeling of the spot aluminum and nickel prices on the London Metal Exchange. The use of the forgetting factor technique to estimation and simulation of financial market variables has been reported by Brailsford, Penm, and Terrell (2002).

Consider a vector autoregression (VAR) model of the following form:

$$y(t) + \sum_{\tau=1}^{q} B_\tau y(t - \tau) = \varepsilon(t) \tag{18.1}$$

$y(t)$ is a $sx1$ vector of wide-sense stationary series. $\varepsilon(t)$ is a $sx1$ vector of independent and identically distributed random process with $E\{\varepsilon(t)\} = 0$ and $E\{\varepsilon(t)\varepsilon'(t - \tau)\} = V$ if $\tau = 0$ and 0 if $\tau > 0$. B_τ, $\tau = 1, ..., q$ are sxs matrices of coefficients. The observations y(t) $\{t = 1, ... , T\}$ are available.

Let $\lambda(t) = [\lambda_1(t) \, ... \, ... \, \lambda_n(t)]$ denotes a $1xs$ vector associated with time t. Following O'Neill, Penm, and Penm (2007), a strategy for determining the value of the forgetting factor $\lambda(t)$ is as follows:

$$\lambda_i(t) = \lambda^{\eta-t+1} \text{ if } 1 \leq t \leq \eta \text{ and } = 1 \text{ if } \eta < t \leq T \text{ for } i = 1, ... n \tag{18.2}$$

Equation (18.2) means that "forgetting" of the past occurs from time η. No forgetting is involved from time $\eta + 1$ to time T. If $\lambda = 1$ for every t, then we obtain the ordinary least squares solution. If $0 < \lambda < 1$, the past is weighted down geometrically from time η. In theory, the value of λ could be different between $\lambda_i(t)$ (a so-called variable forgetting factor). For simplicity, we only consider the fixed forgetting factor case in which the value of λ is constant for $\lambda_i(t)$.

This means that the coefficients in Equation (18.1) are estimated to minimize

$$\sum_{t=1}^{T} \lambda(t) [y(t) - \sum_{\tau=1}^{q} B_\tau y(t - \tau)][y(t) - \sum_{\tau=1}^{q} B_\tau y(t - \tau)]' \tag{18.3}$$

One important issue relating to the use of the forgetting factor in estimation is how to determine the value of λ in applications. The conventional method is based on arbitrary or personal choices. Penm and Terrell (2003) propose to determine the value of λ using bootstrapping. In this study, their recommended method is adopted for the determination of the value of λ. While Brailsford, Penm, and Terrell (2002) also propose a procedure to determine the value of dynamic forgetting factor for nonstationary systems, we have focused on the use of a fixed forgetting factor in this study, because applications of a fixed forgetting factor to forex market movements is likely to be more predictable.

VECM Modeling for an *I*(1) System

In constructing VECM modeling for an $I(1)$ system, from Equation (18.1) we have $B^q(L) = I + \sum_{\tau=1}^{q} B_\tau L^\tau$, where L denotes the lag operator, and $Ly(t) = y(t-1)$. It is assumed that the roots of $|B^q(L)| = 0$ lie outside or on the unit circle to ensure that $y(t)$ can contain $I(1)$ variables.

Of note, $y(t)$ is integrated of order d, $I(d)$, if it contains at least one element which must be differenced d times before it becomes $I(0)$. Further, $y(t)$ is cointegrated with the cointegrating vector, β, of order g, if $\beta'y(t)$ is integrated of order $(d - g)$, where $y(t)$ has to contain at least two $I(d)$ variables.

Following Penm and Terrell (2003), the equivalent VECM for Equation (18.1) can then be expressed as

$$B^q(1)y(t - 1) + B^{q-1}(L)\Delta y(t) = \varepsilon(t) \qquad (18.4)$$

where $y(t)$ contains variables of the types $I(0)$ and $I(1)$. Note that $\Delta = (I - L)$, $\Delta y(t) = y(t) - y(t - 1)$ and $\varepsilon(t)$ is stationary. Equation (18.4) can be rewritten as

$$B^*y(t - 1) + B^q - 1(L)\Delta y(t) = \varepsilon(t), \qquad (18.5)$$

where $B^* = B^q(1)$ and $B^*y(t - 1)$ is stationary and the first term in Equation (18.5) is the error-correction term. The term $B^{q-1}(L)\Delta y(t)$ is the vector autoregressive part of the VECM.

Because $y(t)$ is cointegrated of order 1, the long-term impact matrix, B*, must be singular. As a result, B* = $\alpha\beta'$ and $\beta'y(t-1)$ is stationary, where the rank of B* is r $(0 < r < s)$, and α and β are matrices of dimensions $s \times r$ and $r \times 2s$ respectively. The columns of β are the cointegrating vectors and the rows of are the loading vectors.

A search algorithm proposed by Penm and Terrell (2003) to select the optimal ZNZ patterned α and β is described in the following:

1. To begin this algorithm we first identify the optimal ZNZ–patterned VECM, using model selection criteria.
2. After the optimal ZNZ–patterned VECM is identified, the rank of the long-term impact matrix is then computed using the singular value decomposition method so the number of cointegrating vectors in the system will be known.
3. A tree-pruning algorithm which avoids evaluating all candidates is then implemented for the search of all acceptable ZNZ patterns of the loading and cointegrating vectors.
4. The identified candidates of the ZNZ–patterned cointegrating vectors are estimated by the method based on a triangular ECM representation proposed in Penm and Terrell (2003).
5. The estimation of the associated candidates for the ZNZ–patterned loading vectors is carried out by the regression method with linear restrictions.
6. The optimal ZNZ patterned α and β are finally selected by model selection criteria.

Model development is more convenient using VECMs, rather than the equivalent VARs, if the systems under study include integrated time-series. Penm and Terrell (2003) note that, for $I(1)$ systems, the VARs in first difference will be misspecified and the VARs in levels will ignore important constraints on the coefficient matrices. Although these constraints may be satisfied asymptotically, efficiency gains and improvements in forecasts are likely to result by imposing them. The analogous conclusion applies to $I(1)$ systems, such as those typically encountered in tests of purchasing power parity. Comparisons of forecasting performance of the VECMs versus VARs for cointegrated systems have been reported in studies such as Penm

and Terrell (2003). The results of these studies indicate that, while in the short run there may be gains in using unrestricted VAR models, the VECMs produce long-run forecasts with smaller errors when the variables used in the models satisfy the test for cointegration.

Further to these developments, we consider a hypothesis where every (i,j)-th element, for specified i and j, is zero in all coefficient matrices in a VAR. If this hypothesis is framed in the VAR expressed by Equation (18.1), these zero entries will also hold in the error-correction terms and in the vector autoregressive part of the equivalent VECM, say Equation (18.4). A discussion of this property is provided by Penm and Terrell (2003). Analogously, we can achieve a result that if all (i,j)-th coefficient elements in the error-correction terms and all (i, j)-th coefficient elements in the vector autoregressive part of the VECM are zeros, then every (i,j)-th entry is zero for all coefficient matrices in a VAR. The implications of the above outcome are straightforward. If y_j does not Granger-cause yi, then any (i, j)-th entry must be zero for all coefficient matrices in the VAR. Also all (i, j)-th coefficient elements in the equivalent VECM are zeros.

In a similar way, we can demonstrate that if y_j does Granger-cause y_i, then the (i,j)-th element of $B^q(L)$ in (1) is nonzero. Also, at least a single (i,j)-the coefficient element is nonzero in $B^q(1)$ or $B^{q-1}(L)$ in the equivalent VECM. Of note, an indirect causality from y_j to y_i through y_m indicates y_j causing y_i but only through y_m. Hence, y_j Granger-causes y_m, y_m Granger-causes y_i, and y_j does not Granger-cause y_i directly. We can easily demonstrate that the VAR in (18.2) has nonzero (m,j)-th and (i, m)-th elements and a zero (i, j)-th element in $B^q(L)$. This indirect causality can also be shown in the equivalent VECM, which has at least a single nonzero (m,j)-th element and a single nonzero (i,m)-th elements in $B^q(1)$ and $B^{q-1}(L)$. Also all the (i, j)-th elements in the equivalent VECM are zeros.

The previous discussion indicates that Granger causality, Granger non-causality, and indirect causality detected from both the ZNZ–patterned VECM and its equivalent ZNZ–patterned VAR are identical. Since the use of the VECM is more convenient, it is obvious the ZNZ–patterned VECM is a more straightforward and effective means of testing for the Granger-causal relations. The same benefits will be present if the ZNZ–patterned VECM is used to analyze cointegrating relations.

Cointegration theory is associated with "error-correction" and has important implications for forecasting. If cointegration is found to exist among certain variables, then such long-term relationships should be explicitly identified

when forecasting, which is very important in capturing trading opportunity and setting trading strategies. Recent empirical studies have demonstrated that imposing such restrictions in forecasting would significantly benefit the forecasts, especially in the longer term. Further, the development course of the climate change is a long-term slowly evolving underlying process, and the effects of climate change will be exhibited in the long-term patterned cointegrating relations, which are detected in the error-correction term of the patterned VECM.

DATA AND EMPIRICAL APPLICATION

In this study, monthly observations of economic price indexes and exchange rate variables over the period January 1982 to June 2008 are used ($T = 306$). These data are obtained from the Taiwanese Economic Database. The year 2000 is selected as the base year for all indexes involved. Table 18.1 presents those variables which are examined contemporaneously in a stochastic vector system.

All variables, excluding BOPCF, are log transformed such that $y_1(t) = \log(E)$, $y_2(t) = BOPCF$, $y_3(t) = \log(UCP)$, $y_4(t) = \log(UWP)$, $y_5(t) = \log(UMP)$, $y_6(t) = \log(UXP)$, $y_7(t) = \log(UM2)$, $y_8(t) = \log(UEA)$, and $y_9(t) = \log(UPDY)$, Unit root tests indicate that all transformed series are $I(1)$. Following Brailsford, Penm, and Terrell (2002), we apply a fixed forgetting factor with the value 0.99 to the stochastic system involved. We then conduct the search procedures proposed in Penm and Terrell (2003) to obtain the optimal ZNZ–patterned VECM model over the period January 1982 to March 2007 ($T = 291$).

Table 18.1 Brief Description of Economic Variables Involved in a Stochastic Vector System

Variable	Brief Description
USD	Exchange rate (E): Taiwanese Dollar per U.S. Dollar
BOPCF	Taiwanese capital inflow
UCP	Ratio of price levels (P): Taiwanese CPI relative to U.S. CPI
UWP	Taiwanese WPI relative to U.S. WPI
UMP	Taiwanese import price index relative to U.S. import price index
UXP	Taiwanese export price index relative to U.S. export price index
UM2	Taiwanese M2 relative to US M2
UPDY	Taiwanese industry production index relative to U.S. industry production index

In the course of selecting the optimal lag order (p) for the autoregressive part of the VECM system, we adopt the principle used by Penm and Terrell (2003) to enhance the procedure. That is, we examine whiteness for the residual vectors from the VECM chosen by the Akaike information criterion. If the residual vector process proves to be nonwhite, we sequentially increase q to $q + 1$, and check the resultant residual vector process until the process is a vector white noise process. An optimal value of 5 has been identified for q, as the resultant residual vector process for $q = 5$ becomes a white noise process. The optimal ZNZ–patterned VECM with the lags 1, 3, and 5 for the autoregressive part, and the optimal and are then selected by using the modified Hannan-Quinn criterion (MHQC). Subsequently, we will use MHQC as an abbreviation for the modified criterion, which is defined by MHQC = $\log |\hat{V}| + [2 \log \log f(T)/f(T)]N$, where $f(T) = \sum_{t=1}^{T} \lambda_{T-t}$ is the effective sample size, N is the number of functionally independent parameters, and $\hat{V}$ is the sample estimate of V.

Following the procedure for examining causality in Penm and Terrell (2003), the selected VECM supports the two Granger causality chains which are shown below in Figure 18.1.

Figure 18.1 Two Causal Chains Detected in VECM Modeling
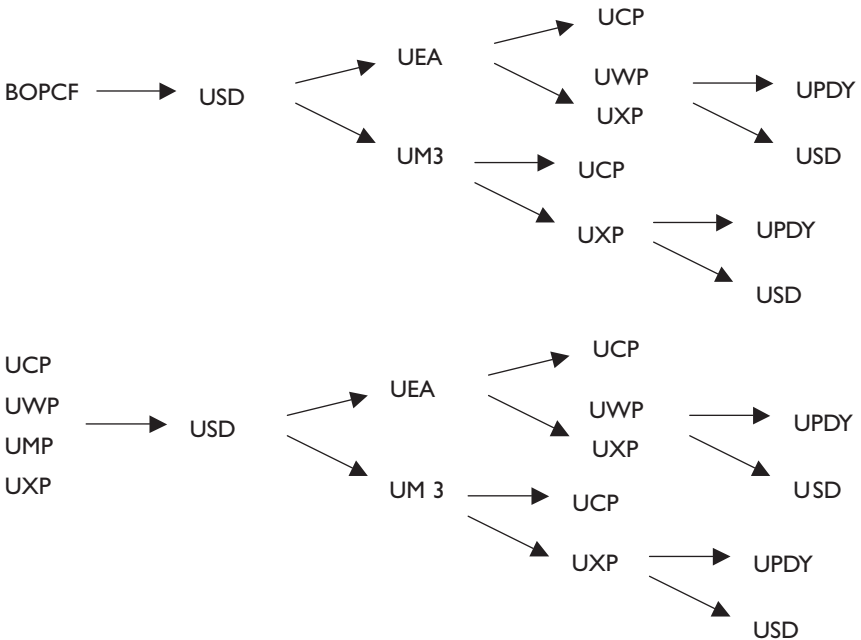
We then utilize the model specification selection approach to select the optimal patterned VECM models at $T = 292$, 293, and 294. An identical VECM specification with the lags 1, 3, and 5 for the autoregressive part is selected by the MHQC at all times. Further, the Taiwanese dollar to USD equation specified in the VECM modeling at $T = 294$ is presented in Table 18.2. The t statistics are shown in brackets.

We then undertake the one-step ahead forecasts over the period July 2007 to June 2008. The forecasts and the actual values are shown in Figure 18.2.

The value of MAE = 3.3 percent over the period July 2007 to June 2008,

$$\text{where } \text{MAE}_i = \sum_i \left| \frac{\text{forecast} - \text{actual value}}{\text{actual value}} \right| .$$

Table 18.2   The Exchange Rate Equation Specified in VECM

$DUSD = 0.31588 \times DUSD_{t-1} - 0.13877 \times ErrorCorrection_{t-1}$
$\qquad\qquad (1.78) \qquad\qquad\qquad (-3.32)$

$ErrorCorrection_{t-1} = .27601USD_{t-1} - 1.17940UWP_{t-1} - 0.01314UCP_{t-1} - 4.75997UMP_{t-1}$
$\qquad\qquad\qquad (2.58) \qquad\qquad (-1.97) \qquad\qquad (-3.82) \qquad\qquad (-3.11)$
$\qquad + 8.83 \times 10^{-6} \times BOPCF_{t-1}$
$\qquad\qquad (2.95)$

Figure 18.2   Forecast Values Against the Actual Values
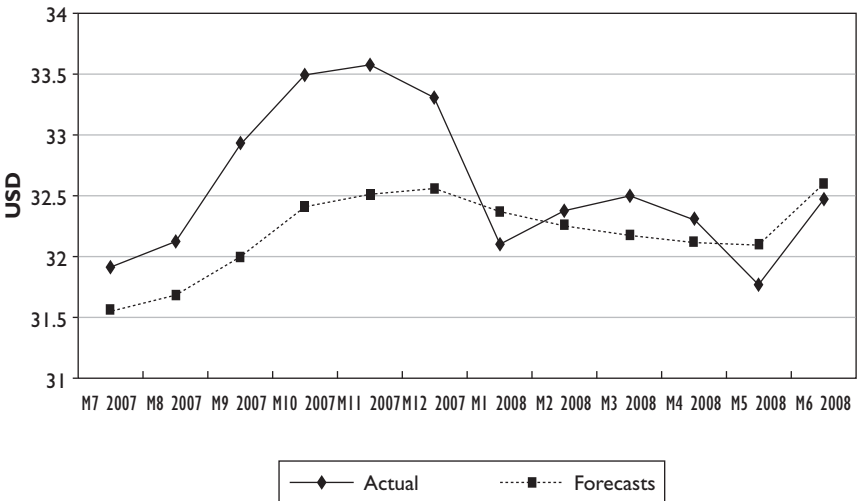
CONCLUSION

The chapter presents the causal links between exchange rates and macro-economic price indexes, supported by patterned VECM modeling and simulations with the forgetting factor in a relevant and complex forex trade environment.

This approach can be used to guide further appropriate use of data in monitoring changes in forex trade environments. Methodologies and technologies currently used to analyze exchange rate, banking, and policy studies will have access to a more rigorous academic methodology for handling databases built up over periods of considerable structural change, resulting in improved and more timely responses in their fields.

As the development course of climate change is a long-term, slowly evolving, underlying process, the trading effects of climate change are exhibited in the long-term patterned cointegrating relations, which are detected in the error-correction term of the patterned VECM.

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THE IMPACT OF ALGORITHMIC TRADING MODELS ON THE STOCK MARKET

Ohaness G. Paskelian

ABSTRACT

The manner in which electronic trading is conducted on international financial markets has dramatically changed in recent decades as more and more stages of the trading process have been radically altered by electronic means. One of the most recent developments is algorithmic trading which primarily focuses on the minimization of implicit transaction costs in order execution. Algorithmic trading models typically strive toward achieving or beating a specified benchmark with their executions. An algorithmic trading model can be distinguished by its underlying benchmark, trading style, or aggressiveness (Kissell and Malamut, 2006). The existing literature addressing the concept of algorithmic trading focuses on the investors' perspective. This research investigates algorithmic trading from a market perspective and its

impact on the market outcome. It emphasizes how the algorithmic trading systems can provide better trade execution and lower market volatility when compared with traditional trading techniques.

INTRODUCTION

During the last decade, automation and new technologies have changed the landscape of traditional trading systems. Algorithmic trading is one of the most widely used computerized automated systems and is very popular among traders and investors. The basic concept of algorithmic trading is to slice an order in such a manner that its impact on the market will be minimal. Using mathematical models and real-time market data, algorithms can determine both the optimum size of the order and its time of submission to the market. This minimizes the impact of the order on the market. The volume of trades using algorithmic trading models has been steadily increasing over the past few years. In 2008 more than 40 percent of the transactions carried on Deutsche Börse's Xetra trading system were performed using algorithmic trading systems. According to Greenwich Associates, "the proportion of US equity trading volume executed electronically increased to 36 per cent in 2008–2009 from 32 per cent in 2007–2008—a shift attributable in large part to the pick-up in algorithmic trading." (Greenwich Associates, 2009). Greenwich Associates report that more than three-quarters of all U.S. institutions and 95 percent of the largest and most active institutional traders use algorithmic trading strategies. This accounts for approximately 18 percent of overall U.S. equity trading volume.

In the financial markets, orders forwarded to brokers-dealers can be either discretionary or nondiscretionary. Nondiscretionary orders are to be executed immediately in a given market. Discretionary orders allow the broker-dealer to decide on the quantities, timing, and method of execution. Algorithmic trading systems are computerized models dealing with nondiscretionary orders without intervention from a human broker-dealer. Algorithms are designed to work discretionary orders within the realities of the market microstructure for securities (Baker and Tiwari, 2004). Algorithmic trading systems are particularly well suited for highly liquid securities traded on electronic limit order books. Since trading volume and price-spread vary continuously over time, algorithms can be designed to track a particular price or volume. Thus, a trading order can be executed

only within parameters specified by the algorithm to minimize its impact on the overall market.

In this chapter, we present an overview of the impact of algorithmic trading systems on market price, liquidity, and movement. We also provide a description of the major strategies used in algorithmic trading systems. We conclude with a note on some future developments in this area.

THE IMPACT OF ALGORITHMIC TRADING ON THE MARKET

Algorithmic trading research is in its beginning stage. The following is a summary of the more prominent articles on this subject. Almgren and Lorenz (2007) provide an overview of the evolution of algorithmic trading systems over time. The first generation of algorithmic strategies aims to meet benchmarks generated by the market itself. The benchmarks are largely independent from the actual securities order. Examples of this strategy are the volume-weighted average price (VWAP) or an average of daily open-high-low-close (OHLC) prices. The second generation of algorithmic trading strategies aims to meet order-centric benchmarks generated at the time of order submission to the algorithm. The execution strategy targets the minimization of the implementation shortfall, i.e., the difference between decision price and final execution price. Second-generation algorithms implement static execution strategies, which predetermine (before the start of the actual order execution) how to handle the trade-off between minimizing market impact costs (by trading slowly) and minimizing the variance of the execution price (by trading immediately) (Gsell, 2007). Third-generation algorithms implement dynamic execution strategies which reevaluate strategy at each single decision time. This enables the model to respond to market developments dynamically. Trading aggressiveness can be altered during the course of the decision making process (Almgren and Lorenz, 2007).

Yang and Jiu (2006) propose a framework to help investors to choose the most suitable algorithm. Morris and Kantor-Hendrick (2005) note some factors that investors take into consideration when deciding to use an algorithmic trading system. Trading style and frequency, regulatory obligations, and trader experience were found to be significant variables when selecting an algorithmic trading system.

The literature provides studies covering the impact of algorithmic trading models on different markets. Konishi (2002) proposes an optimal slicing strategy for VWAP trades. Domowitz and Yegerman (2005) examine the execution quality of algorithms in comparison with brokers' traditional method of handling large orders. They conclude that VWAP algorithms on average have an underperformance of 2 bps. This is counterbalanced by the fact that algorithms can be offered at lower fees than human order handling. Kissel (2007) outlines statistical methods to compare the performance of algorithmic trading solutions. Hendershott, Jones, and Menkveld (2007) present evidence that algorithmic trading and liquidity are positively related.

Chaboud et al. (2009) study the effects of algorithmic trading on the foreign exchange (FX) markets using three widely traded currency pairs. They find that algorithmic trading systems are not related to volatility and that the variance in FX returns is not related to algorithmic trading order flow. The authors suggest that there is a relationship between trade-correlated and trade-uncorrelated information processing patterns when comparing algorithmic trading systems and human traders. They conclude that algorithmic trading systems provide better quotes due to their ability to process more public information than a human trader.

Hendershott and Riordan (2009) provide a continuation of the previous study of Chaboud et al. (2009). They test the average level of algorithmic trading and human information (measured as the variance of the random-walk component of returns) and conclude that algorithmic trading orders and quotes are more informative than are those made by humans. Riordan and Storkenmaier (2009) study the impact of the upgrade of Deutsche Börse electronic trading system on the information content of algorithmic trading systems. They find that the upgrade of the trading system has decreased trading costs and increased overall liquidity. Further, traders using algorithmic trading systems process information much faster than their human counterparts and thus increase the liquidity of the market and the information content of the prices.

Finally, Gsell (2007) provides a simulation result of the implementation of algorithmic trading systems. He finds that algorithmic trading systems have an impact on market outcome in terms of market prices and market volatility. He also finds that the low latency of the algorithmic systems has the potential to significantly lower market volatility. However, when he

simulated trading with larger volumes, the algorithmic trading system resulted in negative market prices.

ALGORITHMIC STRATEGIES

One of the first algorithmic trading strategies consisted of using a volume-weighted average price, as the price at which orders would be executed. The VWAP introduced by Berkowitz et al. (1988) can be calculated as the dollar amount traded for every transaction (price times shares traded) divided by the total shares traded for a given period. If the price of a buy order is lower than the VWAP, the trade is executed; if the price is higher, then the trade is not executed. Participants wishing to lower the market impact of their trades stress the importance of market volume. Market volume impact can be measured through comparing the execution price of an order to a benchmark. The VWAP benchmark is the sum of every transaction price paid, weighted by its volume. VWAP strategies allow the order to dilute the impact of orders through the day. Most institutional trading occurs in filling orders that exceed the daily volume. When large numbers of shares must be traded, liquidity concerns can affect price goals. For this reason, some firms offer multiday VWAP strategies to respond to customers' requests. In order to further reduce the market impact of large orders, customers can specify their own volume participation by limiting the volume of their orders to coincide with low expected volume days. Each order is sliced into several days' orders and then sent to a VWAP engine for the corresponding days. VWAP strategies fall into three categories: sell order to a broker-dealer who guarantees VWAP; cross the order at a future date at VWAP; or trade the order with the goal of achieving a price of VWAP or better (Madhavan, 2000).

The second algorithmic trading strategy is the time-weighted average price (TWAP). TWAP allows traders to slice a trade over a certain period of time, thus an order can be cut into several equal parts and be traded throughout the time period specified by the order. TWAP is used for orders which are not dependent on volume. TWAP can overcome obstacles such as fulfilling orders in illiquid stocks with unpredictable volume. Conversely, high-volume traders can also use TWAP to execute their orders over a specific time by slicing the order into several parts so that the impact of the execution does not significantly distort the market.

Another type of algorithmic trading strategy is the implementation shortfall or the arrival price. The implementation shortfall is defined as the difference in return between a theoretical portfolio and an implemented portfolio. When deciding to buy or sell stocks during portfolio construction, a portfolio manager looks at the prevailing prices (decision prices). However, several factors can cause execution prices to be different from decision prices. This results in returns that differ from the portfolio manager's expectations (Perold, 1988). Implementation shortfall is measured as the difference between the dollar return of a paper portfolio (paper return) where all shares are assumed to transact at the prevailing market prices at the time of the investment decision and the actual dollar return of the portfolio (real portfolio return). The main advantage of the implementation shortfall-based algorithmic system is to manage transactions costs (most notably market impact and timing risk) over the specified trading horizon while adapting to changing market conditions and prices (Kissell and Malamut, 2006).

The participation algorithm or volume participation algorithm is used to trade up to the order quantity using a rate of execution that is in proportion to the actual volume trading in the market. It is ideal for trading large orders in liquid instruments where controlling market impact is a priority. The participation algorithm is similar to the VWAP except that a trader can set the volume to a constant percentage of total volume of a given order. This algorithm can represent a method of minimizing supply and demand imbalances (Kim, 2007).

Smart order routing (SOR) algorithms allow a single order to exist simultaneously in multiple markets. They are critical for algorithmic execution models. It is highly desirable for algorithmic systems to have the ability to connect different markets in a manner that permits trades to flow quickly and efficiently from market to market. Smart routing algorithms provide full integration of information among all the participants in the different markets where the trades are routed. SOR algorithms are critical to the smooth operation of the highly fragmented U.S. market structure. In the United States alone, there are more than 100 trading venues on different electronic communications networks (ECNs). Thus, SOR algorithms allow traders to place large blocks of shares in the order book without fear of sending out a signal to other market participants. The algorithm matches limit orders and executes them at the midpoint of the bid-ask price quoted in different exchanges.

ALGORITHMIC TRADING ADVANTAGES

Algorithmic trading systems provide a number of advantages over traditional methods, including:

1. Increased capacity: Computerized algorithms have much more powerful computational capabilities to handle computationally intensive processes.
2. Decreased costs: Commissions for electronic trading tend to be significantly lower than other types of trades.
3. Real-time feedback and control: Algorithmic trading provides better feedback mechanisms than traditional trading methods. The ability of the algorithmic models to process new information is found to be superior to that of the human trader.
4. Anonymity: Algorithmic trading provides privacy and anonymity by allowing the order originator to remain unknown. Also, since orders can go through several brokers, the original time of the order can remain confidential .
5. Control of information leakage: Algorithmic trading protects traders by preventing them from disseminating their alpha expectations to other market participants.
6. Access to multiple trading markets: Algorithms decide instantaneously where to send the orders depending on the best available market. Thus, orders can be placed on the best available market crossing networks and internal flow.
7. Consistent execution methodology: Consistent execution was one of the key factors behind benchmarks such as VWAP. The knowledge of the algorithm enables the trader to understand how and why the algorithmic systems reacted to the market in any given situation.
8. Best execution and transaction-cost-analysis (TCA) real-time: TCA, including execution, impact, slippage, and correlation information, can be available instantaneously. Thus, analyzing all types of pre- and post-trade scenarios can be performed.
9. Minimization of errors: The absence of human operators makes algorithmic trading systems less prone to errors.

10. Compliance monitoring: Compliance rules including limits, exposure, and short sales can be validated in real-time, and alerts can be issued for any potential scenario.

ALGORITHMIC TRADING BEYOND STOCK MARKETS

Algorithmic trading is also spreading to other asset categories, including foreign exchange, fixed income, futures, options, and derivatives. This trend is driven by the desire for competitive advantage combined with the growing availability of electronic trade execution, third-party trading networks, and robust order management systems. As with the equity sector, the most liquid instruments are receiving the initial focus while most others still require traditional trading techniques. The foreign-exchange market has long depended on phone brokerage with large banks and FX dealers. However, FX ECNs are taking the market forward by providing the services and technology solutions which meet this need for growth and diversity. This in turn adds liquidity to the market as a wider range of players is enabled to participate. Active traders have become an increasingly important part of the global FX market in recent years. They have begun to treat FX as an asset class in its own right. Active traders have found they can successfully employ the same algorithmic trading methods in FX to generate alpha as they have previously applied to equity markets.

Slowly, these different trading venues are opening up and electronic trading can be executed in limited form. Like the futures market, which has both electronically traded and pit-traded contracts, the effectiveness of algorithmic trading will depend on the degree of electronic sophistication in the market place. The prospect of multi-asset algorithmic trading models remains quite intriguing.

CONCLUSION

Algorithmic trading systems are designed to lower transaction costs, reduce market impact, and create liquidity. A large trade executed through an algorithm should be efficient, while creating liquidity and avoiding risk in the

event the market turns in the opposite direction. Another advantage of the algorithmic trading systems is the splicing and execution of multiple small orders from a big order, thus minimizing market impact. Simultaneously, the ability of the algorithmic trading systems to monitor and provide real-time feedback ameliorates the chances of the best execution of these orders. Moreover, a large order using a number of different algorithms to access different markets simultaneously can result in faster and quicker execution of the order.

However, as the market share of algorithmic trading systems increase with time, the interaction of such systems and consequential side effects resulting from it should be investigated. As more and more algorithms are actively trading on securities markets, these algorithms do to some extent conduct trading with one another, i.e., one algorithmic strategy is competing with the other instead of trading with a traditional trader. The changing nature of the trading parties involves policy implications that algorithmic trading systems providers will soon need to consider carefully.

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TRADING IN RISK DIMENSIONS

Lester Ingber

ABSTRACT

Two-shell recursive trading systems were developed in the author's, mostly published, previous work. A parameterized trading rule outer-shell uses the global optimization code adaptive simulated annealing (ASA) to fit the trading system to historical data. A simple fitting algorithm is used for the inner-shell fit. An additional risk management middle-shell has been added to create a three-shell recursive optimization/sampling/fitting algorithm. Portfolio-level distributions of copula-transformed multivariate distributions (with constituent markets possessing different marginal distributions in returns space) are generated by Monte Carlo samplings. ASA is used to importance-sampled weightings of these markets. The core code, trading in risk dimensions (TRD), processes training and testing trading systems on historical data, and consistently interacts with real-time trading platforms at minute resolutions, but this scale can be modified. This approach transforms constituent probability distributions into a common space where it makes sense to develop correlations to further develop probability distributions and risk/uncertainty analyses of the full portfolio. ASA is used for importance-sampling these distributions and for optimizing system parameters.

INTRODUCTION

The work presented in this chapter is largely based on my previous work in several disciplines using a similar formulation of multivariate nonlinear nonequilibrium systems (Ingber, 2001a, 2001b, 2001c), using powerful numerical algorithms to fit models to data (Ingber, 2001d).

Adaptive Simulated Annealing

Adaptive simulated annealing (ASA) (Ingber, 1993) is used in trading in risk dimensions (TRD) to optimize trading-rule parameters and in importance-sampled contracts for risk management.

ASA is a C language code developed to statistically find the best global fit of a nonlinear constrained nonconvex cost-function over a D-dimensional space. This algorithm permits an annealing schedule for "temperature" T decreasing exponentially in annealing time, k, $T = T_0 \exp(-ck^{1/D})$. The introduction of re-annealing also permits adaptation to changing sensitivities in the multidimensional parameter space. This annealing schedule is faster than fast Cauchy annealing, where $T = T_0/k$, and much faster than Boltzmann annealing, where $T = T_0/\text{In } k$. ASA has more than a hundred options to provide robust tuning over many classes of nonlinear stochastic systems.

DATA

A time epoch is chosen to measure possible trading intervals, WINDOW_e.

Enough price (and volume, etc.) data, e.g., hundreds of epochs, is used to gather some representative statistics including "outliers." Define

$$dx_t = \frac{p_t - p_{t-1}}{p_{t-1}} \tag{20.1}$$

Market-differenced variables $\{dx\}$ lead to portfolio variables dM. Here, dM signifies the portfolio returns, based on portfolio values $\{K_i\}$, e.g.,

$$dM_t = \frac{K_t - K_{t-1}}{K_{t-1}} \tag{20.2}$$

EXPONENTIAL MARGINAL DISTRIBUTION MODELS

This chapter uses exponential distributions to detail TRD algorithms. However, the TRD code has hooks to work with other distributions.

Assume that each market is fit well to a two-tailed exponential density distribution p (not to be confused with the indexed price variable p_t) with scale χ and mean m

$$p(dx)dx = \begin{cases} \dfrac{1}{2\chi} e^{-\frac{dx-m}{\chi}} dx, & dx >= m \\[2ex] \dfrac{1}{2\chi} e^{\frac{dx-m}{\chi}} dx, & dx < m \end{cases} = \dfrac{1}{2\chi} e^{-\frac{|dx-m|}{\chi}} dx, \qquad (20.3)$$

which has a cumulative probability distribution of

$$F(dx) = \int_{-\infty}^{dx} dx' \, p(dx') = \frac{1}{2}\left[1 + \operatorname{sgn}(dx - m)\left(1 - e^{-\frac{|dx-m|}{\chi}}\right)\right], \qquad (20.4)$$

where χ and m are defined by averages $<.>$ over a window of data

$$m = < dx > 2\chi^2 = < (dx)^2 > - < dx >^2 . \qquad (20.5)$$

The $p(dx)$ are "marginal" distributions observed in the market, modeled to fit the above algebraic form. Note that the exponential distribution has an infinite number of nonzero cumulants, so that $< dx^2 > - < dx >^2$ does not have the same "variance" meaning for this "width" as it does for a Gaussian distribution, which has only two independent cumulants (and all cumulants greater than the second vanish). The algorithms in the following section are specified to address correlated markets giving rise to the stochastic behavior of these markets.

Note that to establish the exponential distribution (current time-sensitive exponential) moving averages are used to force data into a specific functional form, a form which must be regularly checked for its statistical significance.

