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Automated Versus Floor Trading: An Analysis of Execution Costs on the Paris and New York Exchanges

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ABSTRACT

A global trend towards automated trading systems raises the important question of whether execution costs are, in fact, lower than on trading floors. This paper compares the trade execution costs of similar stocks in an automated trading structure (Paris Bourse) and a floor-based trading structure (NYSE). Results indicate that execution costs are higher in Paris than in New York after controlling for differences in adverse selection, relative tick size, and economic attributes across samples. These results suggest that the present form of the automated trading system may not be able to fully replicate the benefits of human intermediation on a trading floor.

A TRADING MECHANISM IS DEFINED by the distinctive set of rules that govern the trading process. The rules dictate when and how orders can be submitted, who may see or handle the orders, how orders are processed, and how prices are set (see O'Hara (1995)). The rules of trading affect the profitability of various trading strategies (see Harris (1997)), and hence affect trader behavior, price formation, and trading costs. A fundamental question in securities market design is the link between the rules of the trading mechanism and the cost of trade execution. Numerous studies have investigated this issue by comparing bid-ask spreads in the auction-based New York Stock Exchange (NYSE) and the dealer-based Nasdaq.[1] While much of the debate centers on the relative merits of auction and dealer markets, an alternative

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[1] For example, Huang and Stoll (1996) and Bessembinder and Kaufman (1997a) compare execution costs of a matched sample of firms from NYSE and Nasdaq. Christie (1998) provides an excellent summary of related papers.

perspective is the optimal design of an auction market. The current trend toward automation of auction trading mechanisms raises the important question: Would a fully automated auction market provide better execution than a floor-based market structure? This paper compares the execution cost for the common stock of similar firms in an automated limit order market (Paris Bourse) and a floor-based limit order market (NYSE).

Theoretical models on the competition for order flow between an automated and a hybrid limit order book (with specialist) (e.g., Glosten (1994), Seppi (1997), and Parlour and Seppi (1998)) suggest that neither structure is clearly superior. Domowitz and Steil (1999) discuss the benefits of automation of trading structures in the framework of network models of industrial organization. They also survey the empirical literature on the issue and conclude that electronic trading generally yields considerable cost savings over traditional floor-based trading. In contrast, Benveniste, Marcus, and Wilhelm (1992) argue that the professional relationships that evolve on the floor of an exchange, due to repeated trading between the specialist and floor brokers, result in information sharing on forthcoming order flows and intrinsic value of the stock. This helps reduce the information asymmetry and increase the effective liquidity of a traditional floor-based system.

Empirically, several papers examine the role of the human intermediaries on a trading floor.[2] The obligations of the NYSE specialist requires her to maintain meaningful spreads at all times, maintain price continuity, and trade in a stabilizing manner. Institutional investors prefer to use the floor broker to "work" large and difficult orders. The floor broker can react quickly to changing market conditions and execute sophisticated trading strategies, thus reducing market impact and execution costs. On the other hand, anecdotal evidence around the world suggests that markets are moving away from the floor-based trading system. Proponents of the automated system argue that trading floors are inefficient, are overrun with people and paper, have less transparency, and should be replaced with technologically superior electronic systems.[3]

The discussions above suggest that the choice of the trading mechanism involves a trade-off between higher costs of operating a trading floor and potentially better execution due to the beneficial role of the specialist and

[2] See, for example, Hasbrouck and Sofianos (1993), Madhavan and Smidt (1993), Madhavan and Sofianos (1998), Kavajecz (1999), and Madhavan and Panchapagesan (2000) for a discussion on the role of the NYSE specialist. The role of the floor brokers is discussed in Sofianos and Werner (1997) and Handa, Schwartz, and Tiwari (1998). New York Stock Exchange (2000) reports that the trading volume participation of the specialist, floor brokers, and limit order book at the NYSE were 13 percent, 43 percent, and 44 percent, respectively, in 1999.

[3] In the United States, electronic communication networks (ECNs) such as Island, Instinet, Archipelago, and others, are competing for order flow with the NYSE and Nasdaq. Primex Trading, an electronic system backed by Goldman Sachs, Merrill Lynch, and Madoff Securities, is pitching itself as an electronic replacement for the NYSE's trading floor (see McNamee, Reed, and Sparks (1999)). World stock markets with floorless, electronic trading include Tokyo, Frankfurt, Paris, London, Toronto, among others.

floor brokers. While the liquidity-provision role of the specialist and floor brokers is more readily apparent for less active stocks, the role of these agents is less clear for stocks with large trading volume. Madhavan and Sofianos (1998) show that the median specialist participation rate at the NYSE drops from 54.1 percent for illiquid stocks to about 15.4 percent for highly liquid stocks. The off-exchange traders may prefer to route orders in liquid stocks electronically via the SuperDot system at the NYSE, rather than incur the higher commissions of the floor broker. Hence, if the value of human intermediation is lower for highly liquid stocks, then we may expect an automated trading mechanism to have lower execution costs than the NYSE floor for a sample of liquid stocks. To investigate this, I compare execution costs of large and liquid stocks across the two market structures. Therefore, to some extent, I am intentionally biasing my results towards finding lower execution costs in an automated trading system.

An intuitive research design for the above would be to compare the execution costs of cross-listed securities in the two trading mechanisms. However, Piwowar (1997) finds that though execution costs are lower on the home exchange of the stock (i.e., U.S. stocks at the NYSE and French stocks at the Paris Bourse), a very high proportion of trades is also executed on the home market.[4] The larger trading volume in the home country provides significant liquidity benefits that may be unrelated to the relative efficiencies of the trading mechanism. By analyzing execution measures of stocks with similar characteristics in the two markets, this paper attempts to overcome such a limitation and investigate the relative efficiency of the market structures in their normal trading environment.

The CAC40 Index stocks from the Paris Bourse are matched with NYSE stocks using four algorithms: (a) price and trading volume; (b) price and market size; (c) industry, price, and trading volume; and (d) industry, price, and market size. The sample period extends from April 1997 to March 1998. Three measures of trade execution costs are examined: quoted spreads, effective spreads (which allow for the possibility of execution within the quotes), and realized spreads (which measure trading costs after accounting for the risk of adverse selection). The results indicate that the quoted spreads in Paris (0.26 percent) are lower than spreads on similar NYSE stocks when the tick size at the NYSE is an eighth (0.31 percent), but higher than NYSE spreads after the reduction in tick size at the NYSE to the sixteenth (0.24 percent).[5] Institutional features at the NYSE permit price improvement by execution within the quotes. The average NYSE percentage effective spreads in the pre- and post-tick size reduction periods are 0.21 percent and 0.16 percent, respectively, while the Paris Bourse has significantly higher effective

[4] This may be due to many reasons: more information production in the home country may generate higher investor interest; traders may prefer to trade in the market in which other investors trade; and traders may not prefer to trade at midnight or at irregular trading hours.

[5] The NYSE changed the tick size from eighths to sixteenths on June 23, 1997. At the Paris Bourse, there is greater variation of tick sizes across price levels.

spreads of 0.24 percent. The results are robust across all trade sizes and the execution cost differential increases with trade size.

Execution costs continue to be higher in Paris relative to New York after accounting for differences in adverse selection costs, relative tick sizes, and economic variables across the samples.[6] From an economic perspective, the transactions cost in Paris is higher than in New York by 0.14 percent of the amount traded. Stated differently, if the average Paris sample firm was traded on the NYSE, the estimated savings in execution cost is $763,000 per month.

The lower execution costs in a floor-based system suggest that there is a benefit to human intermediation in the trading process. The NYSE specialist helps maintain narrow spreads, anticipates future order imbalances, and helps reduce transitory volatility (see Kavajecz (1999)). The trading floor also allows market participants to manage the risk of order exposure by using the services of a floor broker. These results are consistent with Handa et al. (1998), who document significant reduction in trading costs due to strategic behavior on the part of floor brokers at the AMEX. However, two caveats should be noted. First, although the study attempts to control for the liquidity advantage of a dominant national market by analyzing a matched sample of stocks rather than cross-listed securities, the differences in factors such as insider trading laws, the degree of competition for order flow, and the overall trading volume between the United States and France are very difficult to control. Second, the liquidity providers at the Paris Bourse may be subject to higher inventory and order-processing costs, for which the economic variables employed in this study are not adequate proxies.

This paper is organized as follows. In Section I, I discuss the differences between automated and floor mechanisms and their effects on execution cost. In Section II, I describe the components of the bid-ask spread and the measures of trading costs. Section III describes the data source, sample selection criteria, and descriptive statistics. Section IV presents the results of the univariate analysis of trading costs. The results of the cross-sectional regression analysis of transaction costs are presented in Section V. In Section VI, I discuss the economic significance of the differences in execution costs. In Section VII, I summarize the results and discuss implications for the designers of the automated trading systems.

I. Automated Versus Floor-based Trading Mechanisms

The issues involved in the design of trading systems are complex (see Harris (1996, 1997)). In most continuous auction markets, price-contingent limit orders are arranged on the basis of priority rules in the limit order book and help provide liquidity. A trade occurs when an aggressive trader submits a market order and demands liquidity. To attract demanders of liquidity, designers of trading systems want liquidity providers to fully display their orders. However, displaying limit orders can be risky for two reasons.

[6] Also, brokerage commissions for institutional trades are higher at the Paris Bourse, relative to the NYSE.

First, liquidity providers risk trading with better informed traders, that is, being picked off. To lower this risk, liquidity providers would like the trading system to allow them to trade selectively with counterparties of their choice. Second, they risk being front-run by other traders and, thereby increase the market impact of their orders. To lower this risk, large traders want to hide their orders and expose them only to traders who are most likely to trade with them. Harris (1997, p. 1) says, "The art of trading lies in knowing when and how to expose trading interests. Traders who never expose never trade. Traders who over-expose generate high transactions cost." If traders are forced to display their orders fully, the trading system may not obtain the liquidity. Hence, designers of trading systems (including floor-based and automated systems) formulate trading rules to help liquidity providers better control the risk of order exposure. Rules of trading are very important because they constrain the ability of liquidity providers to control the risk of order exposure. A key implication is that liquidity providers may accept less compensation for their services in trading systems that provide better facilities to control risk.

The rules of trading differ on many dimensions between a floor-based and an automated trading system. In this section, I discuss the important differences in trading rules and their potential effect on order submission strategies and trading cost. The institutional details of the NYSE and the Paris Bourse are presented in Table I. At the Paris Bourse, liquidity providers can specify that a portion of their limit order be "hidden." Traders learn about the "hidden" interest in the limit order book only after they are committed to trading an amount larger than the displayed quantity. This reduces the risk of being front-run by *parasitic* traders and the value of the free trading option. However, all orders (including the hidden portion of the order) are firm commitments to trade and liquidity providers cannot reveal their orders selectively to counterparties of their choice. In addition, the identity of the broker who initiated the trade is not revealed by the trading system (for the most liquid stocks). These features characterize an important distinction from the trading rules at the NYSE. A large trader at the NYSE can use the services of a floor broker to control the risk of order exposure. Handa et al. (1998) mention that a floor broker reveals the order only in response to the arrival of a contra-side order that he or she wants to trade against.[7] This implies that the floor broker has some ability to refuse to trade with well-informed traders and to selectively trade with other brokers with whom she is more comfortable. If traders are concerned about who wants to trade and why they want to trade, then the ability to selectively disclose the order may be an important dimension of the trading process.

Another significant distinction is the role of the specialist on the NYSE. Previous studies (see, e.g., Hasbrouck and Sofianos (1993), Madhavan and Sofianos (1998), and Kavajecz (1999)) show that the specialist's quotes an-

[7] In executing large orders, the floor broker assesses the total liquidity available in the limit order book and in the trading crowd, and trades strategically to minimize market impact (see Sofianos and Werner (1997)).

