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Commonality in liquidity☆

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Abstract

Traditionally and understandably, the microscope of market microstructure has focused on attributes of single assets. Little theoretical attention and virtually no empirical work has been devoted to common determinants of liquidity nor to their empirical manifestation, correlated movements in liquidity. But a wider-angle lens exposes an imposing image of commonality. Quoted spreads, quoted depth, and effective spreads co-move with market- and industry-wide liquidity. After controlling for well-known individual liquidity determinants, such as volatility, volume, and price, common influences remain significant and material. Recognizing the existence of commonality is a key to uncovering some suggestive evidence that inventory risks and asymmetric information both affect intertemporal changes in liquidity.

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1. Introduction

The individual security is the traditional domain of market microstructure research. Topics such as transactions costs and liquidity naturally pertain to the repeated trading of a single homogeneous asset. Typically, we do not think of such topics in a market-wide context, except perhaps as averages of individual attributes.

From the earliest papers (Demsetz, 1968; Garman, 1976), the bid–ask spread and other microstructure phenomena have been modeled with an isolated market maker in the pivotal role, providing immediacy at a cost determined by either inventory risks from a lack of diversification (Stoll, 1978a; Amihud and Mendelson, 1980; Grossman and Miller, 1988), or by the specter of asymmetric information (Copeland and Galai, 1983; Glosten and Milgrom, 1985). Privileged information has pertained to an individual stock, the insider serving as prototype privilegee (Kyle, 1985; Admati and Pfleiderer, 1988).

Empirical work also deals solely with the trading patterns of individual assets, most often equities sampled at high frequencies (Wood et al., 1985; Harris, 1991), or examines micro questions such as the price impact of large trades (Kraus and Stoll, 1972; Keim and Madhavan, 1996; Chan and Lakonishok, 1997). The single-asset focus is exemplified by a prominent recent paper (Easley et al., 1997), whose empirical work is devoted to a single common stock, Ashland Oil, on thirty trading days.

Even articles devoted to market design (Garbade and Silber, 1979; Madhavan, 1992) examine the influence of various trading mechanisms solely on the costs of individual transactions. Studies of topics such as intermarket competition, or the contrast between dealer and auction markets, yield predictions about individual liquidity and transaction costs.

We do not imply even the slightest criticism. The microstructure literature has indeed become a very impressive body of knowledge. But in this paper we aspire to direct attention toward unexplored territory, the prospect that liquidity, trading costs, and other individual microstructure phenomena have common underlying determinants. A priori reasoning and, as it turns out, sound empirical evidence suggest that some portion of individual transaction costs covary through time.

Since completing the first draft of this paper, two other working papers with similar results have appeared; see Hasbrouck and Seppi (1998) and Huberman and Halka (1999). Given the virtual absence of documented commonality in the existing literature, this sudden flurry seems to portend a shift of emphasis from individual assets to broader market determinants of liquidity.

1.1. Plausible reasons for the existence of commonality in liquidity

Commonality in liquidity could arise from several sources. Trading activity generally displays market-wide intertemporal response to general price swings.

Since trading volume is a principal determinant of dealer inventory, its variation seems likely to induce co-movements in optimal inventory levels which lead in turn to co-movements in individual bid–ask spreads, quoted depth, and other measures of liquidity. Across assets, inventory carrying costs must also co-move because these costs depend on market interest rates.

The risk of maintaining inventory depends also on volatility, which could have a market component. Program trading of simultaneous large orders might exert common pressure on dealer inventories. Institutional funds with similar investing styles might exhibit correlated trading patterns, thereby inducing changes in inventory pressure across broad market sectors. Whatever the source, if inventory fluctuations were correlated across individual assets, liquidity could be expected to exhibit similar co-movement.

One might think that little covariation in liquidity would be induced by asymmetric information because few traders possess privileged information about broad market movements. In the prototypical case of a corporate insider, privileged information is usually thought to pertain only to that specific corporation. Indeed, this presumption would be valid for certain types of information, such as fraudulent accounting statements. However, there might be other types of secret information, such as a revolutionary new technology, that could influence many firms, not necessarily all in the same direction. Within an industry, occasional occurrences of asymmetric information could affect many firms in that sector.