COPULA TRANSFORMATION

Aside on Sum of Squared Errors of Gaussian Copula

Gaussian copulas are developed in TRD. Other copula distributions are possible, e.g., student t distributions (often touted as being more sensitive to fat-tailed distributions—here data is first adaptively fit to fat-tailed distributions prior to copula transformations). These alternative distributions can be quite slow because inverse transformations typically are not as quick as for the present distribution.

Copulas are cited as an important component of risk management not yet widely used by risk management practitioners (Blanco, 2005). Gaussian copulas are presently regarded as the Basel II standard for credit risk management (Horsewood, 2005). While real-time risk management for intraday trading is becoming more popular, most approaches still use simpler value-at-risk (VaR) measures (Dionne, Duchesne, and Pacurar, 2006). TRD permits fast as well as robust copula risk management in real time.

The copula approach can be extended to more general distributions than those considered here (Ibragimon, 2005). If there are no analytic or relatively standard math functions for the transformations, then these transformations must be performed explicitly numerically in code such as TRD. Then, the ASA_PARALLEL OPTIONS already existing in ASA (developed as part of the 1994 National Science Foundation Parallelizing ASA and PATHINT Project [PAPP]) would be very useful to speed up real-time calculations (Ingber, 1993).

Transformation to Gaussian Marginal Distributions

A normal Gaussian distribution has the form

$$p(dy) = \frac{1}{\sqrt{2\pi}} e^{-\frac{dy^2}{2}} \tag{20.6}$$

with a cumulative distribution

$$F(dy) = \frac{1}{2}\left[1 + \mathrm{erf}\left(\frac{dy}{\sqrt{2}}\right)\right] \tag{20.7}$$

where the erf( ) function is a tabulated function

$$\mathrm{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x dx'\, e^{-x'^2} \tag{20.8}$$

By setting the numerical values of the above two cumulative distributions, monotonic on interval [0,1], equal to each other, the transformation of the marginal variables to the y marginal variables is effected

$$dy = \sqrt{2}\,\mathrm{erf}^{-1}(2F(dx) - 1)$$
$$= \sqrt{2}\,\mathrm{sgn}(dx - m)\mathrm{erf}^{-1}\left(1 - e^{-\frac{|dx - m|}{\chi}}\right) \tag{20.9}$$

Inverse mapping is used when applying this to the portfolio distribution. Note that

$$dy \geq 0 \rightarrow dx - m \geq 0, \; dy < 0 \rightarrow dx - m < 0 \tag{20.10}$$

yields

$$dx = m - \mathrm{sgn}(dy)\chi \ln\left[1 - \mathrm{erf}\left(\frac{|dy|}{\sqrt{2}}\right)\right] \tag{20.11}$$

Including Correlations

To understand how correlations enter, look at the stochastic process defined by the dy^i marginal transformed variables

$$dy^i = \hat{g}^i\,dw_i \tag{20.12}$$

where dw_i is the Wiener–Gaussian noise contributing to dy^i of market i. The transformations are chosen such that $\hat{g}^i = 1$.

Now, a given market's noise ($\hat{g}^i\,dw_i$) has potential contributions from all N markets, which is modeled in terms of N independent Gaussian processes dz_k

$$\hat{g}^i\,dw_i = \sum_k \hat{g}^i_k dz_k \tag{20.13}$$

The covariance matrix (g^{ij}) of these y variables is then given by

$$g^{ij} = \sum_k \hat{g}^i_k \hat{g}^j_k \tag{20.14}$$

with inverse matrix, the "metric," written as (g_{ij}) and determinant of (g^{ij}) written as g.

Since Gaussian variables are now being used, the covariance matrix is calculated directly from the transformed data using standard statistics, the

point of this copula transformation (Malevergne and Sornette, 2002; Rosenberg and Schuermann, 2004).

Correlations ρ^{ij} are derived from bilinear combinations of market volatilities

$$\rho^{ij} = \frac{g^{ij}}{\sqrt{g^{ii} g^{jj}}} \tag{20.15}$$

Since the transformation to Gaussian space has defined $g^{ii} = 1$, here the covariance matrices theoretically are identical to the correlation matrices.

This transformation is rigorously enforced, i.e., a finite sample of Gaussian-transformed (prefiltered) returns data will not yield a covariance matrix equal to its correlation matrix, so the covariance matrix is properly normalized (by dividing by the square root of the products of the diagonal elements). This step affords some statistical robustness of this procedure over moving windows of data.

This gives a multivariate correlated process P in the dy variables, in terms of Lagrangian L

$$P(dy) \equiv P(dy^1, ..., dy^N) = (2\pi dt)^{-\frac{N}{2}} g^{-\frac{1}{2}} e^{-Ldt} \tag{20.16}$$

where $dt = 1$ above. The Lagrangian L is given by

$$L = \frac{1}{2dt^2} \sum_{ij} dy^i g_{ij} dy^j \tag{20.17}$$

The effective action A_{eff}, presenting a cost function useful for sampling and optimization, is defined by

$$P(dy) = e^{-A_{eff}}$$
$$A_{eff} = Ldt + \frac{1}{2}\ln g + \frac{N}{2}\ln(2\pi dt) \tag{20.18}$$

Copula of Multivariate Correlated Distribution

The multivariate distribution in x space is specified, including correlations, using

$$P(dx) = P(dy)\left|\frac{\partial dy^i}{\partial dx^j}\right| \tag{20.19}$$

where $\left|\dfrac{\partial dy^i}{\partial dx^j}\right|$ is the Jacobian matrix specifying this transformation. This gives

$$P(dx) = g^{-\frac{1}{2}}e^{-\frac{1}{2}\sum_{ij}(dy^i_{dx})^\dagger(g_{ij}-I_{ij})(dy^j_{dx})}\prod_i P_i(dx^i) \tag{20.20}$$

where (dy_{dx}) is the column-vector of $(dy^1_{dx}, \dots, dx^N_{dx})$, expressed back in terms of their respective $(dx^1, \dots, dx^N)$, $(dy_{dx})^\dagger$ is the transpose row-vector, and (I) is the identity matrix (all ones on the diagonal).

The Gaussian copula $C(dx)$ is defined as

$$C(dx) = g^{-\frac{1}{2}}e^{-\frac{1}{2}\sum_{ij}(dy^i_{dx})^\dagger(g_{ij}-I_{ij})(dy^j_{dx})} \tag{20.21}$$

PORTFOLIO DISTRIBUTION

The probability density $P(dM)$ of portfolio returns dM is given as

$$P(dM) = \int\prod_i d(dx^i)P(dx)\delta_D\left(dM_t - \sum_j(a_{j,t}dx^j + b_{j,t})\right) \tag{20.22}$$

where the Dirac delta-function δ_D expresses the constraint that

$$dM = \sum_j(a_j dx^j + b_j) \tag{20.23}$$

The coefficients a_j and b_j are determined by specification of the portfolio current $K_{t'}$, and forecasted K_t, giving the returns expected at t, $dM_t = dM_t$

$$\frac{K_t - K_{t'}}{K_{t'}}$$

$$K_{t'} = Y_{t'} + \sum_i \mathrm{sgn}(NC_{i,t'})NC_{i,t'}(p_{i,t'} - p_{i,@,t'})$$

$$K_t = Y_t + \sum_i (\mathrm{sgn}(NC_{i,t})NC_{i,t}(p_{i,t} - p_{i,@,t}) + SL[NC_{i,t} - NC_{i,t'}])$$

(20.24)

where $NC_{i,t}$ is the current number of broker-filled contracts of market i at time t ($NC > 0$ for long and $NC < 0$ for short positions), $p_{i,@,t'}$ and $p_{i,@,t}$ are the long/short prices at which contracts were bought/sold according to the long/short signal $\mathrm{sgn}(NC_{i,t'})$ generated by external models. Note that all prices are in dollars at this point of the calculation, e.g., including any required FX transformations. Y_t and $Y_{t'}$ are the dollars available for investment. The function SL is the slippage and commissions suffered by changing the number of contracts.

If trading signals were not generated in this project, a_j do not depend on the prices $p_{i,t}$, i.e., trading rules dependent on $p_{i,t}$ cannot cause changes from long (short) to short (long) positions, since trading signals are not generated for forecast prices $p_{i,t}$ (which TRD can be set to process, as discussed below). However, changes in $\mathrm{sgn}(NC_{i,t})$ still can result from the sampling process of NC s.

The function $\mathrm{sgn}(NC_{i,t})$ is a multivariate function if trading rules depend on correlated markets. Furthermore, a proper trading system distinguishes bid and ask prices, which are taken into account in the trading functions $\mathrm{sgn}(NC_{i,t})$ and $\mathrm{sgn}(NC_{i,t'})$ and the cost of trading/cash modifications that enter into the calculation of portfolio returns.

If futures are traded, there are no appreciating asset values to buying or selling contracts; only changes in positions would matter. The profit/loss is calculated as $PL_t = K_t - K_{t'}$.

This necessitates fitting risk-managed contract sizes to chosen risk targets for each set of chosen trading rule parameters, e.g., selected by an optimization algorithm. A given set of trading rule parameters affects the $a_{j,t}$ and $b_{j,t}$ coefficients as these rules act on the forecasted market prices as they are generated to sample the multivariate market distributions.

This process must be repeated as the trading rule parameter space is sampled to fit the trading cost function, e.g., based on profit, Sharpe ratio, etc., of the portfolio returns.

RISK MANAGEMENT

Once $P(dM)$ is developed (e.g., numerically), risk management optimization is defined. The portfolio integral constraint is

$$Q = P(dM < VaR) = \int_{-\infty}^{-|VaR|} dM\, P(M_t \mid M'_t) \tag{20.25}$$

where *VaR* is a fixed percentage of the total available money to invest, e.g., this is specifically implemented as

$$VaR = 0.05,\ Q = 0.01 \tag{20.26}$$

where the value of *VaR* is understood to represent a possible 5 percent loss in portfolio returns in one epoch, e.g., which approximately translates into a 1 percent chance of a 20 percent loss within 20 epochs. Expected tail loss (ETL), sometimes called conditional VaR or worst conditional expectation, can be directly calculated as an average over the tail. While the VaR is useful in determining expected loss if a tail event does not occur, ETL is useful to determine what can be lost if a tail event occurs (Dowd, 2002).

ASA (Ingber, 1993) is used to sample future contracts defined by a cost function, e.g., maximum profit, subject to the constraint

$$Cost_Q = |\ Q - 0.01\ | \tag{20.27}$$

by optimizing the $NC_{i,t}$ parameters. Other postsampling constraints described in the following section can then be applied. (Judgments always must be made whether to apply specific constraints, before, during, or after sampling.)

Note that this definition of risk does not take into account accumulated losses over folding of the basic time interval used to define $P(dM)$, nor does it address any maximal loss that might be incurred within this interval (unless this is explicitly added as another constraint function).

Risk management is developed by (ASA-)sampling the space of the next epoch's $\{NC_{i,t}\}$ to fit the above Q constraint using the sampled market variables $\{dx\}$. The combinatoric space of NC s satisfying the Q constraint is huge, and so additional NC models are used to choose the actual traded $\{NC_{i,t}\}$.

SAMPLING MULTIVARIATE NORMAL DISTRIBUTION

The development of the probability of portfolio returns above certainly is the core equation, the basic foundation, of most work in the risk management of

portfolios. For general probabilities not Gaussian, and when including correlations, this equation cannot be solved analytically.

Other people approximate/mutilate this multiple integral in an attempt to achieve some analytic expression. Their results may in some cases serve as interesting "toy" models to study some extreme cases of variables, but there is no reasonable way to estimate how much of the core calculation has been destroyed in this process.

Many people resort to Monte Carlo sampling of this multiple integral. ASA has an ASA_SAMPLE option that similarly could be applied. However, there are published algorithms specifically for multivariate normal distributions (Genz, 1993).

The multivariate correlated dy variables are further transformed into independent uncorrelated Gaussian dz variables. Multiple normal random numbers are generated for each dz^i variable, subsequently transforming back to dy, dx, and dp variables to enforce the Dirac δ function constraint specifying the VaR constraint.

The method of Cholesky decomposition is used (eigenvalue decomposition also could be used, requiring inverses of matrices, which are used elsewhere in this chapter), wherein the covariance matrix is factored into a product of triangular matrices, simply related to each other by the adjoint operation. This is possible because G is a symmetric positive-definite matrix, i.e., because care has been taken to process the raw data to preserve this structure, as discussed previously.

$$
\begin{aligned}
G &= (g^{ij}) = C^\dagger C \\
I &= C G^{-1} C^\dagger
\end{aligned}
\tag{20.28}
$$

from which the transformation of the dy to dz are obtained. Each dz has 0 mean and standard deviation 1, so its covariance matrix is 1

$$
\begin{aligned}
I &= <(dz)^\dagger (dz)> = <(dz)^\dagger (C G^{-1} C^\dagger)(dz)> \\
&= <(C^\dagger dz)^\dagger G^{-1} (C^\dagger dz)> = <(dy)^\dagger G^{-1}(dy)>
\end{aligned}
\tag{20.29}
$$

where

$$
dy = C^\dagger \, dz
\tag{20.30}
$$

CONCLUSION

The TRD code comprises approximately 50 files containing about 125 TRD-specific functions in about 15,000 modified ASA lines of C code with about 20,000 TRD-specific lines of C code. (The ASA C code comprises seven files containing about 50 functions.) The code compiles and runs under gcc or g++ across platforms, e.g., under ThinkPad/XPPro/Cygwin, Tadpole/SPARC/Solaris, x86/FreeBSD, Linux, etc.

If nonanalytic distributions must be transformed to copulas, and also their inverse transformations calculated, this of course requires additional processing power. ASA has hooks for parallel processing, which have been used by people in various institutions, for some years now, thus additional processing could be better accommodated.

Standard Unix scripts are used to facilitate file and data manipulations. For example, output plots (e.g., 20 subplots per page for multiple indicators, positions, prices, etc., versus time of day) for each market for each day's trading are developed using RDB (a Perl database tool), Gnuplot, and other Unix scripts.

TRD is written to run in batch for training and testing of historical data, and to interface as a function or a DLL call in rea-time with a trading platform, e.g., TradeStation (TS), Fidelity's Active-Trader Wealth-Lab (WL), etc. Batch mode does not require any connection with a real-time trading platform. In real-time mode, after checking data, position, and order information, the batch mode code is used to process new orders, i.e., the same core code is used for real-time, training, and testing, ensuring that all results are as consistent as possible across these three modes. If no risk management and no correlations are to be processed, then TRD can reply asynchronously to multiple markets. Applications can be developed, including equities and their indexes, futures, forex, and options.

All trading logic and control is in the "vanilla" C TRD code, e.g., not using TS EasyLanguage (EL) or WL WealthScript (WS) code, so it can be used with just about any trading platform, e.g., which compiles and runs without warnings under gcc or g++. For example, TRD interacts with TS using a DLL prepared using gcc or g++ under Cygwin.

TRD has an option, DAILY, which trades on daily time scales. This is useful for training and testing trading systems designed for trading on daily time scales.

It should be understood that any sampling algorithm processing a huge number of states can find many multiple optima. ASA's MULTI_MIN OPTIONS are used to save multiple optima during sampling. Some algorithms might label these states as "mutations" of optimal states. It is important to be able to include them in final decisions, e.g., to apply additional metrics of performance specific to applications. Experience shows that all criteria are not best considered by lumping them all into one cost function, but rather good judgment should be applied to multiple stages of pre-processing and post-processing when performing such sampling.

Within a chosen resolution of future contracts and trading parameters, the huge numbers of possible states to be importance-sampled presents multiple optima and sometimes multiple optimal states. While these can be filtered during sampling with various criteria, it is more useful not to include all filters during sampling, but rather to use ASA's MULTI_MIN OPTIONS to save any desired number of these optimal states for further post-processing to examine possible benefits versus risk according to various desired important considerations, e.g., weighting by correlations, adding additional metrics of performance, etc.

While the theory of copula algorithms relevant to financial risk management have been around in published literature for a few years, actual applications to real markets have generally involved approximations to probability distributions of data to permit simple analytic derivations. However, especially in financial markets, "the Buddha is in the details," where realistic adaptive probability distributions and details of specific trades are often required. This chapter details how such computer codes have been developed for risk management of portfolios for real-time intra-day trading.

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DEVELOPMENT OF A RISK-MONITORING TOOL DEDICATED TO COMMODITY TRADING

Emmanuel Fragnière, Helen O'Gorman, and Laura Whitney

ABSTRACT

The market of risk management products contains software dedicated to the financial sector, most of which is expensive and not well adapted to commodity trading. Models often focus on risk metrics as opposed to the more trader-preferred technical analysis methods of calculating risk. This chapter presents both risk metrics and technical analysis models, coded using the programming language Visual Basic for Applications in Excel, as a means to provide an affordable, reliable, and easily accessible risk-monitoring tool for small trading firms and individual traders.

INTRODUCTION

Despite the increasing popularity of commodity trading, insufficient research has been conducted with regard to risk management in this sector. The majority of models are aimed at large financial institutions and often

use risk metrics unknown to commodity traders, as opposed to technical analysis approaches with which they are familiar. In order to help remedy this problem, the goal of this chapter is to develop an open-source risk-monitoring tool dedicated to the commodity market.

The tool was programmed using Visual Basic for Applications (VBA) in Excel with the aim of making it easily accessible to small companies or individual traders. A user interface was designed and macros were written to perform calculations. The tool's capabilities include calculating the risk metric value at risk in several ways, calculating average true range and generating moving averages. Spot price data for corn, soybeans, and soybean meal were used in its development, but it can also be adapted to other commodities. All three of these commodities are traded on the Chicago Board of Trade, which is now part of the CME Group.

Chicago Board of Trade (CBOT)/CME Group

Established in 1848, the Chicago Board of Trade (CBOT) is the world's oldest commodity exchange market. The CBOT was formed to add liquidity to the market for buyers and sellers, and also to mediate credit risk. It provided a centralized location where buyers and sellers could negotiate futures contracts.

Today it has more than 3,600 members, who trade more than 50 different options and futures contracts. In 2003, 454 million contracts were traded, which broke all previous records. On July 12, 2007, the CBOT merged with the Chicago Mercantile Exchange (CME) under the CME Group holding company, creating the world's largest futures exchange.

Corn was one of the original commodities traded on the CBOT. The first forward contract for corn was introduced in 1851; the first futures contracts for other grains were transacted in 1865. Soybeans were added to the exchange in 1936, and soybean products, such as meal and oil, became popular after World War II.

In 2008, 60.0 million corn, 36.4 million soybean, and 13.4 million soybean meal futures contracts were traded. At the end of July 2009, trade of all three commodities is behind where it was in 2008. Corn shows the largest decrease: with a current volume of 30.3 million contracts, it is down 21.7 percent. Soybeans are down 9.9 percent, with a current volume of 20.8 million contracts; and soybean meal is down 11.6 percent, with a current volume of 7.5 million contracts. Volume data can be found on the CME Group Website.

Explanation of the Chapter Structure

This chapter is divided into four sections: the introduction is followed by the literature review, methodology, and conclusions. The second section of this chapter, the literature review, explains value at risk, average true range, and moving averages in detail, including advantages and disadvantages of using each. The capabilities of the risk-monitoring tool are explained in this chapter's third section, the methodology. Conclusions are presented in this chapter's final section.

LITERATURE REVIEW

This section begins by introducing the risk metric value at risk (VaR) and presenting several methods of calculating it. This is followed by discussion of the technical market analysis tools average true range (ATR) and moving averages.

Value at Risk (VaR)

Value at risk is a summary statistic that measures market risk; it represents possible portfolio losses under normal market conditions at a specified confidence level. There are many methods for computing VaR, each with advantages and drawbacks. Delta-normal, historical simulation, and bootstrapping will be discussed, as well as the verification technique of backtesting. All calculations performed using the risk-monitoring tool produce daily VaR values, that is, they do not use a holding period.

The delta-normal method is a one-tail test that incorporates the commodity variance-covariance matrix in order to calculate VaR. This approach is easily implemented as it assumes that all sources of underlying risk follow a normal distribution. However, if the risk sources are not normally distributed, risk can be much higher than what results indicate. The first derivative, delta, is used to measure risk, and the VaR is calculated by assuming that slight variations in the risk source directly contribute to proportional slight variations of the commodity's price over a certain time horizon.

Historical simulation is simple to compute and requires no assumptions about the statistical distributions of portfolio profit and loss returns. Instead, the empirical distribution is calculated by subjecting the current portfolio to the actual changes in the market factors experienced during

each of the last *N* periods. VaR is then computed by sorting the returns in ascending order and finding the return that represents a loss that is met or exceeded x percent of the time, where 100 – x is the chosen confidence level. This approach assumes that past trends will continue in the future, thus if the last *N* periods do not exhibit typical behavior, the VaR could be over- or underestimated.

Bootstrapping is a variation of historical simulation that attempts to produce more reliable VaR results. This procedure, which is used primarily to increase the number of data points in a dataset, involves sampling from the historical data with replacement. As such, no assumptions need to be made about the underlying statistical distribution. Once sufficient samplings have been completed, VaR is calculated in the same way as it was for the historical simulation method. An advantage of this method is that it can take into account departures from a normal or other assumed statistical distribution. However, it relies heavily on the assumption that returns are independent and identically distributed, and that there are no cycles or pattern in the data.

In order to ensure that these VaR calculations were not biased in one way or another, they were tested using the verification technique of backtesting. This method compares the calculated VaR to the next day's profit and loss returns and counts the number of exceptions; that is, the number of times returns are greater than the positive VaR or less than the negative VaR. The Basel Committee has capital requirements for financial institutions based on the number of exceptions, but no such requirements exist for commodity traders.

Average True Range (ATR)

Average true range is a technical analysis aspect of calculating commodity risk and was first mentioned in J. Welles Wilder's book *New Concepts in Technical Trading Systems* in 1978. Wilder was a trader who thought up new ways to reduce the risks involved in trading, and many of his indicators were developed bearing commodities in mind. ATR is a method for calculating the volatility of a commodity and incorporates Wilder's earlier idea of the "true range." However, ATR does not determine the direction or degree of price movement.

ATR uses the opening, high, low, and closing (OHLC) prices of a commodity and takes into consideration the range of the commodity (i.e., the

distance the price of the commodity moves per increment of time). The ATR indicator stemmed from Wilder's concern that when the limit—that is, the lowest or highest price the commodity could attain—of a commodity was reached, the volatility would wrongly be calculated as zero as the OHLC prices remain the same throughout the day when the limit is reached.

ATR is generally calculated using a 14-day period, as extensive studies have shown that this gives the most reliable results. It is common to combine this technical analysis method with another indicator, such as support and resistance levels, to calculate a trader's stop losses.

Moving Averages

Whereas VaR might be a foreign concept to many commodity traders, they are undoubtedly familiar with moving averages. These are used in technical market analysis to find the end or reversal of an existing trend, or to identify the beginning of a new trend. As they show only what has happened in the past and have no forecasting ability, they are known as lagging indicators. A simple moving average (SMA) gives equal weight to all data points, while recent data points are more heavily weighted in an exponential moving average (EMA). Although the EMA lags behind less than the SMA, it is also more likely to generate buy or sell signals, some of which will be false signals.

Multiple moving averages can be used on the same chart: the shorter time period is more sensitive to changing conditions, while the longer time period minimizes the effects of any price irregularities. The crossovers between the two lines represent buying or selling opportunities, depending if the crossover occurs on an uptrend or a downtrend. The moving average convergence-divergence (MACD) is used to quantify the difference between two moving averages, and is often plotted with a signal line that is a moving average of the MACD.

METHODOLOGY

The risk-monitoring tool developed performs the following functions: initializing data, calculating VaR (using the delta-normal approach, historical simulation, and bootstrapping), verifying the VaR models by backtesting, calculating ATR, and generating moving averages.

User Interface

The first tab in the spreadsheet, labeled "Info & Instructions," contains a set of instructions giving examples of the correct way to input the dataset and parameters. It also gives a brief definition of each risk management method used in the tool. Figures 21.1 and 21.2 show the instructions and the top part of the procedures tab as they are found in the tool.

The second tab, labeled "Procedures," is where the user inputs the parameters for whichever macro he wants to run. Each risk management method has its own section with the macro buttons aligned alongside its corresponding section. The third tab, labeled "Results," is where the results of each macro are shown. Similar to the first tab, each risk management macro is assigned its own results section.

The final tab, labeled "Data Input," is where the user inputs the dataset on which they want to perform risk management calculations. It is important that the price of each commodity in the portfolio is in the same currency.

VaR Calculations and Model Verification

The delta-normal daily VaR was coded using equations that can be found in the *Encyclopedia of Finance* (Lee and Lee, 2006, p. 495). First, a loop calculates the arithmetic returns for each commodity in the dataset. Using the arithmetic returns, the variance-covariance matrix is then calculated in two parts. The first part calculates the diagonal values in the variance-covariance matrix and the second part calculates the rest of the elements in the matrix. An array is created to hold all of these values.

The variance-covariance matrix and the weights and amounts invested in each commodity, input by the user in the Data tab, are then used to calculate the portfolio, individual commodity, and commodity component VaRs. (The commodity component VaR is the individual contribution of each commodity to the portfolio risk.) Figure 21.3 shows the main steps of this process.

In order to find VaR using the historical simulation method, daily profit and loss returns are first calculated for individual commodities and for the entire portfolio. Daily portfolio returns are sorted in ascending order. The amount of the return that is met or exceeded x percent of the time, where x is 100 minus the confidence level, is the daily VaR. For example, if the user chose 95 percent confidence, the VaR would be the value that represents a loss that is met or exceeded 5 percent of the time.

Figure 21.1 Instructions for Using the Tool

Instructions

Nb. Profit and Loss and ATR data have to be deleted from Sheet1 before other codes can be used

Instructions for Data Management
1. Enter the appropriate data in the spaces provided

Example:

Start day:	2	End day:	13	Ticker:	rpha.be
Start month:	3	End month:	5	Period:	d
Start year:	2007	End year:	2008		

2. For the period please enter the following: d for daily, m for monthly, y for yearly, and v for dividends
3. Press the 'Data Management' button

Nb. Steps 2 and 3 are for VaR calculations, Bootstrapping and Stress Testing

Instructions for everything other than Data Management and ATR
1. Enter the data in Sheet1 starting with the dates in 'Column C' with the commodity prices in the following columns (no gaps in columns). Ensure you enter commodity names in Row 1
Ensure the data is of the format most recent date list

Example:

	C	D	E	F
1	Date	Gold	Silver	Platinum
2	2/26/87	552	6	662

2. Press the 'Start' button
3. After presing the 'Start' button the commodity names entered into Sheet1 will appear in the 'Weights' and 'Amount Invested' sections on this sheet in the order entered. Please enter the weights and amount invested for each commodity under the commodity names. Make sure to enter total amount invested

Example:

	Gold	Silver	Platinum	Palladium	Total
Weights	0.25	0.25	0.25	0.25	1
Amount Invested	10000	10000	10000	10000	40000

4. Go to the 'Procedures' section of this worksheet and find the section associated with the procedure you want to use and enter the data needed/follow instructions
5. Press the button associated with the procedure you want to use
6. Delete Profit and Loss data in Sheet1 before other codes are used

---

Instructions for ATR
1. Enter the data in 'Sheet1' starting with the dates in 'Column C' and the OHLC prices of your commodity after that. Row1must contain headings only. If no headings enter data in Row2

Example:

	C	D	E	F	G
1	Date	Opening	High	Low	Closing
2	2/26/87	33	34	31	32

or

	C	D	E	F	G
1					
2	2/26/87	33	34	31	32

2. Press the 'ATR' button
3. Delete ATR data from Sheet1

Figure 21.2 Procedures

Macros	Procedures
	Nb. Please enter the data needed for your specific procedure before proceding to press the following buttons

Data Management

Nb. Start month is a month behind; i.e., if you want 6, then enter 5

Start day:	31	End day:	31	Ticker:	rpha.be
Start month:	6	End month:	7	Period:	d
Start year:	2009	End year:	2009		

For everything other than Data Management and ATR

Value at Risk (VaR) Calulations

Nb. Only 95%, 97.5%, and 99% confidence levels can be used for Delta-Normal

	Corn	Soybeans	Soybean Meal	Total
Weights	0.5	0.25	0.25	1
Amount Invested	500000	250000	250000	1000000

Confidence level: 0.95   Has to be entered in decimal form; i.e., 0.95 = 95% VaR

Holding Period: 1 day(s)   If you want daily VaR then enter 1

Profit and Loss (P/L)

Results for this procedure shall be shown in Sheet1

Needs amounts invested

Macros buttons (left column): Data Management, Initialize Data, Delta-Normal, Historical Simulation, Portfolio, Commodity

Figure 21.3 VaR Calculation Using the Delta-Normal Method

Delta-Normal VaR

- Calculate arithmetic returns for each commodity in portfolio and hold in array of dimension (m-1*c)
- Square the arithmetic returns and hold in array of dimension (m-1*c)
- Multiply arithmetic returns for each commodity by arithmetic returns for each other commodity and hold in array of dimension (m-1*(c-1)!)
- Sum up each column of the previous array and hold in array of dimension (1*c)
- Calculate the diagonal values of the var/oovar matrix by multiplying each element in the previous array by (1/m)
- Calculate the var/oovar matrix (minus diagonal values) by multiplying each element in the previous array by (1/m)
- Sum up each column of the previous array and hold in array of dimension (1*(c-1)!)
- Create array of dimension (c*c) to hold all elements of var/covar matrix
- Calculate portfolio VaR and hold in array of dimension (1*1)
- Calculate individual commodity VaR and hold in array of dimension (c*1)
- Calculate commodity component VaR and hold in array of dimension (c*1)

*Note: c = number of commodities; m = number of days in estimation period

Because the VaR represents a magnitude, its sign does not matter; therefore, although it is negative, it is changed to a positive value. The mean of all the returns is calculated, and this value is added to the VaR in order to find the relative VaR (relative to the mean). Data is re-sorted in chronological order, and summary information about the VaR is written to the Results tab. This process is repeated for the individual commodities, and is shown in Figure 21.4.

In addition to increasing the historical dataset, bootstrapping also attempts to give more accurate and reliable VaR results by including simulations. As in the historical simulation macro, portfolio profit and loss is first calculated. A specified number of values n, indicated by the user, are then randomly selected with replacement from these values. This process is simulated a specified number of times s, also indicated by the user, and the values are held in an array of dimension $n \times s$.

Each column in the array is sorted in ascending order and the value corresponding to the appropriate confidence level is chosen as the absolute VaR. The average of all of the absolute VaRs is then calculated to give the overall absolute VaR. The relative VaR is calculated by adding the mean of all the portfolio profit and loss values to the absolute VaR. This process is then repeated for each individual commodity, as shown in Figure 21.5.

Figure 2I.4 VaR Calculation Using the Historical Simulation Method
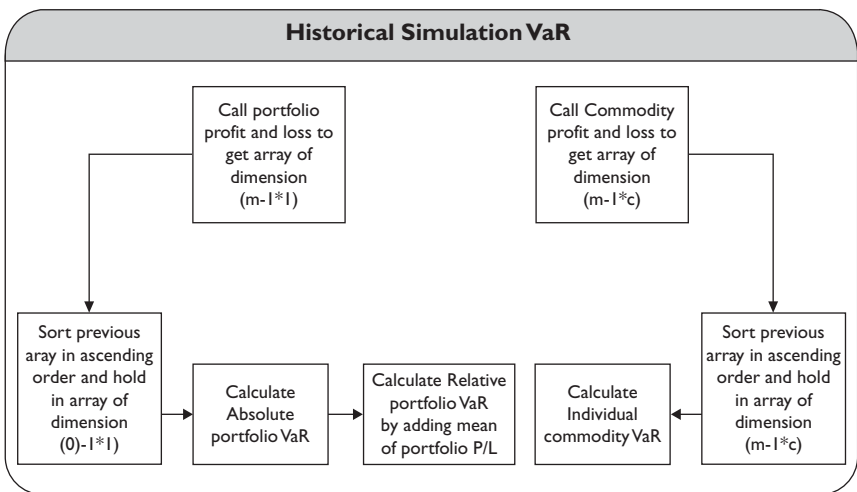
*Note: c = number of commodities; m = number of days in estimation period

Figure 21.5 VaR Calculation Using the Bootstrapping Method
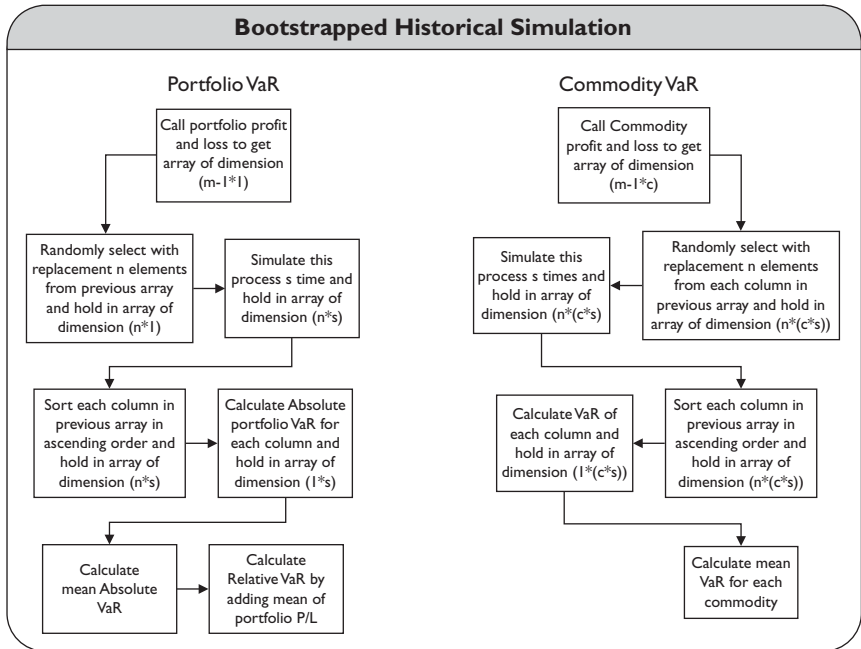
*Note: c = number of commodities; m = number of days in estimation period; n = number of bootstrapped samples wanted; s = number of simulations wanted

In order to verify the effectiveness of these models—delta-normal, historical simulation, and bootstrapping historical simulation—backtesting is conducted. VaR is calculated for a user-specified period of time and this value is compared with the next day's profit and loss return. This is repeated for another user-specified period of time. For example, if the user would like to use one trading year's worth of data (252 days) to calculate VaR and backtest over another 252 days, 252 data points would be used to calculate the VaR for each of the last 252 days of data in the column.