Table I

Description of the Institutional Framework at the NYSE and the Paris Bourse

Institutional Feature	New York Stock Exchange	Paris Bourse
Trading mechanism	Order driven *floor-based* continuous market with specialist. Orders can be routed electronically through the SuperDOT to the central limit order book or can be routed to the trading post using floor brokers. Though the SuperDOT (floor brokers) accounts for 95 percent (5 percent) of the executed orders, it accounts for only 42 percent (45 percent) of the share volume traded (see Bacidore, Ross, and Sofianos (1999)).	Order driven *electronic* continuous market with no specialist (for the large capitalization stocks). All orders are routed electronically via member firms to the central limit order book through an advanced order processing system called the NSC (without any need for reentry by the member firms).
Liquidity provided by	Public limit orders and the specialist. The specialist has obligations to maintain narrow spreads and provide stability when previous price movements are significant. As compensation, the specialist has monopolistic access to order flow information (see Madhavan and Sofianos (1998)).	Public limit orders only (for large capitalization stocks). For medium and low capitalization stocks, preassigned market makers provide additional liquidity by posting quotes for a minimum amount. As compensation, they do not pay trading fees and can be counterparty to all trades.
Types of orders	Market orders and limit orders, with further conditions for execution (Fill-or-kill, Day, GTC, Stop-loss, Market-on-close etc.). Further, a large trader can use the services of a floor broker to execute customized trading strategies (see Sofianos and Werner (1997)).	Order types are similar to those at the NYSE. There are no floor brokers. However, the exchange allows traders to specify partial display of their orders. The system hides the remaining size and displays it only after the displayed size executes (see Harris (1996)).
Order precedence rules	Price, public order, and time.	Price, exposure, and time.
Pre-trade transparency	For off-floor traders, information on the best bid-ask prices in the limit order book and the number of shares at these prices is available. Floor brokers can obtain information on the general trading interest on the floor and the depth in the limit order book from the specialist.	Information on the five best bid and offer prices and the number of shares (displayed quantity) demanded or offered at each of these prices are continuously available to public investors. A member firm can observe the entire limit order book and the ID number of the broker placing the limit order.
The auction process	Execution is *not automated*. An incoming order is exposed to the specialist or traders in the crowd for price improvement. Once exposed, the order is executed against the improved price in the crowd or against the posted quotes (see, e.g., Hasbrouck, Sofianos, and Sosebee (1993)).	An incoming market order is executed *automatically* against the best limit orders in the book. Executions within the inside quotes *occurs rarely* at the Paris Bourse when a member firm facilitates the trade in its capacity as a dealer or a broker (see the discussion on block trading below).

Block trading facility or *Upstairs* market	There exists an informal *upstairs* market where block trades are facilitated by search and negotiation. An upstairs trade needs to be "crossed" on the trading floor using a floor broker with an obligation to execute orders posted at better prices in the limit order book or held by other floor brokers at the time of the cross (see Madhavan and Cheng (1997)).	The informal *upstairs market* for block trades exists at the Paris Bourse. Block trades in eligible stocks can be crossed away from the best bid-offer quotes in the central limit order book at the time of the cross. The exchange rules require only that the block trade price must be within the weighted average quotes (which reflect the depth in the limit order book) at the time of the cross (see Venkataraman (2000)).
Post-trade transparency	All trades (including facilitated trades) are reported immediately to the NYSE. The NYSE publishes all trades with no delay.	All trades are reported immediately to the Paris Bourse. All nonblock trades and block trades in which a member firm acts as a broker are published immediately. Block trades in which a member firm acts as a dealer may be reported with delay.
Market opening	Public limit orders and market-on-open orders are submitted in the preopen to the NYSE's OARS system. At the open, the *specialist sets a single opening price* at which the order imbalances are absorbed (See Madhavan and Panchapagesan (2000)).	Orders accumulate in the central limit order book in the preopen. The system continuously provides information on the Indicative Equilibrium Price, that is, the price at which the trades would be conducted if the opening occurred at that precise instant. At the open, the system calculates the opening price at which the maximum number of bids and asks can be matched (see Biais, Hillion, and Spatt (1999)).
Tick size	Tick size for all shares quoted above \$1 was reduced from an eighth (\$0.125) to a sixteenth (\$0.0625) on June 23, 1997.	For shares quoted below FF5 the tick size is FF0.01; for shares quoted at and above FF5 and below FF100, the tick size is FF0.05; for shares quoted at and above FF100 and below FF500, the tick size is FF0.10; and for shares quoted at or above FF500, the tick size is FF1.0.
Trading halts and circuit breakers	Effective October 19 1988, a decline of 350 (550) points in the DJIA would result in a *market-wide trading halt* for 30 minutes (one hour). Effective April 15 1998, a decline of 10 percent (20 percent) of the DJIA would halt trading by one (two) hours (see NYSE (2000) for details).	A trading halt of 15 minutes occurs for liquid stocks when the price deviates by more than 10 percent from the closing price of the previous day. The two subsequent deviations cannot be larger than five percent. There is no market wide trading halt.
Competition for order flow	From regional exchanges and third markets (ECNs).	From continental bourses and the London Stock Exchange.
Consolidation of order flow	The exchange consolidates more than 80 percent of the turnover value of the NYSE listed stocks (see Blume and Goldstein (1997)).	The exchange consolidates more than 90 percent of the turnover value of the Paris Bourse stocks (see Demarchi and Foucault (1999)).
Ownership structure	Mutual association—member firms are owners.	Privately owned (i.e., not by member firms).

ticipate future order imbalances and help reduce transitory volatility. Madhavan and Panchapagesan (2000) show that the specialist's opening price is more efficient than the price that would prevail in an automated auction market using only public orders. These results suggest that the NYSE specialist may play a beneficial role in price formation. However, for actively traded stocks, the role of a specialist is less clear due to low participation rates.

From an industrial organization perspective, the electronic trading mechanism offers many advantages over the floor (see Domowitz and Steil (1999)). First, the benefit of any trading system increases with the number of locations from which the system can be accessed. While the Paris Bourse can easily offer remote cross-border membership and direct electronic access for institutional investors, the inherent limitations of trading floor space require access limitations at the NYSE. Second, the heavy trading volume and the growing number of new listings raise concern about the capacity limits of a trading floor. A related concern is whether the NYSE specialists have sufficient capital to fulfill their affirmative obligations.[8] Third, the development and maintenance cost of an automated market is considerably lower than that of a trading floor, thus providing significant cost reductions. Fourth, floor-based exchanges (including the NYSE) are typically organized as mutual associations, while automated exchanges (including the Paris Bourse) have typically separated the ownership of the exchange from membership. The mutual structure raises the possibility that members may resist innovations that reduce demand for their intermediation services, but may provide better execution to traders. For these reasons, a floor-based mechanism may have higher execution costs than an automated trading mechanism.

The cumulative effect of the differences in trading rules will be reflected in order submission strategies, price formations, and transactions cost. Some studies (see, e.g., Amihud and Mendelson (1986)) have suggested that investors demand a liquidity premium for holding stocks with higher transactions costs. Considering the current trend toward automation of auction markets, the relative efficiency of an automated versus a floor-based mechanism is an important issue to be addressed.

II. Components of Bid-ask Spread and Measures of Trading Costs

A. Components of Bid-ask Spread

Demsetz (1968) defines the bid-ask spread as the mark-up that is paid for predictable immediacy of exchange in organized markets. Traditional theories in market microstructure (e.g., Stoll (1978)) identify three main components of bid-ask spreads: order processing costs, inventory control costs, and adverse selection costs. The order processing cost refers to the labor, com-

[8] While the average daily trading volume at the NYSE has increased from 189 million shares in 1987 to 527 million shares in 1997, the total capital of specialist firms only increased from \$1 billion to \$1.3 billion during the same time period (see Willoughby (1998a)).

munication, clearing, and record-keeping costs of a trade. This cost is a fixed dollar amount per transaction; hence spreads per share should decrease in dollar value of trade size (see Glosten and Harris (1988)). The discussion in Section I suggests that the order processing cost is expected to be lower in an electronic market, relative to a floor-based structure. Theories of inventory control costs (see, e.g., Stoll (1978)) assume that the market maker has an optimal or a preferred inventory level. Any trade that moves the inventory level away from the optimal increases the market maker's risk and she must be compensated for this risk. This suggests that the inventory risk component of the spread is directly proportional to trade size, market price, and price volatility, and is inversely proportional to trading frequency. The adverse selection component of the spread arises due to the presence of informed traders (see, e.g., Glosten and Milgrom (1985) and Kyle (1985)). Since a market maker incurs a loss on transactions with these traders, she will charge a fee on every transaction to compensate for this loss. In a competitive equilibrium, the gain on trades with uninformed investors just offsets the loss on trades with the informed investor.

B. Measures of Trading Costs

Since the quotes and transactions are denominated in U.S. dollars ($) in New York and in French francs (FF) in Paris, I calculate percentage spread measures to compare execution costs across markets. As public limit orders primarily establish the spread in both markets, this comparison is not subject to the limitations of Demsetz (1997). The simplest measure of trading cost is the quoted spread, which measures the cost of executing a simultaneous buy and sell order at the quotes (i.e., the cost of a round-trip trade). I calculate the percentage quoted spreads defined as

$$\textit{Percentage quoted spread} = 100 * (\textit{Ask}_{it} - \mathrm{Bid}_{it})/\mathrm{Mid}_{it}, \tag{1}$$

where Ask_{it} is the ask price for security i at time t, Bid_{it} is the bid price for security i at time t, and Mid_{it} is the midpoint of the quoted ask and bid prices. The institutional features in many exchanges allow for price improvement by executions within the quotes. Also, the cost of executing a round-trip trade will differ across trade sizes, as the quoted spread is meaningful as a measure only up to the quoted depth.[9] To capture the institutional features of exchanges, I calculate the percentage effective spreads as in Lee (1993), DeJong, Nijman, and Roell (1995), and Bessembinder and Kaufman (1997a):

$$\text{Percentage effective spread} = 200 * D_{it} * (\mathrm{Price}_{it} - \mathrm{Mid}_{it})/\mathrm{Mid}_{it}, \quad \text{for a given trade size,} \tag{2}$$

[9] As discussed in Lee, Mucklow, and Ready (1993), a study of liquidity must consider the depth dimension of the market. Hence an analysis of quoted spreads alone would be insufficient to summarize the liquidity of a market.

where Price_{it} is the transaction price for security i at time t, and Mid_{it} (defined above) is a proxy of the "true" underlying value of the asset before the trade, and D_{it} is a binary variable that equals 1 for market buy orders and -1 for market sell orders, using the algorithm suggested in Lee and Ready (1991).

Since informed investors would continue to trade on the same side of the market, their presence is revealed by the order flow. The market incorporates the informational content of a trade by adjusting the quotes after a trade. This effect is captured by the price impact of the trade that is measured as follows:

$$\text{Percentage price impact} = 200 * D_{it} * (V_{i,t+n} - \text{Mid}_{it})/\text{Mid}_{it}, \quad \text{for a given trade size,} \tag{3}$$

where $V_{i,t+n}$ is a measure of the "true" economic value of the asset after the trade and is proxied by the midpoint of the first quote reported at least 30 minutes after the trade.[10] Finally, I calculate the realized spread, which measures the cost of executing trades after accounting for the risk of adverse selection, as follows:

$$\text{Percentage realized spread} = 200 * D_{it} * (\text{Price}_{it} - V_{i,t+n})/\text{Mid}_{it}, \quad \text{for a given trade size.} \tag{4}$$

As discussed in Bessembinder and Kaufman (1997a), the above measures of transactions cost for individual trades would have measurement errors due to errors in classifying trades as market buy or sell orders, due to the arrival of additional information between time t and $t + n$ (which would effect $V_{i,t+n}$) and due to the use of quote midpoints as a proxy for unobservable post-trade economic value.[11] In addition, errors would also be introduced due to using quote-midpoints as a proxy for pre-trade economic value. However, the average spread measures, calculated over a large number of trades, provide an unbiased estimate of the average execution costs.

III. Data Source, Sample Selection, and Descriptive Statistics

A. Data Source

The source of data for the NYSE stocks is the Trade and Quote (TAQ) database, made available by the NYSE. Trade and quote data on the Paris stocks are obtained from the Paris Bourse's Base de Donnees de Marche (BDM) data-

[10] The first transaction price reported at least 30 minutes after the trade and the midpoint of the first quotes reported after 12 noon on the next trading day are also used as proxies. As the results are very similar, they are not reported in the paper.

[11] To control for the arrival of additional information between t and $t + n$, I weigh each transaction by the inverse of the number of transactions between t and $t + n$.

base. Data on the industry classification of the sample firms and the U.S. dollar ($)/French franc (FF) exchange rate are obtained from Datastream.

B. Sample Selection Methodology

Theoretical models of the bid-ask spread suggest that trading costs differ systematically by firm-specific characteristics such as market size, stock price, trading volume, and volatility. Past empirical research on cross-exchange comparisons has controlled for the above by matching on some of these characteristics. This study matches the component stocks of the CAC40 Index at the Paris Bourse with the NYSE stocks using four algorithms: (a) price and market size; (b) price and trading volume; (c) industry, price, and market size; and (d) industry, price, and trading volume. For each CAC40 Index stock, the NYSE stock is matched by sampling without replacement. The sample selection methodology is similar to Huang and Stoll (1996) and is described in detail in the Appendix.