1.2. Implications of commonality

Covariation in liquidity and the associated co-movements in trading costs have interesting ramifications and pose immediate questions. A key research issue is the relative importance of inventory and asymmetric information. Of equal interest would be other potential sources of commonality, as yet unimagined. How are these causes themselves related to market incidents such as crashes? Does their influence depend on market structure or design?

There are practical implications of the commonality issue for traders, investors, and regulators. For example, sudden pervasive changes in liquidity might have played a key role in otherwise puzzling market episodes. During the summer of 1998, the credit-sensitive bond market seemed to undergo a global liquidity crisis. This event precipitated financial distress in certain highly leveraged trading firms which found themselves unable to liquidate some positions to pay lenders secured by other, seemingly unrelated positions.[1] Similarly, the international stock market crash of October 1987 was associated with no

[1] See the Wall Street Journal (1998) 'Illiquidity means it has become more difficult to buy or sell a given amount of any bond … The spread between prices at which investors will buy and sell has widened, and the amounts [being traded] have shrunk *across the board* …' (emphasis added).

identifiable noteworthy event (Roll, 1988), yet was characterized by a ubiquitous temporary reduction in liquidity.

Trading costs should be cross-sectionally related to expected returns before costs simply because after-cost returns should be equilibrated in properly functioning markets (Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996). But commonality in liquidity raises the additional issue of whether shocks in trading costs constitute a source of non-diversifiable priced risk. If covariation in trading costs is cannot be completely anticipated and has a varying impact across individual securities, the more sensitive an asset is to such shocks, the greater must be its expected return. Hence, there are potentially two different channels by which trading costs influence asset pricing, one static and one dynamic: a static channel influencing average trading costs and a dynamic channel influencing risk. In future work, it would be of interest to determine whether the second channel is material and, if so, its relative importance.

This paper is devoted mainly to documenting the commonality in liquidity, measuring its extent, and providing some suggestive evidence about its sources. However, the precise identification of these sources remains for future research. Section 2 describes the data. Section 3 reports a progression of empirical findings about commonality in liquidity. Section 4 provides some interpretations, makes suggestions for additional empirical research, calls on theorists for help, and concludes.

2. Data

Transactions data for New York Exchange (NYSE) stocks were obtained from the Institute for the Study of Securities Markets (ISSM) during the most recently available calendar year, 1992. The ISSM data include every transaction, time-stamped, along with the transaction price, the shares exchanged, the nearest preceding bid and ask prices quoted by the NYSE specialist,[2] and the number of shares the specialist had guaranteed to trade at the bid and ask quotes.

The data do not reveal the identities of buyer and seller, so one cannot tell for sure when the specialist is involved nor on which side. However, since the quoted spread is given, it seems reasonable to deduce that an outsider is usually the buyer (seller) when the transaction price is nearer the ask (bid)

Some stocks are rarely traded and would not provide reliable observations. To be included here, we require that a stock be continually listed throughout

[2] Transactions are matched to best bid and offer quotes that existed at least five seconds prior to the transaction time because Lee and Ready (1991) find that quote reporting has about a 5 second delay.

1992 on the NYSE, trading at least once on at least ten trading days that year. To circumvent any possible problems with trading units, stocks are excluded if they split or paid a stock dividend during the year. Because their trading characteristics might differ from ordinary equities, we also expunge assets in the following categories: certificates, American depository receipts, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, and real estate investment trusts; 1169 individual unalloyed equities remain.

There are 29,655,629 transactions in the 1169 stocks on the 254 trading days during 1992. Not all stocks traded every day. To avoid any contaminating influence of the minimum tick size, we delete a stock on a day its average price falls below \$2. Opening batch trades and transactions with special settlement conditions are excluded because they differ from normal trades and might be subject to distinct liquidity considerations. For obvious reasons, transactions reported out of sequence or after closing are not used. After all this filtering, $289{,}612 < 296{,}926 = 1169(254)$ total stock-days remain, an average of 102.4 transactions per stock-day or about 99.9 transactions averaged over the 1169 stocks and 254 trading days. All but 13 of the 1169 stocks have transactions on more than 100 days.[3] The number of transactions is, of course, extremely right-skewed; the largest stocks have thousands of daily trades.