The positive and negative VaR are recorded as well as the portfolio's arithmetic return for the next day. If this return does not fall between the positive and negative VaR, it is considered an exception. The number and magnitude of exceptions are totaled up, and shown graphically by presenting those three values—the positive VaR, the negative VaR, and the next day's return—on a chart. This allows the user to see when there are exceptions, whether they are above the positive VaR or below the negative VaR, and their magnitude.

Average True Range (ATR)

The ATR indicator uses the OHLC prices of a commodity. First, the macro calculates the daily true range (DTR) of the dataset by performing the following operations: high price minus low price, absolute high price minus previous closing price, and absolute low price minus previous closing price. This is shown in Equation (21.1), where t is the time horizon for measuring DTR.

$$
\begin{aligned}
&DTR_t = \max(H_t - L_t, Abs(H_t - C_{t-1}), Abs(L_t - C_{t-1})), \qquad \forall \ \ 1 < t \le 14 \\
&DTR_1 = H_1 - L_1
\end{aligned}
\tag{21.1}
$$

The 14-day ATR is then calculated using Equation (21.2), where v is the time horizon for measuring ATR.

$$
\begin{aligned}
ATR_1 &= \frac{\displaystyle\sum_{t=1}^{14} DTR_t}{14} \\
ATR_v &= \frac{((ATR_{v-1} \times 13) + DTR_m)}{14}, \qquad \forall \ \ v > 1
\end{aligned}
\tag{21.2}
$$

Lastly, a graph is drawn plotting the ATR readings over the entire dataset, as shown in Figure 21.6.

Moving Averages

This macro works for a portfolio of three commodities and uses one trading year of data, or 252 days. Twelve- and 26-day simple moving averages are calculated using the Excel moving averages add-in, which computes the following formula:

$$
SMA_t = \left(\frac{1}{N}\right) \sum_{i=1}^{N} price_{t-i}
\tag{21.3}
$$

The MACD line, which is the difference between the two SMAs, is calculated next, and from that the signal line is calculated. The signal line is a

Figure 21.6 Calculation of Average True Range
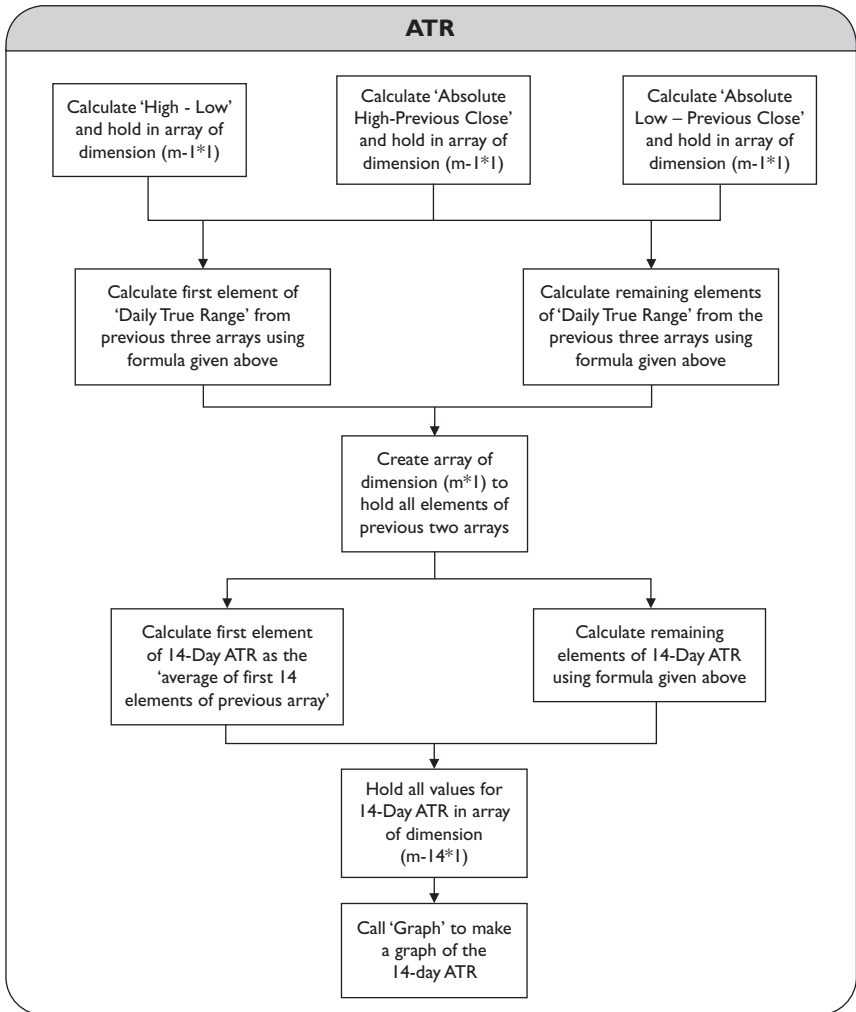
*Note: m = number of data points in estimation period

nine-day EMA of the MACD line, calculated according to the following formula:

$$EMA_t = ((price_t - EMA_{t-1}) \times multiplier) + EMA_{t-1} \qquad (21.4)$$

A chart is then drawn, showing the MACD and signal lines and enabling the user to see the results graphically, as shown in Figure 21.7.

Figure 2I.7 Calculation of Moving Averages
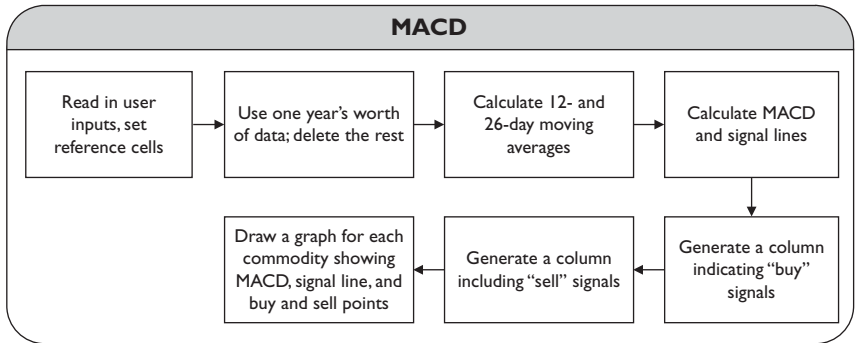
The full code for the risk-monitoring tool can be obtained for free by e-mailing the authors.

CONCLUSION

The risk-monitoring tool developed for this project has the following capabilities: initializing commodity price data input by the user, calculating VaR using the delta-normal method, calculating VaR using historical simulation, bootstrapping historical simulation, model verification by backtesting, calculating ATR, and generating moving averages. In this way, traders who were previously only familiar with technical market indicators can be introduced to VaR.

The risk metric VaR, calculated at 95 percent confidence, quantifies to the user the amount he can expect to lose 1 day in 20. It can provide a useful insight into potential losses for an individual commodity and for the portfolio as a whole; however, it does not take into consideration the potential of extreme outliers. Therefore, VaR can provide a false sense of security to traders, and according to some it was a factor in losses made throughout the subprime crisis.

ATR, on the other hand, portrays price volatility that VaR cannot: it looks at the commodity's performance over a certain period and determines whether the commodity is undergoing an active or a quiet trading period. However, it cannot determine the direction or duration of price movement for a commodity. While it is an effective risk management indicator on its own, it is much more useful if combined with other risk analysis methods, such as stop and resistance levels. Unfortunately, it is often difficult to find specific opening, high, low, and closing prices.

The use of multiple moving averages on the same chart in order to generate "buy" and "sell" signals is a tried and tested trading technique. The moving average with a shorter time period is more sensitive to changing conditions, while the one with longer time period minimizes the effects of any price irregularities. Using a crossover between the two is more reliable than acting when one day's price crosses the moving average, because any given price could be an outlier. At the same time, this crossover lags more and the investor may realize a lower return as a result of waiting for it.

Using VBA in Excel is an effective way to develop a risk-monitoring tool adapted to the commodity market. It is relatively simple to learn and also affordable, as anyone who has access to Microsoft applications does not need to make any further investment to use software programmed in VBA. Its affordability is important for small companies or individual traders, who might want the capabilities of big name risk management software but unfortunately do not have the means with which to purchase it. On the other hand, a downside to using VBA is that its computational power is somewhat limited, and as such, it can be slow. Because of this, portfolio size and complexity is restricted.

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TRADING VOLUME AND BEHAVIOR

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SECURITIES TRADING, ASYMMETRIC INFORMATION, AND MARKET TRANSPARENCY

Mark D. Flood, Kees G. Koedijk, Mathijs A. van Dijk, and Irma W. van Leeuwen

ABSTRACT

We examine the consequences of transparency in an experimental multiple-dealer market with asymmetrically informed dealers. Five professional securities traders make a market for a single security. In each trading round, one of the dealers (the "insider") is told the security's true value. We vary both pre-trade and post-trade transparency by changing the way quote and trade information is published. The insider's profits are greatest when price efficiency is lowest. Price efficiency, in turn, is reduced by pre-trade transparency and increased by post-trade transparency. Market liquidity, measured by dealers' bid-ask spreads, is improved by pre-trade transparency and reduced by post-trade transparency.

INTRODUCTION

Information is central to the structure and performance of financial markets. Indeed, a primary function of financial markets is to assemble and digest information into an accurate valuation of investment prospects. The interactions among participants—the brokers, dealers, market makers, and specialists transacting on exchange floors and over-the-counter networks—are central in this regard. Asymmetric information is thus of obvious importance; the ability of financial markets to weigh information from disparate sources and impound it in prices is basic to their function. We consider the role of asymmetric information across dealers in an experimental multiple-dealer securities market, and specifically its impact on market performance and the impact of the institutional structure on information aggregation and dissemination.

Asymmetric information has well-documented and substantial effects on the performance of financial markets, with "insider trading" as the most important example. We distinguish sharply, however, between traditional corporate insiders and securities dealers who are better informed than their peers in a multiple-dealer environment. The nature of interdealer informational asymmetries is fundamentally different from those generated by corporate insiders. Interdealer asymmetries typically arise from information, such as private order flow or the rumor mill, that should already be impounded in prices in a semi-strong-form efficient market. On the other hand, the information available to corporate insiders should only be impounded in prices if markets are fully strong-form efficient.[1] An important empirical question concerns the benefits of interdealer trade. If markets are not already semi-strong-form efficient, interdealer trading can impound information from dealers' private order flow, improving price quality.

We are interested in the interaction between interdealer information asymmetries and microstructural rules for publication of quote details and transaction details, because this interaction affects the revelation and aggregation of information. For example, in the 1990s, market makers on the Stock Exchange Automated Quotation system in London argued for delayed publication of the details of trades, ostensibly to encourage the provision of liquidity to investors for large transactions (see Office of Fair Trading, 1994). Such delays create interdealer information asymmetries, allowing an affected dealer to unwind her resulting inventory before her competitors recognize her predicament. The informational question thus

extends to issues of dealer inventories, risk bearing, and capitalization. More recently, some exchanges have facilitated "flash trades," which allow certain participants very brief advanced knowledge of incoming orders; once again, the rationale offered by participants is that the mechanism attracts trading volume and improves liquidity (see *The Economist*, 2009).

We consider here the publication of both transaction details (*post-trade transparency*, e.g., via a public ticker) and live quotes (*pre-trade transparency*, e.g., a public limit-order book), and focus on price discovery and transaction costs. As Glosten (1999) emphasizes, the issues and results in this area can be complex and counterintuitive.[2] The obvious presumption is that increased transparency would always simultaneously speed price discovery and facilitate counterparty matching and therefore improve both price efficiency and transaction costs. The empirical picture is more complex, however, especially regarding pre-trade transparency. Boehmer, Saar, and Yu (2005), for example, find that an increase in pre-trade transparency through expanded availability of the NYSE's OpenBook service is associated both with a decline in effective spreads and an improvement in the informational efficiency of prices. Madhavan, Porter, and Weaver (2005) find that increased pre-trade transparency on the Toronto Stock Exchange increases the risk to limit orders of being "picked off" by other traders, leading to wider spreads, lower liquidity, and lower stock prices. Simaan, Weaver, and Whitcomb (2003) find a similar relation between pre-trade transparency and posted spreads in the NASDAQ market. Hendershott and Jones (2005) find that a decrease in pre-trade transparency on the Island electronic communications network is associated with increased autocorrelations in prices, suggesting that price discovery deteriorates when transparency falls. The empirical situation for post-trade transparency is more clear-cut. Edwards, Harris, and Piwowar (2007), Bessembinder, Maxwell, and Venkataraman (2006), and Goldstein, Hotchkiss, and Sirri (2007), all find that increased post-trade transparency in the U.S. corporate bond market is associated with narrower spreads and/or lower estimated transaction costs.

It is difficult to study the interaction of microstructure and asymmetric information using empirical data. Even if it were possible to identify asymmetries, it would still not be feasible to isolate the effect of a static trading mechanism. We therefore adopt an experimental methodology (see Sunder, 1995 for a survey). Results from prior experimental studies mirror some of the complexity of the empirical work. Bloomfield and O'Hara (1999) and

Flood, Huisman, Koedijk, and Röell (FHKR, 1997) both find that post-trade transparency does speed price discovery. On the other hand, Flood, Huisman, Koedijk, and Mahieu (FHKM, 1999) find that increased pre-trade transparency actually slows price discovery in a multiple-dealer market; they conclude that dealers in an opaque market reprice more aggressively to attract order flow. In contrast, dealers in a pre-trade transparent market can typically offer much smaller price improvements and nonetheless guarantee a place atop the public limit order book. Our study differs from most experimental double-auction studies (but not all; see Forsythe, Palfrey, and Plott, 1982; and Plott and Sunder, 1982), in that our traders can *both* buy and sell the asset. Moreover, all our dealers act as market makers, providing bid-ask quotes to other dealers at all times.

Our market framework is based on Glosten and Milgrom's (1985) model; it is a quote-driven, continuous securities market in which five market makers trade a single imaginary security. We use three groups of professional securities dealers as experimental subjects. The market makers set quotes and trade with each other and with computerized external customers. The latter are either informed traders or noise traders. In each trading round, one of the market makers is randomly chosen to be the "insider," who knows the underlying value of the security. Since he is a market maker, he both trades and competes on price with the other market makers. In these experiments, we use the notion of pre-trade and post-trade transparency to distinguish between four different trading mechanisms. Following Pagano and Röell (1996), we define pre-trade transparency as the amount of quoted price information available to market makers, and post-trade transparency as the amount of transaction information available to market makers. We measure the relative private gains (in terms of insider profits) and public gains (in terms of speed of price discovery and size of dealer spreads) associated with various trading mechanisms when information asymmetries are present.

The contribution of this study is three-fold. First, we consider four different trading mechanisms in which we explicitly distinguish between pre-trade and post-trade transparency in our analysis. (Other studies examining insider trading in different trading mechanisms use a quite general notion of transparency; see, e.g., Pagano and Röell, 1996, and Schnitzlein, 1996.) The distinction between price and transaction information is important, as the different types of information flows have different effects on market outcomes. It is also important in terms of intermarket competition,

as competing exchanges worldwide implement trading mechanisms that indeed differ in the levels of both pre-trade and post-trade transparency.

Second, we use an experimental setting in which continuous trading is possible. This provides us with extensive time-series data: thousands of transactions and hundreds of quote settings for each of the trading mechanisms. Most experimental studies on microstructure have only a fraction of this available. Moreover, we use professional market makers as the subjects in our experiment. This is an important advantage over experiments using students as subjects.

Third, we offer an alternative view of asymmetric information by giving the insider a different role compared with other studies (e.g., Kyle, 1985; Glosten and Milgrom, 1985; Easley and O'Hara, 1992; and Schnitzlein, 1996). Generally, the insider is regarded as an external customer submitting orders to the financial market. Market makers then compete for the order via their quoted prices, and the order is typically executed against the best price. In contrast, our insider is a market maker, competing directly on price with other market makers. (Lyons, 1996, for example, examines the role of private order flow as a source of interdealer information asymmetries in a multiple-dealer market.) Our setup is closest institutionally to multiple-dealer markets such as NASDAQ, the London Stock Exchange, or the foreign exchange market.

We find an inverse connection between insider profits and price efficiency. Slow price discovery allows insiders greater opportunities to accumulate speculative inventories at advantageous prices. At the same time, however, we find that post-trade transparency (e.g., a public ticker) improves price discovery, while pre-trade transparency reduces price discovery. Consequently, post-trade transparency reduces insider profits, while pre-trade transparency increases them. Meanwhile, increased pre-trade transparency reduces dealers' uncertainty and reduces market liquidity (as measured by bid-ask spreads), while post-trade transparency induces dealers to compete for private order flow, thus reducing spreads and increasing liquidity.

EXPERIMENTAL DESIGN AND TERMINOLOGY

This section briefly presents the experimental setup. For a full description of the experiments we refer to Flood, Koedijk, van Dijk, and van Leeuwen (FKDL, 2002), which is an earlier working paper version of this study that contains all the details about the experimental setup. Our tests involve a

computerized experimental securities market in which a number of human dealers (including one with an information advantage, the "insider") trade continuously with each other and a computerized, non-market-making customer (the "robot") for a single imaginary security.

Market Design

Our experimental microstructure is a continuous multiple-dealer version of the pure dealership market used by Glosten and Milgrom (1985). This market is quote driven, in the sense that the specialist first sets quotes and then confronts orders from traders. This is the main difference between our experimental design and Kyle's (1985) order-driven framework in which the market maker determines a market-clearing price for a batch of orders. (See Madhavan, 1992 for an overview of the differences between quote-driven and order-driven markets.)

The Role of the Dealers

A priori, the security's true (underlying) value is unknown to all human dealers but one. Each participant is the insider in either two or three rounds. All dealers are informed that there is exactly one insider in every round. The true value is revealed publicly at the end of each trading round. Dealers are instructed to maximize their end-of-round wealth by trading on the security. Wealth is expressed in esquires (a fictional numéraire currency). Dealers can gain or lose wealth during each round by buying and selling the security (i.e., by jobbing) and by building a long or short inventory of the security that is converted into cash at the security's true value at the end of each round (speculating). The true value is set at random and differs in each practice and session round (the values are available from the authors). Trading in every round can be regarded as trading for a new security. At the start of each round, the non-insider only knows that the true value in that round is uniformly distributed over [1,200].

Quoting, Trading, and Pre-Trade Transparency

At the start of each round, each dealer is obliged to enter a quote (that is, a bid price and an ask price) within 10 seconds. Dealers who fail to enter an initial quote within the first 10 seconds are penalized at the rate of 10 esquires per second after that, until an initial quote is entered. Thereafter,

every dealer always has a quote outstanding, at which the other market makers and the robot can trade. The maximum individual spread is limited to 30 esquires.

The primary parameters in our experiments are the level of pre-trade transparency and the level of post-trade transparency. Both variables can assume one of two values: high or low. When the level of pre-trade transparency is high ("full quote disclosure"), all outstanding price quotes appear continuously on the trading screen of each market maker. Bid and ask prices appear in separate queues in the center of the screen. Next to every price, the identity of the dealer (human or robot) who quoted this price appears. If at any time the bid (ask) price of several dealers is the same, then the most recently quoted price is at the top. When a dealer opts to buy (sell), he automatically does so at the lowest (highest) quoted ask (bid) price.

When the level of pre-trade transparency is low ("no quote disclosure"), no price information is publicly available. Instead, prices and transactions are communicated on a strictly bilateral basis. Dealers call each other to obtain price quotes. The dealer who receives a call does not respond actively. She does not even notice that she is being called; instead, her most recently quoted bid and ask prices automatically appear on the caller's screen. Then, the caller has the option to buy, sell, or do nothing.

Transaction Information and Post-Trade Transparency

A high level of post-trade transparency implies that there is full and immediate trade disclosure. The information appears in a transaction history window on the trading screen and consists of the identities of the buyer and seller, the transaction size (which always equals one share in our setup) and the price at which the transaction cleared. When the level of post-trade transparency is low, only transactions in which a particular dealer was involved are listed in his window. There is no delay in trade disclosure.

Robot Behavior

The robot is programmed to trade every 7 seconds against the best prices in the market. Prior to each robot transaction, it is determined by chance whether the trade is an informed or an uninformed one. The noise level— i.e., the a priori probability α that a trade is informed—equals 0.5 in all rounds. At the start of the experiment, the dealers are told this probability.

Given their knowledge of the probability that a robot is informed (α), dealers may be able to filter relevant price information by observing robot transactions.

If the robot initiates an informed trade, it buys (sells) if the lowest ask price (highest bid price) at that time is below (above) the true value of the security. The robot does not trade if quoted bid-ask spreads surround the true value. Note that the robot maximizes its expected profits only at the trade level; there is no dynamic strategy. If a robot initiates an uninformed trade, a binomial random draw (with probability one half) determines whether the robot sells or buys; if it sells (buys), it does so against the highest bid price (lowest ask price) available.

Rounds and Parameters

We ran the experiments with three groups of human subjects. Each group traded in two "sessions" consisting of six 5-minute trading rounds per session. To control for possible learning effects, the first group started with a session with no quote disclosure, and then moved on to a session of full quote disclosure; the second group followed the opposite sequence. The third group followed the same sequence as the first. Within each session, post-trade transparency alternated between low and high from round to round. Each trading session followed two 5-minute practice rounds, one in which the level of post-trade transparency was low and the other in which it was high. The practice rounds acquaint the subjects with the trading system and provide a chance to ask questions. In the "real" (i.e., the non-practice) rounds, subjects were paid for their results. The data reported here come from the real sessions. At the end of each round, all dealers learn their final wealth. Esquires are translated into Dutch guilders according to a payment scheme that is explained to the dealers before the start of the experiment (1 USD $\approx$1.75 NLG). In every round, 15 guilders are divided among all market makers, making this a fixed-sum game. Details on the payment scheme are provided in FKDL (2002).

DATA

The data were collected from experiments held at the laboratory of the Center for Research in Experimental Economics and Political Decision Making (CREED) at the University of Amsterdam. The subjects in the

first experiment, conducted on January 27, 1997, are five professional option traders from Optiver. In the second experiment, conducted on 3 February 1997, five professional equity traders from ABN Amro Bank, de Generale Bank, and Oudhoff Effecten participated. These subjects acted as market makers in 12 independent rounds, divided into two six-round sessions. The third replication, involving five professional options traders from Amsterdam Options Traders, was conducted on April 21, 1999. Unfortunately, an operating system failure at the CREED lab forced us to abandon this set of replications before we were done. Eight rounds of usable data were produced, however. Table 22.1 presents some basic summary statistics.

Table 22.1 Summary Statistics for Each Trading Mechanism

Variable	LL	LH	HL	HH
Number of Quotes Set	47.3	43.8	67.2	62.4
Number of Trades				
Total	248.1	445.8	528.9	516.0
Outsiders	108.8	150.5	191.1	202.4
Insider	104.0	256.6	302.6	279.0
Robot	35.4	38.6	35.1	34.6
Average Dealer Spreads				
Outsiders	23.9	25.1	20.1	21.1
Insider	21.8	26.4	22.8	17.3
Average End-of-Round Capital				
Outsiders	−518.1	−1737.5	−2024.5	−358.6
Insider	1837.3	6361.6	7722.5	1337.9
Price Discovery				
Time to Convergence*	185.8	241.3	138.6	105.5
Percentage price error[†]				
after 100 seconds	0.39	0.57	0.39	0.32
after 200 seconds	0.12	0.23	0.32	0.15
after 300 seconds	0.06	0.09	0.18	0.14

In Table 22.1, the summary statistics for individual rounds are averaged over all three groups and eight rounds to obtain summary statistics for the four trading mechanisms.

LL=low pre-trade and low post-trade; LH=low pre-trade and high post-trade; HL=high pre-trade and low post-trade; HH=high pre-trade and high post-trade.

*Average number of seconds until the average quote midpoint for all dealers has converged to less than 5 esquires away from the underlying true value.

[†]Average price error after t seconds, divided by the average price error after 20 seconds.

More detailed tables with the settings in each round and summary statistics for individual rounds and the three groups of subjects are available in FKDL (2002).

RESULTS

In this section, we analyze the speed of price discovery, the level of insider profitability, and the bid-ask spreads (as measures of efficiency, unfairness, and liquidity, respectively) as a function of pre-trade and post-trade transparency. We consider the full-factorial 2×2 matrix of transparency arrangements. We adopt a two-letter notational shorthand, in which the first letter indicates pre-trade transparency and the second letter indicates post-trade transparency. For example, "HL" indicates a high pre-trade and low post-trade transparency regime.

Price Efficiency

Following Bloomfield and O'Hara (1999), FHKR (1997), and FHKM (1999), we use price errors to measure the informational efficiency of prices in the market. We define price errors as the absolute difference between the average midpoint of all outstanding quotes and the underlying value of the security. Our hypothesis on the effect of transparency on price efficiency is based on the results of, among others, Bloomfield and O'Hara (1999), FHKR (1997), and Pagano and Röell (1996). These studies find that increasing post-trade transparency leads to greater efficiency. The presumption would be that it is relatively hard for insiders to hide private information when transaction information is widely available to the non-insider market makers. In contrast, FHKM (1999) find a search-cost effect that causes increased pre-trade transparency to reduce efficiency in a multiple-dealer market.

Figure 22.1 shows the average price error time path for each of the four trading mechanisms. Since the only ex ante information that the uninformed market makers have about the underlying value is that it lies between 1 and 200, their best initial guess should be that the underlying value is around 100. This guess is reflected in the value of the price error at the beginning of each round, which is generally close to the absolute difference between the true value and 100. As shown in Figure 22.1 and the last panel of Table 22.1, price errors clearly move towards zero after the first 20 seconds, a pattern observed in all four trading mechanisms.

Figure 22.1 Price Errors
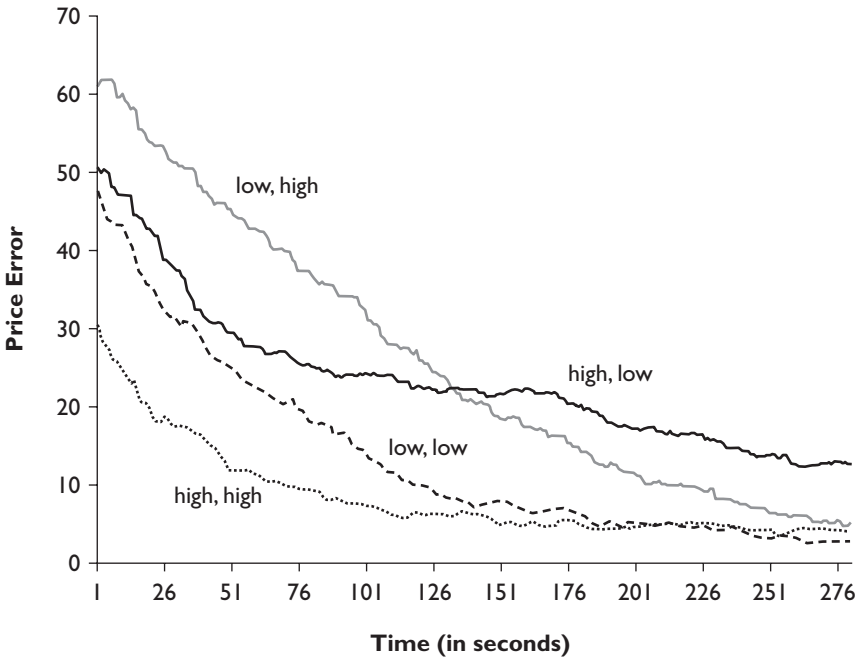
Figure 22.1 shows the average price errors for each combination of transparency variables; e.g., "low, high" refers to low pre-trade and high post-trade transparency. Price errors are defined as the absolute difference between the true value of the security and the average midpoint of outstanding quotes. The price errors are averaged across all rounds with the specified combination of transparency variables. The first 20 seconds of each round are omitted, to allow time for all dealers to submit their first quotes.

Price errors decline as more information about the underlying value of the security is brought into the market. By definition, the better the market's ability to transmit information, the faster price errors decline. While the average price error paths in Figure 22.1 disguise considerable round-to-round variation in initial errors and convergence rates, the most and least transparent cases (HH and LL) appear to perform well relative to the others. This supposition is borne out by a more controlled statistical analysis. In Table 22.2, we average price errors across all three groups and all rounds with a common transparency regime. Averages of dealer spread midpoints are taken at 50-second intervals throughout the trading round (plus an early reading after the first 20 seconds of trading), and are normalized by the starting error for the round. (The starting error is defined as abs(100 – *TrueValue*), since the expected starting quote for the uninformed dealers is 100.) Normalization compensates for differences in the

Table 22.2 Normalized Price Errors in Different Trading Mechanisms

Time (in sec)	LL	LH	HL	HH
50	0.58	0.78	0.65	0.48
100	0.33	0.56	0.44	0.25
150	0.15	0.36	0.38	0.17
200	0.11	0.22	0.35	0.13
250	0.08	0.13	0.27	0.14
300	0.05	0.08	0.22	0.11

Table 22.2 presents normalized price errors for four different transparency regimes. The normalized price errors are based on the absolute difference between the true value of the security in each round and the average midpoint of all outstanding quotes. The errors are then averaged over eight rounds to obtain the average price errors for each trading mechanism. The results are corrected for the average initial price error in each transparency regime, so that price errors are directly comparable across trading mechanisms. The initial price error is defined as abs (100 − *TrueValue*).

LL=low pre-trade and low post-trade; LH=low pre-trade and high post-trade; HL=high pre-trade and low post-trade; HH=high pre-trade and high post-trade.

true value of the security across rounds, allowing meaningful averages and comparisons. The bulk of price discovery occurs during the first 150 seconds of trading, and the HH and LL regimes clearly outperform HL and LH over this interval. After 150 seconds, average price errors are over twice as large for HL (38 percent) and LH (36 percent) as they are for either HH (17 percent) or LL (15 percent).

More formally, we estimate an individual effects panel model to examine the price efficiency in each of the four different trading mechanisms used in the experiments. We regress the price errors obtained in all 32 rounds on a constant, 32 individual-round dummies and four trend dummies. The dummy variables are included to isolate the effects of transparency. The estimated equation is

$$\left| P_{tr} - TrueValue_r \right| = \beta_0 + \sum_{i=1}^{32} \beta_i \, I(r = i) + \sum_{k=LL,LH,HL,HH} \beta_k \, I(r = k)t + \varepsilon_{tr} \qquad (22.1)$$

where t denotes time in seconds and r the trading round, P_{tr} is the average midpoint over all bid and ask quotes at time t, $I(\cdot)$ is a dummy variable for trading round and trading mechanism, and ε_{tr} is an independent and identically distributed (i.i.d.) error term. Since dealers' behavior changes after price discovery is achieved—trends in prices typically level off abruptly at this point—we discard observations after the point in time at which price errors

have converged to a value less than or equal to 5. Moreover, we omit transactions completed in the first 20 seconds of each trading round to ensure that all market makers have submitted bid and ask quotes. Ordinary least squares (OLS) estimates for Equation (22.1) are presented in Table 22.3. Larger negative values for the slope coefficient imply faster price discovery. The estimates of the 32 individual-round dummies represent differences in the underlying value in each round and the identity of the insider. They are omitted to conserve space.

Table 22.3 generally confirms the conclusions from Table 22.2, with the exception that the LL regime does not perform relatively as well in the regression analysis as it did in Table 22.2. Table 22.3 thus largely supports the hypothesis that efficiency is greater when transparency is higher. The results show a clear ranking of the different trading mechanisms, although estimates of the slope coefficients in Table 22.3 are not significantly different from one another at a 5 percent level.[3]

The exception to the notion that more transparency is better is the least transparent microstructure (LL), in which efficiency is better than in the case with high pre-trade and low post-trade transparency (HL); this difference is marginally statistically significant. This confirms the

Table 22.3 Price Efficiency

	Pre-Trade Transparency	Post-Trade Transparency	Estimated Intercept	Estimated Slope Coefficient
LL	Low	Low		−0.207*
				(0.030)
LH	Low	High	β_0: 57.72*	−0.228*
			(2.449)	(0.034)
HL	High	Low		−0.138*
				(0.021)
HH	High	High		−0.317*
				(0.141)

Table 22.3 presents the estimated intercept and the coefficients of the trading mechanism dummies from the fixed effects panel model depicted in Equation (22.1). Robust standard errors are presented in parentheses. Significance at the 5 percent level is denoted by*. The number of data points is 4,535. The R-squared of the regression is equal to 0.756.

LL=low pre-trade and low post-trade; LH=low pre-trade and high post-trade; HL=high pre-trade and low post-trade; HH=high pre-trade and high post-trade.

*Significant at 5 percent level.

earlier work of FHKM (1999), who find that price discovery is faster under LL than HL; they argue that search costs can explain this counterintuitive result, as high pre-trade transparency reduces the incentives for aggressive price improvements. The results of Table 22.3 also confirm the conclusions of FHKR (1997), who find that price discovery is faster under LH than LL.

Lastly, we consider the implications of conditioning on only one of the transparency variables at a time. Row A of Table 22.4 reports the results of estimating a modified version of Equation (22.1), in which there are only two transparency dummies, based on the degree of pre-trade transparency (i.e., the HL and HH and the LL and LH rounds are pooled). The difference across coefficients for the pooled groups is marginally significant, and the search-cost effect described by FHKM (1999) appears to dominate: price discovery is faster when pre-trade transparency is low. Similarly, row B pools the HL and LL rounds (as well as the LH and HH rounds) to examine the impact of post-trade transparency. In this case, the transparency effect described by FHKR (1997) seems to dominate, as price discovery is faster when post-trade transparency is high. This difference is also marginally statistically significant.

Table 22.4 Pooled Effects of Pre-Trade and Post-Trade Transparency on Efficiency

Regression	Estimated Intercept	Slope Estimate Low Transparency	Slope Estimate High Transparency
A: Pre-trade transparency	57.053*	−0.221*	−0.160*
	(2.162)	(0.023)	(0.026)
B: Post-trade transparency	57.146*	−0.170*	−0.235*
	(2.400)	(0.021)	(0.033)

In the fixed-effects panel model depicted in the first row (case A) of Table 22.4, LL and LH rounds are pooled (first column), as are HL and HH (second column), to examine the effect of conditioning solely on pre-trade transparency. In the second row (case B), LL and HL are pooled, as are LH and HH for a similar analysis of the effect post-trade transparency. Robust standard errors are in parentheses. Significance at the 5 percent level is denoted by *. The differences between low-transparency and high-transparency estimates are not significantly different from zero at the 95 percent confidence level in either case A or B. The number of data points is 4,535. The R-squared of regression A (B) is equal to 0.748 (0.750).

LL=low pre-trade and low post-trade; LH=low pre-trade and high post-trade; HL=high pre-trade and low post-trade; HH=high pre-trade and high post-trade.