The sample period covers one year from April 1997 to March 1998. Only trades and quotes that occurred on the two exchanges during the normal trading hours are analyzed.[12] I use filters to delete trades and quotes that have a high likelihood of reflecting errors or were nonstandard.[13] Lee and Ready (1991) show that trade reports lag quotes in the NYSE, and I correct for the same by comparing the trade to the quote in effect five seconds earlier. In contrast, the data from the Paris Bourse are relatively error free as they are produced by the automated trading system. In the Paris Bourse, a large marketable limit order to buy (sell) can exhaust the depth on the inside quote and walk up (down) the limit order book. Such a large order is reported as multiple trades occurring at the same time in the BDM database. I classify these simultaneous trades as one large trade. In addition, block trades in Paris that involve a member firm as the counterparty are reported to the market after a two-hour delay.[14] Hence, I use quotes that were effective two hours and thirty minutes after the transaction time as a proxy for the post-trade value of the security.

[12] The NYSE faces competition for order flow from the regional exchanges and third markets, and consolidates about 80 percent of the overall volume (see Blume and Goldstein (1997)). Similarly, the Paris Bourse faces competition for order flow from the London Stock Exchange and other continental bourses, and consolidates more than 90 percent of the turnover value (see Demarchi and Foucault (1999)). This study does not consider trades and quotes away from the NYSE and the Paris Bourse.

[13] Trades were omitted if they are indicated to be out of time sequence, or coded involving an error or cancellation. Trades were also omitted if they involved a nonstandard settlement or were indicated to be exchange acquisitions or distributions. Trades were also omitted if trade price is negative or involved a price change (since the prior trade) greater than an absolute value of 10 percent. Quotes are deleted if bid or ask is nonpositive; bid-ask spread is negative; the change in the bid or ask price is greater than absolute value of 10 percent; bid or ask depth is nonpositive; or nonfirm quotes or quotes were disseminated during trading halt or a delayed opening.

[14] A trade in a stock is classified as a block trade if the trade size exceeds the normal market size (NMS) for that stock. The NMS is calculated quarterly for each stock on the basis of its daily trading volume and depth in the limit order book (see SBF Bourse de Paris (1995)).

C. Descriptive Statistics

Table II presents the stock characteristics of the Paris and New York sample matched on industry, price, and size. The sample firms on both exchanges represent a broad cross-section of industries. While the distribution of market size is very similar across the two samples, the distribution of market price in the Paris sample is higher than in the New York sample.[15] Though a joint match on three stock characteristics (i.e., including industry) results in larger deviations among the matched samples than a match on two characteristics, I find that the differences in execution cost measures between the two exchanges are similar across the four matching algorithms. To save space, I report the analysis of execution costs using two algorithms: (1) price and trading volume, and (2) industry, price, and market size, in all the tables and discuss the results of the match on industry, price, and market size in detail in this paper.[16]

Table III reports additional descriptive statistics on the trading patterns of the matched sample. The statistics for each exchange are pooled time-series cross-sectional averages across the sample firms for the 12-month sample period. Daily and hourly return volatility, computed using quote midpoints, indicates relatively similar patterns for the Paris and New York samples.[17] The Paris sample has a higher number of quote updates per day (1,055) than the New York sample (427). Biais, Hillion and Spatt (1995) show that a large fraction of order placements at the Bourse improves the best bid or ask quotes (reflecting competition in the supply of liquidity), which would result in more frequent quote updates. Also, as suggested in Harris (1996), frequent quote updates are also consistent with higher frequencies of order cancellations by liquidity providers to discourage front-running strategies.

An average stock in the NYSE sample had 4,435 trades per month, which translates into an average monthly dollar trading volume of \$508 million. During the same period, an average stock in the Paris Bourse sample had 11,851 trades per month and an average monthly dollar trading volume of \$650 million. Average trade sizes are \$103,675 in New York and \$50,850 in Paris. Further, the trades are broken down into categories based on the trade size. I define a trade to be: (1) very small if trade size $<$ \$20,000; (2) small if \$20,000 $\leq$ trade size $<$ \$50,000; (3) medium/small if \$50,000 $\leq$ trade size $<$ \$100,000; (4) medium/large if \$100,000 $\leq$ trade size $<$ \$300,000; (5) large if \$300,000 $\leq$ trade size $<$ \$500,000; (6) very large if trade size $\geq$ \$500,000. In each trade-size category, the average trade size (in dollars) com-

[15] On April 1, 1997, the average stock price in Paris (\$142) is substantially larger than the NYSE (\$41). This result is consistent with Angel (1997), who shows that the average stock price in the French market is significantly higher than in the U.S. and world markets.

[16] The results of the match on price and market size, and industry, price, and trading volume are available from the author on request.

[17] Return volatilities computed using transactions prices would be biased upwards due to bid-ask bounce. While this bias would affect volatilities in both exchanges, the exchange with the higher spreads would have a higher bias.

pares favorably across the two samples. As documented in Biais, Hillion and Spatt (1995), I find that a high proportion (62 percent) of the Paris trades are small trades (relative to New York (32 percent)). This could reflect the presence of a higher proportion of smaller investors at the Bourse or the strategic behavior of traders to split their larger orders into smaller orders to minimize market impact. This may also be due to the siphoning of small orders away from the NYSE by third market broker-dealers and the regional exchanges.

D. Research Design

During the sample period, the New York sample had 2.9 million quotes and 1.5 million trades, while the Paris sample had 7.1 million quotes and 3.8 million trades. My research design and interpretations are similar to Bessembinder and Kaufman (1997a), and use a two-stage approach to overcome data processing constraints. In the first stage, I calculate the average measures of execution costs for each stock on a calendar month basis. The second stage OLS regression specification follows:[18]

$$Y_{it} = \alpha_{\text{Paris}} D_{\text{Paris}} + \alpha_{\text{Pre-NYSE}} D_{\text{Pre-NYSE}} + \alpha_{\text{Post-NYSE}} D_{\text{Post-NYSE}} + \epsilon_{it}, \qquad (5)$$

where Y_{it} denotes the average execution cost measure for stock i for month t; D_{Paris} equals one for all Paris stocks and zero for all NYSE stocks; $D_{\text{pre-NYSE}}$ equals one for all NYSE stocks in the sample period before the reduction in tick size and zero otherwise; and $D_{\text{post-NYSE}}$ equals one for all NYSE stocks in the sample period after the reduction in tick size and zero otherwise.

The dummy coefficient measures the average execution costs at each exchange. Since regression (5) is performed on a pooled time-series cross-sectional data set, error terms would not satisfy the classical conditions of heteroskedasticity and autocorrelation. Hence I adopt a bootstrapping procedure to assess the statistical significance of the regression coefficients. A bootstrap NYSE sample, with the same sample size as in regression (5), is drawn by random sampling with replacement from the original sample of NYSE stocks. A bootstrap sample for the Paris stocks is constructed by choosing the matched Paris stock.[19] Regression (5) is estimated for the bootstrapping sample and the dummy coefficients are saved. This process is repeated 500 times to obtain 500 bootstrapping coefficients. Since the bootstrap sample is drawn from the original sample (as against the error terms), the distribution of the bootstrap coefficient is centered on the sample mean. The bootstrap p-value for the null hypothesis of zero realized spreads at each

[18] The analysis using weighted least squares, where the weight is the trading frequency, produces similar results. I also estimated regression (5) using pre- and postdummies for the Paris sample and find similar results.

[19] As a robustness check, the bootstrap Paris sample is also constructed by random sampling with replacement from the original sample of Paris firms. The bootstrap p-values are very similar and are not reported separately.

Table II

Statistics of the NYSE and the Paris Bourse Sample Matched on Industry, Market Price, and Market Size

The Paris sample consists of the component firms of the CAC40 Index with trading data for the entire sample period (April 1997 to March 1998). The New York sample consists of all NYSE-listed stocks in the TAQ database in April 1997 and with trading data for the entire sample period. For the Paris sample, the stock price and market size on April 1, 1997, is obtained from the BDM database, and converted to U.S. dollars using the spot exchange rates (obtained from DataStream). Similarly, for the New York sample, the stock price and market size on April 1, 1997, is obtained from the TAQ database. DataStream provides the global industry classification. The Paris sample firms are matched with the New York sample firms with the same DataStream industry classification code. Next, for each Paris firm, the New York firm with the smallest average characteristic deviation statistic (defined below) is identified as the match.

$$\text{Average Deviation} = \left[\frac{\text{Price}_{\text{Paris}} - \text{Price}_{\text{NYSE}}}{(\text{Price}_{\text{Paris}} + \text{Price}_{\text{NYSE}})/2}\right] + \left[\frac{\text{Size}_{\text{Paris}} - \text{Size}_{\text{NYSE}}}{(\text{Size}_{\text{Paris}} + \text{Size}_{\text{NYSE}})/2}\right] \Big/ 2$$

			Stock Price (in Dollars)		Market Size (in Dollars)		
Industry Classification	Paris Bourse Firm	Matched NYSE Firm	CAC40	NYSE	CAC40	NYSE	Average Deviation
Insurance	AGF	Excel Limited	35.3	42.4	4,800,044,691	4,700,593,625	0.10
Electrical and Telecom	Alcatel Alsthom	Ameritech Corp.	118.1	60.3	19,109,780,058	35,482,092,675	0.62
Insurance	AXA	Allstate Corp, The	65.1	60.3	19,796,380,280	27,142,205,056	0.19
Banks	BNP	Suntrust Banks Inc.	43.0	46.4	8,920,529,328	10,712,899,322	0.13
Building and Construction	Bouygues	Vulcan Materials Company	97.6	64.5	2,351,316,206	3,004,834,441	0.33
Media and Broadcasting	Canal +	Washington Post Company	187.0	345.7	5,745,737,115	6,274,052,318	0.34
Banks	CCF	Marcantile Bancorp, Inc.	46.9	53.4	3,354,988,678	3,381,234,087	0.07

Finance	CLF Dexia France	MBIA, Inc.	102.4	95.3	3,758,697,855	4,127,132,544	0.08
Oil	Elf Aquitaine	Texaco, Inc.	98.2	108.8	26,789,017,894	29,840,477,847	0.11
Food Processing	Groupe Danone	Ralston-Ralston Purina Group	153.9	77.6	11,175,845,078	8,898,314,240	0.44
Media and Broadcasting	Havas	Interpublic Group Cos, Inc.	71.7	53.1	4,600,640,677	4,828,961,200	0.17
Building and Construction	Lafarge	Fluor Corp.	67.4	52.6	6,358,739,445	4,371,912,862	0.31
Electronic Equipment	Lagardere	Digital Equipment Corp.	31.3	26.6	3,035,377,900	4,185,371,819	0.24
Diversified	Lyonnaise Des Eaux	Textron Inc.	99.7	103.0	5,911,165,783	9,730,878,776	0.26
Tires and Rubber	Michelin	Goodyear Tire Rubber Co.	58.4	51.9	6,967,003,087	10,152,714,541	0.24
Finance	Paribas	Household Intl Corp.	68.1	85.0	8,459,169,001	9,794,557,767	0.18
Textiles and Distillers	Pernod-Ricard	Brown-Forman Corp.	54.2	47.8	3,056,400,183	1,913,876,675	0.29
Autos and Parts	Renault	Tenneco, Inc.	24.5	39.0	5,864,676,132	6,715,855,769	0.30
Pharma and Chemicals	Rhone-Poulenc	Pharmacia Upjohn Inc.	32.5	36.0	10,691,354,923	18,321,884,815	0.31
Pharma and Chemicals	Sanofi	Rohm and Hass Company	94.1	73.8	9,877,602,838	5,798,014,021	0.38
Electrical and Telecom	Schneider	AMP, Inc.	54.8	34.2	7,498,089,815	7,951,003,551	0.26
Banks	Societe Generale	BankBoston Corp.	112.8	67.6	10,331,994,367	10,353,275,319	0.25
Defense and Aerospace	Thomson-CSF	Sunstrand Corp.	32.8	44.0	3,923,764,373	3,320,189,813	0.23
Oil	Total	Atlantic Richfield Company	84.1	133.7	20,286,188,315	21,536,983,727	0.26
Autos and Parts	Valeo	Johnson Controls, Inc.	65.8	40.0	4,596,893,358	3,514,147,342	0.38
		10th Percentile	32.7	37.2	3,175,835,581	3,344,607,523	0.10
		25th Percentile	46.9	44.0	4,596,893,538	4,185,371,819	0.18
		Median	67.4	53.4	6,358,739,445	6,715,855,769	0.26
		75th Percentile	98.2	77.6	10,331,994,367	10,353,275,319	0.31
		90th Percentile	116.0	106.5	19,521,740,191	24,900,116,524	0.38
		Average	76.0	73.7	8,690,455,902	10,242,138,566	0.26

Table III

Detailed Descriptive Statistics of the NYSE and the Paris Bourse Sample

Statistics include market size, market price, daily and hourly return volatility, relative tick size, quote update frequency, trading frequency, and trading volume for the NYSE and the Paris Bourse samples. The data source is the BDM database for the Paris Bourse sample and the TAQ database for the NYSE sample. Return volatility is computed using quote midpoints. All statistics are pooled time-series cross-sectional averages across sample firms from April 1997 to March 1998. The French francs values are converted to U.S. dollars using the daily spot exchange rates. Trades are broken into sizes as follows: (1) Very small if trade size $<$ \$20,000; (2) small if \$20,000 $\leq$ trade size $<$ \$50,000; (3) medium/small if \$50,000 $\leq$ trade size $<$ \$100,000; (4) medium/large if \$100,000 $\leq$ trade size $<$ \$300,000; (5) large if \$300,000 $\leq$ trade size $<$ \$500,000; (6) very large if trade size $\geq$ \$500,000.