Corresponding to every transaction, five different liquidity measures are computed: the quoted and effective bid–ask spreads, the proportional quoted and effective spreads, and quoted depth. Their acronyms and definitions are given in the first panel of Table 1.

The quoted spread and the depth are announced by the specialist and become known to other traders prior to each transaction, though the lead time may be only seconds. The effective spread is devised to measure actual trading costs, recognizing that (a) many trades occur within the quoted spread and (b) if the proposed transaction exceeds the quoted depth, NYSE specialists are allowed, though not obliged, to execute that portion of the order in excess of the quoted depth at an altered price.

To smooth out intraday peculiarities and thus to promote greater synchroneity, and to reduce our data to more manageable levels, each liquidity measure is averaged across all daily trades for each stock. Thus, for each of the 1169 stocks, the working sample consists of at most 254 observations, one for each trading day during the year. Table 1 presents summary statistics for the five liquidity measures.

As would be anticipated, there is some right skewness in the cross-section of daily average spreads; sample means exceed medians. The effective spread is

[3] Since the available data cover only a single calendar year, there is always the possibility that our results are not representative. We have no reason to suspect that 1992 data are peculiar but an extended time period would be reassuring.

Table 1
Liquidity variables: definitions and summary statistics

P denotes price and subscripts indicate: t = actual transaction, A = ask, B = bid, M = bid–ask midpoint. Q denotes the quantity guaranteed available for trade at the quotes, (with subscripts: A = ask, B = bid). Each measure is calculated for every transaction during calendar year 1992 using all NYSE stocks with at least one transaction on at least ten trading days, 1169 stocks. Transaction observations are then averaged within each day to obtain a sample of 254 trading days.

Panel A: Definitions

Liquidity measure	Acronym	Definition	Units
Quoted spread	QSPR	$P_A - P_B$	$
Proportional quoted spread	PQSPR	$(P_A - P_B)/P_M$	None
Depth	DEP	$\frac{1}{2}(Q_A + Q_B)$	Shares
Effective spread	ESPR	$2\lvert P_t - P_M\rvert$	$
Proportional effective spread	PESPR	$2\lvert P_t - P_M\rvert/P_t$	None

Panel B: Cross-sectional statistics for time-series means

	Mean	Median	Standard deviation
QSPR	0.3162	0.2691	1.3570
PQSPR	0.0160	0.0115	0.0136
DEP	3776	2661	3790
ESPR	0.2245	0.1791	1.3051
PESPR	0.0111	0.0077	0.0132

Panel C: Cross-sectional means of time series correlations between liquidity measure pairs for an individual stock

	QSPR	PQSPR	DEP	ESPR
PQSPR	0.844			
DEP	− 0.396	− 0.303		
ESPR	0.665	0.549	− 0.228	
PESPR	0.555	0.699	− 0.156	0.871

somewhat smaller than the quoted spread, evidently reflecting within-quote trading. All measures of spread are positively correlated with each other across time and negatively correlated with depth.

There is substantial variability over time in all the liquidity measures. Table 2 provides summary statistics about daily percentage changes. For example, the time-series/cross-section mean of the absolute value of the percentage change in the quoted spread is almost 24% per day. The cross-sectional standard deviations of individual mean daily changes is rather modest, thereby

Table 2
Absolute daily proportional changes in liquidity variables

QSPR is the quoted spread. PQSPR is the proportional quoted spread. DEP is quoted depth. ESPR is the effective spread. PESPR is the proportional effective spread. 'D' preceding the acronym, e.g., DQSPR, denotes a proportional change in the variable across successive trading days, i.e., for liquidity measure L, $DL_t \equiv (L_t - L_{t-1})/L_{t-1}$ for trading day t. $|DL_t|$ denotes the absolute value of the daily proportional change. 1169 stocks, calendar year 1992.

	Mean	Median	Standard deviation
Cross-sectional statistics for time-series means			
|DQSPR|	0.2396	0.2373	0.0741
|DPQSPR|	0.2408	0.2386	0.0742
|DDEP|	0.7828	0.6543	0.4533
|DESPR|	0.3148	0.2976	0.1367
|DPESPR|	0.3196	0.2977	0.1811

revealing that substantial time series variability is shared by many stocks. Depth is even more volatile across time than spreads.