*Significant at 5 percent level.

Insider Profits

Our evidence thus far indicates that the speed of price discovery is positively dependent on market transparency, with the exception that the least transparent regime (LL) performs relatively well in this regard. With this exception, then, we expect a generally inverse relation between insider profits and transparency, since insider profitability should be inversely related to the speed of price discovery (faster price discovery reduces the insider's ability to acquire inventory at advantageous prices). This expectation is consistent with the conclusions of Bloomfield and O'Hara (1999) and Pagano and Röell (1996).

When the true value is extreme (i.e., far from 100), insiders are likely to make larger profits than when it is moderate. As this effect is not due to transparency differences, we normalize total insider profits by the absolute difference between the true value and 100 in each round. Moreover, we look at both average insider profits and average insider profits per transaction. Although it does not affect our conclusions, we regard the latter number as more meaningful, as the number of transactions differs substantially across trading mechanisms (search costs impose a logistical obstacle that reduces transaction rates substantially in the LL case). The penultimate section of Table 22.1 presents insider profits (and average outsider losses) under each trading mechanism, averaged across all rounds. Unsurprisingly, outsider losses are closely related to insider profits. More importantly, insider profits are smallest in the most transparent market (HH), which was also the market in which price discovery occurred most quickly. Interestingly, however, the least transparent market (LL) shows similarly small insider profits, a fact consistent with its relatively speedy price discovery, established in the preceding subsection.

We again estimate a fixed effects panel model in which we regress total profits per transaction in each of 32 rounds on four trading mechanism dummies. The model is given in Equation 22.2.

$$\frac{\pi_r}{\left|100 - TrueValue_r\right|} = \sum_{i=1}^{32} \beta_i \, \mathrm{I}(r = i) + \sum_{k=LL,LH,HL,HH} \beta_k \, \mathrm{I}(r = k) + \varepsilon_{tr} \quad (22.2)$$

where r denotes the trading round, π_r is the average insider profit (either normalized by the number of transactions or non-normalized) in round

r, $\mathbf{I}(\cdot)$ is a dummy variable for trading mechanism and ε_r is an i.i.d. error term. OLS estimates of Equation (22.2) appear in Table 22.5. Estimates of the 32 individual-round dummies are omitted from the table to conserve space. Again, we see that insider profits are lowest in the most transparent (HH) and least transparent (LL) cases.[4] On the other hand, insiders are best off in the mixed-transparency cases (HL and LH). The pairwise differences in regression slope coefficients between the HH case and each of the two mixed-transparency cases (i.e., HH vs. HL, and HH vs. LH) are marginally significant. We conclude that insider profitability is inversely and causally related to the speed of price discovery in the market.

As with price discovery, we also consider the implications of conditioning on only one transparency variable at a time. Table 22.6 reports insider profits averaged across each subsample of rounds. Row A of Table 22.6 pools results based on pre-trade transparency, with the pooled LL and LH results (pooled HL and HH results) in the first (second) column. Row B similarly pools LL and HL (LH and HH) in the first (second) column. Although the standard errors are too large for either of the intercolumn differences to be statistically significant, the pattern in the calculated averages fits neatly with the results in Table 22.4. We confirm our conclusion that price discovery is the determining factor for our insider profitability results.

Table 22.5 Insider Profits

Pre-Trade Transparency	Post-Trade Transparency	Raw Profits	Profits per Transaction
Low	Low	31.43*	0.2657*
		(20.84)	(0.0704)
Low	High	91.07*	0.3608*
		(20.84)	(0.0704)
High	Low	115.25*	0.3554*
		(20.84)	(0.0704)
High	High	34.16*	0.1957*
		(20.84)	(0.0704)

*Significant at 5 percent level.

Table 22.5 depicts the fixed effects panel coefficients for the trading mechanism dummies in Equation (22.2). For the first column, π_r is the coefficient on total insider profits; for the second column, π_r is the coefficient on total insider profits divided by the total number of insider transactions. The data is pooled over 32 rounds. Robust standard errors appear in parentheses. Significance at the 5 percent level is denoted by*. The number of observations is equal to 32. The R-squared amounts to 0.301 for the raw profits and 0.119 for the profits per transaction.

In sum, the results for insider profits show a clear negative relation between insider profits and the speed of price discovery, as anticipated. However, because the relation between price discovery and transparency is a nonlinear one, the relation between insider profits and transparency is similarly nonlinear.

Spreads

The spread between market makers' bid and ask quotes is generally assumed to consist of three different components: order-processing costs, inventory-holding costs, and adverse-selection costs. The first two components are nominally equal to zero in our experiments, and we focus on the latter. The standard adverse-selection component represents compensation to the dealer for losses to informed investors. However, a number of papers (e.g., Madhavan, 1995) argue that dealers in a multiple-dealer market should narrow their spreads in an effort to "purchase" informative order flow, with the goal of exploiting the resulting information in subsequent trading, a tactic that should be enforced by interdealer competition. Thus, adverse-selection costs subsume both the degree of uncertainty in the market and the degree of (imperfect) competition.

The existing literature also indicates that an explicit distinction between pre-trade and post-trade transparency is necessary when examining the relation between transparency and bid-ask spreads. Pagano and Röell (1996) find that the spread size decreases when more price information is available in the market. The argument is that uncertainty decreases when market makers

Table 22.6 Effects of Pre-Trade and Post-Trade Transparency on Average Profits

Transparency Variable	Average Low Transparency	Average High Transparency
A: Pre-trade transparency	4,099	4,530
	(3,933)	(6,784)
B: Post-trade transparency	4,780	3,850
	(6,524)	(4,309)

Table 22.6 presents the effect of transparency on insider profits by averaging the insider profits over two different transparency regimes. In the first row (case A), average insider profits in LL and LH rounds are computed (first column), as are HL and HH (second column), to examine the effect of conditioning solely on pre-trade transparency. In the second row (case B), average insider profits in LL and HL are calculated, as are LH and HH for a similar analysis of the effect post-trade transparency. Standard deviations are in parentheses.

know more about each other's quotes. On the other hand, Bloomfield and O'Hara (1999) find that spreads increase when more transaction information becomes available in the market. Madhavan's (1995) model concludes that market makers compete more fiercely when they cannot observe other market makers' transactions, since in this case they must attract transactions to themselves to gain the information implicit in the order flow. We thus conjecture that reduced pricing uncertainty under pre-trade transparency should reduce spreads, while reduced competition under post-trade transparency should increase them. This conjecture translates to the following four hypotheses: (1) $S_{LL} > S_{HL}$; (2) $S_{LH} > S_{HH}$; (3) $S_{HH} > S_{HL}$; and (4) $S_{LH} > S_{LL}$; where S_k is the average spread size under trading regime k.

Figure 22.2 shows the average outsider spreads in the four different microstructures for all three groups of subjects. The average spread in each trading round is defined as the average size of the spread between the bid

Figure 22.2 Dealer Spreads
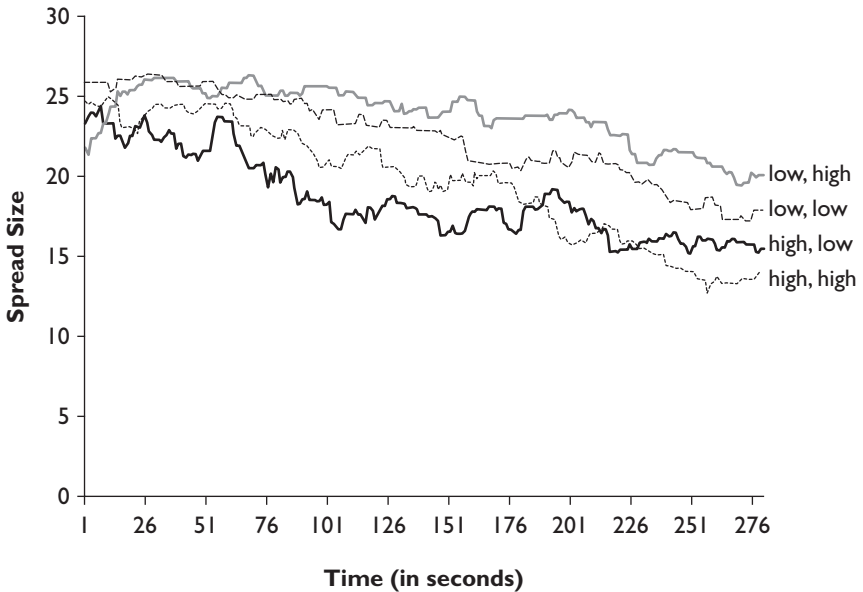
Figure 22.2 shows the average spread size in each of the trading mechanisms, measured as the average bid-ask spread of all outside dealers in the relevant trading rounds. None of our spread results is changed markedly by including or excluding the insider. The initial spreads are high and similar in each trading mechanism, but spreads decrease as information is brought into the market over time. The spreads are nearly uniformly consistent with our hypothesis. For at least the first 230 seconds of trading, the average spread size is lowest when pre-trade transparency is high and post-trade transparency is low, indicating that uncertainty is relatively low and competition relatively severe. The reverse holds for the LH market, in which spreads are relatively large.

Table 22.7 Effects of Pre and Post-Trade Transparency on Average Spreads

Transparency Variable	Average Low Transparency	Average High Transparency
A: Pre-trade transparency	24.5	20.6
	(2.39)	(3.65)
B: Post-trade transparency	22.0	23.1
	(3.88)	(3.36)

Table 22.7 presents the effect of transparency on dealer spreads by averaging the spreads over two different transparency regimes. In the first row (case A), average outsider spreads in LL and LH rounds are computed (first column), as are HL and HH (second column), to examine the effect of conditioning solely on pre-trade transparency. In the second row (case B), average outsider spreads in LL and HL are calculated, as are LH and HH for a similar analysis of the effect post-trade transparency. Standard deviations are in parentheses.

and ask quotes of all market makers. The lines in this graph were constructed by averaging the spreads of eight individual rounds with the same trading mechanism. The first 20 seconds of each trading round were omitted from the calculation, as dealers used this time period to enter their first bid and ask quotes.

To buttress the evidence in Figure 22.2, Table 22.7 presents the average outsider spreads pooled for all trading rounds with the specified transparency treatment. For example, row A of Table 22.7 presents in the first (second) column the average outsider spread for all LL and LH (HL and HH) rounds. As predicted, increased pre-trade transparency narrows dealer spreads. Similarly, in row B, we see that increased post-trade transparency increases spreads. The predictions of our hypothesis continue to hold under a finer-grained analysis. Thus, on average, $S_{LL} = 23.9$, $S_{LH} = 25.1$, $S_{HL} = 20.1$, and $S_{HH} = 21.1$. Although neither of the intercolumn differences in Table 22.7 is statistically significant at the 5 percent level, our hypothesis is nonetheless clearly supported by the available evidence.

CONCLUSION

In this study, we follow the recommendations of Leland (1992), Pagano and Röell (1996), and Schnitzlein (1996) to examine the extent to which market microstructure interacts with asymmetric information to affect market performance. Specifically, we consider an experimental multiple-dealer market in which one of the dealers begins with fundamental information unavailable to the other dealers. We create four different trading mechanisms by varying the following two transparency rules: the pre-trade publication of dealer

quotes (private information or broadcast) and the post-trade publication of transactions (public ticker or private information). The characteristics of the trading mechanism affect how difficult it is for uninformed dealers to detect an insider and infer his strategies; conversely, they affect the ability of the insider to exploit his informational advantage.

We obtain our data from a series of 5-minute trading rounds for three groups of five professional securities traders. Our results clearly indicate an inverse connection between insider profits and the price efficiency of the market. Slow price discovery allows insiders greater opportunities to accumulate speculative inventories at advantageous prices. However, the connection between insider profitability and transparency is somewhat more complex, because the connection between transparency and price efficiency is nonlinear. Post-trade transparency (e.g., a public ticker) improves efficiency. Conversely, however, and consistent with the earlier work of FHKM (1999), pre-trade transparency in our multiple-dealer market slows price discovery and increases insider profitability. Market liquidity, measured by average bid-ask spreads, behaves consistently with theoretical predictions. Increased pre-trade transparency reduces dealers' uncertainty and reduces spreads. Eliminating post-trade transparency creates an incentive for dealers to compete for private order flow, thus reducing spreads.

ACKNOWLEDGMENTS

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NOTES

1. Moreover, the potential social benefits of insider trading-namely, that it draws insiders into the market to reveal their information via trading (see Leland, 1992)—do not obtain as readily for asymmetrically informed dealers, since by definition dealers are already active in the market. Note that, in many markets, dealers broker trades for corporate insiders, so that the dealer effectively becomes a surrogate corporate insider.

2. The main theoretical issues are considered by O'Hara (1995), and Pagano and Röell (1996).

3. We also attempted to confirm whether these slope estimates differ significantly from one another, based on matched-pair tests of the transparency effect, calculated with robustness to heteroscedasticity. Holding constant one transparency dimension (e.g., fixing low post-trade transparency and comparing LL vs. HL), we compared the difference in slopes (e.g., $HL - LL = 0.069$). There are four such comparisons: LL vs. HL; LH vs. HH; LL vs. LH; and HL vs. HH. In none of the comparisons is the difference in slopes significant at a 95% confidence threshold.

4. Once again, we performed matched-pair comparisons across regimes of the slope coefficient for insider profits (i.e., the final column in Table 22.5). Once again, in none of the four comparisons do the coefficients differ significantly at a 95% confidence threshold.

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ARBITRAGE RISK AND THE HIGH-VOLUME RETURN PREMIUM

G. Geoffrey Booth and Umit G. Gurun

ABSTRACT

This chapter provides new insights into the visibility hypothesis, which maintains that increased attention to a stock should attract and convince more investors to buy the stock. We find a negative relation between arbitrage risk and abnormal trading volume, and we provide empirical evidence that arbitrage risk helps explain the previously documented high-volume return premium.

INTRODUCTION

Miller (1977) argues that increased attention to a stock should attract more investors and convince them to buy the stock. His argument is used by Gervais, Kaniel, and Mingelgrin (2001) to explain the relationship between abnormal trading activity and subsequent price increases, but does not address why particular stocks experience high trading volume in the first place. We conjecture that stocks with low arbitrage risk are more likely to experience abnormal trading activity when their prices deviate from their fundamentals, and we postulate that this trading signals the intentions of the traders. Thus, in a market where short sales

are restricted, stocks with substitutes are more likely to be "visible" when they are underpriced.

DATA AND METHOD

To test our conjecture, we classify stocks into groups based on their observable visibility attributes. We use abnormal shares traded and firm size for our measures of visibility. Using Gervais, Kaniel, and Mingelgrin's (2001) approach, we split daily data from the Center for Research in Security Prices for NYSE stocks between July 1, 1963 and December 31, 2006 into 216 nonintersecting intervals of 50 trading days. Each interval is divided into a reference period, the first 49 days, and a formation day, the 50th day. The reference period acts as a benchmark to judge how unusual the trading volume is in the formation period. In a trading interval, a stock is classified as a high (low) volume stock if its formation period volume is in the top (bottom) decile of the 50 daily volume samples. All NYSE Common stocks are considered except those with missing data, those with a price of below $5 at the month end, and those that experienced an earnings announcement during the 3-day window centered on the formation day. We separated the sample in three parts according to company size (market capitalization) and calculated the return on high- and low-volume stocks. We classify the firms in size deciles 9 and 10 as large size, those in deciles 6 through 8 as medium size, and those in deciles 2 to 5 as small size. Firms in the first decile are excluded because most do not survive the filters. This procedure eliminates sample selection bias and reduces the dependency between observations in different trading intervals. Moreover, the 50-day difference between observations minimizes any systematic biases that caused by calendar anomalies. We end up with 16,126 small-size/low-volume, 15,204 small-size/high-volume, 10,234 medium-size/low-volume, 10,430 medium-size/high-volume, 6,387 large-size/low-volume and 6,812 large-size/high-volume stocks.

On the formation date, we create portfolios based on the trading volume classification of the stocks in the corresponding reference period. We construct zero-investment portfolios by longing a total of $1 in all high-volume stocks in a size group and shorting a similar short position in all low-volume stocks in that same group. Each stock in the high- (low-) volume category is given equal weight. The cumulative returns of high-volume, low-volume, and zero-investment portfolios for different size groups are summarized in Table 23.1. Our

Table 23.1 High-Volume Premium across Size Groups

	Large Size	Medium Size	Small Size
High Volume	1.77	1.85	1.95
Low Volume	0.67	0.81	0.34
Zero Investment	1.10	1.04	1.61
	(<.00)	(<.00)	(<.00)

p values (in parentheses) are associated with the two-tailed null hypothesis that a zero-investment portfolio earns a zero profit.

results confirm the high-volume premium documented by Gervais, Kaniel, and Mingelgrin (2001) for a marginally longer data period using slightly different methods. The cumulative return differential between high-volume and low-volume stocks is statistically positive for all size groups (all *p* values <.00). Furthermore, the high-volume return premium is more apparent for small than large companies.

We use three approaches to measure the arbitrage risk. First, following Wurgler and Zhuravskaya (2002), our measure of a portfolio's arbitrage risk at time t is based on the following ordinary least squares (OLS) regression:

$$R_{P,i} - R_{RF,i} = \alpha + \beta_M(R_{M,i} - R_{RF,i}) + \varepsilon_{t,} \qquad (23.1)$$

where $i = t - 1,\ t - 2,\ldots,\ t - k$ (k is the estimation window length). R_{Pi} corresponds to return to portfolio P at time i. R_{RFi} corresponds to risk-free rate and $R_{M,i}$ represents the market return. This approach assumes that market is a close substitute for any diversified portfolio. The root mean square error of the regression captures the volatility of the zero-investment portfolios, i.e., the arbitrage risk of the investment strategy. For each high-volume and low-volume portfolio for various size groups, we calculate the variance of residuals and the standard error of regression using the previous 250 days.

Second, we estimate the following four-factor model's root mean square error to calculate a measure arbitrage risk that is orthogonal to well documented risk factors:

$$R_{P,i} - R_{RFi} = \alpha + \beta_M (R_{M,i} - R_{RFi}) + \beta_H HML_i + \beta_S SMB_{t,i}$$
$$+ \beta_U UMD_{t\,i} + \varepsilon_t \qquad (23.2)$$

where $i = t - 1, t - 2,..., t - k$ and $R_{P,i}$, R_{RFi}, and R_{Mi} are previously defined. The purpose of adding other factors to Equation (23.1) is to capture the idiosyncratic risk that potentially creates major obstacles for the arbitrageur. We use book-to-market (high minus low, or HML) and size (small minus big, or SMB) to control for other sources of risk. HML and SMB are obtained from Kenneth French's Web site. To control for possible momentum effects, we use the six value-weighted portfolios formed on size and prior 2- to 12-month returns. The portfolios are the intersections of the two portfolios formed on size and the three portfolios formed on prior return. The monthly size breakpoint is the median NYSE market equity. The monthly prior return breakpoints are the 30th and 70th NYSE percentiles. Momentum (up minus down, or UMD) is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. We do not include a liquidity variable in Equation (23.2) because Gervais, Kaniel, and Mingelgrin (2001) show that liquidity is not an explanation for the high-volume return premium, but our conclusions are not affected if we do.

Third, we create a fifth risk factor, LMS, which is the average return on the portfolio that longs stocks in the top 20th percentile of arbitrage risk and shorts stocks in the lowest 20th percentile of arbitrage risk. Arbitrage risk for individual stocks is calculated based on OLS regression found in Equation (23.2). Sorting based on arbitrage risk is performed before the trading interval i; therefore, it is information available to investors before the portfolio formation period. If arbitrage risk is indeed higher for less visible stocks, then inclusion of LMS (long minus short) should reduce or eliminate the alpha differential between most visible and less visible portfolios.

TESTS

The first implication of our conjecture is that arbitrage risk of visible stocks should be lower than that of less visible ones. This translates into comparing arbitrage risk of high-volume stocks and low-volume stocks within the same size group, and large-size and small-size firms within the same volume group. In Table 23.2, we report that high-volume stocks have lower arbitrage risk than low-volume stocks regardless of size firms (p values $\leq$.01) and that large-size firms have lower arbitrage risk than small-size firms

Table 23.2 Arbitrage Risk Differences

	Panel A.		
	High Volume, Large Size/ Low Volume, Large Size	High Volume, Medium Size/ Low Volume, Medium Size	High Volume Small Size/ Low Volume, Small Size
Risk Difference	−0.483	−0.220	−0.116
	(<.00)	(<.00)	(.01)
	Panel B.		
	Large Size, High Volume/ Small Size, High Volume	Large Size, Low Volume/ Small Size, Low Volume	
Risk Difference	−0.630	−0.228	
	(<.00)	(<.00)	

p values (in parentheses) show the results of the one-tailed null hypothesis.

regardless of volume (*p* values <.00). These results support the notion that arbitrage risk may be capable of explaining the high-volume premium.

The *p* values (in parentheses) in Panel A show the results of the one-tailed null hypothesis that arbitrage risk of high-volume stocks is greater than that of low-volume stocks. The *p* values (in parentheses) in Panel B show the results of the one-tailed null hypothesis that arbitrage risk of large-size firms is greater than that of small-size firms. We estimate Equation (23.2) with and without LMS for the more and less visible portfolios for all 216 20-day trading intervals. The results are displayed in Table 23.3. These indicate that four-factor model alone cannot account for the return premium across high- and low-volume portfolios for all firm size groups. The alpha differences in all size groups are significant and positive. However, if the LMS factor is included in the four-factor model, the alpha difference is reduced substantially for all size groups. For large-size stocks the difference reduces from 0.66 percent (*p* value <.00) to 0.08 percent (*p* value = .70). Adding LMS also reduces alpha for medium-size stocks. Alpha goes down from 1.31 percent (*p* value <.00) to –0.03 percent (*p* value = .58). In the small-size stocks, however, inclusion of LMS does not eliminate the significance of alpha but alpha is reduced from 2.05 percent (*p* value <.00) to 0.59 percent (*p* value = .09).

Table 23.3 Four-Factor Alphas with and without LMS

	Large-Size		Medium-Size		Small-Size	
	Without LMS	With LMS	Without LMS	With LMS	Without LMS	With LMS
High Volume	0.80	0.23	1.85	0.48	1.95	0.69
	$(<.00)$	(.04)	$(<.00)$	(.01)	$(<.00)$	(.01)
Low Volume	0.14	0.15	0.54	0.51	−0.10	0.10
	(.08)	(.06)	(.04)	(.01)	(.15)	(.07)
Alpha Difference	0.66	0.08	1.31	−0.03	2.05	0.59
	$(<.00)$	(.70)	$(<.00)$	(.58)	$(<.00)$	(.09)

LMS=long minus short.
Two-tailed p values are in parentheses.

CONCLUSION

Our empirical evidence shows that arbitrage risk explains the premium between high- and low-volume stocks. Our results confirm those of Gervais, Kaniel, and Minglegrin (2001) who document the existence of a high-volume premium. They are also consistent with the findings of Ang et al. (2006) who show that U.S. stocks with high lagged idiosyncratic volatility earn very low future average returns. Moreover, our arbitrage interpretation of the visibility hypothesis complements Chan and Lakonishok (1993), who suggest that buy decisions convey more information to the market than sell decisions because the latter are typically liquidity motivated. That the information effect on trading volume, however, is only part of the story. Investors, who provide the liquidity to other investors with limited investment opportunity sets and who profit from any price discrepancy between market segments, care about the availability of perfect substitutes (arbitrage risk). Their demand for such assets increases the visibility of those assets and forces other investors to consider them. When assets with low arbitrage risk are underpriced, increased visibility causes prices to increase and expected returns to decrease. Overall, our results suggest that the visibility and investor recognition related hypotheses should consider the arbitrage risk of the underlying asset because a shock to trading activity may signal possible price corrections.

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THE IMPACT OF HARD VERSUS SOFT INFORMATION ON TRADING VOLUME
Evidence from Management Earnings Forecasts

Paul Brockman and Jim Cicon

ABSTRACT

We examine the impact of hard (quantitative) versus soft (qualitative) information on trading volume around the release of management earnings forecasts. We use textual analysis to identify and measure the level of two soft information variables, *Optimism* and *Certainty*, in each forecast. We posit and confirm that soft information has a significant impact on trading volume, even after controlling for the effect of hard information. In fact, we show that soft information explains more of the trading volume impact of management forecasts than hard information. Our empirical results contribute to the growing literature that examines the economic significance of qualitative information.

INTRODUCTION

In this chapter, we investigate how the release of management earnings forecasts impacts the announcing firm's trading volume. Our main interest is to differentiate the impact of hard, or quantitative, information from the impact of soft, or qualitative, information. Since a typical management forecast announcement contains roughly 99 words for every one number, we expect that soft information (i.e., words instead of numbers) plays a significant role in providing relevant information to the market. The more informative the announcement, all else equal, the more abnormal trading volume the announcement will generate. We use textual analysis to identify and measure the level of two specific soft information variables, *Optimism* and *Certainty*, in each management forecast. Our empirical results confirm that soft information has a significant impact on trading volume, even after controlling for the effect of hard information. More specifically, we find that *Optimism* has a positive and significant impact on abnormal trading volume at the time of the forecast, while *Certainty* has a negative and significant impact on abnormal trading volume at the time of the forecast. These results suggest that qualitative information associated with greater optimism increases investors' propensity to trade, while qualitative information associated with greater certainty decreases their propensity to trade. In contrast, we find no significant relation between abnormal trading and quantitative information.

Our chapter is motivated by combining the management forecast literature and the textual analysis literature. Previous studies show that management earnings forecasts contain substantial value-relevant information (Hirst, Koonce, and Venkataraman, 2008). Pownall, Wasley, and Waymire (1993) show that voluntary disclosures generate a significant price effect at the time of the announcement. The market reassesses the firm's prospects as a result of the voluntary disclosure and adjusts its price accordingly. Coller and Yohn (1997) show that such announcements also have a significant impact on firm liquidity, and Baginski and Hassell (1990) find a significant impact on analyst revisions. Recent research by Aboody and Kasznik (2000), Cheng and Lo (2006), and Brockman, Khurana, and Martin (2008) finds that managers exercise considerable leeway in the timing and content of their voluntary disclosures. For our purposes, the combination of value-relevant information and considerable managerial discretion offers an ideal setting in which to examine

qualitative versus quantitative information. While required financial reports specify the form and content of disclosures, voluntary disclosures (e.g., management earnings forecasts) are open-ended. Managers not only choose whether or not to issue forecasts, they also choose the combination of hard and soft information contained in their announcements.

There is a growing literature in accounting and finance that uses textual analysis to examine the soft information content of firm announcements (e.g., Das and Chen, 2007; Tetlock, 2007; and Das, Martinez-Jerez, and Tufano, 2005). Many, if not most, of these studies analyze the relation between soft information and the firm's reported earnings (e.g., Li, 2006; Engelberg, 2007; Davis, Piger, and Sedor, 2007; Tetlock, Saar-Tsechansky, Macskassy, 2008; Demers and Vega, 2008). Demers and Vega (2008), for example, investigate the price effect of hard versus soft information using more than 20,000 earnings announcements. Their results show that soft information has a significant impact on stock prices at the time of the earnings announcement. Brockman and Cicon (2009) find similar, affirmative results for the role of soft information during the announcements of more than 15,000 management earnings forecasts.

The rest of this chapter proceeds as follows: we describe our data and methods of analysis in this chapter's second section. We present and analyze our empirical findings in the third section of this chapter, and then provide a brief conclusion in the final section.

DATA AND METHODOLOGY

Data

Our chapter analyzes the soft information found in the text of company-issued, guidance press releases. We use LexisNexis as the source of these press releases. Specifically, we restrict our search to the LexisNexis "Company Press Releases" database and further limit our search to the following news providers: PR Newswire (US), Business Wire, and Canada Newswire. Our timeframe is 1994 to 2007.

Our query analyzes the "subject" line and the "headline" of each candidate press release. Starting with the subject line, we keep only those press releases which fall into the following categories: ("earnings preannouncements" or "earnings projections or forecasts") and not ("interim financial results"). We exclude the "interim financial results" hits because press

releases in this category tend to originate from noncompany sources (e.g., analyst commentary). We scan the headlines of the remaining documents and retain only those that contain the following terms: (guidance OR forecast OR predict OR prediction OR projection OR forward OR future OR expect OR expected OR expectation OR update OR anticipate OR reaffirm) AND ((cash W/S flow) OR earn OR earning OR share OR stock OR EPS OR fiscal OR price OR revenue OR results OR profit OR profitability OR targets OR growth OR raise OR lower OR upward OR upwardly OR downward OR downwardly). The AND connector between the two groups of words means that one of the first group of words AND one of the second group of words must appear in the headline in order for the press release to be retained.

This LexisNexis search yields 74,603 candidate press releases, many of which are duplicates and/or commentary by third parties subsequent to the original press release. To ensure uniqueness and relevancy, we match the candidate press releases with the First Call "Company Issued Guidelines" database. Since the 74,603 press releases downloaded from Lexis-Nexis are in PDF format, they are not readily identifiable by a machine. Therefore, we write custom software to scan and extract the ticker symbol and the announcement date from each press release. We retain only those press releases which match the First Call ticker symbol and which occur on the same day as the First Call guidance release. Where more than one press release occurs on the same day for the same company, we keep the earliest. We also discard press releases that do not contain at least 100 words.

After these steps, we are left with 15,010 press releases. We randomly sample these press releases to ensure uniqueness and relevancy. We then run custom algorithms to clean up the press releases. We first remove all punctuation. Hyphenated words are concatenated. Numerical terms are counted and then removed, with a record of their count retained. If tables are found, they are removed, although we keep record of their presence with a dummy variable. Words which do not occur more than two times in a given document are discarded. We truncate press releases which are longer than 750 words. This effectively removes company-description and safe-harbor paragraphs in the longer press releases. Shorter press releases do not typically contain these boilerplate paragraphs.

Methodology

Our methodology analyzes each press release for the presence of semantic features, specifically, for the presence of *Optimism* and *Certainty*. We base our analysis on Diction, a language processing software package which has been used extensively in prior research to analyze political and economic speeches, corporate reports, and earnings announcements. Diction analyzes a document by counting the frequency of specific key words. It compares these counts to norms calculated from a broad sample of English text consisting of 20,000 documents drawn from political speeches, newspaper editorials, business reports, scientific documents, telephone conversations, etc.

Diction defines *Net Optimism* (equivalent to our term *Optimism*) as language endorsing some person, group, concept or event, or highlighting their positive accomplishments (Carroll, 2000). The program generates an aggregate standardized score for *Optimism* by counting words in defined categories and combining the standardized scores for each category as shown

$$Optimism = (praise + satisfaction + inspiration) \\ - (blame + hardship + denial) \tag{24.1}$$

Diction defines *Certainty* as language indicating resoluteness, inflexibility, completeness, and a tendency to speak ex cathedra. The program generates an aggregate standardized score for *Certainty* by counting words in defined categories and combining the standardized scores for each category as shown

$$Certainty = (tenacity + leveling + collectives + numerical\_terms) \\ - (ambivalence + self\_reference + variety) \tag{24.2}$$

These two semantic features, *Net Optimism* and *Certainty* serve as the soft information variables in our chapter.

In addition to standardizing our qualitative information variables using Diction's out-of-sample mean and variance values, we replicate all empirical tests using in-sample mean and variance values. We find no substantive difference between either approach and conclude that our empirical results and conclusions are not sensitive to the standardization procedure.

EMPIRICAL RESULTS

In Table 24.1 we present summary statistics (Panel A) and correlations (Panel B) for the following dependent and independent variables. *ATV*, which is cumulative abnormal trading volume, is computed as follows:

$$\frac{\dfrac{\sum\limits_{i=-1}^{+1} return_i}{3} - \dfrac{\sum\limits_{i=-5}^{-14} return_i}{10}}{\dfrac{\sum\limits_{i=-5}^{-14} return_i}{10}}.$$

Table 24.1 Descriptive Statistics

Panel A. Summary Statistics					
	Mean	**Median**	**SD**	**25th**	**75th**
ATV	1.46	0.77	2.17	0.19	1.88
SUFE	0.00	−0.04	1.00	−0.30	0.25
Optimism	0.00	−0.04	1.00	−0.62	0.56
Certainty	0.00	−0.11	1.00	−0.70	0.58
Market Cap	6,153,216	1,041,741	21,030,688	351,864	3,749,533
Analyst Coverage	2.67	2.00	2.95	1.00	4.00
Intangibility	0.13	0.04	0.18	0.00	0.21
SD Returns	0.03	0.02	0.02	0.02	0.03

Panel B. Correlations							
	CATVS	**SUFE**	*Optimism*	*Certainty*	**Market Cap**	**Analyst Coverage**	**Intangibility**	**SD Returns**
CATVS	1							
SUFE	−0.02	1						
Optimism	0.00	0.02	1					
Certainty	−0.06	0.03	0.01	1				
Market Cap	−0.19	0.03	0.19	0.05	1			
Analyst Cov	0.03	0.01	0.07	−0.02	0.46	1		
Intangibility	−0.02	0.05	0.09	0.06	0.13	0.05	1	
SD Returns	0.10	0.00	−0.09	−0.14	−0.47	−0.08	−0.20	1

See text for definition of terms.

SUFE is the standardized unexpected earnings forecast. *Optimism* is "a measure of language endorsing some person, group, concept or event, or highlighting their positive entailments." *Certainty* consists of words indicating resoluteness, inflexibility, and completeness. *Market cap* is the natural logarithm of the firms' market capitalization. *Analyst coverage* is the number of analysts covering firm j in quarter t. *Intangibility* is intangible assets divided by total assets. Standard deviation (SD) of returns is the standard deviation of returns from -30 days to -7 days from the announcement date. The sample period spans 1994 to 2007 and includes those firms which appeared in the First Call company-issued, guidelines database and for which a matching company press release was found in LexisNexis for a total of 14,938 company-issued, guidance press releases.

Our dependent variable, *ATV*, is measure of abnormal trading volume that compares trading volume around management guidance announcements with trading volume in the preannouncement period. *ATV* is defined as follows:

$$\frac{\dfrac{\sum\limits_{i=-1}^{+1} return_i}{3} - \dfrac{\sum\limits_{i=-5}^{-14} return_i}{10}}{\dfrac{\sum\limits_{i=-5}^{-14} return_i}{10}} \tag{24.3}$$

Our main treatment variables include a quantitative variable, *SUFE*, and two qualitative variables, *Optimism* and *Certainty*. *SUFE* is the standardized unexpected earnings forecast. We construct *SUFE* by subtracting the management earnings forecast of firm j for time period t from the firm's actual (reported) earnings in time period $t - 1$. This difference is used as the unexpected component in the manager's forecast. Lastly, we calculate *SUFE* by subtracting the sample mean and dividing by the sample standard deviation. Our first qualitative variable, *Optimism*, is "a measure of language endorsing some person, group, concept or event, or highlighting their positive entailments." Our second qualitative variable, *Certainty*, consists of words indicating resoluteness, inflexibility, and completeness.