	Matching Algorithm			
	Market Price and Trading Volume		Industry, Market Price, and Market Size	
	NYSE	Paris Bourse	NYSE	Paris Bourse
Market price (in \$)	79.3	81.2	73.7	76.0
Market size (in \$ millions)	10,022	7,797	10,242	8,690
Return volatility for a month				
daily return	0.020	0.021	0.018	0.021
hourly return	0.006	0.007	0.005	0.006
Relative tick size	0.13%	0.08%	0.13%	0.08%
Average number of quotes/day	417	1,002	427	1,055
Average number of trades/month				
Very small trades	1,419	6,829	1,413	7,230
Small trades	1,190	1,808	1,148	1,823
Medium/small trades	879	1,173	840	1,301
Medium/large trades	851	972	749	1,152
Large trades	180	154	167	184
Very large trades	197	128	176	161
Overall	4,701	11,064	4,435	11,851
Average trade size (in \$)				
Very small trades	11,174	5,392	10,679	5,267
Small trades	33,192	32,411	33,611	32,672
Medium/small trades	71,049	69,800	71,443	69,702
Medium/large trades	165,814	161,288	166,521	161,678
Large trades	380,633	377,108	382,027	376,410
Very large trades	1,124,995	1,409,486	1,336,835	1,400,315
Overall	106,149	46,798	103,675	50,850
Monthly trading volume (in \$)				
Very small trades	15,214,612	32,490,351	14,900,935	33,940,235
Small trades	39,359,028	59,199,567	38,473,405	59,993,805
Medium/small trades	62,273,520	82,276,971	59,849,240	91,072,947
Medium/large trades	140,355,066	158,779,750	125,655,424	187,774,545
Large trades	68,348,144	58,438,540	63,886,173	69,708,941
Very large trades	226,166,596	169,590,709	207,489,560	208,456,472
Overall	551,564,819	560,775,888	508,275,437	650,946,943

exchange is the proportion of bootstrap coefficient estimates that are less than or equal to zero. The bootstrap p-value for the null hypothesis of equal execution costs across exchanges is the proportion of bootstrap observations in which the difference between the bootstrap coefficient estimates has the opposite sign as the difference between the sample coefficient estimates.

To minimize the effect of outliers in the sample, I calculate the percentage of the Paris sample's execution costs that is higher than the matched NYSE sample's execution costs. I also calculate the Wilcoxon p-value, which pertains to a Wilcoxon signed rank test of the hypothesis that median spreads are equal across exchanges. The results are robust to the effect of outliers and hence, not reported in the tables. The results of average execution costs in the exchanges are presented in the next section.

IV. Transaction Cost Measures at the NYSE and the Paris Bourse

A. Quoted Spread

Table IV presents the results of average time-weighted percentage quoted spreads on the NYSE and the Paris Bourse. For Paris, the average percentage quoted spreads (0.26 percent) are significantly lower than NYSE spreads before the reduction in tick size in the NYSE in June 1997 (0.31 percent), but higher after the reduction in tick size (0.24 percent). The average percentage quoted spreads in the NYSE declined after the reduction in tick size, which is consistent with results in Jones and Lipson (2001) and Goldstein and Kavajecz (2000). Since trades can occur within the quotes at the NYSE and quoted spreads only measure execution costs for small trades, I look at a more accurate measure of a trader's execution cost: The effective spread.

B. Effective Spread

Results from Table IV show that effective spreads are higher on the Paris Bourse than on the NYSE, and the difference is more pronounced after the NYSE reduced its tick size. The difference is about nine basis points for very small trades, six basis points for medium/small trades, and 15 basis points for very large trades, with all differences highly significant. In both exchanges, the average percentage effective spreads increase with trade size, which is consistent with large trades walking up/down the limit order book after using up depth on the inside quotes. Since the auction process in the NYSE allows for executions within the quotes, the average percentage effective spreads in New York are lower than the quoted spreads. I also find a statistically significant reduction in percentage effective spreads across all trade sizes at the NYSE due to the reduction in tick size.

This section provides evidence to support the hypothesis that the cost of executing trades across similar firms is considerably lower in New York compared to Paris. But higher trading costs at the Paris Bourse could just re-

Table IV

Transaction Cost Measures at the NYSE and the Paris Bourse

Percentage quoted spreads is time-weighted percentage quoted spreads for each firm. Percentage effective spreads is computed as [200 ∗ dummy ∗ (price-mid)/mid], where the dummy equals one for a market buy and negative one for a market sell, price is the transaction price, and mid is the midpoint of the bid-ask quote at the time of the trade. Percentage price impact is computed as [200 ∗ dummy ∗ (Qmid30-mid)/mid], where Qmid30 is the midpoint of the first quote observed after 30 minutes. Percentage realized spreads is computed as [200 ∗ dummy ∗ (Price-Qmid30)/mid]. Effective spreads are equally weighted across trades for each firm while price impact and realized spreads are weighted by the inverse of the number of transactions during the 30 minutes after the trade. All spread measures are pooled time-series cross-sectional averages across sample firms from April 1997 to March 1998. Trades are broken into sizes as follows: (1) Very small if trade size < \$20,000; (2) small if \$20,000 ≤ trade size < \$50,000; (3) medium/small if \$50,000 ≤ trade size < \$100,000; (4) medium/large if \$100,000 ≤ trade size < \$300,000; (5) large if \$300,000 ≤ trade size < \$500,000; and (6) very large if trade size ≥ \$500,000. Confidence intervals and p-values are obtained using bootstrapping samples with 500 iterations. All spread measures in percentage basis points.

	Matching Algorithm Is Market Price and Trading Volume					Matching Algorithm Is Industry, Market Price, and Market Size				
		NYSE: Tick = Eighth		NYSE: Tick = Sixteenth			NYSE: Tick = Eighth		NYSE: Tick = Sixteenth	
	Paris		Difference		Difference	Paris		Difference		Difference
Quoted spread	26.97[a]	32.39[a]	−5.42[a]	24.32[a]	2.65[a]	25.60[a]	31.11[a]	−5.52[a]	24.01[a]	1.59[a]
Effective spread										
Very small	24.45[a]	19.37[a]	5.08[a]	13.79[a]	10.66[a]	23.29[a]	19.78[a]	3.51[a]	14.20[a]	9.09[a]
Small	23.18[a]	20.74[a]	2.44[b]	15.46[a]	7.72[a]	22.09[a]	20.80[a]	1.29[c]	15.86[a]	6.22[a]
Medium/small	24.72[a]	22.30[a]	2.42[b]	16.85[a]	7.87[a]	23.41[a]	22.12[a]	1.28[c]	17.01[a]	6.39[a]
Medium/large	28.39[a]	23.36[a]	5.04[a]	18.32[a]	10.08[a]	26.77[a]	23.18[a]	3.58[a]	18.45[a]	8.32[a]
Large	33.16[a]	23.78[a]	9.38[a]	19.47[a]	13.69[a]	31.30[a]	23.63[a]	7.66[a]	20.34[a]	10.96[a]
Very large	38.34[a]	25.16[a]	13.18[a]	20.66[a]	17.68[a]	36.53[a]	24.90[a]	11.63[a]	21.34[a]	15.19[a]
Overall	24.59[a]	21.22[a]	3.36[a]	15.79[a]	8.80[a]	23.50[a]	21.06[a]	2.45[a]	16.05[a]	7.46[a]

Price impact										
Very small	5.85[a]	10.33[a]	−4.49[a]	9.19[a]	−3.34[a]	5.19[a]	10.36[a]	−5.17[a]	8.99[a]	−3.80[a]
Small	13.17[a]	15.98[a]	−2.81[a]	14.59[a]	−1.43[a]	12.63[a]	16.08[a]	−3.45[a]	14.74[a]	−2.10[a]
Medium/small	17.83[a]	19.43[a]	−1.60[b]	17.49[a]	0.34	16.68[a]	18.73[a]	−2.05[a]	16.84[a]	−0.17
Medium/large	21.18[a]	21.63[a]	−0.45	18.32[a]	2.86[a]	19.98[a]	20.47[a]	−0.49	17.63[a]	2.35[a]
Large	19.78[a]	25.00[a]	−5.21[c]	17.59[a]	2.20[a]	19.17[a]	21.67[a]	−2.50[c]	17.78[a]	1.39
Very large	11.15[a]	23.36[a]	−12.21[a]	16.41[a]	−5.26[a]	12.20[a]	22.35[a]	−10.14[a]	18.12[a]	−5.92[a]
Overall	9.50[a]	15.83[a]	−6.33[a]	14.07[a]	−4.57[a]	8.96[a]	15.43[a]	−6.47[a]	13.76[a]	−4.80[a]
Realized spread										
Very small	19.53[a]	8.99[a]	10.54[a]	4.52[a]	15.02[a]	18.92[a]	9.35[a]	9.57[a]	5.20[a]	13.72[a]
Small	10.65[a]	4.62[a]	6.03[a]	0.73[b]	9.93[a]	10.02[a]	4.64[a]	5.38[a]	1.06[a]	8.96[a]
Medium/small	7.44[a]	2.72[b]	4.73[a]	−0.79[b]	8.23[a]	7.24[a]	3.28[a]	3.96[a]	0.08	7.16[a]
Medium/large	7.50[a]	1.52[b]	5.97[a]	−0.41	7.91[a]	7.10[a]	2.66[a]	4.44[b]	0.67[a]	6.43[a]
Large	12.35[a]	−1.56[c]	13.91[a]	1.30[b]	11.06[a]	11.27[a]	1.49[b]	9.79[a]	2.29[a]	8.98[a]
Very large	25.03[a]	1.00	24.03[a]	3.20[a]	21.83[a]	22.71[a]	1.50	21.21[a]	2.58[a]	20.13[a]
Overall	15.82[a]	5.20[a]	10.61[a]	1.47[a]	14.34[a]	15.20[a]	5.48[a]	9.73[a]	2.16[a]	13.05[a]

[a] p-value < 0.01.
[b] $0.01 \leq p$-value < 0.05.
[c] $0.05 \leq p$-value < 0.10.