3. Empirical commonality in measures of liquidity

As a natural and simple first step on our empirical expedition, Section 3.1 below reports the empirical covariation between individual stock liquidity and market and industry liquidity. Given evidence of common liquidity variation, Section 3.2 then asks a deeper question: Is time-series variation in individual stock liquidity related to market or industry trading activity after controlling for trading activity in the individual stock?

Cross-sectional variation in liquidity is known to depend on such individual stock attributes as trading volume, volatility, and price level. An important issue, investigated in Section 3.3, is whether commonality contributes any additional cross-sectional explanatory power. Finally, in Section 3.4, we shift focus to uncover evidence that liquidity covariation is much stronger for portfolios than individual stocks, a finding relevant for investment managers who turn over their holdings frequently.

3.1. Some basic empirical evidence

We calculate simple 'market model' time series regressions; daily percentage changes in liquidity variables for an individual stock regressed on market measures of liquidity, i.e.,

$$DL_{j,t} = \alpha_j + \beta_j DL_{M,t} + \varepsilon_{j,t}, \tag{1}$$

where $DL_{j,t}$ is, for stock j, the percentage change (D) from trading day $t-1$ to t in liquidity variable L ($L =$ QSPR, PQSPR, etc.), and $DL_{M,t}$ is the concurrent change in a cross-sectional average of the same variable. We examine percentage changes rather than levels for two reasons: first, our interest is fundamentally in discovering whether liquidity co-moves, and second, time series of liquidity levels are more likely to be plagued by econometric problems (e.g., non-stationarity).

Statistics about the β_j's from these regressions are reported in Table 3. One lead and one lag of the market average liquidity (i.e., $DL_{M,t-1}$ and $DL_{M,t+1}$) plus the contemporaneous, leading and lagged market return and the contemporaneous change in the individual stock squared return are included as additional regressors. The leads and lags are designed to capture any lagged adjustment in commonality while the market return is intended to remove spurious dependence induced by an association between returns and spread measures. This could have particular relevance for the effective spread measures since they are functions of the transaction price. Their changes are thus functions of individual returns, known to be significantly correlated with broad market returns. Finally, the squared stock return is included to proxy for volatility, which from our perspective is a nuisance variable possibly influencing liquidity.[4]

In computing the market liquidity measure, DL_M, stock j is excluded, so the explanatory variable in (1) is slightly different for each stock's time series regression. This removes a potentially misleading constraint on the average coefficients reported in Table 3. For example, when the market liquidity measure in an equal-weighted average of *all* stocks, the cross-sectional mean of β is constrained to exactly unity. Although dropping 1/1169 of the sample from each index calculation makes only a small difference in the coefficients of any individual equation, those small differences can accumulate to a material total when averaged across all equations.[5]

The discreteness that plagues empirical spread data is an excellent reason to focus on the cross-sectional sampling distribution of coefficients. During 1992, the minimum quoted spread was \$1/8, which was also the minimum increment. Consequently, a scatter diagram of the variables in an individual regression such as (1) takes on a lumpy appearance in the vertical (y-axis) dimension. Discreteness implies too that the disturbances in (1) are not normally-distributed; this

[4] Because the tables are already voluminous, we do not report coefficients for the nuisance variables: the market return and squared stock return.

[5] Even though the explanatory variable in (1) is constructed to exclude the dependent variable, there is still some cross-sectional dependence in the estimated coefficients because each individual liquidity measure (i.e., the dependent variable) *does* appear as one component of the explanatory variables for all other regressions. Later, we investigate the materiality of this and other possible sources of cross-equation dependence.

Table 3
Market-wide commonality in liquidity 1169 stocks, calendar year 1992, 253 daily observations

Daily proportional changes in an individual stock's liquidity measure are regressed in time series on proportional changes in the equal-weighted average liquidity for all stocks in the sample (the 'market'). QSPR is the quoted spread. PQSPR is the proportional quoted spread. DEP is quoted depth. ESPR is the effective spread. PESPR is the proportional effective spread. 'D' preceding the acronym, e.g., DQSPR, denotes a proportional change in the variable across successive trading days, i.e., for liquidity measure L, $DL_t \equiv (L_t - L_{t-1})/L_{t-1}$ for trading day t. In each individual regression, the market average excludes the dependent variable stock.