Our control variables include market capitalization, analyst coverage, intangibility, and standard deviation of returns. *MktCap* is the natural

logarithm of the firms' market capitalization. *Analyst coverage* is the number of analysts covering firm *j* in quarter *t*. *Intangibility* is intangible assets divided by total assets. *StdDevRet* is the standard deviation of returns from −30 days to −7 days from the announcement date. Our sample period is from 1994 to 2007. The sample includes those firms which appeared in the First Call company-issued, guidelines database and for which a matching company press release was found in LexisNexis for a total of 14,938 company-issued, guidance press releases.

We present our baseline regression results in Table 24.2. We estimate the following regression:

$$ATV_i = \beta_0 + \beta_1\ SUFE_i + \beta_2\ Optimism_i + \beta_3\ Certainty_i + \beta_4\ MktCap_i$$
$$+ \beta_5\ Analyst_i + \beta_6\ Intangibility_i + \beta_7\ StdDevRet_i + \varepsilon_i \qquad (24.4)$$

where all variables are defined above. The sample period spans 1994 to 2007 and includes those firms which appeared in the First Call company-issued, guidelines database and for which a matching company press release was found in LexisNexis for a total of 14,938 company-issued, guidance press releases. We control for industry effects, not shown. Our main variables of interest are the treatment variables *SUFE*, *Optimism*, and *Certainty*. The coefficient on *SUFE* is negative and insignificant, suggesting that the unexpected component of guidance forecasts does not have a significant impact on trading volume. In contrast, the coefficients for both qualitative variables are significant. The coefficient on *Optimism* is positive and significant.

Table 24.2 Baseline Regression—Impact of Soft Information on Trading Volume

	Coefficient	t stat	p value
SUFE	−0.0246	−1.399	0.1619
Optimism	0.0804	4.458	0.0000****
Certainty	−0.0977	−5.454	0.0000****
MktCap	−0.5798	−24.92	0.0000****
Analyst Coverage	0.3125	15.499	0.0000****
Intangibility	−0.0441	−2.326	0.0200**
SD Returns	−0.1025	−4.804	0.0000****
Adjusted R^2	6.32%		

**** denotes significance at 0.1%, *** at 1%, ** at 5%, and * at 10%.

This result means that the more optimistic the language contained in the management guidance, the larger the increase in abnormal trading. The coefficient on *Certainty* is negative and significant, suggesting that the more certain the language contained in the management guidance, the smaller the increase in abnormal trading. Overall, these findings show that trading volume is very sensitive to soft information. All else equal, more optimist language increases trading volume and more certain language decreases trading volume.

The coefficients on the control variables in regression in Equation (24.3) show that abnormal trading increases with analyst coverage and decreases with market capitalization, intangibility, and the standard deviation of returns.

In Table 24.3, we estimate the following augmented regression model that includes interaction terms between the soft and hard variables:

$$
\begin{aligned}
ATV_i = {} & \beta_0 + \beta_1 SUFE_i + \beta_2 Optimism_i + \beta_3 Certainty_i + \\
& \beta_4 SUFE_i * Optimism_i + \beta_5 SUFE_i * Certainty_i + \\
& \beta_6 MktCap_i + \beta_7 Analyst_i + \beta_8 Intangibility_i + \beta_9 StdDevRet_i + \varepsilon_i
\end{aligned}
\tag{24.5}
$$

where all variables are defined above. The sample period spans 1994 to 2007 and includes those firms which appeared in the First Call company-issued, guidelines database and for which a matching company press release was found in LexisNexis for a total of 14,938 company-issued, guidance press

Table 24.3 Substitution/Complementary Effects of Soft Information for Earnings Forecast Information

	Coefficient	t stat	*p* value
SUFE×Optimism	0.0062	0.416	0.6771
SUFE×Certainty	0.0201	1.127	0.2597
SUFE	−0.0229	−1.296	0.1951
Optimism	0.0805	4.461	0.0000****
Certainty	−0.0981	−5.473	0.0000****
MktCap	−0.5792	−24.9	0.0000****
Analyst Coverage	0.3125	15.5	0.0000****
Intangibility	−0.0437	−2.302	0.0213**
SD Returns	−0.1018	−4.767	0.0000****
Adj R^2	6.32%		

**** denotes significance at 0.1%, *** at 1%, ** at 5%, and * at 10%.

releases. We control for industry effects, not shown. We are primarily interested in the coefficients on the two interaction terms, *SUFE×Optimism and SUFE×Certainty*. These coefficients allow us to test if there are significant interaction effects between hard and soft information (e.g., the full impact of *Optimism* on *ATV* is composed of a direct effect (measured by β_2) and an indirect or interaction effect (measured by $\beta_4 \times SUFE$). The indirect effects tell us if soft and hard information behave as complements or substitutes to one another. Our results in Table 24.3 show that there are no significant interaction effects for either soft variable. Both interaction coefficients are positive but insignificant. This finding suggests that the impact of *Optimism* and *Certainty* on abnormal trading volume is a direct effect; that is, the impact is not dependent on the level of *SUFE*.

We examine additional interaction effects in Table 24.4. We estimate the following four regressions with interaction terms for each of our control variables (included one at a time):

$$ATV_i = \beta_0 + \beta_1\ SUFE_i + \beta_2\ Optimism_i + \beta_3\ Certainty_i + \beta_4\ ControlVar_i\ * \\ Optimism_i + \beta_5\ ControlVar_i\ * Certainty_i + \beta_6\ MktCap_i + \beta_7\ Analyst_i + \\ \beta_8\ Intangibility_i + \beta_9\ StdDevRet_i + \varepsilon_i \qquad (24.6)$$

where all variables are defined above, and the term *ControlVar* stands for either *MktCap*, *Analyst*, *Intangibility*, or *StdDevRet*, depending on the regression. The sample period spans 1994 to 2007 and includes those firms which appeared in the First Call company-issued, guidelines database and for which a matching company press release was found in LexisNexis for a total of 14,938 company-issued, guidance press releases. We control for industry effects, not shown. We report the results of interacting *MktCap* with our soft information variables in Panel A. The interaction between *Optimism* and *MktCap* is negative and insignificant, while the interaction between *Certainty* and *MktCap* is positive and significant. This latter result suggests that *Certainty* has a larger impact on the trading volume of large firms than small firms. We find a similar interaction effect between *Certainty* and *Intangibility* in Panel C. That is, the interaction between *Optimism* and *Intangibility* is negative and insignificant, while the interaction between *Certainty* and *Intangibility* is positive and significant. *Certainty* has a larger impact on the trading volume of firms with more intangible assets. In contrast, we find no significant interaction effects for *Analyst Coverage* and *StDevRet* in Panels B and D, respectively.

Table 24.4 Substitution/Complementary Effects of Soft Information for Other Firm Characteristics

	Panel A. Market Capitalization	Panel B. Analyst Coverage
	Coefficient	Coefficient
MktCap×*Optimism*	−0.0119	0.0242
MktCap×*Certainty*	0.0763****	−0.0237
SUFE	−0.0236	−0.0251
Optimism	0.0829****	0.0784****
Certainty	−0.1100****	−0.0963****
MktCap	−0.5703****	−0.5804****
Analyst Coverage	0.3117****	0.3119****
Intangibility	−0.0442**	−0.0449**
SD Returns	−0.1074****	−0.1022****
Adjusted R^2	6.43%	6.33%

	Panel C. Intangibility	Panel D. Standard Deviation of Returns
	Coefficient	Coefficient
Intangibility×*Optimism*	−0.0247	0.0116
Intangibility×*Certainty*	0.0466***	−0.0210
SUFE	−0.0243	−0.0249
Optimism	0.0791****	0.0808****
Certainty	−0.1004****	−0.1010****
MktCap	−0.5803****	−0.5797****
Analyst Coverage	0.3141****	0.3127****
Intangibility	−0.0434**	−0.0436**
SD Returns	−0.1052****	−0.1074****
Adjusted R^2	6.37%	6.32%

**** denotes significance at 0.1%, *** at 1%, ** at 5%, and * at 10%.

CONCLUSION

The primary objective of this chapter is to examine the impact of hard (quantitative) versus soft (qualitative) information on trading volume around the release of management earnings forecasts. Our chapter is motivated by the growing literature that links soft information to market reactions, as well as previous studies showing that management forecasts contain value-relevant information. We use textual analysis to identify and measure the level of two soft information variables, *Optimism* and *Certainty*. We hypothesize that these soft information variables will have a

significant impact on trading volume at the time of earnings guidance announcements. Our empirical results confirm this hypothesis. We find a positive and significant relation between abnormal trading volume and *Optimism*, and a negative and significant relation between abnormal trading volume and *Certainty*. In contrast, we do not find a significant relation between abnormal trading volume and our measure of hard information, the standardized unexpected earnings forecast. Overall, our chapter contributes to the growing literature that examines the economic significance of qualitative information.

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MODELING BUBBLES AND ANTI-BUBBLES IN BEAR MARKETS
A Medium-Term Trading Analysis

Dean Fantazzini

ABSTRACT

The current volatile market situation with sudden changes seems all but predictable. However, some recent works have suggested that, prior to crashes as well as after crashes, financial asset prices can be characterized by a power law acceleration decorated with log-periodic oscillations. Johansen and Sornette (1999) and Zhou and Sornette (2005) show that these processes take place because of the traders' herding behavior which can progressively occur and strengthen itself into "bullish" or "bearish" market phases, thus forming bubbles and anti-bubbles, respectively. We briefly review the theory behind this kind of modeling and we perform an empirical analysis with different world stock market indexes to verify whether a medium-term trading strategy based on this modeling can outperform simple buy-and-hold or short-and-hold strategies.

INTRODUCTION

The current global financial crisis which began in 2007 has probably become one of the most interesting examples of how the bursting of a bubble can be dealt with by creating new bubbles. While this consideration may be seen at

first a little bit strong (but not new; see, e.g., Sornette and Woodard, 2009, and references therein), it has been recently confirmed by Lou Jiwei, the chairman of the $298 billion sovereign wealth fund named China Investment Corporation (CIC). This fund was created in 2007 for managing part of the People's Republic of China's foreign exchange reserves, with the specific goal to generate higher returns through advanced asset management techniques. On August 28, 2009, Lou told reporters on the sidelines of a forum organized by the Washington-based Brookings Institution and the Chinese Economists 50 Forum, a Beijing think tank, that "both China and America are addressing bubbles by creating more bubbles and we're just taking advantage of that. So we can't lose." Moreover, asked whether CIC would be a keen buyer in the United States, Lou said, "CIC can buy anywhere in the world, but it cannot avoid buying U.S. assets because the U.S. economy and capital markets are so large." Besides, Lou added that "CIC was building a broad investment portfolio that includes products designed to generate both alpha and beta; to hedge against both inflation and deflation; and to provide guaranteed returns in the event of a new crisis." See the full Reuters article by Zhou Xin and Alan Wheatley (2009) at http://www.reuters.com/article/ousiv/idUSTRE57S0D420090829 for more details. Clearly, the previous comments highlight how important is to have an appropriate model for bubbles and so-called anti-bubbles, which refer to the period following the burst of a bubble.

A model which has quickly gained a lot of attention among practitioners and academics due to many successful predictions is the so-called *log periodic power law* (LPPL) model proposed by Sornette, Johansen, and Bouchaud (1996), Sornette and Johansen (1997), Johansen, Ledoit, and Sornette (2000), and Sornette (2003). These authors suggested that, prior to crashes, the mean function of an index price time-series is characterized by a power law acceleration decorated with log-periodic oscillations, leading to a finite-time singularity that describes the onset of the market crash. Within this model, this behavior would hold for months and years in advance, allowing the anticipation of the crash from the log-periodic oscillations exhibited by the prices. The underlying hypothesis of this model is the existence of a growing cooperative action of the market traders due to an imitative behavior among them. Particularly, Johansen, Ledoit, and Sornette (2000) put forward the idea that stock market crashes are caused by the slow build up of long-range correlations leading to a collapse of the

stock market in one critical instant. For a recent review of the theoretical framework of the log-periodic model and a compilation of empirical evidences, see Sornette (2003). Johansen and Sornette (1999) and Zhou and Sornette (2005) addressed the problem of whether there exist critical times t_c at which the market peaks and then follows a power law decrease with decelerating log-periodic oscillations; in the latter case we have a so called anti-bubble. Johansen and Sornette (1999) and Zhou and Sornette (2005) showed that the traders' herding behavior can progressively occur and strengthen itself also in "bearish" decreasing market phases, thus forming anti-bubbles with decelerating market devaluations following market peaks.

What we do in this chapter is to briefly review the theory behind this kind of modeling and perform an empirical analysis with different world stock market indexes to verify whether a medium-term trading strategy based on this modeling can outperform simple buy-and-hold or short-and-hold strategies.

The rest of the chapter is organized as follows. In the second section of this chapter, we review the log-periodic models for bubble and anti-bubble modeling, and in the third section we show an empirical application with world stock market indexes. We perform an out-of-sample analysis in this chapter's fourth section, and the fifth section briefly concludes.

LOG-PERIODIC MODELS: A REVIEW

Johansen, Ledoit, and Sornette (2000) considered an ideal market in a scenario purely speculative that does not pay dividends. For simplicity, interest rates, risk aversion, and market liquidity constraints are ignored. In this scenario, there is at least a rational agent, risk neutral and with rational expectations. Given these assumptions, the price at time t, $p(t)$, of financial assets should follow a martingale stochastic process. If we consider that there is a nonzero probability of a *crash* taking place, formally, we can define a counter function for the occurrence of the crash, given by a step function $j(t) = \Omega(t-t_c)$ whose value is zero before the crash and one after the occurrence of the crash at the time t_c. Since t_c is unknown, it is described by a stochastic variable subject to a probability density function $q(t)$ and a cumulative distribution function $Q(t) = \int_{-\infty}^{\infty} q(t')dt'$. If we define the hazard rate $h(t)$ as the probability per unit of time of the crash taking place in the next instant, given that it has not yet occurred, that is

$h(t) = q(t)/[1 - Q(t)]$, then the martingale condition implies that the expected price rise must be just sufficient to compensate for the known risk of a crash. As a consequence, the dynamics of the price is given by

$$dp = k\, p(t)\, h(t)\, dt \qquad (25.1)$$

where dp is the price change over the time interval dt, while $k \in (0,1)$ is the fixed proportion by which the price is expected to drop, and we remark that all the terms on the right hand side of Equation (25.1) are positive. If we reorder the previous equation, we have $dp/p(t) = k\, h(t)\, dt$, and after integrating we get

$$\ln p(t) = k \int_{t_0}^{t} h(t')dt' \quad \text{or} \quad p(t) = p(t_0)\exp\left(k\int_{t_0}^{t} h(t')dt' \right) \qquad (25.2)$$

Equation (25.2) shows an interesting result: the higher the probability of a crash (given it has not yet taken place), the faster the price growth has to be. Intuitively, investors must be compensated with higher returns for the risk of higher losses. The significant deviation of prices in relation to its fundamental value for long periods of time is an issue still being debated in financial literature and in particular has been examined by Blanchard (1979), who introduced a model for bubble with rational expectations.

This effect is not particular to the specific dynamics described by Equation (25.2). If we alternatively assume that *during the crash the price drops a fixed percentage $k \in (0,1)$ of the speculative price increase in relation to a certain fundamental value p^**, then the dynamics of the price before the of the crash is given by

$$dp = k\, [p(t) - p^*]\, h(t)\, dt \qquad (25.3)$$

If we integrate Equation (25.3) and assume that $p(t) - p(t_0) << p(t_0) - p^*$, we have

$$p(t) = p(t_0) + k\int_{t_0}^{t}(p(t') - p^*)h(t')dt' = p(t_0) + k(p(t_0) - p^*)k\int_{t_0}^{t}h(t')dt' \qquad (25.4)$$

The model therefore does not impose any constraint on the dimension of the crash: if we assume that it is proportional to the current market price, then we have to deal with the natural logarithm of prices, as shown by Equation (25.1) and Equation (25.2). Instead, if we assume that the amplitude of the crash is a fraction of the gain observed during the bubble, then the variable to consider is the price in levels, according to Equation (25.3) and Equation (25.4). In both cases, conditionally on staying in a bubble with no crash occurrence, the asset price should grow rationally to compensate buyers for taking the risk of a market crash.

However, it is important to remark that there is a small probability that the system, starting from time t, will reach the end of the bubble without the occurrence of a crash

$$1 - \int_t^{t_c} h(t)dt \tag{25.5}$$

This residual probability is crucial for the consistency of the model because, otherwise, the agents would anticipate the crash and quit the market.

According to Equation (25.2) or Equation (25.4), the temporal evolution of prices during the bubble depends on the hazard rate $h(t)$, whose determination is developed by using models coming from statistical physics.

Johansen, Ledoit, and Sornette (2000) propose a model where each trader i can be in one of two states, either bull ($s_i = +1$) or bear ($s_i = -1$), while at the next time step the state of trader is determined by the following formula:

$$s_i = sign\left(K \sum_{j \in N(i)} s_j + \sigma \varepsilon_i\right) \tag{25.6}$$

where K is an imitation factor, $N(i)$ is the group of neighboring traders who influence trader i, σ is the tendency towards idiosyncratic behavior amongst all traders, whereas ε_i is a random draw from a standard normal distribution. Moreover, they assume that during a bubble the value of K increases until it reaches a critical value K_c, and this increase is developed such that $K_c - K(t)$ depends on the time span $t_c - t$. As a consequence, the hazard rate h varies in the same way as K/K_c.

By using these assumptions, Johansen, Ledoit, and Sornette (2000) show that the hazard rate follows the following dynamics (the meaning of the parameters will be defined following Equation (25.10)):

$$h(t) \approx B'(t_c - t)^{-\alpha} [1 + C'\cos(\omega \ln (t_c - t) + \phi']$$ (25.7)

If we substitute the previous expression Equation (25.7) in Equation (25.2),

$$\ln p(t) = k \int_{t_0}^{t} B'(t_c - t')^{-\alpha}[1 + C' \cos(\omega \ln (t_c - t') + \phi']dt'$$ (25.8)

and then substitute $\beta = 1 - \alpha$ and $\psi(t) = \omega \ln(t_c - t) + \phi'$ in the integral, we get

$$\int (t_c - t)^{-\alpha} \cos(\omega \ln (t_c - t) + \phi']dt = \int (t_c - t)^{\beta-1} \cos \psi(t)$$
$$dt = \frac{-(t_c - t)^{\beta}}{\omega^2 + \beta^2}\{\omega \sin \psi(t) + \beta \cos \psi(t)\}$$ (25.9)

Finally, if we integrate Equation (25.8) by using Equation (25.9) and we perform the following change of variables, $A = \ln p(t_c)$, $B = -k\ B'/\beta$, $C = \beta^2 C'/(\omega^2 + \beta^2)$, we obtain the famous LPPL equation used by Sornette and his co-authors in many works.

$$\ln p(t) \approx A + B(t_c - t)^{\beta}[1 + C \cos(\omega \ln (t_c - t) + \phi]$$ (25.10)

where $t < t_c$ is any time before the bubble, $A > 0$ is the value of $\ln p(t_c)$ at the critical time, $B < 0$ the increase in $\ln p(t)$ over the time unit before the crash if C were to be close to zero, $C \neq 0$ is the proportional magnitude of the oscillations around the exponential growth, β should be positive to ensure a finite price at the critical time t_c of the bubble and quantifies the primary power law acceleration of prices, $t_c > 0$ is the critical time, ω is the frequency of the oscillations during the bubble, while $0 \leq \phi \leq 2\pi$ is a phase parameter.

A similar procedure can be followed in case of Equation (25.4) and we would obtain an Equation very close to Equation (25.10), with the only difference being the dependent variable given by the price in levels instead of the log price. The two crucial parameters in this specification are β and ω; Johansen, Ledoit, and Sornette (2000), Sornette (2003), and references therein show that for the underlying mechanism to be validated β should be included in $0 < \beta < 1$, while $4 < \omega < 15$. By using a large collection of empirical evidence they found that $\beta = 0.33 \pm 0.18$, while $\omega = 6.36 \pm 1.56$.

However, we want to remark that even though the specific underlying theoretical mechanism is not always validated (for example, it is not unusual to find $\beta > 1$), the LPPL with suitable parameters can provide a good fit to the examined bubble and help forecasting its future development. For more discussion about these issues as well as recent criticism, we refer the interested reader to Chang and Feigenbaum (2006) and Lin Ren, and Sornette (2010).

Johansen and Sornette (1999) and Zhou and Sornette (2005) examined the problem of whether the cooperative herding behavior of traders might also produce market evolutions that are symmetric to the accelerating speculative bubbles often ending in crashes. They show that there seems to exist critical times t_c at which the market peaks and then decreases following a power law with decelerating log-periodic oscillations; in the latter case we have a so called anti-bubble. Therefore, given this symmetric nature of anti-bubbles, a straightforward way to model them is by simply inverting the term $(t_c - t)$ in Equation (25.10).

$$\ln p(t) \approx A + B(t - t_c)^\beta [1 + C \cos(\omega \ln (t - t_c) + \phi] \qquad (25.11)$$

$$p(t) \approx A + B(t - t_c)^\beta [1 + C \cos(\omega \ln (t - t_c) + \phi] \qquad (25.12)$$

if we use log prices or if we use price in levels, instead. Clearly, in the latter case the values of the parameters A, B, C will be much different with respect to the corresponding ones obtained with Equation (25.11), while the parameters β, ω, and φ should have similar values in both the two specifications.

Due to space limits, we do not discuss here about model estimation: we only remark that even though Equations (25.10), (25.11), and (25.12) can

be estimated by nonlinear least squares, these formula are highly nonlinear and local maxima are very easy to find. Therefore, Johansen, Ledoit, and Sornette (2000) proposed a multistep procedure involving grid searches as well as the use of the Nelder-Mead simplex search. The estimation of such models is not an easy task and the author of this chapter has used a new alternative method which seems to be very promising, but still needs more beta-testing and future work. We leave this as avenue for future research. Anyway, some computational tips will be described in the next section.

EMPIRICAL ANALYSIS WITH WORLD STOCK MARKET INDEXES

We report below the in-sample estimation results for Equations (25.11) and (25.12) for the most important world stock market indexes (the time t is converted in units of one year, $1/365 = 0.002739...$). We found that estimating LPPL for anti-bubbles was much easier when using a single-digit time variable t, for example "9", instead of a triple-digit variable "2009." Furthermore, estimating models with log-prices was much simpler than models with prince in levels: in the latter case a more careful choice of the starting values has to be made. Interestingly, we noticed that *if a time series was clearly NOT following a LPPL anti-bubble pattern*, then the *model using prices in levels was never able to reach numerical convergence*, even after a careful choice of starting values. Instead, the *model using log-prices always converged but with the parameters $\beta > 1$ and $\omega < 4$.*

To increase estimation efficiency and to reduce the parameter space, we used here for the first time the following computational solution: differently from bubbles, *when we work with anti-bubbles we do know the date of the global maxima* as well as the corresponding price. As a consequence, the parameter t_c *need not be estimated and can be fixed a priori*. The same solution can be implemented for A, but we found it less crucial, from a numerical point of view, than fixing t_c. The estimated parameters for the model with log-prices in Equation (25.11) and prices in levels in Equation (25.12), as well as the fitted series are reported below for each stock market index.

German DAX Index (12/12/2007–08/20/2009)

Figure 25.1 DAX Index and Fitted Series from Model 25.11 and Model 25.12
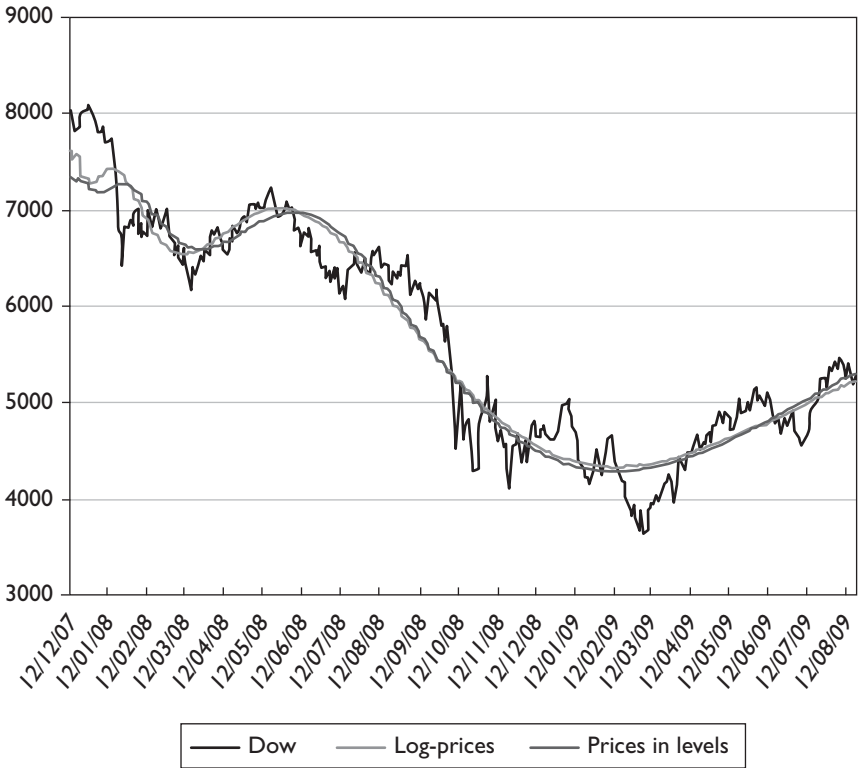
Table 25.1 DAX, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-Prices
A	7,644.31	8.90
B	−2,078.80	−0.30
Beta	0.72	1.15
C	998.83	0.19
Omega	4.08	4.49
Phi	3.02	3.07

U.S. Dow Jones Index (10/09/2007–08/20/2009)

Figure 25.2 Dow Jones Index and Fitted Series from Model 25.11 and Model 25.12

| | Dow | Log-prices | Prices in levels |
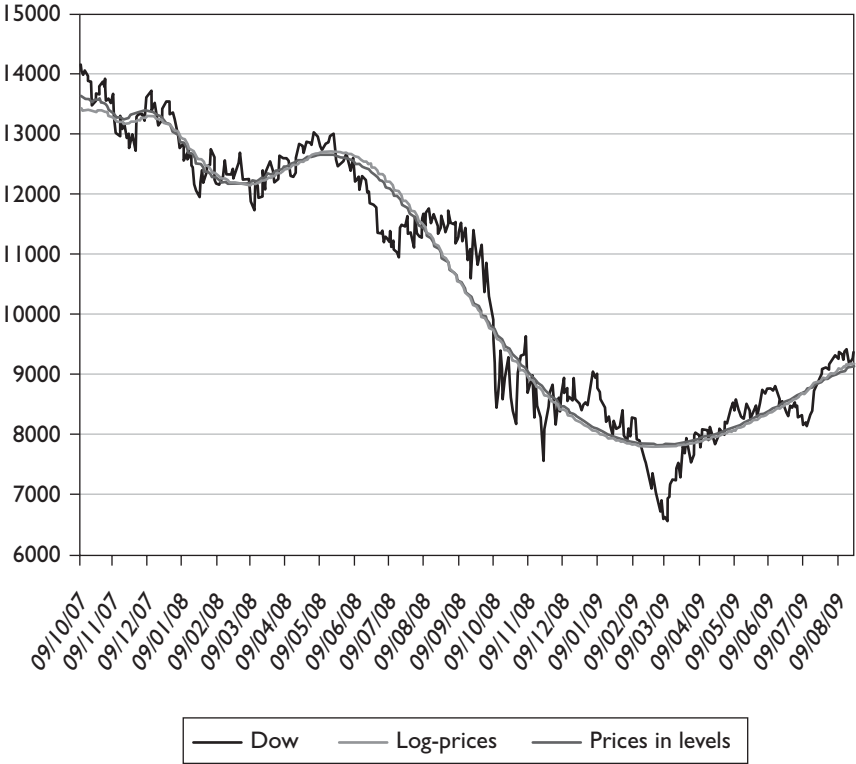
Table 25.2 Dow Jones, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-Prices
A	13,659.53	9.51
B	−3,052.60	−0.24
Beta	1.05	1.35
C	1,388.09	0.14
Omega	4.82	4.97
Phi	2.24	2.22

(Figures for the market indexes in Tables 25.3 to 25.7 are not reported due to space limits).

British FTSE Index (10/12/2007–08/20/2009)

Table 25.3 FTSE, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-Prices
A	13659.53	9.51
B	−3052.60	−0.24
Beta	1.05	1.35
C	1,388.09	0.14
Omega	4.82	4.97
Phi	2.24	2.22

Korean KOSPI Index (10/31/2007–08/20/2009)

Table 25.4 KOSPI, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-prices
A	1,975.55	7.57
B	−510.36	−0.29
Beta	0.68	0.92
C	292.32	0.21
Omega	4.65	4.82
Phi	2.84	2.86

Italian MIBTel Index (10/12/2007–08/20/2009)

Table 25.5 MIBTel, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-Prices
A	40,991.96	10.59
B	−15,392.28	−0.45
Beta	0.82	1.14
C	3,924.46	0.17
Omega	5.16	5.37
Phi	2.31	2.19

Japanese Nikkei Index (07/09/2007–08/20/2009)

Table 25.6 Nikkei, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-Prices
A	17,617.62	9.76
B	−5,301.38	−0.35
Beta	0.90	1.19
C	1,525.32	0.14
Omega	7.58	7.61
Phi	0.35	0.33

Brazilian Bovespa Index (05/28/2008–08/20/2009)

Table 25.7 Bovespa, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-Prices
A	Not converged	11.09
B	Not converged	−1.31
Beta	Not converged	1.65
C	Not converged	−1.18
Omega	Not converged	2.21
Phi	Not converged	2.66

U.S. S&P 500 Index (10/09/2007–08/20/2009)

Table 25.8 S&P 500, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-Prices
A	1518.69	7.31
B	−375.51	−0.28
Beta	1.01	1.33
C	174.34	0.16
Omega	5.07	5.27
Phi	2.17	2.16

Figure 25.3 S&P 500 Index and Fitted Series from Model 25.11 and Model 25.12
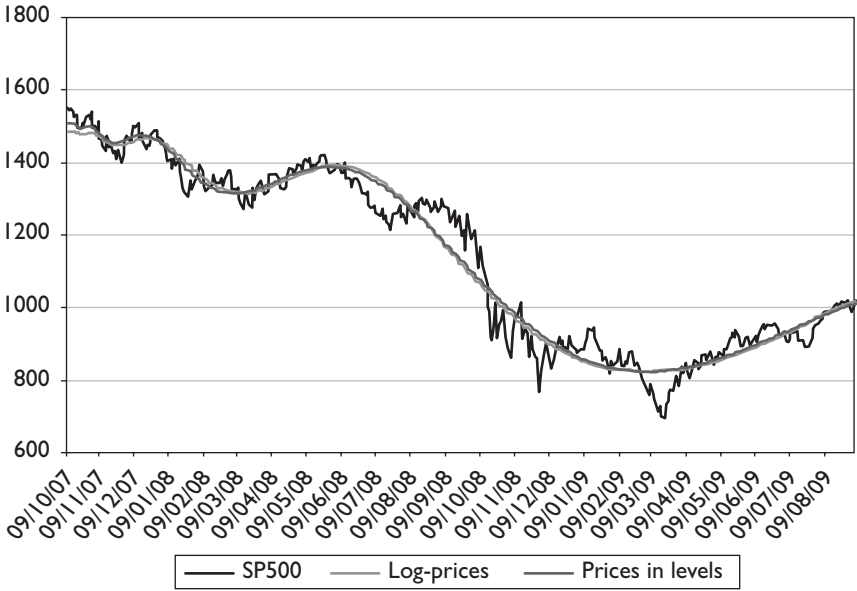
Russian RTS Index (05/19/2008–08/20/2009)

Figure 25.4 RTS Index and Fitted Series from Model 25.11 and Model 25.12
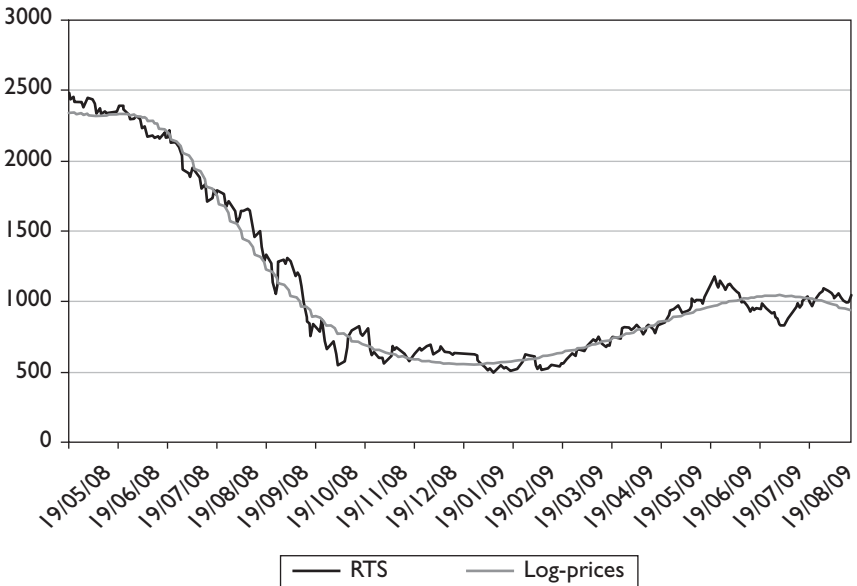
Table 25.9 RTS, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-Prices
A	Not converged	7.76
B	Not converged	−3.38
Beta	Not converged	**2.01**
C	Not converged	−2.81
Omega	Not converged	**2.49**
Phi	Not converged	**2.63**

Chinese SSE Composite Index (10/16/2008–08/20/2009)

Figure 25.5 SSE Composite Index

Table 25.10 Shanghai Composite, Fitted Parameters Model 25.11 and Model 25.12

	Prices in Levels	Log-Prices
A	Not converged	Not converged
B	Not converged	Not converged
Beta	Not converged	Not converged
C	Not converged	Not converged
Omega	Not converged	Not converged
Phi	Not converged	Not converged

Comments on Anti-bubble Empirical Results

The previous analysis highlights some interesting results: the log-periodic model 25.11, which considers log-prices reached numerical convergence in almost all cases, but at the same time the parameter β was almost always greater than 1, thus invalidating the underlying theoretical mechanism. Instead, the model which makes use of the prices in levels almost always showed values of β included between 0 and 1, and similarly $4 < \omega < 15$ (except for the U.S. markets; see discussion below); therefore, our analysis seems to support the assumption that the speculative price decreases in relation to a certain fundamental value p^*; see Equations (25.3) and (25.4). Moreover, when the model using price in levels did not converge, such as for the Chinese, Russian, and Brazilian markets, it is clear by looking at the market plots that we are *not* in front of a possible anti-bubble structure; see Figures 25.4 and 25.5.