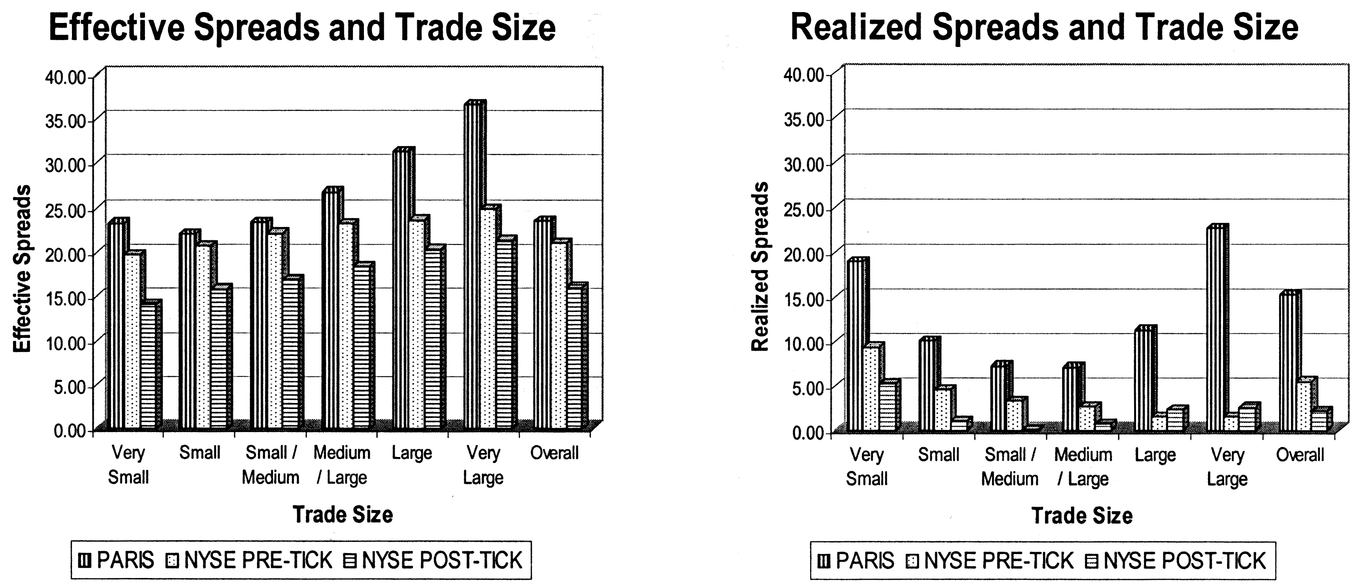


Figure 1. Comparison of effective and realized spreads on the NYSE and the Paris Bourse. Percentage effective spreads is computed as [200 $*$ dummy $*$ (price-mid)/mid], where the dummy equals one for a market buy and negative one for a market sell, price is the transaction price, and mid is the midpoint of the bid-ask quote at the time of the trade. Percentage realized spreads is computed as [200 $*$ dummy $*$ (price-Qmid30)/mid], where Qmid30 is the midpoint of the first quote observed after 30 minutes. Effective spreads are equally weighted across trades for each firm while realized spreads are weighted by the inverse of the number of transactions during the 30 minutes after the trade. The firms are matched on industry, price, and market size. All spread measures are pooled time-series cross-sectional averages across sample firms from April 1997 to March 1998. NYSE PRE-TICK and NYSE-POST-TICK spreads represent the spreads at the NYSE before and after the reduction in tick size in June 1997. Trades are broken into sizes as follows: (1) Very small if trade size $<$ \$20,000; (2) small if \$20,000 $\leq$ trade size $<$ \$50,000; (3) medium/small if \$50,000 $\leq$ trade size $<$ \$100,000; (4) medium/large if \$100,000 $\leq$ trade size $<$ \$300,000; (5) large if \$300,000 $\leq$ trade size $<$ \$500,000; (6) very large if trade size $\geq$ \$500,000. All spread measures are in percentage basis points.

flect compensation for higher private information in trades. This explanation is investigated in the next section.

C. Do Trades Contain More Private Information in Paris?

Table IV presents results on the average informational content (price impact) of trades at the two exchanges. The price impact measures the average permanent effect of a trade on the true economic value of a security. The average price impact of Paris trades is either comparable or lower than that of New York trades in a majority of the trade-size categories. These results suggest that the adverse selection component of the spread cannot explain the higher execution costs for Paris. In both exchanges, price impact increases with trade size, which is consistent with the predictions of Easley and O'Hara (1987).

D. Realized Spreads

The results in Table IV show that average realized spreads in Paris are significantly higher than in New York, and this holds across the sample period. The average difference between Paris and New York before the change in tick size is 10 basis points, and increases to 13 basis points subsequently. Also, the transactions cost after controlling for adverse selection is significantly higher in Paris for very small trades (14 basis points) and very large trades (20 basis points). Figure 1 provides a graphical relationship between spread measures and trade sizes in the two exchanges. The graph clearly shows that spread measures in Paris are higher than in New York for all trade sizes, and are substantially higher than in New York for very small and very large trades.

This section provides evidence that higher transactions costs in Paris are not driven by the higher risk of adverse selection. A structural feature that may account for the difference in execution costs between Paris and New York is the tick size. The next section investigates this explanation.

E. Can Tick Size Explain Differences in Execution Costs?

The tick size can be viewed as the cost of gaining priority over the existing quotes in a limit order market. The effect of tick size on transaction costs remains ambiguous. Harris (1994) argues that a smaller tick size increases competition among liquidity providers and forces a reduction in quoted spread, thus decreasing their willingness to provide liquidity. This might reduce the cumulative depth in the limit order book and increase execution costs. The above discussion suggests that a smaller tick size is likely to reduce the cost of trading small trades; however, the effect on transaction costs of large trades is unclear.

The Paris sample has prices ranging from around 150 FF to 2,500 FF. Hence the Paris firms are in two categories of tick sizes: 0.10 FF (1.7 cents) and 1.0 FF (17 cents). Similarly, the New York firms are in two categories of tick sizes: Eighth (or 12.5 cents) from April 1997 to June 1997, and sixteenth (or 6.25 cents) from July 1997 to March 1998. To investigate the effect of tick size on execution costs, I partition my sample into four subsamples based on the difference in tick sizes among firm pairs, and calculate execution cost measures. The results of this analysis are presented in Table V. The tick size in Paris is larger than the tick size in New York for subsamples 2 and 4, while smaller in subsamples 1 and 3. If results are driven by larger tick sizes in Paris, then differences in execution costs in subsamples 2 and 4 will be substantially higher than subsamples 1 and 3. For quoted and effective spread measures, the higher tick size of Paris firms may be partly driving the differences across exchanges. However, the realized spread measures at the Paris Bourse remain higher than the matched NYSE spreads in subsamples 1 and 3, in which the tick size in Paris is significantly smaller than the tick size in New York.

The univariate analysis in this section provides weak evidence that the differences in tick size between the exchanges are driving the differences in execution costs. However, it is possible that part of the higher transactions cost in Paris can be explained by cross-sectional differences in economic variables in the two samples. I investigate this explanation in the next section.

V. Can Economic Variables Explain the Differences in Execution Costs?

Although the firms are matched on a few firm-specific characteristics, a possibility is that heterogeneity in other economic variables, such as volatility and trading patterns, could explain the difference in execution costs. In this section, I employ a cross-sectional regression framework similar to Bessembinder and Kaufman (1997a) to investigate this possibility. The economic variables employed include: (1) monthly averages of the transaction price for each firm (in dollars); (2) market size (in dollars); (3) the standard deviation of hourly returns (using quote midpoint); (4) the average monthly trading volume (in dollars); and (5) the monthly number of trades. I include exchange dummy variables for the New York and Paris firms: The NYSE (Paris) dummy variable equals 1 (0) for all NYSE firm months, and equals 0 (1) otherwise. I control for the average relative tick size of the sample firms during the month, where the relative tick size is defined as the tick size at the time of the transaction divided by the transaction price. I also include month dummy variables to control for monthly variations in execution costs.

I transform each of the economic variables and the relative tick size variable by deducting the variable's sample mean (which is computed across the New York and Paris samples), and estimate the regression using the transformed variables. This method allows us to make an intuitive interpretation of the dummy coefficients of the regression. The intercept coefficient measures the estimated cost of executing a trade on each exchange for an average firm from the entire sample (i.e., a firm with market capitalization, stock price, trading volume, volatility, and relative tick size equal to the means observed over the pooled Paris Bourse and NYSE sample). Table VI presents the results of three regression specifications: (1) a simple noninteractive model, (2) a noninteractive model with month dummies, and (3) a fully interactive model with month dummies.

As predicted by theory, trading costs vary inversely with trading volume, reflecting economies of scale, lower inventory control costs, and lower adverse selection costs. Percentage spreads decrease with stock price, reflecting the fixed order-processing component of the spread. Percentage spread measures vary directly with stock volatility, which reflects higher adverse selection and inventory risk associated with more volatile stocks. As predicted by Harris (1994), an increase in relative tick size increases the transactions cost to the liquidity demanders.

After controlling for cross-sectional differences in economic variables and the relative tick size, the execution cost on the Paris Bourse continues to be higher than on the NYSE. From Table VI, we see that the results are consistent across different regression specifications. The difference in effective spreads between the two exchanges is 10 basis points. After accounting for adverse selection, transactions cost continues to be higher in Paris (16 basis points) than in New York (2 basis points), and the difference is statistically significant.

Table VII presents the results of the regression analysis of execution costs by trade-size categories. The executions cost measures are higher in Paris than in New York for all the trade-size categories. The difference in effective spreads is about 17 basis points for very small trades, 8 basis points for medium/small trades, and 13 basis points for very large trades, with all differences highly significant. After accounting for differences in adverse selection, the difference in execution cost increases to 19 basis points for very large and very small trades.

Figures 2 and 3 present scatter plots of the actual spread measures of the New York (Paris) sample at the NYSE (Paris Bourse) against the predicted spread measures if the New York (Paris) sample were traded at the Paris Bourse (NYSE). The predicted spread measures were obtained using the coefficients estimates of a fully interactive regression of execution cost measures on economic variables, relative tick sizes, and monthly dummies (as reported in Tables VI and VII). The coefficient estimates of the regression on Paris are used to predict the trading cost of the NYSE stocks if they were traded on Paris (by month and trade size), and vice versa. If both trading mechanisms provided similar execution for the same stock, then all points in the scatter plot will lie along the 45-degree line. From Figure 2, we see that while a few (29) observations in the Paris sample have lower quoted spreads in Paris than their predicted quoted spreads in New York, the NYSE is clearly predicted to provide better execution in terms of effective spreads. The plot of effective spread shows that the vast majority of observations of the Paris Bourse firms lies below the 45-degree line, while the vast majority of observations of the NYSE firms lies above the 45-degree line. This suggests that a vast majority of the Paris Bourse firms will have lower execution costs if

Table V

Effect of Tick Size on Execution Costs

Percentage quoted spreads is time-weighted percentage quoted spreads for each firm. Percentage effective spreads is computed as [200 ∗ dummy ∗ (price-mid)/mid], where the dummy equals one for a market buy and negative one for a market sell, price is the transaction price, and mid is the midpoint of the bid-ask quote at the time of the trade. Percentage realized spreads is computed as [200 ∗ dummy ∗ (Price-Qmid30)/mid], where Qmid30 is the midpoint of the first quote observed after 30 minutes. Effective spreads are equally weighted across trades for each firm while realized spreads are weighted by the inverse of the number of transactions during the 30 minutes after the trade. The sample is partitioned into four subsamples based on the tick sizes of the NYSE and the Paris Bourse firm-pairs. Confidence intervals and *p*-values are obtained using bootstrapping samples with 500 iterations. All spread measures are in percentage basis points. The *p*-value pertains to the null hypotheses that mean spreads are equal across exchanges in each subsample. All measures in percentage basis points.

	Quoted Spread			Effective Spread			Realized Spread		
	Paris	NYSE	Diff	Paris	NYSE	Diff	Paris	NYSE	Diff
Panel A: Matching Algorithm Is Market Price and Trading Volume									
Subsample 1 NYSE tick = 12.5 cents Paris tick = 1.7 cents N = 46	26.51^{a}	3.17^{a}	−12.66^{a}	23.46^{a}	25.87^{a}	−2.41^{b}	14.97^{a}	8.69^{a}	6.28^{a}
Subsample 2 NYSE tick = 12.5 cents Paris tick = 17 cents N = 24	27.94^{a}	21.47^{a}	6.47^{a}	25.97^{a}	13.81^{a}	12.16^{a}	16.20^{a}	−0.26	16.46^{a}
Subsample 3 NYSE tick = 6.25 cents Paris tick = 1.7 cents N = 130	26.93^{a}	29.23^{a}	−2.30^{b}	24.31^{a}	18.75^{a}	5.56^{a}	15.69^{a}	2.81^{a}	12.88^{a}
Subsample 4 NYSE tick = 6.25 cents Paris tick = 17 cents N = 82	26.57^{a}	17.28^{a}	9.29^{a}	24.82^{a}	11.52^{a}	13.30^{a}	16.15^{a}	−0.33	16.48^{a}

Panel B: Matching Algorithm Is Industry, Market Price, and Market Size									
Subsample 1									
NYSE tick = 12.5 cents									
Paris tick = 1.7 cents	26.51[a]	36.03[a]	−9.52[a]	23.46[a]	24.82[a]	−1.36[c]	14.97[a]	7.80[a]	7.17[a]
N = 46									
Subsample 2									
NYSE tick = 12.5 cents									
Paris tick = 17 cents	24.76[a]	23.24[a]	1.52[a]	23.39[a]	15.38[a]	8.01[a]	14.78[a]	1.89[a]	12.89[a]
N = 24									
Subsample 3									
NYSE tick = 6.25 cents									
Paris tick = 1.7 cents	26.22[a]	27.28[a]	−1.06[c]	23.70[a]	18.06[a]	5.64[a]	15.39[a]	3.15[a]	12.24[a]
N = 124									
Subsample 4									
NYSE tick = 6.25 cents									
Paris tick = 17 cents	24.20[a]	19.80[a]	4.40[a]	22.94[a]	13.52[a]	9.42[a]	15.04[a]	1.01[a]	14.03[a]
N = 91									

[a] p-value < 0.01.
[b] $0.01 \leq p$-value < 0.05.
[c] $0.05 \leq p$-value < 0.10.

Table VI

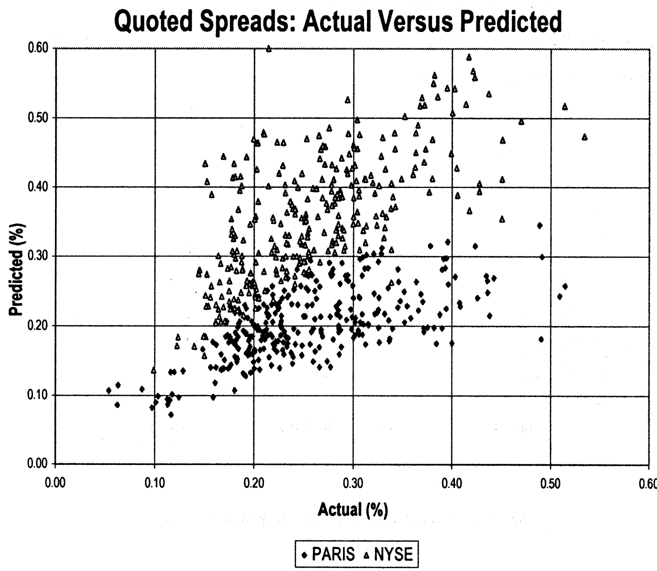
Transaction Cost Analysis in a Controlled Regression Framework

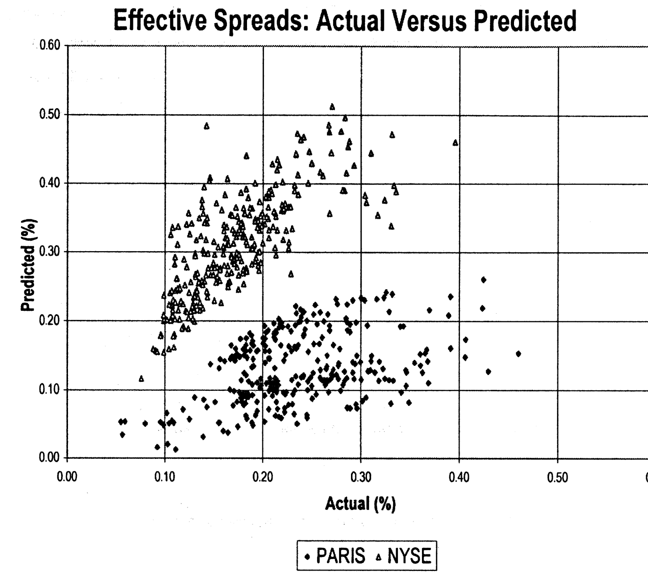
Reported are coefficients from regressions of execution cost measures for each firm by month, on exchange indicators, month dummies, demeaned economic determinants of trading cost, and relative tick size. The NYSE dummy equals one for a NYSE firm and zero otherwise, and the PARIS dummy equals one for a Paris firm and zero otherwise. For each firm, market size is the end of the month market capitalization (in dollars), stock price is the average stock price (in dollars) calculated using daily closing prices for the month, return volatility is the standard deviation of returns calculated using intraday hourly quote midpoints, trading volume is the average monthly dollar trading volume calculated using transaction price and sizes, and relative tick size is the monthly average of the relative tick sizes for each transaction during the month. All p-values are obtained using bootstrapping samples with 500 iterations.

	Matching Algorithm Is Market Price and Trading Volume								
Dependent Variables (in %)	Quoted Spread			Effective Spread			Realized Spread		
NYSE	0.242[a]	0.215[a]	0.226[a]	0.156[a]	0.137[a]	0.141[a]	0.021[a]	0.025[a]	0.030[a]
Paris	0.291[a]	0.283[a]	0.266[a]	0.261[a]	0.254[a]	0.251[a]	0.161[a]	0.169[a]	0.156[a]
log(market size)	−0.002	0.003		0.002	0.006[b]		0.010[a]	0.010	
log(market size) * NYSE			−0.005[c]			0.001			0.004
log(market size) * Paris			0.027[a]			0.010[a]			0.013[c]
log(inverse price)	0.038[a]	0.042[a]		0.014[a]	0.017[a]		0.020[a]	0.021[a]	
log(inverse price) * NYSE			0.022			−0.006			−0.006
log(inverse price) * Paris			0.020[a]			0.017[a]			0.027[a]
Return_volatility	0.187[a]	0.190[a]		0.182[a]	0.182[a]		0.011	0.009	
Return_volatility * NSYE			0.091[a]			0.116[a]			−0.078[a]
Return_volatility * Paris			0.234[a]			0.210[a]			0.062[a]
log(trad. volume)	−0.046[a]	−0.040[a]		−0.036[a]	−0.032[a]		−0.042[a]	−0.040[a]	
log(trad. volume) * NYSE			−0.001			0.000			0.007
log(trad. volume) * Paris			−0.062[a]			−0.046[a]			−0.062[a]
log(numb. trades)	−0.021	−0.040[a]		−0.019[a]	−0.322[a]		−0.020[b]	−0.016[a]	
log(numb. trades) * NYSE			−0.038[a]			−0.036[a]			0.000
log(numb. trades) * Paris			−0.075[a]			−0.056[a]			0.005
Relative tick size	59.550[a]	61.920[a]		39.877[a]	41.730[a]		36.525[a]	39.090[a]	
Relative tick size * NYSE			100.194[a]			72.231[a]			74.745[a]
Relative tick size * Paris			28.840[a]			34.330[a]			44.460[a]
Month dummy	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Interactive dummy	No	No	Yes	No	No	Yes	No	No	Yes
(Paris–NYSE)	0.049[a]	0.068[a]	0.039[a]	0.105[a]	0.118[a]	0.109[a]	0.140[a]	0.145[a]	0.126[a]

	Matching Algorithm Is Industry, Market Price, and Market Size								
Dependent Variables (in %)	Quoted Spread			Effective Spread			Realized Spread		
NYSE	0.232[a]	0.208[a]	0.229[a]	0.155[a]	0.138[a]	0.156[a]	0.022[a]	0.027[a]	0.040[a]
Paris	0.282[a]	0.268[a]	0.265[a]	0.253[a]	0.246[a]	0.248[a]	0.160[a]	0.168[a]	0.153[a]
log(market size)	−0.007[a]	−0.001		−0.002	0.002		0.001	0.002	
log(market size) ∗ NYSE			−0.003[c]			0.002			0.000[a]
log(market size) ∗ Paris			0.023[a]			0.011[b]			0.010[a]
log(inverse price)	0.045[a]	0.048[a]		0.026[a]	0.029[a]		0.027[a]	0.029[a]	
log(inverse price) ∗ NYSE			0.021[a]			−0.009[b]			0.000[a]
log(inverse price) ∗ Paris			0.026[a]			0.022[a]			0.023[a]
Return_volatility	0.188[a]	0.198[a]		0.172[a]	0.173[a]		0.029[b]	0.033[b]	
Return_volatility ∗ NSYE			0.104[a]			0.073[a]			−0.077[a]
Return_volatility ∗ Paris			0.227[a]			0.204[a]			0.069[a]
log(trad. volume)	−0.029[a]	−0.028[a]		−0.025[a]	−0.024[a]		−0.018[a]	−0.013[a]	
log(trad. volume) ∗ NYSE			−0.025			−0.022[a]			0.009[a]
log(trad. volume) ∗ Paris			−0.052[a]			−0.038[a]			−0.059[a]
log(numb. trades)	−0.032[a]	−0.042[a]		−0.022[a]	−0.030[a]		0.003	−0.001	
log(numb. trades) ∗ NYSE			−0.015[a]			−0.003			−0.001[a]
log(numb. trades) ∗ Paris			−0.078[a]			−0.058[a]			0.007[a]
Relative tick size	50.840[a]	51.560[a]		40.430[a]	42.190[a]		29.500[a]	31.120[a]	
Relative tick size ∗ NYSE			83.420[a]			80.130[a]			59.280[a]
Relative tick size ∗ Paris			32.520[a]			38.330[a]			43.870[a]
Month dummy	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Interactive dummy	No	No	Yes	No	No	Yes	No	No	Yes
(Paris–NYSE)	0.050[a]	0.060[a]	0.036[a]	0.098[a]	0.108[a]	0.092[a]	0.138[a]	0.141[a]	0.112[a]

[a] p-value < 0.01.
[b] $0.01 \leq p$-value < 0.05.
[c] $0.05 \leq p$-value < 0.10.





Quoted Spread – Overall	NYSE	PARIS
Actual Cost ≤ Predicted Cost	289	29
Actual Cost > Predicted cost	11	271

Effective Spread - Overall	NYSE	PARIS
Actual Cost ≤ Predicted Cost	300	0
Actual Cost > Predicted cost	0	300

Figure 2. Quoted and effective spreads—actual versus predicted. Scatter plot of actual quoted and effective spread of the New York (Paris) sample at the NYSE (Paris Bourse) against the predicted quoted and effective spreads if they were traded at the Paris Bourse (NYSE) during the sample period (April 1997 to March 1998). The firms are matched on industry, price, and market size. The coefficient estimates of the fully interactive regression of execution costs measures on economic variables, relative tick sizes, and monthly dummies are used to predict the trading costs of the NYSE (Paris) firms, by month, if they were traded at the Paris Bourse (NYSE). If both exchanges provided similar executions for the same stock, then all points in the scatter plot will lie along the 45-degree line.

they were traded on the NYSE. On the other hand, a majority of the NYSE firms will have higher execution costs if they were traded at the Paris Bourse. From Figure 3, we see that a detailed analysis of effective spread by trade size provides similar results.

To conclude, the results thus far suggest that the execution costs are lower in the NYSE than in the Paris Bourse for all trade-size categories. The difference in average trading cost remains statistically significant after controlling for differences in adverse selection, relative tick sizes, and economic attributes across samples. Next, I investigate whether the difference in execution costs is economically significant.

VI. Are Differences in Execution Costs Economically Significant?

Though the difference in execution costs is statistically significant, investors are more concerned about the dollar difference in the costs of executing a similar trade in both markets. In this section, I investigate the economic significance of the difference in execution costs. First, I predict the execution costs of the Paris sample if stocks were traded on the NYSE (by month and trade size) using the coefficients estimates of a fully interactive regression of execution costs measures on economic variables, relative tick sizes, and monthly dummies. Next, I calculate the difference between the actual trading costs of the Paris sample at the Paris Bourse and the predicted trading costs (in percentage) if stocks were traded on the NYSE. Finally, I estimate the savings in execution costs (in dollars) for the Paris sample by multiplying the predicted savings for the month with the average trade size and monthly trading volume of the Paris sample. Results of this analysis are presented in Table VIII.

For a small trade, the estimated savings in effective spreads is \$30 per trade. The dollar savings in execution costs for large trades rises steeply to \$519 per trade. Across all trade sizes, the savings in execution costs is \$43 per trade, for an average trade size of \$50,850. Though the savings in execution costs for each trade provides some perspective of economic significance, the cumulative benefits of lower execution costs depends on the frequency of trading. If the average Paris stock in this sample is traded on the NYSE, the monthly savings in execution costs is estimated to be \$449,156 (on a monthly trading volume of \$650 million). Results of the estimated savings in realized spread suggests that the benefits of executing trades in the NYSE continue to exist after accounting for the differences in the risk of adverse selection. For an average trade size of \$50,850, the savings in execution cost for the average Paris firm is \$67 per trade. The savings are \$36 for a small trade and increase to \$400 for a large trade. The estimated savings in execution cost for the average Paris stock in my sample is \$763,000 per month.

Another important component of an investor's trading cost is the brokerage commission. If brokerage commissions are lower at the Paris Bourse compared to the NYSE, it is possible that the total cost of executing a trade

Table VII

Transaction Size and Execution Costs

Reported are the execution costs measures, by transactions size, in the NYSE and the Paris Bourse. The measures are obtained from regressions of execution costs measures for each firm by month on exchange indicators, month dummies, demeaned economic determinants of trading cost, and relative tick size (identical to regression specification in Table VI). Trades are broken into sizes as follows: (1) Very small if trade size $<$ \$20,000; (2) small if \$20,000 $\leq$ trade size $<$ \$50,000; (3) medium/small if \$50,000 $\leq$ trade size $<$ \$100,000; (4) medium/large if \$100,000 $\leq$ trade size $<$ \$300,000; (5) large if \$300,000 $\leq$ trade size $<$ \$500,000; and (6) very large if trade size $\geq$ \$500,000. Confidence intervals and *p*-values are obtained using bootstrapping samples with 500 iterations.