Interestingly, the markets which most benefited from state intervention, like the U.S., Russian, and Chinese markets, are the ones for which the estimated coefficient β was greater than 1, or for which the log-periodic model (in price levels) did not converge. We remind that β is the parameter governing the bubble growth and should be positive to ensure a finite price at the critical time t_c of the anti-bubble. In this regard, Zhou and Sornette (2005) highlighted that the cumulative effect of strong exogenous shocks, such as the U.S. Federal Reserve interest rate and monetary policies can progressively detune the anti-bubble pattern; this seems exactly what has happened with the U.S., Russian, and Chinese markets, where the massive injections of liquidity in the market has strongly modified the log-periodic

structure. However, did these huge money injections finish to build up new market bubbles?

Bubbles in Bear Markets

Bastiaensen et al. (2009) were the first to analyze the bubble nature of the market growth in the SSE Composite Index in July 2009, a month in advance of the subsequent crash. They noted that "the Shanghai Composite is the best performing large stock market in 2009 and is up 65 percent for the year, and rising. To reach a targeted GDP growth of 8 percent, Chinese policy has turned to a bank model of massive lending, which has provided China with sufficient liquidity to fuel this bubble." Moreover, they predicted that "the Shanghai Composite Index will reach a critical level around July 17–27, 2009." The market peaked on August 4, 2009, and then lost 20 percent in two weeks.

We repeat the previous analysis with a new computational methodology still under development (as previously anticipated) but very promising, and we consider also the case for the U.S. S&P 500 in August 2009, for the Russian RTS market in May 2009, and the S&P 500 in July 2007 for sake of comparison, being that the peak of the market in the decade. The in-sample results for the model given by Equation (25.10), computed using data spanning from the global minima until one day before the market peak, are reported in Table 25.11.

Not surprisingly, all four markets show very similar estimated parameters, particularly with respect to the key coefficients β and ω. Besides, we

Table 25.11 In-sample Fitted Parameters for Model 25.10

	S&P 500 2007	S&P 500 2009	SSE 2009	RTS 2009
A	7.346	6.950	8.243	6.989
B	−0.171	−0.498	−0.854	−1.804
Beta	**0.801**	**0.778**	**0.552**	**0.818**
C	0.037	−0.143	−0.031	0.207
Omega	**5.140**	**4.102**	**5.702**	**6.371**
Phi	3.035	2.180	3.952	5.931
t_c	**7.534**	**9.657**	**9.599**	**9.412**
Estimation	06/13/2006–	03/09/2009	11/04/2008–	01/23/2009
Sample	07/12/2007–	08/28/2009	07/31/2009–	05/29/2009

Figure 25.6 Crash Lock-in Plots for the S&P 500, SSE Composite, and Russian RTS Indexes
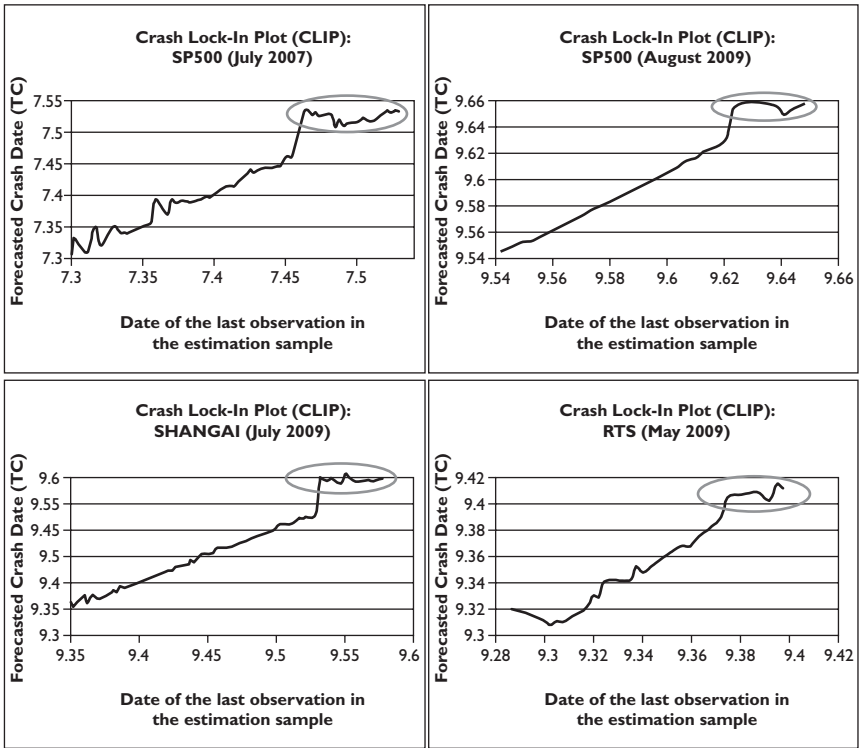
want to propose here a graphical tool that we found extremely useful to track the development of a bubble and to understand if a possible crash is in sight, or at least a bubble deflation: we plot on the horizontal axis the *date of the last observation in the estimation sample*, and on the vertical axis the *forecasted crash date* $\hat{t}_c$. If a change in the stock market regime is approaching, the (recursively) estimated $\hat{t}_c$ should stabilize around a constant value close to the turning point. We called such a plot the crash lock-in plot (CLIP). We report in Figure 25.6 the CLIPs for the previous four cases.

OUT-OF-SAMPLE EMPIRICAL ANALYSIS

We now examine the out-of-sample performances of the anti-bubble models and compare them with simple *buy-and-hold* and *short-and-hold* strategies.

We consider two possible ways to employ the previous log-periodic models 25.11 and 25.12:

- **STRATEGY A:** *Estimate the model once and then buy or short the underlying market index depending on the forecasted path: a forecasted positive slope imply a buy (long) position, while a negative slope a sell (short) position.* We consider as possible length for the initialization sample the following cases: 25, 50, 100, 200 days.

- **STRATEGY B:** *Re-estimate recursively the model every* h *days, compute the corresponding* h-*step-ahead forecast, and rebalance the portfolio accordingly: if the* h-*step-ahead forecast is higher than the current price, open a long position, and if it is lower open a short position.* We consider here only the market where both log-periodic models converged, and the U.S. markets, too, even though we remark that their estimated coefficients β were slightly greater than 1, thus representing a sort of borderline case. We consider the following possible values for *h*: 25, 50, 100 days.

Due to space limits we report below the results only for two indexes: DAX, SP500.

As it is possible to observe by looking at Tables 25.12 to 25.15, log-periodic models can outperform not only the simple buy-and-hold strategy (which is easy, given that we are in a bear market), but also the short-and-hold strategy, with better returns with basically the same (daily) risk measures. We also note that model 25.12 which uses prices in levels sometimes delivers higher returns than the model in log-prices 25.11; however, this result depends crucially on the length of the initialization sample used and model 25.12 is usually more difficult to estimate than model 25.11. Furthermore, there seems to be an optimal length for the initialization sample (for strategy A) and the forecasting step *h* (for strategy B); approximately 100 days for the initialization sample if strategy A is employed; instead, if strategy B is chosen, the optimal time length *h* to rebalance the portfolio is usually between 25 and 50 days. Moreover, strategy B outperforms the short-and-hold strategy more frequently than strategy A (these results are also confirmed by the stock market indexes not reported here for sake of space).

Table 25.12 Out-of-Sample Results for DAX Index, Model 25.11 with Log-Prices

Log-periodic model in LOG-PRICES (2.11)	Cumulative Performance (%)	Std.Dev (%)	Skewness	Kurtosis	VaR (99%)	VaR (99.9%)	ES (99%)	ES (99.9%)
STRATEGY A (25 days)	−4.09%	0.72%	−0.55	26.73	1.88%	4.27%	3.12%	4.64%
Buy-and-Hold	−24.26%	2.24%	0.38	6.94	5.76%	10.69%	8.39%	10.74%
Short-and-Hold	24.26%	2.24%	−0.38	6.94	6.06%	7.27%	6.75%	7.30%
STRATEGY A (50 days)	21.44%	2.25%	−0.39	7.04	6.06%	7.27%	6.89%	7.30%
Buy-and-Hold	−27.58%	2.25%	0.40	7.05	5.90%	10.69%	8.92%	10.74%
Short-and-Hold	27.58%	2.25%	−0.40	7.05	6.06%	7.27%	6.89%	7.30%
STRATEGY A (100 days)	−48.62%	2.35%	0.48	6.83	5.23%	10.69%	8.78%	10.74%
Buy-and-Hold	−28.12%	2.35%	0.41	6.75	5.90%	10.69%	8.92%	10.74%
Short-and-Hold	28.12%	2.35%	−0.41	6.75	6.06%	7.27%	6.89%	7.30%
STRATEGY A (200 days)	9.75%	2.67%	−0.37	5.71	6.71%	7.27%	7.10%	7.30%
Buy-and-Hold	−8.93%	2.67%	0.36	5.71	7.36%	10.69%	9.67%	10.74%
Short-and-Hold	8.93%	2.67%	−0.36	5.71	6.71%	7.27%	7.10%	7.30%
STRATEGY B (25 days)	34.36%	2.25%	−0.39	6.93	6.06%	7.27%	6.89%	7.30%
Buy-and-Hold	−26.35%	2.25%	0.39	6.91	5.90%	10.69%	8.92%	10.74%
Short-and-Hold	26.35%	2.25%	−0.39	6.91	6.06%	7.27%	6.89%	7.30%
STRATEGY B (50 days)	61.11%	2.30%	−0.45	7.02	6.06%	7.27%	6.89%	7.30%
Buy-and-Hold	−39.33%	2.31%	0.44	6.95	5.90%	10.69%	8.92%	10.74%
Short-and-Hold	39.33%	2.31%	−0.44	6.95	6.06%	7.27%	6.89%	7.30%
STRATEGY B (100 days)	33.95%	2.42%	−0.39	6.57	6.71%	7.27%	7.10%	7.30%
Buy-and-Hold	−39.87%	2.42%	0.46	6.60	7.36%	10.69%	9.67%	10.74%
Short-and-Hold	39.87%	2.42%	−0.46	6.60	6.71%	7.27%	7.10%	7.30%

Table 25.13 Out-of-Sample Results for DAX Index, Model 25.12 with Prices in Levels

Log-periodic model PRICES IN LEVELS (2.12)	Cumulative Performance (%)	Std.Dev (%)	Skewness	Kurtosis	VaR (99%)	VaR (99.9%)	ES (99%)	ES (99.9%)
STRATEGY A (25 days)	−7.20%	0.27%	−16.55	290.09	0.00%	0.00%	0.00%	0.00%
Buy-and-Hold	−24.26%	2.24%	0.38	6.94	5.76%	10.69%	8.39%	10.74%
Short-and-Hold	24.26%	2.24%	−0.38	6.94	6.06%	7.27%	6.75%	7.30%
STRATEGY A (50 days)	82.62%	2.24%	−0.48	7.26	6.06%	7.27%	6.89%	7.30%
Buy-and-Hoid	−27.58%	2.25%	0.40	7.05	5.90%	10.69%	8.92%	10.74%
Short-and-Hold	27.58%	2.25%	−0.40	7.05	6.06%	7.27%	6.89%	7.30%
STRATEGY A (100 days)	24.29%	2.35%	0.37	6.87	5.15%	10.69%	8.34%	10.74%
Buy-and-Hold	−28.12%	2.35%	0.41	6.75	5.90%	10.69%	8.92%	10.74%
Short-and-Hold	28.12%	2.35%	−0.41	6.75	6.06%	7.27%	6.89%	7.30%
STRATEGY A (200 days)	9.75%	2.67%	−0.37	5.71	6.71%	7.27%	7.10%	7.30%
Buy-and-Hold	−8.93%	2.67%	0.36	5.71	7.36%	10.69%	9.67%	10.74%
Short-and-Hold	8.93%	2.67%	−0.36	5.71	6.71%	7.27%	7.10%	7.30%
STRATEGY B (25 days)	53.70%	2.25%	−0.38	6.98	6.06%	7.27%	6.89%	7.30%
Buy-and-Hold	−26.35%	2.25%	0.39	6.91	5.90%	10.69%	8.92%	10.74%
Short-and-Hold	26.35%	2.25%	−0.39	6.91	6.06%	7.27%	6.89%	7.30%
STRATEGY B (50 days)	22.24%	2.31%	−0.39	6.89	6.06%	7.27%	6.89%	7.30%
Buy-and-Hold	−39.33%	2.31%	0.44	6.95	5.90%	10.69%	8.92%	10.74%
Short-and-Hold	39.33%	2.31%	−0.44	6.95	6.06%	7.27%	6.89%	7.30%
STRATEGY B (100 days)	1.48%	2.43%	−0.34	6.48	6.71%	7.27%	7.10%	7.30%
Buy-and-Hold	−39.87%	2.42%	0.46	6.60	7.36%	10.69%	9.67%	10.74%
Shiort-and-Hold	39.87%	2.42%	−0.46	6.60	6.71%	7.27%	7.10%	7.30%

Table 25.14 Out-of-Sample Results for S&P500 Index, Model 25.11 with Log-Prices

Log-periodic model in LOG-PRICES (2.11)	Cumulative Performance (%)	Std.Dev (%)	Skewness	Kurtosis	VaR (99%)	VaR (99.9%)	ES (99%)	ES (99.9%)
STRATEGY A (25 days)	84.59%	2.32%	0.12	6.61	6.84%	9.35%	8.29%	9.41%
Buy-and-Hold	−35.67%	2.32%	−0.07	6.60	6.17%	10.25%	7.86%	10.60%
Short-and-Hold	35.67%	2.32%	0.07	6.60	6.31%	9.35%	8.20%	9.41%
STRATEGY A (50 days)	−27.72%	2.36%	−0.04	6.50	6.13%	10.25%	7.75%	10.60%
Buy-and-Hold	−36.76%	2.36%	−0.07	6.49	6.17%	10.25%	7.86%	10.60%
Short-and-Hold	36.76%	2.36%	0.07	6.49	6.31%	9.35%	8.20%	9.41%
STRATEGY A (100 days)	36.31%	2.47%	0.17	6.12	6.84%	9.47%	8.74%	9.86%
Buy-and-Hold	−27.88%	2.47%	−0.07	6.14	6.27%	10.25%	8.20%	10.60%
Short-and-Hold	27.88%	2.47%	0.07	6.14	6.95%	9.35%	8.58%	9.41%
STRATEGY A (200 days)	44.89%	2.78%	0.07	5.17	7.92%	9.35%	8.99%	9.41%
Buy-and-Hold	−21.78%	2.78%	−0.08	5.17	6.69%	10.25%	8.68%	10.60%
Short-and-Hold	21.78%	2.78%	0.08	5.17	7.92%	9.35%	8.99%	9.41%
STRATEGY B (25 days)	56.86%	2.36%	0.36	6.35	6.84%	10.25%	8.93%	10.60%
Buy-and-Hold	−41.11%	2.37%	−0.05	6.41	6.17%	10.25%	7.86%	10.60%
Short-and-Hold	41.11%	2.37%	0.05	6.41	6.31%	9.35%	8.20%	9.41%
STRATEGY B (50 days)	57.74%	2.41%	0.11	6.29	6.69%	10.25%	8.79%	10.60%
Buy-and-Hold	−42.20%	2.41%	−0.05	6.30	6.27%	10.25%	8.20%	10.60%
Short-and-Hold	42.20%	2.41%	0.05	6.30	6.95%	9.35%	8.58%	9.41%
STRATEGY B (100 days)	38.13%	2.67%	0.02	5.52	7.92%	9.35%	8.99%	9.41%
Buy-and-Hold	−38.13%	2.67%	−0.02	5.52	6.69%	10.25%	8.68%	10.60%
Short-and-Hold	38.13%	2.67%	0.02	5.52	7.92%	9.35%	8.99%	9.41%

Table 25.15 Out-of-Sample Results for S&P500 Index, Model 25.12 with Prices in Levels

Log-periodic model PRICES IN LEVELS (2.12)	Cumulative Performance (%)	Std.Dev (%)	Skewness	Kurtosis	VaR (99%)	VaR (99.9%)	ES (99%)	ES (99.9%)
STRATEGY A (25 days)	−21.54%	2.32%	−0.23	6.58	5.41%	9.35%	7.40%	10.16%
Buy-and-Hold	−35.67%	2.32%	−0.07	6.60	6.17%	10.25%	7.86%	10.60%
Short-and-Hold	35.67%	2.32%	0.07	6.60	6.31%	9.35%	8.20%	9.41%
STRATEGY A (50 days)	−13.03%	2.36%	0.25	6.51	6.27%	10.25%	8.37%	10.60%
Buy-and-Hold	−36.76%	2.36%	−0.07	6.49	6.17%	10.25%	7.86%	10.60%
Short-and-Hold	36.76%	2.36%	0.07	6.49	6.31%	9.35%	8.20%	9.41%
STRATEGY A (100 days	23.57%	2.47%	0.18	6.12	6.84%	9.47%	8.74%	9.86%
Buy-and-Hold	−27.88%	2.47%	−0.07	6.14	6.27%	10.25%	8.20%	10.60%
Short-and-Hold	27.88%	2.47%	0.07	6.14	6.95%	9.35%	8.58%	9.41%
STRATEGY A (200 days	46.14%	2.78%	0.07	5.18	7.92%	9.35%	8.99%	9.41%
Buy-and-Hold	−21.78%	2.78%	−0.08	5.17	6.69%	10.25%	8.68%	10.60%
Short-and-Hold	21.78%	2.78%	0.08	5.17	7.92%	9.35%	8.99%	9.41%
STRATEGY B (25 days)	54.68%	2.36%	0.37	6.35	6.84%	10.25%	8.93%	10.60%
Buy-and-Hold	−41.11%	2.37%	−0.05	6.41	6.17%	10.25%	7.86%	10.60%
Short-and-Hold	41.11%	2.37%	0.05	6.41	6.31%	9.35%	8.20%	9.41%
STRATEGY B (50 days)	57.74%	2.41%	0.11	6.29	6.69%	10.25%	8.79%	10.60%
Buy-and-Hold	−42.20%	2.41%	−0.05	6.30	6.27%	10.25%	8.20%	10.60%
Short-and-Hold	42.20%	2.41%	0.05	6.30	6.95%	9.35%	8.58%	9.41%
STRATEGY B (100 days)	38.13%	2.67%	0.02	5.52	7.92%	9.35%	8.99%	9.41%
Buy-and-Hold	−38.13%	2.67%	−0.02	5.52	6.69%	10.25%	8.68%	10.60%
Short-and-Hold	38.13%	2.67%	0.02	5.52	7.92%	9.35%	8.99%	9.41%

CONCLUSION

We reviewed the theory of log-periodic models for bubble and anti-bubble modeling and we performed an empirical analysis with different world stock market indexes to verify whether a medium-term trading strategy based on these models can outperform simple buy-and-hold or short-and-hold strategies. We found that these models can outperform both the buy-and-hold strategy (easy) and the short-and-hold strategy, but this result depends crucially on the initialization sample and/or the frequency for portfolio rebalancing, where the latter is usually between 25 and 50 days.

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STRATEGIC FINANCIAL INTERMEDIARIES WITH BROKERAGE ACTIVITIES

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ABSTRACT

In this chapter, we study the strategic use by banks of their brokerage activities. We consider a situation where N competing banks are engaged in brokerage activities and have access to private information about the liquidation value of a risky asset. Selling brokerage activities, banks collect orders from their clients and can use their brokerage divisions to enhance their own profits. This order flow is considered in our model as uninformative, i.e., as being noise. The banks' ability to observe part of the total order flow, i.e., its own volume and the one of its clients, even though it does not incorporate any private information, gives valuable information concerning the level of noise trading in the market. We show that taking advantage of that information, i.e., the strategic use of their brokerage activities, increases the banks' expected profits. However, we prove that the aggregate expected profit is lower when banks strategically use their brokerage activities.

INTRODUCTION

Investment banks and financial institutions invest in the collection and the production of information; in particular, they possess their own research divisions. One of the uses of this information is proprietary trading whereby banks trade for their own account. Nevertheless, financial institutions may have other sources of information. They can infer private information from their clients. Indeed, some banks may know that some of their clients have private information and infer that private information from their clients' trading. Moreover, as financial institutions can also act as brokers and transmit noninformative orders on behalf of their customers, they are also able to infer part of the total order flow observed by market makers. This duality in the role of banks that on the one hand act as traders and on the other hand act as brokers can induce a conflict of interest between the clients and the financial institutions as the banks could use their clients' information strategically.

Empirical evidence in Michaely and Womack (1999) shows a particular conflict of interest faced by investment banks. On the one hand, they have incentives to transmit reliable information to their customers to maintain their reputation. On the other hand, they can use this information for serving their own interests and distort it. Some financial scandals in the United States have highlighted this type of conflict of interest for the use of the information by banks. Indeed, the banks' financial analysts who gather information can release false information to the market to serve the banks' or their clients' financial interests.

This raises the following issues. What are the consequences of such leakages in the Chinese walls of financial institutions? Should brokerage activities be banned for financial institutions which develop their own trading divisions?

We develop a model where financial institutions produce information, trade for their own account, and observe their clients' orders in the frame of their brokerage activities. We assume that the banks' customers do not possess private information and are, therefore, considered to be noise traders. Small customers using the banks to transmit their orders to the market are not reputed to be informed. The customer's order flow is then pure noise and does not contain any private information. Given these brokerage activities, banks have access to some valuable information concerning part

of the liquidity trading in the market stemming from their customers. When engaging in proprietary trading, banks can use this knowledge to their benefit.

This chapter is close to the models of Fishman and Longstaff (1992), Roell (1990), and Sarkar (1995) who study dual trading for brokerage firms. The main difference between these models and our work is that, in the present model the financial institutions also trade for their own account. In Fishman and Longstaff (1992), the brokers bear a fixed cost of maintaining a brokerage business and a variable cost for filling an order. Under such a framework, the authors derive the competitive commission for filling orders. Nevertheless, Fishman and Longstaff (1992) do not model the competition between broker houses in the market. In our model, banks compete in the financial market when trading and face the same cost structure.

Biais and Germain (2002) and Germain (2005) study the conflict of interest between financial institutions that trade for their own account and at the same time set up a fund for their clients. They derive the optimal contracts that solve this conflict of interest. In particular, Germain (2005) shows that at the equilibrium the banks can commit to add an optimal level of noise to diminish their competition. In our model, we do not study what would be the optimal contract but derive the optimal trading strategy for financial intermediaries. Brennan and Chordia (1993) analyze the case where banks undertake brokerage activities. They study the optimal brokerage schedule for the case where the broker sells information to the customers. We do not address the question of selling information but focus on the critical issue of free riding on information derived by the order flow transmitted by the customers.

Rochet and Vila (1994) study the case of a monopolistic trader who observes the noise trading. In our chapter, we consider the case of N banks. However, we restrict our analysis to a linear/normal model which is not the case in the Rochet and Vila (1994) paper. We assume that the banks are strategic, informed, and have heterogeneous beliefs, for such a framework we derive the following results. At the equilibrium, the financial institutions that observe some noise trading behave optimally by trading in the opposite direction of their customers' orders. Moreover, we find that the liquidity and the banks' responsiveness to private information are reduced. We show that the expected profit of a bank that observes part of the noise trading is always greater than

the profit she would get otherwise. In addition, we also show that if part of the liquidity order flow is observed the aggregate expected profit is reduced.

The chapter is organized as follows. In the next section, we study the case where informed traders do not observe any noise from their customers. In the third section of this chapter, we analyze the general case where some noise can be observed. In the last section we conclude. All proofs are gathered in the chapter's Appendix.

THE BENCHMARK MODEL: NO NOISE IS OBSERVED

This model is identical to Didri and Germain (2009), hereafter DG (2009).

Consider a financial market with a risky asset whose final value $\tilde{V}$ is normally distributed with zero mean and variance σ^2_v. There are three types of agents:

- N risk neutral informed traders who observe a signal S_i concerning the future value of the asset before trading, such that

$$\forall i = 1,...,N \ S_i = V + \varepsilon_i, \text{ where } \forall i = 1,...,N, \ \varepsilon_i \to N\left(0,\sigma^2_i\right).$$

- Liquidity traders who submit market orders U, where $U \to N(0,\sigma^2_U)$.
- Risk neutral market makers, who observe the aggregate volume W and set rationally the price in a Bayesian way.

Assume that $\tilde{V}, \varepsilon_1,...,\varepsilon_N, U$ are mutually independent.

A strategy for the informed agent i is a function X_i corresponding to his market order and depending on the observed signal S_i. These strategies determine the aggregate order flow $W = \sum_{i=1}^{N} X_i + U$. Let P denote the equilibrium price determined by the market makers and $\pi_i = (V - P)X_i$ the resulting trading profit of insider i. The market makers behave competitively, upon observing the aggregate order flow W, their expected profit is equal to zero, i.e., $E(V - P|W) = 0$. Each informed agent i chooses X_i to maximize her expected profit $E(\pi_i |S_i)$. Moreover, the equilibrium is said to be linear if there exists λ, such that $P = \lambda W$.

We now derive the unique perfect Bayesian linear equilibrium of this game.

Proposition 1: *There exists a unique linear equilibrium defined by*

$$\begin{cases} \forall\, i = 1,...,N;\ X_i = \beta_i^{**} S_i \\ P = \lambda^{**} W \end{cases}, \text{ where } \left(\text{with } \tau_j = \dfrac{\sigma_j^2}{\sigma_v^2}\right)$$

$$\beta_i^{**} = \frac{\sigma_U}{\sigma_v}\frac{1}{\left(1 + 2\tau_i\right)}\left(\sum_{j=1}^{N}\frac{1+\tau_j}{\left(1+2\tau_j\right)^2}\right)^{-\frac{1}{2}} \quad \text{and} \quad \frac{1}{\lambda^{**}} = \frac{\sigma_U}{\sigma_v}\left(\sum_{j=1}^{N}\frac{1+\tau_j}{\left(1+2\tau_j\right)^2}\right)^{-\frac{1}{2}}\left[1 + \sum_{j=1}^{N}\frac{1}{1+2\tau_j}\right]$$

Proof: See Appendix.

Proposition 2: Expected Profits

- *At the equilibrium, the expected profit of agent i is given by*

$$\forall i = 1,...,N, \pi_i^{**} = \frac{\sigma_U\sigma_v\dfrac{1+\tau_i}{\left(1+2\tau_i\right)^2}}{\left(\displaystyle\sum_{i=1}^{N}\frac{1+\tau_i}{\left(1+2\tau_i\right)^2}\right)^{\frac{1}{2}}\left[1 + \displaystyle\sum_{i=1}^{N}\frac{1}{1+2\tau_i}\right]}$$

- *At the equilibrium, the expected aggregate profit is given by*

$$\pi^{**} = \sum_{i=1}^{N}\pi_i^* = \frac{\sigma_U\sigma_v\left(\displaystyle\sum_{i=1}^{N}\frac{1+\tau_i}{\left(1+2\tau_i\right)^2}\right)^{\frac{1}{2}}}{\left[1 + \displaystyle\sum_{i=1}^{N}\frac{1}{1+2\tau_i}\right]}$$

Proof: See Appendix.

This case is considered as the benchmark case and will be compared to the subsequent results. This situation is equivalent to the one where no banks or financial institutions undertake brokerage activities and as a result do not have access to any of the liquidity order flow.

In the next section, we analyze the case where some of the noise trading is observed by financial institutions.

THE GENERAL MODEL: WHEN SOME NOISE IS OBSERVED

Our objective is to study how a better knowledge of the noise trader order flow will affect the profit of the agents.

In order to distinguish between observed and unobserved liquidity trading, we decompose the global order U into two parts $U = U^0 + U^{un}$, where U^0 represents the observed liquidity trading (decomposed in subparts corresponding to the N informed traders) and U^{un} the unobserved part. The observed part $U^o = \sum_{i=1}^{N} U_i^o$ is itself decomposed into N subparts corresponding to the N informed traders: each informed trader i can observe the liquidity order U_i^o. This decomposition of the total variance of the liquidity trading will prove useful when studying the impact of observing some of this liquidity trading by informed traders.

We assume that: $U^0 \rightarrow N(0, \theta\sigma_U^2)$, $U^{un} \rightarrow N(0,(1 - \theta)\sigma_U^2)$ with $0 \leq \theta \leq 1$, and, $\forall i=1,\ldots, N, U_i^o \rightarrow N(0\alpha_i\sigma_U^2)$, with $\forall i=1,\ldots, N, 0 \leq \alpha_i \leq 1$ and $\sum_{i=1}^{N} \alpha_i = 1$.

The parameters θ and $\alpha_1,\ldots, \alpha_N$ capture the impact of observing noise trading. This can be understood as follows. Assume that the liquidity traders who want to trade U_i^o, do not submit this order directly to the market but instead direct bank i to do it on their behalf. As this bank trades for her own account, she might use this piece of information (size of her clients order) when deciding the quantity to trade. The parameter α_i can be understood as the fraction of the overall observed noise trading observed by agent i, in other words, this corresponds to the particular banks' brokerage activity. When, $\alpha_i = 0$, this implies that $U_i^o = 0$ in that case agent i does not observe any of the noise trading order flow. The parameter θ corresponds to the overall brokerage activity in the market.

To summarize, we can consider the following different situations:

- $\theta = 0$: No noise is observed (no brokerage activity). This setting is identical to DG (2009).
- $\theta > 0$: Part of the noise is observed. If, $\theta = 1$, there is no unobserved liquidity order flow. In that case all the customers' orders are channeled to the market by the banks. When $\forall i = 1, \ldots, N, \alpha_i > 0$, all informed traders observe part of the liquidity trading. If for one bank i we have that $\alpha_i = 0$, then at least one financial institution does

not observe any liquidity order. On the contrary, if for bank i $\alpha_i = 1$ and $\theta = 1$, then that bank observes all the liquidity order flow.

Assume that $\tilde{V}$, $\varepsilon_1,...,\varepsilon_N$, $U_1^0,...,U_N^0$, U^{un} are mutually independent.

A strategy for the informed agent i is a function X_i corresponding to his market order and depending on S_i and on the amount of liquidity trading observed if any is observed. Given the informed market orders and the liquidity order flow, the aggregate order flow is equal to $W = \sum_{i=1}^{N} X_i + U$. Let P denote the equilibrium price determined by the market makers and $\pi_i = (V - P)X_i$ the resulting trading profit of insider i. As before, due to competition in market making, the price must be such that $E(V - P|W) = 0$. Each informed agent i chooses X_i to maximize her expected profit $E(\pi_i |S_i, U_1^0)$. We now derive the unique perfect Bayesian linear equilibrium of this game.

Proposition 3: *There exists a unique equilibrium defined by*

$$\forall i \geq 1, X_i = \beta_i^* S_i - \frac{1}{2} U_i^o, \qquad \text{where } (\forall i = 1,...,N, \tau_i = \frac{\sigma_i^2}{\sigma_v^2})$$

$$P = \lambda^* \left(\sum_{j=1}^{N} X_j + U \right)$$

$$\beta_i^* = \frac{\sigma_U \sqrt{1 - \frac{3}{4}\theta}}{\sigma_v (1 + 2\tau_i)} \left(\sum_{i=1}^{N} \frac{1 + \tau_i}{(1 + 2\tau_i)^2} \right)^{-\frac{1}{2}} \quad \text{and} \quad \frac{1}{\lambda^*} = \frac{\sigma_U \sqrt{1 - \frac{3}{4}\theta}}{\sigma_v} \left(\sum_{i=1}^{N} \frac{1 + \tau_i}{(1 + 2\tau_i)^2} \right)^{-\frac{1}{2}} \left[1 + \sum_{i=1}^{N} \frac{1}{1 + 2\tau_i} \right].$$

Proof: See Appendix.

Proposition 4: Expected Profits

- *At the equilibrium, the expected profit of agent i is given by:* $\forall i = 1,...,N,$

$$\pi_i^* (\alpha_i, \theta) = \frac{\sigma_U \sigma_v \dfrac{1 + \tau_i}{(1 + 2\tau_i)^2} \sqrt{1 - \frac{3}{4}\theta}}{\left(\sum_{i=1}^{N} \dfrac{1 + \tau_i}{(1 + 2\tau_i)^2} \right)^{\frac{1}{2}} \left[1 + \sum_{i=1}^{N} \dfrac{1}{1 + 2\tau_i} \right]} + \frac{\alpha_i \theta \sigma_U \sigma_v \left(\sum_{i=1}^{N} \dfrac{1 + \tau_i}{(1 + 2\tau_i)^2} \right)^{\frac{1}{2}}}{4\sqrt{1 - \frac{3}{4}\theta} \left[1 + \sum_{i=1}^{N} \dfrac{1}{1 + 2\tau_i} \right]}$$

- *At the equilibrium, the expected aggregate profit is given by*

$$
\pi^*(\theta) = \sum_{i=1}^{N} \pi_i^*(\alpha_i, \theta) = \frac{\sigma_U \sigma_v \left(\sum_{i=1}^{N} \frac{1+\tau_i}{\left(1+2\tau_i\right)^2} \right)^{\frac{1}{2}}}{\left[1 + \sum_{i=1}^{N} \frac{1}{1+2\tau_i} \right]} \quad \frac{2-\theta}{2\sqrt{1-\frac{3}{4}\theta}}
$$

Proof: See Appendix.

Interpretation of the Equilibrium

The strategy of bank i depends explicitly on the part of the order flow U_i^o that she observes. Half of the observed order flow is revealed by her market order. This reduces the "amount" of noise in the aggregate order flow. As a result market makers price more aggressively leading to a decrease in market's liquidity. It is then optimal for the banks to scale down the size of their market order to reduce their impact on the price. Banks are then revealing less of their private information. Moreover, one can see that the bank i's responsiveness to private information does not depend on the particular fraction of the order flow observed by bank i, α_i. It only depends on the overall fraction of the order flow observed, θ. The more of the order flow is channeled to the market by banks, the more banks scale down their trading.