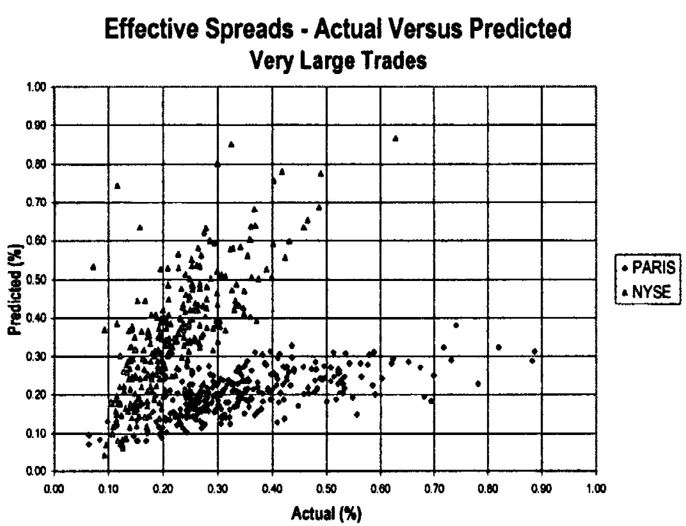
	Matching Algorithm Is Market Price and Trading Volume						Matching Algorithm Is Industry, Market Price, and Market Size					
Dependent Variables (in %)	Effective Spread			Realized Spread			Effective Spread			Realized Spread		
Panel A: Trade Size Is Very Small												
NYSE	0.105[a]	0.097[a]	0.126[a]	0.012[c]	0.006	0.025	0.108[a]	0.097[a]	0.153[a]	0.037[a]	0.044[a]	0.128[a]
Paris	0.292[a]	0.292[a]	0.272[a]	0.240[a]	0.249[a]	0.207[a]	0.281[a]	0.280[a]	0.266[a]	0.215[a]	0.235[a]	0.203[a]
(Paris–NYSE)	0.187[a]	0.195[a]	0.147[a]	0.227[a]	0.243[a]	0.182[a]	0.173[a]	0.183[a]	0.113[a]	0.178[a]	0.191[a]	0.075[a]
Panel B: Trade Size Is Small												
NYSE	0.157[a]	0.143[a]	0.146[a]	0.007[a]	0.008[b]	0.025[a]	0.162[a]	0.148[a]	0.147[a]	0.014[a]	0.016[b]	0.030[a]
Paris	0.243[a]	0.232[a]	0.220[a]	0.116[a]	0.117[a]	0.103[a]	0.228[a]	0.216[a]	0.206[a]	0.106[a]	0.107[a]	0.093[a]
(Paris–NYSE)	0.086[a]	0.089[a]	0.074[a]	0.109[a]	0.109[a]	0.078[a]	0.066[a]	0.068[a]	0.060[a]	0.092[a]	0.092[a]	0.063[a]

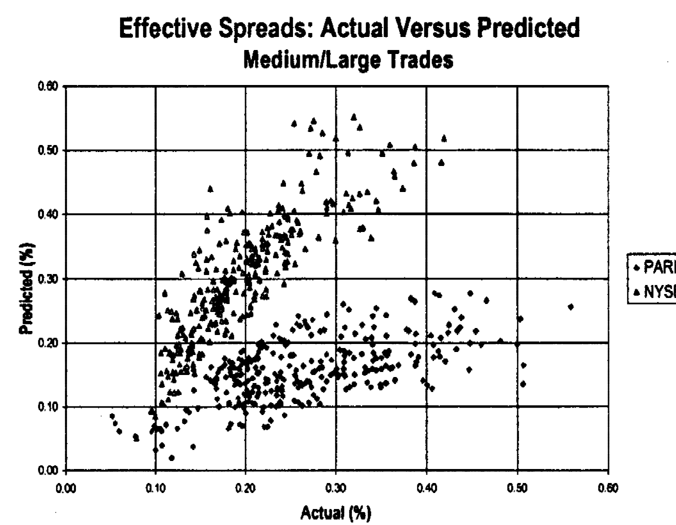
Panel C: Trade Size Is Medium/Small												
NYSE	0.168[a]	0.143[a]	0.157[a]	−0.016[a]	−0.015[a]	0.016[c]	0.169[a]	0.155[a]	0.157[a]	−0.003	0.004	0.027[a]
Paris	0.261[a]	0.240[a]	0.229[a]	0.091[a]	0.094[a]	0.078[a]	0.247[a]	0.236[a]	0.221[a]	0.084[a]	0.091[a]	0.077[a]
(Paris–NYSE)	0.093[a]	0.097[a]	0.072[a]	0.107[a]	0.109[a]	0.063[a]	0.078[a]	0.082[a]	0.064[a]	0.087[a]	0.087[a]	0.049[a]
Panel D: Trade Size Is Medium/Large												
NYSE	0.191[a]	0.171[a]	0.184[a]	−0.013[a]	−0.023[a]	0.001	0.185[a]	0.167[a]	0.172[a]	−0.004	−0.018[b]	0.011
Paris	0.288[a]	0.273[a]	0.266[a]	0.088[a]	0.081[a]	0.084[a]	0.279[a]	0.266[a]	0.260[a]	0.087[a]	0.074[a]	0.076[a]
(Paris–NYSE)	0.097[a]	0.102[a]	0.083[a]	0.101[a]	0.104[a]	0.083[a]	0.094[a]	0.099[a]	0.088[a]	0.091[a]	0.092[a]	0.065[a]
Panel E: Trade Size Is Large												
NYSE	0.211[a]	0.197[a]	0.210[a]	0.013[b]	−0.009	0.027[c]	0.212[a]	0.196[a]	0.189[a]	0.010	0.004	0.47[b]
Paris	0.325[a]	0.313[a]	0.291[a]	0.115[a]	0.094[a]	0.080[b]	0.313[a]	0.299[a]	0.282[a]	0.122[a]	0.115[a]	0.098[b]
(Paris–NYSE)	0.114[a]	0.116[a]	0.081[a]	0.102[a]	0.103[a]	0.054	0.101[a]	0.104[a]	0.093[a]	0.112[a]	0.111[a]	0.052
Panel F: Trade Size Is Very Large												
NYSE	0.231[a]	0.219[a]	0.218[a]	0.054[a]	0.053	0.047[a]	0.227[a]	0.213[a]	0.205[a]	0.029[a]	0.026	−0.010
Paris	0.369[a]	0.362[a]	0.360[a]	0.222[a]	0.221[a]	0.228[a]	0.360[a]	0.352[a]	0.342[a]	0.221[a]	0.212[a]	0.253[a]
(Paris–NYSE)	0.138[a]	0.143[a]	0.143[a]	0.168[a]	0.168[a]	0.181[a]	0.133[a]	0.139[a]	0.138[a]	0.192[a]	0.186[a]	0.264[a]

[a] p-value < 0.01.
[b] $0.01 \le p$-value < 0.05.
[c] $0.05 \le p$-value < 0.10.

Effective Spreads – Very Large	NYSE	PARIS
Actual Cost ≤ Predicted Cost	273	11
Actual Cost > Predicted cost	25	287

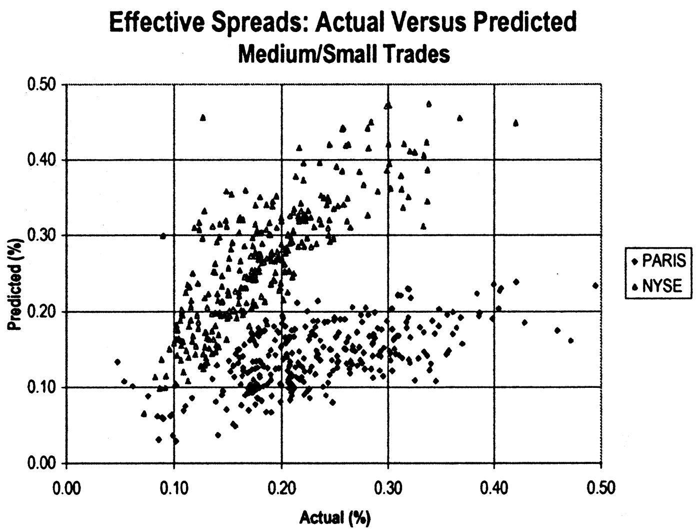
Effective Spreads – Medium / Large	NYSE	PARIS
Actual Cost ≤ Predicted Cost	294	3
Actual Cost > Predicted cost	6	297





Effective Spreads – Medium / Small	NYSE	PARIS
Actual Cost ≤ Predicted Cost	294	5
Actual Cost > Predicted Cost	6	295

Effective Spreads – Very small	NYSE	PARIS
Actual Cost ≤ Predicted Cost	300	9
Actual Cost > Predicted Cost	0	291



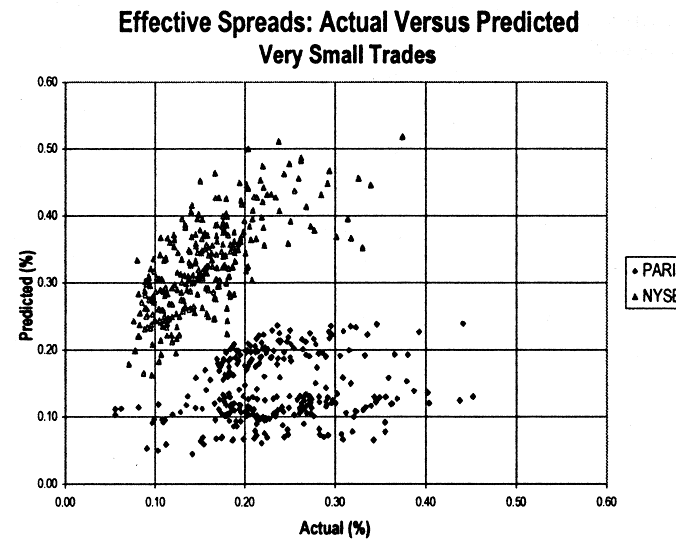


Figure 3. Effective spreads by trade size—actual versus predicted. Scatter plot of actual effective spreads of the New York (Paris) sample at the NYSE (Paris Bourse) against the predicted effective spreads if stocks were traded at the Paris Bourse (NYSE), by trade size category, during the sample period (April 1997 to March 1998). The firms are matched on industry, price, and market size. The coefficient estimates of the fully interactive regression of execution costs measures on economic variables, relative tick sizes, and monthly dummies are used to predict the trading costs of the NYSE (Paris) firms, by month and trade size, if they were traded at the Paris Bourse (NYSE). Trades are broken into sizes as follows: (1) Very small if trade size < \$20,000; (2) small if \$20,000 ≤ trade size < \$50,000; (3) medium/small if \$50,000 ≤ trade size < \$100,000; (4) medium/large if \$100,000 ≤ trade size < \$300,000; (5) large if \$300,000 ≤ trade size < \$500,000; (6) very large if trade size ≥ \$500,000. If both exchanges provide similar executions for the same stock, then all points in the scatter plot will lie along the 45-degree line.

Table VIII

Predicted Savings in Execution Costs for the Paris Sample

Percentage effective spreads is computed as [200 ∗ dummy ∗ (price-mid)/mid], where the dummy equals one for a market buy and negative one for a market sell, price is the transaction price, and mid is the midpoint of the bid-ask quote at the time of the trade. Percentage realized spreads is computed as [200 ∗ dummy ∗ (price-Qmid30)/ mid], where Qmid30 is the midpoint of the first quote observed after 30 minutes. Trades are broken into sizes as follows: (1) Very small if trade size < \$20,000; (2) small if \$20,000 ≤ trade size < \$50,000; (3) medium/small if \$50,000 ≤ trade size < \$100,000; (4) medium/large if \$100,000 ≤ trade size < \$300,000; (5) large if \$300,000 ≤ trade size < \$500,000; and (6) very large if trade size ≥ \$500,000. The coefficients estimates of the fully interactive regression with economic variables, relative tick size, and monthly dummies are used to predict the trading cost of the Paris sample (by month and trade size) if they were traded on the NYSE. The difference between the actual execution costs of the Paris sample at the Paris Bourse and their predicted execution costs if they were traded on the NYSE is the predicted savings (in percentage). The predicted savings (in \$) is calculated for each Paris firm using the average dollar trade size and the dollar trading volume for a month. Reported are the predicted average and cumulative monthly savings in execution costs of a Paris firm if it was traded on the NYSE. All numbers are in U.S. dollars.

	Trade-size Categories						
	Overall	Very Small	Small	Med/Small	Med/Large	Large	Very Large
Panel A: Match on Market Price and Trading Volume							
Average trade size	46,798	5,379	32,411	69,800	161,288	377,108	1,409,486
Average monthly trading volume	560,775,888	32,571,502	59,199,567	82,276,971	158,779,750	58,438,540	169,590,709
Difference in effective spreads							
per trade	56	9	34	72	187	548	3,247
per month	583,264	47,872	58,872	66,080	116,131	53,321	221,504
Difference in realized spreads							
per trade	72	13	41	81	186	521	4,026
per month	775,962	75,308	69,351	80,088	121,816	32,370	243,882
Panel B: Match on Industry, Market Price, and Market Size							
Average trade size	50,850	5,219	32,672	69,702	161,678	376,410	1,402,500
Average monthly trading volume	650,946,943	34,493,182	59,993,805	91,072,947	187,774,545	69,708,941	209,604,904
Difference in effective spreads							
per trade	43	5	30	66	178	519	2,762
per month	449,156	26,261	53,798	65,983	126,939	61,703	262,954
Difference in realized spreads							
per trade	67	4	36	60	130	400	3,273
per month	763,613	13,500	62,677	61,789	102,578	45,707	288,414

at the Bourse is no different than at the NYSE. Detailed information on commissions charged in each market is difficult to obtain. However, some information on brokerage commissions for large institutional trades in many international markets have been compiled by Elkins McSherry Co., Inc., who are consultants to large institutional investors.[20] The commissions and other fees on trades for large institutions in France average 22.84 basis points.[21] However, the commissions and other fees for institutional trades in U.S. stocks in the NYSE average 13.40 basis points. The brokerage commission for small trades in the United States and France has been dramatically reduced with the entry of online brokerage houses, and are comparable across the two markets.[22] These results suggest that the difference in execution costs across exchanges may not be explained by differences in brokerage commissions.

VII. Conclusions and Discussion

Anecdotal evidence around the world suggests a move away from the floor-based trading system to an electronic trading system. This trend toward automation raises the important question of the relative efficiencies of the two trading mechanisms. In this paper, I investigate this issue by comparing the trade execution costs for the common stock of similar firms in an automated limit order market (Paris Bourse) and a floor-based market structure (NYSE). This study is of particular interest to regulators, economists, investors, and stock exchanges that are considering the design of trading structures.

This paper compares the execution costs of large and liquid firms across the NYSE and the Paris Bourse. The Paris sample consists of the component firms of the CAC40 Index, while the NYSE sample is obtained by matching the Paris sample using four algorithms: (1) price and market size; (2) price and trading volume; (3) industry, price, and market size; and (4) industry, price, and trading volume. Although the quoted spread measures on the two exchanges are reasonably similar, effective spreads are significantly lower for NYSE firms, reflecting trade executions within the quotes. The difference in average trading costs remains statistically significant after controlling for differences in adverse selection, relative tick size, and economic attributes across samples. From an economic perspective, the transaction

[20] Elkins/McSherry Co., Inc, receives trade data (including commissions and other fees) on global trades by 135 large institutions (see Willoughby (1998b)).

[21] My conversations with a broker in Paris suggested that the brokerage commissions are typically 25 basis points for large trades.

[22] It is important to mention that most orders submitted to the online brokers in the United States are routed to the regional exchanges (i.e., preferenced) and are typically executed at the quotes without price improvement (see Bessembinder and Kaufman (1997b)). Hence, the quoted spread is a better measure of execution costs of such orders for the NYSE-listed stocks. However, the loss of price improvement does not necessarily reflect any limitations with the trading rules at the NYSE. In France, orders submitted to the online brokers are routed automatically to the Paris Bourse (after checking for margin requirements). As price improvement is rare at the Paris Bourse, these orders are typically executed at the quotes.

cost in Paris is higher than in New York by 0.14 percent of the amount traded, or $763,000 per month for an average stock in the Paris sample.[23] To the extent that the value of human intermediation is expected to be lower for my sample of liquid stocks, these results may be viewed as conservative estimates of the value of a trading floor.

Higher execution cost at the Paris Bourse suggests that issuers of limit orders in Paris require larger compensation for providing liquidity than in New York. Since no barriers to entry are apparent at the Paris Bourse, the larger compensation may not reflect higher economic rents, as competition among liquidity providers will drive the rents to zero. Hence, I suggest that they are compensation for higher risks that may be related to the structural differences in the trading mechanisms. Past empirical research has shown that the price continuity and stabilization obligations of the NYSE specialist help maintain narrow spreads, reduce transitory volatility, and set efficient prices. Large institutional investors can execute customized (state-contingent) trading strategies through a floor broker at the NYSE, and reduce the risk of order exposure. In contrast, the institutional features at the Paris Bourse may not allow similar flexibility. Since submission strategies for limit orders at the Paris Bourse are relatively simple (i.e., they are price contingent) and the traders do not have the ability to selectively reveal their order to counterparties of their choice, the liquidity providers may require larger compensation for the additional risk.

The possibility that human intermediation may enhance liquidity has important implications for stock exchanges and electronic communication networks (ECNs) that are considering moving to the present form of electronic trading system. If large traders are not able to trade strategically in an automated market, then they may either demand larger compensation for their risk or prefer to trade in alternative avenues. Consistent with this conjecture, Venkataraman (2000) finds that a substantial amount (65 percent) of the block trading volume at the Paris Bourse is executed in the informal *upstairs* market where the upstairs broker facilitates the trade through search and negotiation. This mechanism allows a large trader to selectively participate in block trades and better control the risk of order exposure. Similarly, on the Toronto Stock Exchange, a large proportion of the institutional order flow moved to the upstairs market after an automated system replaced the trading floor (see Handa et al. (1998)). To conclude, the results of this paper suggest that the present form of automated trading systems may not be able to fully replicate the benefits of human intermediation on a trading floor. But the results do not necessarily imply that the trading floor will survive in the future. As exchanges design the next generation of electronic trading systems, they can formulate trading rules that are sufficiently flexible to meet the requirements of a variety of market participants.

[23] To provide a different perspective of economic significance, Handa et al. (1998) document that the total dollar gain of using floor brokers for all AMEX stocks in the month of October 1996 is $36 million.

However, two caveats should be noted. First, it is possible that the economic variables employed in this study are not adequate proxies for order processing costs and inventory risks. While the uncontrolled economic variables could potentially explain the difference in execution costs, they also need to be uncorrelated with the economic variables employed in the study to have any explanatory power. Second, it is very difficult to control for differences in factors such as insider trading laws, the degree of competition for order flow, and the overall trading volume between the markets in the United States and France. Nevertheless, these results raise many interesting questions. First, what are the welfare implications of higher execution costs in a market where public investors trade with other public investors? Second, how would the execution costs of less liquid firms compare across automated and floor structures? Third, how can the next generation of automated trading systems allow large traders to better manage the risk of order exposure? These questions are beyond the scope of this paper and should be avenues for further research.

Appendix: Matching Algorithm

The Paris sample consists of the component firms of the CAC40 Index with trading data for the entire sample period (April 1997 to March 1998). The NYSE sample consists of all NYSE listed stocks in the TAQ database in April 1997, with trading data for the entire sample period. Using an algorithm similar to Huang and Stoll (1996), the Paris sample is matched with the NYSE sample as follows:

1. A joint match on stock price and market size as on April 1, 1997.
2. A joint match on average stock price and monthly trading volume over the sample period.
3. A joint match on industry, stock price, and market size as on April 1, 1997.
4. A joint match on industry, average stock price, and monthly trading volume over the sample period.[24]

For the Paris sample, the stock price and market size on April 1, 1997, and the average stock price and monthly trading volume during the sample period are obtained from the BDM database and converted to U.S. dollars using the daily spot exchange rates (obtained from Datastream). Similarly, for the NYSE sample, the stock price and market size on April 1, 1997, and the average stock price and monthly trading volume during the sample period are obtained from the TAQ database. The match on industry is problematic as the SIC codes that are used frequently in the literature are specific

[24] I also match on (5) industry and trading volume, and (6) industry and market size. However, due to the large differences in average price levels in the NYSE ($41) and the Paris Bourse ($140), the above matches result in significantly large differences in the average prices in the matched samples. Hence, matches (5) and (6) are not investigated further.

Table AI

Matching Algorithms and Sample Statistics

The Paris sample consists of the component firms of the CAC40 Index with trading data for the entire sample period (April 1997 to March 1998). The New York sample consists of all NYSE listed stocks in the TAQ database in April 1997 and with trading data for the entire sample period. For the Paris sample, the average market price, market size, and trading volume during the sample period is obtained from the BDM database, and converted to U.S. dollars using the daily spot exchange rates (obtained from DataStream). Similarly, for the New York sample, the average market price, market size, and trading volume during the sample period is obtained from the TAQ database. DataStream provides the global industry classification. For Panels C and D, the Paris sample firms are matched with the New York sample firms with the same DataStream industry classification code. For each Paris firm, the New York firm with the smallest average characteristic deviation statistic is identified as the match.

	Market Price (in $)			Market Size (in $ ml)			Trading Volume (in $ ml)			Average Deviation
	CAC40	NYSE	Dev	CAC40	NYSE	Dev	CAC40	NYSE	Dev	
Panel A: Matching Algorithm Is Market Price and Market Size										
25th percentile	52.4	50.7	0.01	4,600	4,524	0.01				0.02
Mean	93.6	92.8	0.05	9,437	9,682	0.05	660.1	569.1		0.05
Median	69.9	72.2	0.03	6,663	6,822	0.03				0.03
75th percentile	104.5	107.7	0.06	11,192	11,158	0.05				0.07
Panel B: Matching Algorithm Is Market Price and Trading Volume										
25th percentile	54.3	52.7	0.01				258.2	258.7	0.01	0.02
Mean	81.2	79.2	0.06	7,797	10,022		611.6	603.6	0.06	0.06
Median	70.4	70.1	0.03				480.9	453.2	0.02	0.02
75th percentile	103.4	100.9	0.05				827.9	825.6	0.06	0.05
Panel C: Matching Algorithm Is Industry, Market Price, and Market Size										
25th percentile	46.9	44.0	0.12	4,597	4,185	0.09				0.18
Mean	76.0	73.7	0.29	8,691	10,242	0.18	650.9	508.3		0.26
Median	67.4	53.4	0.24	6,359	6,716	0.23				0.26
75th percentile	98.2	77.6	0.46	10,331	10,353	0.37				0.31
Panel D: Matching Algorithm Is Industry, Market Price, and Trading Volume										
25th percentile	56.7	45.9	0.11				252.4	265.3	0.06	0.09
Mean	88.8	67.0	0.30	8,392	11,689		669.4	613.6	0.18	0.24
Median	76.2	63.7	0.25				480.9	440.8	0.11	0.19
75th percentile	112.6	88.8	0.43				988.2	900.1	0.20	0.28

to the U.S. markets. In order to obtain consistent industry classifications in the United States and France, I use the global industry classification provided by Datastream.[25]

For (1) and (2) above, the component firms of the CAC40 Index were matched with all the NYSE sample firms. For (3) and (4), the Paris sample firms were matched with the NYSE sample firms with the same Datastream industry classification code. Firm pairs were deleted if

$$\text{Characteristic deviation (Dev)} = \left[\frac{X_{\text{Paris}} - X_{\text{NYSE}}}{(X_{\text{Paris}} + X_{\text{NYSE}})/2}\right] > 0.75, \qquad \text{(A1)}$$

where X refers to the stock characteristic used in the matching algorithm (i.e., stock price, market size, or monthly trading volume). The purpose of this screen is to eliminate candidate pairs for which the stock characteristics are extremely far apart. Next, for each matched pair, I compute the following statistic:

$$\text{Average characteristic deviation} = \sum\left[\frac{X_{\text{Paris}} - X_{\text{NYSE}}}{(X_{\text{Paris}} + X_{\text{NYSE}})/2}\right]\Big/ 2, \qquad \text{(A2)}$$

Finally, for each Paris firm, I pick an NYSE firm with the smallest statistic and delete pairs with duplicate NYSE firms.

The results of the match are summarized in Table AI. From Panels A and B, we observe that the average deviation between samples from a match on two stock characteristics is very small. Not surprisingly, a joint match on three stock characteristics (i.e., including industry) results in larger deviation among the matched samples.

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