Interpretation of the Individual Profit

- The individual expected profit for bank i is the sum of two terms: the first one corresponds to the individual expected profit with no noise multiplied by $\sqrt{1-\frac{3}{4}\theta}$ and the second one depends explicitly on α_i. The former term takes into account the effect of the observation of a fraction θ of the entire liquidity order flow, i.e., on the overall brokerage activity in the market. It affects all the banks whether they undertake brokerage activities or not. The latter term embodies the impact for bank i of her own brokerage activity which gives her the observation of part of the noise trading $\alpha_i\theta$.
- The first term decreases with θ. As the fraction of the observed noise trading increases, banks decrease their trading intensity and liquidity

decreases. This leads to a decrease in the individual expected profit of the banks. This term captures the negative effect of brokerage activities in the market. The second term increases with both θ and α_i. In other words, the more bank i observes of the liquidity order flow the larger her expected profit.

- The bank undertaking brokerage activities earns an expected profit larger than that of a bank that cannot observe any noise. The more noise is observed by bank i, through an increase of α_i, the less the other banks earn in expectation.

Interpretation of the Aggregate Profit

- When $\theta = 0$, we find the results obtained in DG (2009).
- The impact of brokerage on aggregate profit is given by the multiplicative term $A(\theta) = \dfrac{2-\theta}{2\sqrt{1-\frac{3}{4}\theta}}$, which is always less or equal to 1.

  In particular, we have $A(0) = A(1) = 1$. The aggregate expected profit when no noise is observed is the same as when all the noise is observed. Moreover, when some noise is observed, the aggregate expected profit diminishes. However, it decreases for $0 \leq \theta \leq 2/3$ and increases for $2/3 \leq \theta \leq 1$.

Particular Case: All the Noise Trading Is Observed ($\theta = 1$)

In the case where $\theta = 1$, all the customers' order flow is directed to the market by the financial institutions.

- The aggregate profit is the same as when no noise is observed.
- The expected profit of trader i is equal to $\forall i = 1,\ldots, N,$

$$\pi_i^*(\alpha_i,\theta) = \frac{1}{4} \frac{\sigma_U \sigma_v \dfrac{1+\tau_i}{\left(1+2\tau_i\right)^2}}{\left(\displaystyle\sum_{i=1}^{N} \dfrac{1+\tau_i}{\left(1+2\tau_i\right)^2}\right)^{\frac{1}{2}} \left[1+\displaystyle\sum_{i=1}^{N} \dfrac{1}{1+2\tau_i}\right]} + \frac{\alpha_i \sigma_U \sigma_v}{2} \frac{\left(\displaystyle\sum_{i=1}^{N} \dfrac{1+\tau_i}{\left(1+2\tau_i\right)^2}\right)^{\frac{1}{2}}}{\left[1+\displaystyle\sum_{i=1}^{N} \dfrac{1}{1+2\tau_i}\right]}$$

- The banks reveal half of the liquidity trading observed. If we compare that with Proposition 1, we find that banks reduce their trading intensity by half. The market liquidity is also reduced by half.
- The individual expected profit is increasing with the proportion of the noise observed by the particular bank. However, if the entire noise is observed, the aggregate expected profit is not affected and is equal to the one in the DG (2009) model.

CONCLUSION

In this model we analyze the case where financial institutions sell brokerage activities and trade for their own account. We show that the banks optimally incorporate half of the noise trading observed, due to their brokerage activities, and decrease their information responsiveness as well. When analyzing both the banks' individual expected profit and the aggregate expected profit, the following results are obtained. For each financial institution the expected profit is increasing with the noise observed or her amount of brokerage activities. This implies that if a bank does not engage in brokerage activities her expected profit is smaller than if she does. The aggregate profit when some of the order flow is channeled to the market by banks is always lower than the aggregate profit in DG (2009), where no noise is observed. However, for the extreme case where all the noise trading order flow is directed to the market by banks, the aggregate expected profit is equal to the one in DG (2009). In a different paper, we generalize this approach to the case where the banks trade for their account, sell brokerage activities, and sell information to their clients.

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APPENDIX

Proof of Proposition 1: Proposition 1 is a particular case of Proposition 3 with $\theta = 0$, $\forall i = 1,..., N$ $\alpha_i = 0$ and then $U^0 = 0$.

Proof of Proposition 2: Follow the steps of Proposition 4 with $\theta = 0$ and $\forall i=1,..., N$ $\alpha_i = 0$.

Proof of Proposition 3: Agent i maximizes her conditional expected profit:

$$\max_{x \in R} E\left(x\left[\tilde{V} - \lambda\left(x + \sum_{j \neq i} X_j + U \right) \right] \middle| S_i, U_i^o \right), i = 1,..., N$$

Using that $\tilde{V}, \varepsilon_1,...,\varepsilon_N, U_1^o,...,U_N^o, U^{un}$ are mutually independent, we denote, for $i = 1,... N$,

$$q_i(x) = E\left(x\left[\tilde{V} - \lambda\left(x + \sum_{j \neq i} X_j + U_i^o + \sum_{j \neq i} U_j^o + U^{un} \right) \right] \middle| S_i, U_i^o \right)$$

$$= xE\left(\tilde{V} \middle| S_i, U_i^o \right) - \lambda x^2 - \lambda x E\left(\sum_{j \neq i} X_j \middle| S_i, U_i^o \right) - \lambda x E\left(U_i^o \middle| S_i, U_i^o \right)$$

$$q_i(x) = xE\left(\tilde{V} \middle| S_i \right) - \lambda x^2 - \lambda x \sum_{j \neq i} E\left(X_j \middle| S_i, U_i^o \right) - \lambda x U_i^o .$$

Moreover, using the assumption that $\forall j = 1,...N$, X_j is a function of S_j and U_i^0 and is independent of U_i^0 for all $i \neq j$, we obtain

$$q_i(x) = xE\left(\tilde{V}\big|S_i\right) - \lambda x^2 - \lambda x \sum_{j \neq i} E\left(X_j\big|S_i, U_i^o\right) - \lambda x U_i^o$$

$$= x\frac{S_i}{1+\tau_i} - \lambda x U_i^o - \lambda x^2 - \lambda x \sum_{j \neq i} E\left(X_j\big|S_i\right),$$

with $\tau_i = \dfrac{\sigma_i^2}{\sigma_v^2}$. The necessary and sufficient first order conditions are

$$X_i = \frac{1}{2\lambda}\frac{S_i}{1+\tau_i} - \frac{1}{2}U_i^o - \frac{1}{2}\sum_{j \neq i} E\left(X_j\big|S_i\right), i = 1,...,N$$

$$\Leftrightarrow$$

$$\tilde{X}_i = \frac{1}{2\lambda}\frac{S_i}{1+\tau_i} - \frac{1}{2}\sum_{j \neq i} E\left(\tilde{X}_j\big|S_i\right), i = 1,...,N$$

, with $\tilde{X}_i = X_i + \frac{1}{2}U_i^o, i = 1,...,N$

We can then derive the same proof as in DG (2009) and prove that there exists a unique linear solution $\tilde{X}_i^* = \beta_i^* S_i, i = 1,..., N$. Using the normality assumption and the mutual independence of $\tilde{V}, \varepsilon_1, ..., \varepsilon_N, U_N^0, U^{un}$, we can write β_i^* and λ^* as follows:

$$\beta_i^* = \frac{a}{1+2\tau_i} \text{ and } \frac{1}{\lambda^*} = a\left[1 + \sum_{j=1}^{N} \frac{1}{1+2\tau_j}\right],$$

with a being independent of i. Both the normality of each component and the mutual independence assumption allow us to identify the parameter λ^*.

$$\lambda^* = \frac{\text{cov}(\tilde{V},W)}{\text{var}(W)} = \frac{\text{cov}(\tilde{V}, \sum_{i=1}^{N} X_i + U)}{\text{var}(\sum_{i=1}^{N} X_i + U)} = \frac{\text{cov}(\tilde{V}, \sum_{i=1}^{N}\left(\beta_i^* S_i - \frac{1}{2}U_i^o\right) + U)}{\text{var}(\sum_{i=1}^{N}\left(\beta_i^* S_i - \frac{1}{2}U_i^o\right) + U)}$$

$$\lambda^* = \frac{\sum_{i=1}^{N} \beta_i^* \sigma_v^2}{\left(\sum_{i=1}^{N} \beta_i^*\right)^2 \sigma_v^2 + \sum_{i=1}^{N}\left(\beta_i^*\right)^2 \sigma_i^2 + (1-\theta)\sigma_u^2 + \frac{1}{4}\theta\sigma_u^2}$$

$$\frac{1}{\lambda^*} = \sum_{i=1}^{N} \beta_i^* + \frac{\sum_{i=1}^{N} \left(\beta_i^*\right)^2 \tau_i}{\sum_{i=1}^{N} \beta_i^*} + \frac{\left(1 - \frac{3}{4}\theta\right)\sigma_u^2}{\sum_{i=1}^{N} \beta_i^* \sigma_v^2} = a \sum_{i=1}^{N} \frac{1}{1 + 2\tau_i} + a \frac{\sum_{i=1}^{N} \frac{\tau_i}{(1+2\tau_i)^2}}{\sum_{i=1}^{N} \frac{1}{1+2\tau_i}} + \frac{\left(1 - \frac{3}{4}\theta\right)\sigma_u^2}{a\sigma_v^2 \sum_{i=1}^{N} \frac{1}{1+2\tau_i}}$$

We then identify $a = \dfrac{\sqrt{1 - \frac{3}{4}\theta}.\sigma_u}{\sigma_v \left(\sum_{i=1}^{N} \dfrac{1+\tau_i}{(1+2\tau_i)^2}\right)^2}$ and both parameters $\dfrac{1}{\lambda^*}$ and

$\beta_i^*, i = 1,\dots, N$. This ends the proof of Proposition 3.

Proof of Proposition 4: We have, for all $i = 1,\dots, N$.

$$\pi_i^*(\alpha_i, \theta) = E\left[X_i\left(\tilde{V} - P\right)\right] = E\left[\left(\beta_i^* S_i - \frac{1}{2}U_i^o\right).\left(\tilde{V} - \lambda^*\left\{\sum_{i=1}^{N} \beta_i^* S_i + \frac{1}{2}U^o + U^{un}\right\}\right)\right].$$

Using the $\pi_i^*(\alpha_i, \theta) = \beta_i^* \sigma_v^2 - \lambda^* \beta_i^* \sigma_v^2 \sum_{j=1}^{N} \beta_j^* - \lambda^* \left(\beta_i^*\right)^2 \sigma_v^2 \tau_i + \frac{\lambda^*}{4}\alpha_i \theta \sigma_u^2$

expressions $\beta_i^* = \dfrac{a}{1+2\tau_i}$ and $\dfrac{1}{\lambda^*} = a\left[1 + \sum_{j=1}^{N} \dfrac{1}{1+2\tau_j}\right]$, we obtain:

$$\pi_i^*(\alpha_i, \theta) = \left[\frac{a\sigma_v^2\left(1+\tau_i\right)}{\left(1+2\tau_i\right)^2} + \frac{\alpha_i \theta \sigma_u^2}{4a}\right]\left(1 + \sum_{j=1}^{N} \frac{1}{1+2\tau_j}\right)^{-1}.$$ Replacing the parameter

a by its expression allows us to derive the final result. The aggregate profit is simply obtained by computing $\pi^*(\theta) = \sum_{i=1}^{N} \pi_i^*(\alpha_i, \theta)$. This ends the proof of Proposition 4.

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FINANCIAL MARKETS, INVESTMENT ANALYSIS, AND TRADING IN PRIMARY AND SECONDARY MARKETS

André F. Gygax

ABSTRACT

Over the past four decades trading volumes in most financial markets have steadily increased. This paper investigates the motivations for trading using fundamental analysis, arbitrage and technical analysis. It is argued that the large trading volumes in primary markets could be a consequence of the automation of the trading process, the growth of electronic trading and the emergence of hig-frequency trading strategies. Similarly, increased levels of investor sophistication and the involvement of financial specialists with technical backgrounds have led to many financial innovations in secondary or derivatives markets. Although trading volumes in option markets and many futures markets are high, U.S. single stock futures (SSFs) volumes are low when compared to the trading volume in the underlying equity securities and corresponding options contracts. This is surprising as SSFs can be utilized as a cost effective technique to hedge and rebalance portfolio positions.

INTRODUCTION

Most financial markets have undergone a rapid evolution over the past four decades. Many of the changes have coincided with seminal developments in financial economics, such as the pricing of options, the pricing of debt, and arbitrage pricing (Black and Scholes, 1973; Merton, 1974; Ross, 1976). This extent of the evolution of financial markets, however, would not have been possible without significant advances in the underlying technology of computing and the advancement of the Internet and electronic communication networks (ECNs). The deeper understanding of the pricing of securities along with the automation of the trading process have changed the role and nature of traditional exchanges (Di Noia, 2001; Chemmanur and Fulghieri, 2006), allowed new players to enter financial markets (Stoll, 2008), and have generally led to an increase in trading volumes, reduction in bid ask spreads and the speed at which buy or sell orders are executed. These developments raise a few questions: What types of financial analysis motivate contemporary trading? How can the large volumes of trading be explained? Where does trading take place? Each of these questions will be discussed in the following sections.

INVESTMENT ANALYSIS AND TYPES OF TRADING

Using a broad classification, investment analysis can be performed in two ways: through fundamental or technical analysis. The goal of this section is to investigate how various forms of investment analysis motivate or result in the trading of securities rather than to engage in the debate whether technical analysis is a sound financial approach compared with classical analysis such as fundamental analysis or the identification of arbitrage opportunities (Treynor and Ferguson, 1985; Brock, Lakonishok, and LeBaron, 1992; Sullivan, Timmermann, and White, 1999).

Trading Motivated by Fundamental Analysis

Fundamental analysis is an approach motivated by classical finance principles of valuation. Here an analyst decides whether a security is over- or undervalued relative to its fundamental value. If, for example, a security is undervalued, an agent would buy the security and hold it until it has

reached its fair valuation level. This is commonly referred to as a buy-and-hold trading strategy.

Arbitrage Motivated Trading

A second motivation for trading is that an agent has identified an arbitrage opportunity in the market. This could be the case when a trader knows that the price of a security differs from its fundamental value (Dow and Gorton, 1994). The agent then decides whether to try to take advantage of the perceived mispricing or to wait and benefit from a potential gain due to additional possible divergence in prices (Kondor, 2009). Most arbitrage opportunities do not persist in the market and that is the reason for why electronic trading using sophisticated algorithms is a widely used technique to exploit short-term mispricing in the market.

Technical Analysis and Technical Trading

In the academic literature technical analysis has received little attention relative to fundamental analysis (Lo, Mamaysky, and Wang, 2000). In contrast, the practitioner literature provides many illustrations of how technical trading is used in trading by investment institutions. Technical analysis is mostly based on historical information and does not deal with the estimation or calculation of expected prices based on a theoretical asset pricing model. It has been most successfully used in currency markets (Osler, 2003).

The goal of technical analysis is to identify patterns in historical price and/or volume data (Blume, Easley, and O'Hara, 1994). These patterns could be used to implement a trading strategy using technical rules (Taylor, 1994). This could be achieved by employing genetic algorithms (Allen and Karjalainen, 1999; Lo, Mamaysky, and Wang, 2000; Wang, 2000). Some simple and popular technical trading rules are the moving average and trading break rules such as "head-and-shoulders" or "double-bottoms" (Brock, Lakonishok, and LeBaron, 1992; Kho, 1996; Zhu and Zhou, 2009). Technical analysis could also be employed by an agent to identify to what extent new information has been priced into a security (Treynor and Ferguson, 1985; Brown and Jennings, 1989; Grundy and McNichols, 1989). Brunnermeier (2005) shows that informed traders can benefit from technical analysis if they know both past prices and some private information. Such a private information signal could be imprecise or noisy. Technical analysis

could also motivate a trader to pursue a momentum or contrarian trading strategy (Keim and Madhavan, 1995; Okunev and White, 2003).

Other Motivations for Trading

Trading can also be motivated by noninformation-based reasons. For example, fund managers adjust portfolio holdings when cash contributions or withdrawals take place (Keim and Madhavan, 1995). Such situations could arise due to workplace changes or retirement of fund unit holders. Cash inflows or outflows could also be related to good "relative" or poor "absolute" fund performance (Ikovic and Weisbenner, 2009). Furthermore, index funds have to trade shares when the constituents of an index change. Finally, trading could also be induced for tax or seasonality reasons (Poterba and Weisbenner, 2001; Ikovic, Poterba, and Weisbenner, 2005).

COMPOSITION OF TRADING VOLUME AND TRADING

How can the large increases in trading volumes in primary equity, bond, or currency markets be explained? Three major trends in the development of financial markets serve as possible explanations: (1) the growth of electronic trading; (2) the emergence of high-frequency trading; and (3) the level of investor sophistication. These trends have all contributed to the dramatic increase in trading volumes. Below, these trends are discussed in more detail.

Over the past 20 years electronic trading has gradually substituted floor trading of securities. Simultaneously, the level of investor sophistication has increased and financial markets have witnessed the hiring of people with nontraditional and nonfinancial backgrounds such as engineers, physicists, mathematicians, and computer scientists. These professionals have not only been able to employ complex financial formulae but also to develop powerful electronic platforms through which they operate sophisticated and often automated trading algorithms. This combination of skill sets has contributed to the rapid growth of electronic trading.

By 2008, electronic trading accounted for 40 percent of daily trading volume according to Deutsche Börse (Grant and Gangahar, 2008). In the U.S. equities markets, according to the Tabb Group, the emergence of

electronic trading has also led to a substantial increase in high-frequency trading through the use of flash orders amounting to about 73 percent of daily trading volume (Mackenzie, 2009). Flash orders are high-frequency orders which are executed within a fraction of a second by using automated trading platforms and algorithms. This practice is most common on the NASDAQ OMX market and BATS, an ECN, but not encouraged by the NYSE Euronext exchange.

The popularity of electronic and high-frequency trading has helped BATS to become the third largest U.S. equity market behind NYSE Euronext and NASDAQ. A possible reason for this rapid climb of BATS could be that ECNs have helped to improve quote quality (Huang, 2002). Other reasons that have helped ECNs to attract trading, and in particular informed trading, are greater anonymity and the speed of order execution (Barclay, Hendershott, and McCormick, 2003). In addition, electronic trading has facilitated the emergence of alternative trading systems such as day and after-hours crossing systems (Conrad, Johnson, and Wahal, 2003).

TRADING IN PRIMARY VERSUS SECONDARY MARKETS

Trading is not confined to the primary markets but also takes place in the secondary or derivatives markets. To implement a trading strategy a trader might establish long or short positions in the derivatives market rather than in the underlying security. This approach has the advantage of being less capital intensive. Options can also play an important role during takeover attempts. In addition, a trader can combine call and put options to execute a volatility trading strategy. However, the statistics in Lakonishok et al. (2007) show that the combination of call and put options, such as straddles and strangles, represent only a small percentage of trading. In contrast, Pan and Poteshman (2006) show that informed trading represents a significant fraction of option trading and that this can create some predictability about future stock prices. Table 27.1 provides stock and index option volume and open interest information for the first three quarters of 2008 for all U.S. listed option contracts. The volume data demonstrate a stark difference in trading volumes between stock options and index options. Apart from March 2008 stock call option volumes are always higher than put stock option volumes. The opposite is true for index options. In each month

Table 27.1 All U.S. Stock Option and Index Option Volumes

	Panel A. Stocks Options					
	Volume			**Open Interest**		
	Calls	**Puts**	**Total**	**Calls**	**Puts**	**Total**
Jan/08	164,863,582	162,577,389	327,440,971	2,787,486,997	2,352,060,992	5,139,547,989
Feb/08	113,629,295	110,324,655	223,953,950	2,299,005,758	2,007,339,688	4,306,345,446
Mar/08	125,442,966	132,671,831	258,114,797	2,506,635,301	2,177,091,881	4,683,727,182
Apr/08	137,261,360	121,604,449	258,865,809	2,709,660,351	2,451,425,869	5,161,086,220
May/08	136,605,443	108,735,893	245,341,336	2,692,163,966	2,442,542,741	5,134,706,707
Jun/08	141,556,582	136,417,967	277,974,549	2,906,753,700	2,622,849,544	5,529,603,244
Jul/08	168,879,346	166,435,758	335,315,104	3,113,805,533	2,746,027,248	5,859,832,781
Aug/08	130,134,666	109,667,947	239,802,613	3,108,147,331	2,716,049,065	5,824,196,396
Sep/08	170,649,814	167,279,967	337,929,781	3,273,017,745	2,797,846,760	6,070,864,505
Oct/08	NA	NA	NA	NA	NA	NA

	Panel B: Index Options					
	Volume			**Open Interest**		
	Calls	**Puts**	**Total**	**Calls**	**Puts**	**Total**
Jan/08	11,610,340	16,136,206	27,746,546	140,445,184	195,322,595	335,767,779
Feb/08	8,384,652	10,948,548	19,333,200	151,968,144	202,065,093	354,033,237
Mar/08	9,595,668	13,002,477	22,598,145	168,222,816	216,537,159	384,759,975
Apr/08	8,764,244	12,438,005	21,202,249	166,582,000	222,651,994	389,233,994
May/08	8,963,756	11,131,053	20,094,809	175,361,964	232,469,358	407,831,322
Jun/08	10,854,207	13,237,193	24,091,400	180,988,251	240,790,697	421,778,948
Jul/08	12,778,501	15,496,436	28,274,937	194,410,430	250,389,270	444,799,700
Aug/08	9,380,424	12,385,514	21,765,938	198,355,937	259,682,628	458,038,565
Sep/08	14,221,706	18,542,850	32,764,556	203,242,998	266,725,621	469,968,619
Oct/08	NA	NA	NA	NA	NA	NA

Source: OptionMetrics and WRDS.

more put index options are traded than index call options. A possible explanation for this finding could be that traders and investors were more concerned about overvaluation at the market level but at the same time were not too concerned about valuation levels at the individual stock levels.

In other financial markets, particularly the bond, currency, and commodities markets, futures contracts are more frequently traded than options. A major benefit of the futures market is that both long and short positions can be established easily and cost-effectively. In addition, the problem of short-sales constraints in the primary market does not arise in the futures market (Nagel, 2005). Despite this, in the United States short selling in the equities market by far outweighs trading volumes in short positions in the secondary SSF market (Shastri, Thirumalai, and Zutter, 2008). The high volumes are illustrated in Diether, Lee, and Werner (2009) who show that short selling represents approximately a quarter of all NYSE and 31 percent of NASDAQ transactions.

In contrast, the relatively low volumes in the SSF market are shown in Tables 27.2 and 27.3. Columns 2 and 3 in Table 27.2 show that in the United States trading volumes in SSFs have declined markedly in August 2008. This is one month prior to the dramatic fall in equities markets in September and October 2008. Column 5 in Table 27.2 shows the corresponding trading volumes for the NYSE Liffe Universal Stock Futures (USF) market. The data show a low volume for August but a high volume for September 2009. Table 27.3 presents OneChicago SSF trading volumes over the period –5 to +5 trading days relative to the Lehman Brothers bankruptcy announcement on September 15, 2008. Although trading volumes fell during and around the announcement, they increased within a few days.

A possible explanation for the low level of trading in SSF contracts could be that these contracts were previously banned in the United States due to the Shad-Johnson Accord and only reintroduced on November 8, 2002 by the OneChicago and NQLX (a joint venture of NASDAQ and Liffe) (Shastri, Thirumalai, and Zutter, 2008). The comparison in Table 27.2 of OneChicago with other markets that trade SSFs shows that only the London- (UK) based NYSE Liffe market has significantly higher volumes and open interest than OneChicago. SSF volumes on the Hong Kong Exchange (HKEX) have remained low and the Sydney Futures Exchange (SFE), a division of the Australian Stock Exchange (ASX), has delisted SSF contracts in March 2008 apparently due to low volumes and the emergence of contracts for difference (CFDs).

Table 27.2 Single Stock Futures Volume Statistics for the U.S., UK, Hong Kong, and Australia

	OneChicago				NYSE LIFFE		HKEX		SFE (ASX)
	Number of Futures on Single Stocks	Average Daily Volume SSF	Annual / Monthly Volume SSF	Open Interest SSF	Annual / Monthly Volume USF	Open Interest USF	Annual / Monthly Volume SF	Open Interest SF	Annual / Monthly Volume SF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2000	NA	NA	NA	NA	3,664,560	75,207	3,322	21	8,817
2001	NA	NA	NA	NA	6,193,283	429,139	6,945	455	12,545
2002	79	NA	NA	NA	7,570,175	193,944	21,006	405	29,286
2003	NA	15,556	NA	153,866	7,004,235	444,996	18,654	1,020	47,822
2004	NA	NA	1,922,726	154,621	13,115,815	181,473	17,274	1,821	29,986
2005	NA	21,937	5,528,046	1,600,000	11,365,103	411,125	13,069	1,750	38,156
2006	482	32,000	7,923,499	1,351,320	18,147,980	1,130,568	102,010	4,260	10,843
2007	491	NA	8,105,963	370,420	45,249,036	4,713,663	351,514	5,954	11,242
Jan/08	491	28,157	591,297	581,712	1,483,291	4,376,255	NA	NA	NA
Feb/08	527	11,551	219,476	NA	3,510,457	4,768,434	NA	NA	NA
Mar/08	601	13,354	267,076	365,441	5,607,523	5,038,164	NA	NA	DEL
Apr/08	694	14,646	322,205	492,882	6,796,541	8,167,882	NA	NA	DEL
May/08	800	12,382	260,024	294,896	8,690,132	5,922,453	NA	NA	DEL
Jun/08	800	26,840	563,641	423,867	11,428,282	5,465,938	NA	NA	DEL

Jul/08	800	17,852	392,744	314,158	3,371,143	6,439,136	NA	NA	DEL
Aug/08	800	7,924	166,399	270,516	2,812,466	5,100,107	19,209	7,592	DEL
Sep/08	989	8,800	184,792	199,566	12,477,190	4,734,828	41,891	8,269	DEL
Oct/08	1,148	7,164	164,778	127,600	7,457,505	7,416,847	36,300	8,122	DEL
Nov/08	1,142	7,192	136,647	91,511	6,441,116	4,762,983	31,987	9,973	DEL
Dec/08	1,120	6,142	135,122	68,290	9,378,708	4,707,192	23,396	9,449	DEL
2008	1,120		3,404,201	68,290	79,454,354	4,707,192	257,015	9,449	100
Jan/09	1,131	6,721	134,411	98,962	9,680,449	7,605,483	23,750	6,350	DEL
Feb/09	1,137	6,032	114,604	85,918	5,121,659	5,382,386	16,619	6,310	DEL
Mar/09	1,134	6,628	145,808	70,606	9,647,551	5,551,249	31,168	9,208	DEL
Apr/09	1,132	3,632	76,279	72,734	14,160,668	10,663,839	22,228	12,136	DEL
May/09	1,141	4,684	93,676	87,607	16,049,208	8,138,571	15,888	4,600	DEL
Jun/09	1,150	NA	NA	NA	14,750,555	5,179,549	31,433	14,806	DEL
Jul/09	1,166	NA	NA	NA	13,438,543	7,747,484	26,081	10,477	DEL

Source: SIRCA, OneChicago, NYSE LIFFE, Hong Kong Exchange, ASX Sydney.

Table 27.3 U.S. SSF Volumes around Lehman Brothers Bankruptcy

Date	Number of Contracts	Total Volume	Exchange for Physical Volume	Block Volume	Open Interest
09/08/2008	3,165	7,569	26	1,590	280,925
09/09/2008	3,165	9,322	1,544	125	281,784
09/10/2008	3,165	13,624	8	8,820	282,067
09/11/2008	3,173	5,138	1,406	0	282,543
09/12/2008	3,173	6,497	37	3,500	286,989
09/15/2008	3,169	5,400	1,437	244	286,271
09/16/2008	3,169	6,014	827	0	286,991
09/17/2008	3,173	7,707	168	0	287,641
09/18/2008	3,173	14,838	720	296	294,540
09/19/2008	3,173	18,507	1,688	0	300,266
09/22/2008	3,131	10,563	2,105	2,500	175,000

Source: SIRCA and OneChicago.

CONCLUSION

The volume of trading in financial markets has experienced tremendous growth during the past four decades. This growth was possible due to changes in the regulatory environment but was mostly driven by the rapid expansion of electronic trading platforms and the sophisticated use of technical algorithms which have greatly increased the speed of order execution. So far, equity and currency markets have experienced the greatest technological changes. Other financial markets, such as bonds, real estate, derivatives, and over-the-counter markets are developing in response to regulatory calls for increased transparency. Finally, increasingly sophisticated investors require even more efficient and effective platforms for trade execution.

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TRADING AND OVERCONFIDENCE

Ryan Garvey and Fei Wu

ABSTRACT

Using proprietary data from a U.S. broker-dealer, we test Gervais and Odean's (2001) learning model of overconfidence in professional stock traders. We find that traders place more bets following prior trading gains. Traders who are most influenced by their prior trading profits experience lower performance, but not the lowest. While we find a strong link between prior performance and subsequent trading activity, our results indicate that the relationship weakens with time. Traders who are active for longer (shorter) periods of time are less (more) likely to be overconfident.

INTRODUCTION

Theoretical models predict that traders in financial markets are overconfident, i.e., they have a tendency to overestimate the precision of their beliefs or forecasts, and they tend to overestimate their abilities.[1] Overconfidence is an important issue for traders because traders who are overconfident will lower their performance by entering into suboptimal bets and/or engaging in too many bets. While financial models predict that, on average, traders in financial markets are overconfident, there is little empirical research directly testing the theoretical predictions of overconfidence models on individual traders.[2] In our chapter, we test whether or not the actions of U.S. stock traders are consistent with the learning model of overconfidence developed by Gervais and Odean (2001), hereafter GO

(2001). In GO (2001), overconfidence is determined endogeneously and fluctuates over time as traders learn from their prior experiences. Early on, when traders are less experienced, they are more likely to overweight the possibility that their success is due to superior ability. This learning bias (i.e., self-attribution bias) can cause traders to be overconfident. As traders gain more experience over time, though, they gain a better understanding of their abilities, and trader's level of overconfidence subsequently declines.

Using unique data on U.S. stock traders, we find empirical evidence supporting three key predictions of the GO (2001) overconfidence model.

1. Traders learn from their prior successes and become overconfident.
2. Overconfident traders experience lower performance, though not necessarily the lowest.
3. Experience matters. Traders become less overconfident over time.

The remainder of our study is organized as follows. First, we describe the sample data. Next, we provide empirical testing of overconfidence theory. Our empirical testing is focused around the GO (2001) learning model of overconfidence. Lastly, we provide concluding remarks.

DATA

The purpose of our study is to empirically examine how traders learn about their ability and how (if) a bias in this learning can create overconfident traders. Such an analysis requires data on traders who are active over an extended period of time. To satisfy this requirement, we collect sample data from a U.S. broker-dealer who provides their clients with direct market access (DMA). Brokers providing DMA services tend to attract more sophisticated traders because they allow their users to control where and how their orders are routed for execution. Consequently, they also tend to attract clients who trade often and in large sizes. A considerable amount of daily trading activity in U.S. equity markets flows through DMA brokerage firms. For example, Goldberg and Lupercio (2004) find that approximately 40 percent of NASDAQ and NYSE trading volume is executed by active traders (25+ trades per day) who use U.S. brokers offering DMA services.

We collect data over the sample period October 7, 1999 to August 1, 2003. The firm mainly attracted clients who had an interest in trading NASDAQ-listed stocks. This is because NASDAQ stocks trade in multiple

trading venues and the primary benefit of using a DMA broker is the ability to route orders to various trading venues. In contrast, NYSE-listed trading is mainly confined to a single trading location during our sample period.[3] Because clients opened an account at our firm with the primary intent of benefiting their NASDAQ trading, and because a high percentage of trading activity occurs on NASDAQ stocks, our analysis focuses on traders NASDAQ-listed stock trading. The data are in the form of a transaction database and provide information such as the identity of the trader, the time of submission, the time of execution, the market where the order was sent, the execution size, the execution price(s), the stock symbol, the order type, the contra party, and various other information concerning the trade execution (or cancellation) and executing account.

In order to examine traders who are active over an extended period of time, we first restrict our analysis to traders who are active during more than 250 trading days (approximately one trading year) over the sample period (969 trading days). We then select accounts that have an intraday roundtrip match rate exceeding 90 percent. A high intraday match rate is desirable because it enables us to calculate a robust measure of performance and ensures that we are examining traders who receive frequent feedback on their performance. Because we lack opening position data, we cannot accurately measure performance for traders who engage in longer term trading strategies. Performance is based on matching up the intraday trades, using a first-in, first-out matching algorithm. For each stock and trader, we match opening trades with the subsequent closing trade(s) in the same day. In order to do this, we search forward in time each day until the opening position is closed out, keeping track of accumulated intraday inventory and the corresponding prices paid or received.

Table 28.1 provides some summary statistics on the sample data. Overall, the analysis is based on 109 traders, who combined to execute more than 6 billion shares (3.6 million trades) over the near four-year sample period. The dollar value traded exceeds $60 billion and the traders managed to generate over $4 million in trading profits during a bearish market. Our sample period was considered a very "challenging" market trading environment. For example, the revenues of NASDAQ broker-dealers with a market-making operation fell over 70 percent during 2000 to 2004 (GAO, 2005). The GAO cited the sharp decline in stock prices, heightened competition, the switch to a smaller tick size, etc., for the sharp decline in trading revenues during our sample period.

Table 28.1 Summary Statistics

	Aggregate	Daily Average
Dollar Value Traded	$60,732,249,829	$557,176,604
Shares Traded	6,084,739,456	55,823,298
Number of Trades	3,673,442	33,701
Profits	$4,145,121	$38,029

Table 28.1 provides summary statistics for 109 traders, who traded through a U.S. broker-dealer, over the approximate four-year period ending August 2003. Each trader is active for more than 250 sample trading days.

EMPIRICAL RESULTS

Our empirical results are organized around three key predictions from the GO (2001) learning model of overconfidence. The three hypotheses we test are as follows.

Hypothesis 1: Past Success Leads to Subsequent Increases in Trader Activity (i.e., Overconfidence)

GO (2001) suggest that trader activity is the primary testable implication of overconfidence theory and that traders increase their activity when they have experienced prior gains. We empirically test this prediction by estimating a trader fixed-effects regression.[4]

$$Log(Shares_{i,t}) = \alpha_i + \beta_1 Cum.Prof._{i,t-1} + \Sigma \ Contols + \varepsilon_{i,t} \qquad (28.1)$$

Using trader-specific constant terms, α_i is desirable to control for variations across traders. The regression dependent variable $Log (Shares_{i,t})$ is the log number of daily shares traded and the main independent variable of interest, $Cum. Proof_{i,t-1}$ is trader cumulative performance (divided by $10,000) from the first day availabe up to $t - 1$. Because factors other than past performance might (also) cause traders to increase (decrease) their activity, we include several regression control variables that have been shown in prior financial studies to serve as motives for trading. The control

variables are the log-daily trading volume on NASDAQ, the daily volatility of NASDAQ, which is measured by the difference in the NASDAQ composite index daily high/low divided by the opening level, the daily (lagged) return on the NASDAQ composite index, and a dummy variable that takes the value of 1, or 0 otherwise, if trading occurs at the end of the calendar year (i.e., December).

Regression results are reported in Table 28.2. The cumulative performance coefficient is positive (0.0113) and highly significant (t stat = 10.15), indicating that increases in trader prior performance lead to subsequent increases in trader activity. This result is consistent with H1. The control variables reveal the influence of other factors on trader activity. When daily volume and price returns are higher, trader activity is also higher. Traders increase their activity at the end of the year (i.e., December), too. When price volatility is higher, traders decrease their activity.

The fixed-effects regression dependent variable is trader activity (log-daily number of shares traded). The independent variable include trader cumulative profit up to time $t-1$ (1/\$10,000), the log-daily trading volume on NASDAQ, the daily volatility of NASDAQ, which is measured by the difference in the NASDAQ composite index daily high/low divided by the opening level, the daily (lagged) return on the NASDAQ composite index, and a dummy variable that takes the value of 1, or 0 otherwise, if trading occurs in the month of December.

Table 28.2 Prior Performance and Subsequent Trading Activity

	Coefficient	t Statistic
Cumulative Profit (1/\$10,000)	>0.0113**	10.15
Daily NASDAQ Volume (Log)	0.2999**	12.65
Daily NASDAQ Volatility	−5.5038**	−11.86
Daily NASDAQ Return	1.4075**	6.58
NASDAQ Return ($t-1$)	−0.0626	−0.28
NASDAQ Return ($t-2, t-20$)	0.4174**	7.51
December Dummy	0.0690**	3.64
Trader Fixed Effects	Yes	
Adjusted R^2	0.0124	

**,*Indicates significance at the 1% and 5% level, respectively.

Hypothesis 2: Overconfident Traders Experience Lower Performance, Though Not Necessarily the Lowest

To test this hypothesis, we first conduct individual trader ordinary least squares regressions using the same regression variables described above (H1 testing). For example, trader activity is used as the dependent variable and cumulative performance is used as the main independent variable. The regressions also use the volume, return, volatility, and year-end controls. After estimating regressions for each of the 109 traders, we then group traders into quintiles based on the magnitude of their cumulative performance coefficient. Traders in Q1 have the highest cumulative performance coefficient (or they are the most overconfident) and traders in Q5 have the lowest cumulative performance coefficient. Lastly, we compute the mean total/daily profit (performance) for each group. The results are reported in Table 28.3.

Traders with high overconfidence regression coefficients are, on average, profitable in a bearish market, yet they underperform Q3 traders, who can be considered neutral traders. The performance differences are quite large. For example, the average daily profit of Q3 traders is more than 18 times higher than Q1 traders and nearly 3 times higher than Q2 traders. The most overconfident traders underperform the average across all traders, though they do not have the worst performance. For example, Q5 traders who are negatively influenced by their past success perform much worse than Q1 traders.

Individual ordinary least squares regressions are conducted for each trader (109) by regressing log-daily number of shares traded on cumulative profit and controls (see Table 28.2 regression variables). Traders are then sorted into quintiles based on the magnitude of their cumulative profit

Table 28.3 Overconfidence and Performance

	Mean Cumulative Profit Coefficient	Mean Total Profit	Mean Daily Profit
Q1 Largest	0.2679	$8,627	$16
Q2	0.0133	$48,382	$101
Q3	−0.0022	$139,593	$294
Q4	−0.0347	$3,277	$22
Q5 Smallest	−0.2477	−$5,119	−$13

coefficient. The mean cumulative profit coefficient, total profit and daily profit are reported for each quintile.

Hypothesis 3: Traders Learn from Trading and Overconfidence Declines Over Time

Gervais and Odean (2001) predict that as traders gain more trading experience, they will also gain a better understanding of their abilities and overconfidence will subsequently diminish over time. This can be empirically tested by including a time effect in our prior regression used to test H1. We add two more variables to our fixed-effects regression.

$$Log(Shares_{i,t}) = \alpha_i + \beta_1 \ Cum. \ Prof._{i,t-1} + \beta_2 \ Time_t + \beta_2$$
$$Time_t \times Cum. \ Prof._{i,t-1} + \Sigma \ Contols + \varepsilon_{i,t} \qquad (28.2)$$

The first added variable, $Time_t$, measures elapsed calendar time in months starting at the beginning of our sample period ($Time = 1$ for the first month of our sample period, $Time = 2$ for the second month, etc.). Time is included in order to separate general effects associated with the passage of time from time varying (or declining) overconfidence. The second added variable $Time_t \times Cum. \ Prof._{i,t-1}$ is an interaction term. This is used to account for the possibility that traders learning bias will dissipate with time as their experience grows or that cumulative profit will have a declining influence on subsequent trader decisions. As predicted by H3, we expect a negatively significant cumulative profit*time coefficient.

The regression results are reported in Model 1 of Panel A, Table 28.4. Consistent with H3, the cumulative profit*time coefficient is negative (−0.0479) and highly significant (t stat = 8.03), which suggests that traders overconfidence tendency decreases over time through learning by trading. In Table 28.4, Panel B, we report the estimated deviations of trader activity (shares traded) with respect to trader cumulative profits, evaluated for each period of *Time* (1 through 46). The deviations steadily decrease and remain statistically significant up to *Time* 27. This implies that, on average, traders' learning bias (or overconfidence tendency) runs its course by about 27 months.

The fixed-effects regression dependent variable is trader activity (log-daily number of shares traded). Independent variables include: time, which

Table 28.4 Time and Overconfidence

Panel A. Regression Results

	Model 1		Model 2	
	Coefficient	**t Statistic**	**Coefficient**	**t Statistic**
Time	0.0270**	36.87	0.0291**	39.22
Cumulative Profit (1/$10,000)	0.0146**	6.74	0.0186**	8.55
Cumulative Profit (1/$10,000)* Time	−0.0479**	−8.03	−0.0496**	−8.34
Cumulative Profit (1/$10,000)* Time*$D_{active\ trader}$			−0.2625**	−17.18
Daily NASDAQ Volume (Log)	0.2788**	11.88	0.3103**	13.23
Daily NASDAQ Volatility	−2.7877**	−6.02	−3.0115**	−6.53
Daily NASDAQ Return	1.4607**	6.94	1.4183**	6.76
NASDAQ Return (t − 1)	0.3485	1.59	0.2953	1.35
NASDAQ Return (t − 2, t − 20)	0.5495**	10.01	0.5259**	9.61
December Dummy	0.0881**	4.73	0.0861**	4.63
Trader Fixed Effects	Yes		Yes	
Adjusted R^2	0.0432		0.0498	

Panel B. Shares Traded/Cumulative Profit (Evaluated at Various Values of the Time Variable)

Time	Shares Traded / Cumulative Profit	t Statistic
1	0.0014**	19.47
2	0.0014**	18.81
3	0.0013**	18.15
4	0.0013**	17.49
5	0.0012**	16.83
10	0.0010**	13.53
20	0.0005**	6.92
27	0.0002*	2.30
28	0.0001	1.64
29	7.1E-05	0.98
30	2.3E-05	0.32

**,*Indicates significance at the 1% and 5% level respectively.

measures elapsed calendar time in months starting at the beginning of the sample period (*Time* = 1 for the first sample month, *Time* = 2 for the second month, etc.), trader cumulative profit up to time t − 1 (1/$10,000), cumulative profit*time, Cumulative Profit*Time* $D_{active\ trader}$, where the

dummy variable $D_{active\ trader}$ takes the value of 1, or 0 otherwise, if an observation is associated with an active trader (top 30 percent based on total number of trades), the log-daily trading volume on NASDAQ, the daily volatility of NASDAQ, which is measured by the difference in the NASDAQ composite index daily high/low divided by the opening level, the daily (lagged) return on the NASDAQ composite index, and a dummy variable that takes the value of 1, or 0 otherwise, if trading occurs in the month of December. Panel B. (Model 1) shows the estimated deviations of shares traded with respect to cumulative profit, evaluated at various values of time.

If traders learn from their experiences and overconfidence diminishes with time, then traders who receive feedback about their ability more often (i.e., more active traders) should learn faster and overconfidence should decline more rapidly with these traders. We test this hypothesis by first identifying the most active traders in our sample data. If traders are in the top 30 percent based on number of trades, we consider them to be the most active. We rerun the regression testing Hypothesis 3, including an additional variable (Cumulative Profit*Time* $D_{1(active\ trader)}$). The dummy variable $D_{active\ trader}$ takes the value of 1, or 0 otherwise, if an observation is associated with an active trader. The results are reported in Model 2 of Panel A, Table 28.4. They indicate that the most active traders learn faster and that overconfidence declines more rapidly with these traders. For example, trader overconfidence (Cumulative Profit*Time) declines 0.0497 over time for average traders, but 0.3122 (-0.0497 to 0.2625) for active traders (Cumulative Profit*Time* $D_{1(active\ trader)}$), holding all other variables constant. The decline in overconfidence among the most active traders is six times greater than normal.

CONCLUSION

Prior research indicates that overconfidence is greatest for difficult tasks, for forecasts with low predictability, and for undertaking lacking fast clear feedback.[5] This suggests, then, that overconfidence is likely to flourish in trading settings. For example, trading profitably in competitive securities markets is a difficult task. Future price changes are hard to predict and distinguishing trading skill from luck takes time. Understanding overconfidence is important for traders because overconfident traders are likely to lower their returns by making poor bets and/or engaging in too many bets.

Despite a widespread belief among many that trader's in financial markets are, on average, overconfident there remains little empirical support for such a belief. In our chapter, we empirically test the predictions of overconfidence theory using data on professional traders. Our analysis focuses on testing the learning model of overconfidence developed by Gervais and Odean (2001). In GO (2001), traders are more likely to be overconfident when they are relatively inexperienced. Early on, a trader is likely to take too much credit for his successes as he attempts to recognize his own abilities. With more experience, though, traders become better able to assess their abilities and overconfidence diminishes. GO (2001) note that overconfident traders will experience lower performance, though not necessarily the lowest.

Using proprietary data from a U.S. broker-dealer, we find that professional stock traders increase their activity following prior trading gains. Traders who are most influenced by their prior trading profits experience lower profits, but not the lowest. Although a strong link exists between prior performance and subsequent trading activity, our results indicate that the relationship weakens with time. Traders who are active for longer (shorter) periods of time are less (more) likely to be overconfident.

While our findings provide empirical support for overconfidence theory, our analysis is based on professional traders at one U.S. broker-dealer. Whether or not these results hold for traders at other broker-dealers, or among other types of market participants (mutual fund managers, hedge fund managers, etc.), are interesting questions for future research.

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NOTES

1. See, for example, De Long et al. (1991), Kyle and Wang (1997), Benos (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Odean (1998), and Gervais and Odean (2001).
2. Statman, Thorley, and Vorkink (2006) examine market data over time and find a positive lead-lag relationship between aggregate market returns and volume, which is consistent with overconfidence theory.
3. More than 80 percent of NYSE-listed volume was executed at the NYSE during our sample period. Source: NYSE reports.
4. We also standardize the observations across traders, and estimate an ordinary least squares regression. The results are qualitatively similar results to those reported and are omitted for brevity.
5. See Barber and Odean (2001) for a discussion on some of the nonfinancial literature.

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CORRELATED ASSET TRADING AND DISCLOSURE OF PRIVATE INFORMATION

Ariadna Dumitrescu

ABSTRACT

This chapter studies the trading behavior of informed and uninformed traders in an environment with two correlated assets. In this setup, informed traders receive a signal about the liquidation value of an asset that also conveys information about the other asset. I extend Kyle's (1985) model to a multi-asset market and show that public disclosure of information about one asset affects the trading behavior and market performance both in the market of this asset and the market of the correlated asset.

INTRODUCTION

The information firms disclose about their own business can be valuable information about the performance of all the firms in the industry. Since the returns of the firms in the same industry are correlated, the disclosure of information about a specific firm can provide information about the others. Hence the disclosure of information reduces the asymmetry of information

not only in the market where this disclosure takes place, but also in the markets of correlated assets. Moreover, the existence of markets of correlated assets increases the value of acquiring information because insiders can use their informational advantage when trading different correlated assets.

In this chapter, I develop a strategic trading model where I consider the existence of two firms with correlated liquidation values and I study how the disclosure of information about the liquidation value of one of the firms affects the market liquidity of the shares of both firms. I analyze the optimal strategies of the managers of the two firms who have private information about the payoff of their firm and the pricing strategy of the market maker. I model the interactions between managers as insiders and market makers, as in Kyle (1985). Both the managers and the noise traders submit market orders and the market maker sets the price to clear the market. However the information structure in my model is different. One of the firms discloses information about the realization of the firm's payoff and this reduces the asymmetry of information between managers and noise traders. However, since the firms have correlated payoffs, the information disclosed about the liquidation value of one asset can be used also in the other market to reduce the asymmetry of information. Consequently, my model shows that the performance of a firm in the financial markets might be determined by the actions of other firms in the same industry.

The rest of this chapter is organized as follows: the second section of this chapter provides a review of literature while the third section presents the model. I establish the information structure and characterize the equilibrium: a unique equilibrium in which price functions and managers' demands are linear. This chapter's fourth section studies the impact of disclosure of information on market liquidity. Finally, the fifth section of this chapter summarizes the results.

Literature Review

This chapter brings together two lines of research: the literature about multi-asset security markets and the literature that studies the effect of information disclosure by firms. The literature concerned with multi-security markets starts with the work of Admati (1985) who extends Grossman and Stiglitz's (1980) analysis of endogenous information acquisition to multiple assets and shows how individuals face different risk-return tradeoffs when differential

information is not fully revealed in equilibrium. Thus in Admati (1985), since agents submit multi-asset demand schedules conditioning on the prices of all assets, it is therefore possible to have a price that decreases with the liquidation value of the asset. This is due to the fact that agents use various signals that are correlated, hence the direct effects can be dominated by the indirect effects.

Subrahmanyam (1991) considers a multi-asset model where strategic liquidity traders can choose the market in which they execute their trades. He shows that the adverse selection problem of liquidity traders is reduced if they trade in a security index basket as opposed to trading a single security. The outcome is a liquidity-based explanation of the large use of stock index futures. Similarly, Bhushan (1991) also considers a multi-asset setup to examine cross-sectional variation in trading costs and liquidity and shows that liquidity traders diversify their trading across assets. A similar setup, where assets are correlated is considered by Chan (1993). In his model, one of the market makers observes only the order flow of the asset for which he sets the price. He does not observe the order flows in other markets but deduces information about these order flows from the prices set by other market makers.

In the papers mentioned above, traders ignore the effect their trade has both on prices and other traders' strategies. To account for the impact of their trading, Caballé and Krishnan (1994) consider a setup with multiple traders and multiple correlated assets, but unlike Admati (1985), they allow for the strategic behavior of traders. They extend thus the model of Kyle (1985) to a multi-asset framework. The market makers in their model can glean information from the order flows of the other assets and use this information strategically when setting prices. They extrapolate the result of Kyle (1985) that more noise leads to more aggressive trading and show that portfolio diversification arises in their model due to the strategic behavior of the agents and not because of risk considerations.

Pasquariello and Vega (2009) extend Caballé and Krishnan (1994) by allowing for the release of news about fundamental values and they found also empirical evidence for cross-asset informational effects. In addition, Bernhardt and Taub (2008) develop a multi-asset model where underlying asset values are correlated and show that, if correlated, the profits of informed speculators are lower. They study how the information contained in the prices of assets is used by speculators and market makers to trade and

set up the prices of the assets. Their model extends the model of Admati (1985) along the lines of Kyle (1989) in the sense that traders behave strategically and choose their demand conditioning on prices too.

Other papers have extended the previous models to a dynamic setting with multiple risky assets. Thus, the model of Bernhardt and Taub (2008) is extended by Seiler and Taub (2008), who answer a similar question but in a dynamic setting. The dynamic modeling allows them to show how this cross-asset information evolves dynamically over time. Zhou (1998) also extends in a dynamic setting the model of Admati (1985) and studies portfolio choices in a multi-asset securities market with differential information. He shows that the information structure has a significant impact both on asset prices and portfolio choices.

Another group of models addressing a multi-asset setup are the studies concerned with contagion among financial markets—the propagation of a shock to an asset to other unrelated assets. Some of these papers have focused on contagion through correlated information or a correlated liquidity shock channel. The correlated liquidity shock channel assumes that when some market participants need to liquidate some of their assets, they choose to liquidate assets in a number of markets, effectively transmitting the shock. There are several other alternative explanations for contagion: wealth effects (Kyle and Xiong, 2001), portfolio rebalancing (Kodres and Pritsker, 2002), borrowing constraints (Yuan, 2005), and the heterogeneity of insiders' beliefs and strategic portfolio rebalancing (Pasquariello, 2007).

Finally, Pagano (1989), Chowdhry and Nanda (1991), Huddart, Hughes, and Brunnermeier (1999), and Baruch, Karolyi, and Lemmon (2007) examine the distribution of trades between different marketplaces. Pagano (1989) focuses on the role of traders' expectations of other traders' actions and show that both markets can survive only with a certain exchange design (equal transaction costs and equal numbers of traders in each market). Chowdhry and Nanda (1991) allow for both discretionary and nondiscretionary liquidity trading, and show that informed and uninformed trades concentrate in markets with more stringent disclosure policies. Similarly, Huddart, Hughes, and Brunnermeier (1999) show that insiders always choose to list their company on the stock exchange with the highest disclosure requirement in order to benefit from the presence of the discretionary liquidity traders. Baruch, Karolyi, and Lemmon (2007) develop a model to explain the differences in the foreign share of the trading volume of internationally cross-listed stocks and show that the trading volume of a cross-listed

stock is proportionally higher on the exchange in which asset returns are more correlated to the returns of other assets traded on that market.

On the other hand, this chapter is linked to the stream of literature about the disclosure of information by firms. The disclosure of private information transforms private information into public information and as a result, the asymmetry of information between market participants is reduced. Diamond (1985) develops a model in which he shows that the disclosure of information improves welfare because it eliminates the costs of information acquisition. Disclosure of information helps firms attract investors because it reduces the asymmetry of information and therefore reduces the cost of capital. Diamond and Verrecchia (1991) and Kim and Verrecchia (1994) show that voluntary disclosure reduces the asymmetry of information between uninformed and informed investors, and thus increases the liquidity of a firm's stock. Similarly, Botosan (1997) shows that there is a negative relationship between the voluntary level of disclosure and the cost of capital when there is a low analyst following.

Firms that want to disclose information face the problem that truthful credible disclosure is costly, so they have to take into account these costs when they take their disclosure decision. To exemplify this, Verrechia (1983) develops a model where the seller of an asset has to decide whether to reveal or conceal information about the asset. Revealing information is costly but concealing it can be perceived as a bad signal by investors who then bid low prices for the asset. Narayanan (2000) extends Verrechia's (1983) model by endogenizing the disclosure costs by allowing the seller of the asset to trade upon his private information. Also, Fishman and Hagerty (1989) show that firms have incentives to disclose a certain amount of information but they claim that mandatory disclosure is not socially optimal since the benefits outweigh the costs. Admati and Pfleiderer (1990) examine the sale of financial information and demonstrate that externalities between buyers affect the value of information and how broadly a given packet of information should be sold.

THE MODEL

I consider an economy with two firms in the same industry, so their liquidation values are correlated. Shares in the two firms are both traded on the financial market. We assume that the first firm has a project with liquidation value $\tilde{v}_1 = \tilde{v}$ that is normally distributed with mean $\bar{v}$ and variance V_v and the second firm has a project $\tilde{v}_2 = \tilde{v} + \tilde{e}$, where $\tilde{e}$ is normally distributed with

mean 0 and variance V_e. Consequently, the second firm's payoff is normally distributed with mean $\tilde{v}$ and variance $V_v + V_e$.

Both managers learn the realization of the payoff of their firms and make use of their private information by trading the shares of both firms in the two financial markets. I denote by M_i the manager of the firm i, $i = 1, 2$. The market participants in each of the two markets are, therefore, two informed traders—the two managers, some noise traders, and a market maker. I assume that noise traders' order in the market for the shares of firm j, ω_j is a random variable normally distributed with mean 0 and variance $V_{\omega j}$, with $j = 1, 2$. The market maker in the market for the shares of firm j observes the total order flow and sets a price p_j for the firm j's shares.

The sequence of events is as follows:

1. The firms' payoffs $\tilde{v}_1$ and $\tilde{v}_2$ are realized and observed privately by the manager of each firm, respectively.

2. Firm 1 discloses information about asset 1, $\tilde{s} = \tilde{v}_1 + \tilde{\varepsilon}$, where ε, is a random variable normally distributed with mean 0 and variance V_ε.

3. The manager M_i, $i = 1, 2$, submits an order x_i^j for shares in the firm j, $j = 1, 2$ to a market maker who is in charge of setting the price in the stock market.

4. The market maker in the market for asset j observes the total order flow $u_j = x_1^j + x_2^j + \omega_j$ consisting of the managers' orders x_1^j and x_2^j and the order made by noise traders ω_j but cannot observe x_1^j, x_2^j or ω_j individually. Upon observing the total order flow, the market maker sets a price p_j for the firm j's shares and trading takes place.

The pricing rules for the market maker and the trading strategies for informed traders are such that each trader takes the trading strategies of all the other traders and the pricing rules of the market makers as given. Each informed trader maximizes his expected profit from trading conditional on his information and each market maker earns zero expected profits. Thus, the demand of the manager M_i for asset j is as follows:

$$x_i^j = \arg \max_{x_i^j} E\left((v_j - p_j)\, x_i^j | v_i, s\right), \quad i, j = 1, 2.$$

We assume that in each financial market there is a market maker who sets the price such that to satisfy the semi-strong efficiency condition $p_j = E(v_j | u_j) = \mu_j + \lambda_j u_j, \quad j = 1, 2.$

The Equilibrium

In the following proposition, I describe the equations that characterize the symmetric Bayesian-Nash equilibrium. This equilibrium has linear trading and pricing rules and is shown to be unique among all linear, symmetric Bayesian-Nash equilibria. As in most Kyle-type models, linearities are not imposed beforehand in the agent's strategy sets: as long as informed traders use linear trading strategies, the pricing rule will be linear and vice versa.

Proposition 1: *There is a unique linear equilibrium in the market of asset 1, where the demands of the managers and the equilibrium price are*

- $x_1^1(v_1, s) = \dfrac{1}{3\lambda_1 U}\left(\dfrac{3}{2}(U - V_v V_\varepsilon)(v_1 - \overline{v}) - 2V_v V_e(S - \overline{v})\right)$

- $x_2^1(v_2, s) = \dfrac{V_v}{3\lambda_1 U}\left(3V_\varepsilon(v_2 - \overline{v}) + 4V_e(s - \overline{v})\right)$

- $p_1(u_1) = \overline{v} + \lambda_1 u_1$

- $\lambda_1 = \dfrac{1}{3U}\sqrt{\dfrac{V_v}{V_{\omega_1}}(U(2U + V_e V_\varepsilon) - 6V_v V_e V_\varepsilon^2)}$

There is a unique linear equilibrium in the market of asset 2 where the demands of the managers and the equilibrium price are

- $x_1^2(v_1, s) = \dfrac{1}{3\lambda_2 U}\left(3(V_v V_\varepsilon + V_v V_e + V_\varepsilon V_e)(v_1 - \overline{v}) + V_v V_e(s - \overline{v})\right)$

- $x_2^2(v_2, s) = \dfrac{1}{3\lambda_2 U}\left(3(V_v V_\varepsilon + 2V_v V_e + 2V_\varepsilon V_e)(v_2 - \overline{v}) - 2V_v V_e(s - \overline{v})\right)$

- $p_2(u_2) = \overline{v} + \lambda_2 u_2$

- $\lambda_2 = \dfrac{1}{3U}\sqrt{\dfrac{K}{V_{\omega_2}}}$, where

$K = 72V_v V_e^3 V_\varepsilon + 48V_v^3 V_\varepsilon + 36V_v^2 V_v^3 + 32V_v^3 V_e^2 + 18V_v^3 V_\varepsilon^2 + 36V_v^3 V_\varepsilon^2$
$\quad + 81V_v V_e^2 V_\varepsilon^2 + 63V_v^2 V_e V_\varepsilon^2 + 113V_v^2 V_e^2 V_\varepsilon$, *and* $U = 3V_v V_\varepsilon + 4V_v V_e$
$\quad + 4V_\varepsilon V_e.$

Notice that manager M_i trades twice as aggressively on the information revealed by the public signal s in the market for shares in his own firm than in the market where shares in the other firm are traded. Moreover, in the market for asset j the demand of manager M_i decreases with the signal about the liquidation value of firm s, when $i = j$ while the demand for the shares of the other firm increases with the signal, when $i \neq j$. When some information is disclosed, the manager weighs his private signal against the public signal when he trades in his own market. However, when manager M_i trades in the market of the shares in the other firm j he uses the signal about the liquidation value of asset 1 as a signal about the liquidation value of asset j, thereby weighs the signal positively.

DISCLOSURE OF INFORMATION AND MARKET LIQUIDITY

I study next the effects of releasing information about the payoff of one asset on the market performance of both assets. I limit my study of market performance only in terms of market liquidity since it is recognized as the most important characteristic of financial markets. To measure market liquidity I use market depth as defined by Kyle (1985): the volume needed to move the price by one unit.

The price schedules defined in Proposition 1 show that the volume needed to move the price p_j by one unit is $\dfrac{1}{\lambda_j}$. In finding the equilibrium, I solve for λ_j and I obtain that market depths in the two markets equal to

$$\frac{1}{\lambda_1} = 3U \sqrt{\frac{V_{\omega_1}}{V_v(U(2U + V_e V_\varepsilon - 6V_v V_e V_\varepsilon^2)}}$$

$$\frac{1}{\lambda_2} = 3U \sqrt{\frac{V_{\omega_2}}{K}}.$$

I will firstly analyze the impact of the disclosure of information on the market liquidity of the two markets. Therefore, in the case of both markets I consider the economy with and without the disclosure of private information. To obtain the case without disclosure I calculate the limit when the

Figure 29.1 Market Liquidity Effects of Disclosing Information in the Two Markets. Parameter Values:
$V_e = 0.5, V_\varepsilon = 1, V_{\omega 1} = 0.5, V_{\omega 1} = 2.$
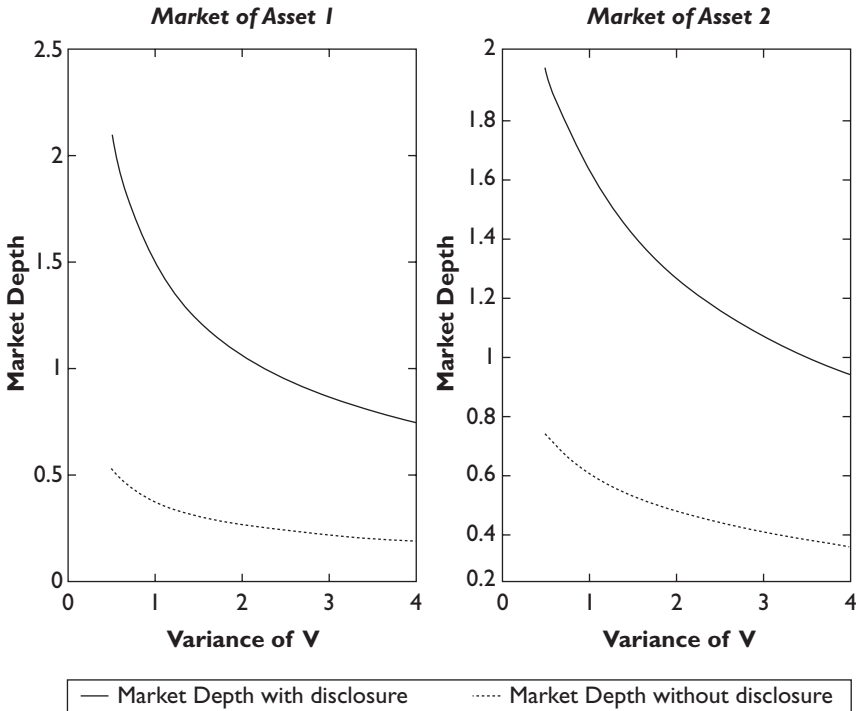
variance of the signal becomes very large. In this case the signal provides no information, so the managers use only their own private signals in setting the demand schedules.

As can be seen in Figure 29.1, I show that disclosing information about one asset improves the market liquidity in both markets. As expected, the disclosure of information reduces the asymmetry of information between market makers and informed traders. Consequently, the adverse selection problem of the market maker is less severe and therefore disclosure of information improves market liquidity. Since the two assets are correlated, the disclosure of information in the market of asset 1 affects the liquidity of the market of asset 2. The effect disclosing private information has on market liquidity depends not only on the asymmetry of information between managers and noise traders but also on the quality of the signal about the liquidation value of firm 1.

Proposition 2: Market liquidity is higher in the market of asset 1 than the market liquidity of asset 2 if and only if

$$\frac{V_{\omega_1}}{V_{\omega_2}} > \frac{V_v(U(2U + V_e V_\varepsilon) - 6V_v V_e V_\varepsilon^2)}{K}.$$

I compare market liquidity in the two markets and show that the market of asset 1 is more liquid if the ratio of the amount of noise in market 1 to the amount of noise in market 2 is sufficiently high. This suggests that when firm 1 releases information about the liquidation of value of their shares, this reduces the asymmetry of information and therefore improves market liquidity in this market. However, the disclosure of information in the market of the first asset also reduces the asymmetry of information in the second market and therefore also increases market liquidity in the second market.

Should the first firm not disclose information, the market liquidity of each market will depend only on the asymmetry of information between managers and noise traders. When the first firm discloses information about its liquidation value it affects this asymmetry of information between managers and noise traders. This effect depends on the quality of the signal about the liquidation value of the asset (i.e., on the variance of the noise introduced by the firm), but it is not the same in the two markets and for the two managers.

In the market of asset 1, the lower the variance of the signal's noise V_ε the lower the asymmetry of information about the liquidation value of the asset between manager M_1 and the noise traders. So the higher disclosure decreases the informational advantage of first manager M_1. However, manager M_2 improves his informational advantage. He had private information about the liquidation value of asset 2 (and since the assets are correlated he could use it as private information about asset 1), but now he can also use the information disclosed by firm 1. So the quality of his private information improves. In the market of asset 2, the effects are similar. However, the effect of a reduction in the asymmetry of information between manager M_2 and the noise traders caused by the disclosure of information about the liquidation value of asset 1 is now not so strong. The reason is that the signal *s* as a signal about the liquidation value of asset 2 is noisier than when we use it as a signal about the liquidation value of asset 1. Also, manager M_1

Figure 29.2 Comparison of the Increase in Liquidity after Disclosure of the Signal About the Liquidation Value of Firm 1. Parameter Values: $V_e = 0.5$, $V_\varepsilon = 1$, $V_{\omega 1} = 0.5$, $V_{\omega 1} = 2$.

Increase in liquidity after disclosure

Market Depth (y-axis), Variance of V (x-axis)

— Increase in liquidity in Market 1   ⋯⋯ Increase in liquidity in Market 2
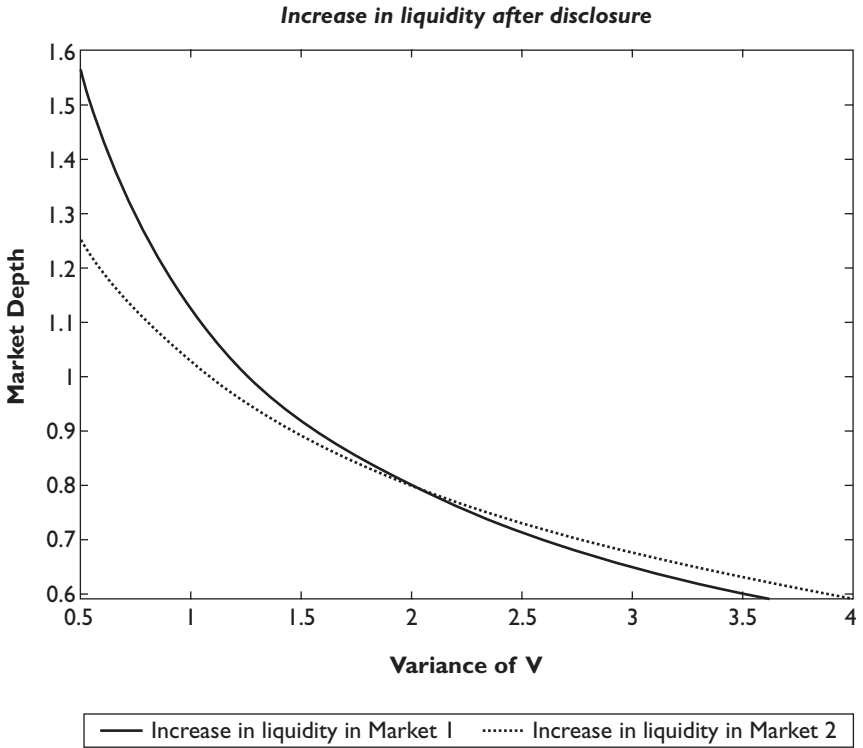
uses the signal *s* as a signal about the liquidation value of asset 2, but in this case too the quality of this signal is poorer.

As can be seen in Figure 29.2, the increase in market liquidity as a result of the release of a public signal about the liquidation value of the asset can be higher either in market 1 or in market 2, depending on the amount of the noise trading in the two markets and on the asymmetry of information about the liquidation values of the two assets. The increase in liquidity in market 1 is higher only if the amount of noise trading in market 2 is relatively small in comparison with the amount of noise trading in market 1. As can be seen in Figure 29.2, when all other things are equal, the asymmetry of information about the liquidation value of the asset determines whether the impact of disclosure of information is higher in the market where the signal is disclosed or in the other market. When the

asymmetry of the liquidation value is low in both markets (V_v is low) and there is not too much noise trading, the increase in liquidity after disclosure is higher in the first market. As asymmetry climbs above a given threshold, the increase in liquidity becomes higher in the second market. This result is a consequence of the relative asymmetry of information of the managers with respect to the noise traders.

CONCLUSION

I study the effect the disclosure of information in one market has on the market performance in the markets of correlated assets. I develop a two-asset model similar to Kyle (1985) and I show that the disclosure of a signal about the liquidation value of one asset affects the market liquidity of both the market in which this asset is traded and the market in which a correlated asset is traded. Disclosure of information increases market liquidity in both markets, but the impact of disclosure in the two markets depends on the relative amount of noise trading, the variance of the liquidation values of the two assets, and the quality of the signal about the liquidation value.

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INDEX