Cross-sectional averages of time series slope coefficients are reported with t-statistics in parentheses. 'Concurrent', 'Lag', and 'Lead' refer, respectively, to the same, previous, and next trading day observations of market liquidity. '% positive' reports the percentage of positive slope coefficients, while '% + significant' gives the percentage with t-statistics greater than $+1.645$ (the 5% critical level in a one-tailed test).

'Sum' = Concurrent + Lag + Lead coefficients. The 'p-value' is a sign test of the null hypothesis, H_0: Sum Median = 0. The lead, lag and concurrent values of the equal-weighted market return and the proportional daily change in individual firm squared return (a measure of change in return volatility) were additional regressors; coefficients not reported.

	DQSPR	DPQSPR	DDEP	DESPR	DPESPR
Concurrent	0.690	0.791	1.373	0.280	0.778
	(28.29)	(30.09)	(15.50)	(10.64)	(2.06)
% positive	84.86	84.26	81.61	68.61	71.00
% + significant	34.65	33.27	31.05	14.88	14.29
Lag	0.123	0.169	− 0.047	0.058	0.179
	(4.72)	(6.46)	(− 0.72)	(2.63)	(1.80)
% positive	58.60	59.80	47.65	53.04	55.95
% + significant	8.81	9.50	4.62	6.93	7.96
Lead	0.053	0.050	0.336	0.042	− 0.156
	(2.33)	(1.87)	(5.55)	(1.99)	(− 0.65)
% positive	55.35	56.29	56.54	53.21	55.00
% + significant	6.84	7.01	7.19	5.73	6.76
Sum	0.866	1.009	1.662	0.380	0.801
	(21.19)	(23.48)	(12.29)	(8.67)	(3.00)
Median	0.880	1.092	1.213	0.289	0.442
p-value	0.00	0.00	0.00	0.00	0.00
Adjusted R^2 mean	0.017	0.017	0.010	0.013	0.014
Median	0.011	0.012	0.002	0.003	0.004

casts doubt on small sample inferences from any single equation. However, a well-known version of the Central Limit Theorem, Judge et al. (1985), Chapter 5), stipulates that the estimated coefficients from (1) are asymptotically normally-distributed under mildly restrictive conditions. It follows that the cross-sectional mean estimated coefficient is probably close to Gaussian, particularly if the sampling errors in the individual regressions are independent across assets and have stationary distributions across time.

Table 3 reveals ample evidence of co-movement. For example, the change in the percentage quoted spread, DPQSPR, displays an average value of 0.791 for the contemporaneous β_j in (1) and an associated t-statistic of 30. Approximately 84% of these individual β_j's are positive while 33% exceed the 5% one-tailed critical value. The cross-sectional t-statistic for the average β is calculated under the assumption that the estimation errors in β_j are independent across regressions, a presumption we shall check subsequently.

Although the leading and lagged terms are usually positive and often significant, they are small in magnitude. The most significant effects are for a lagged market liquidity on the quoted spreads (DQSPR and DPQSPR), where roughly eight to nine percent of the coefficients exceed the 5% critical level.

The penultimate panel reports the combined contemporaneous, lead, and lag coefficients, labeled 'Sum'. Its t-statistic reveals high significance in most cases. A non-parametric sign test that 'Sum' has a zero median rejects with p-values zero to two decimal places in all instances. This test also assumes independent estimation error across equations.

However, the explanatory power of the typical individual regression is not impressive. The average adjusted R^2 is less than two percent. Clearly, there is either a large component of noise and/or other influences on daily changes in individual stock liquidity constructs.

Similar regressions, not shown here, are estimated with a value-weighted market liquidity variable. The contemporaneous slope coefficient from Eq. (1) is larger when the market spread measure is equal-weighted, a contrast particularly pronounced for the percentage effective spread measure, DPESPR, which is not significant when the market spread measure is value-weighted.[6] This pattern is exactly the opposite of market model regressions involving individual and market returns. Return 'betas' are typically smaller when the market index is equal-weighted, as opposed to value-weighted, because smaller stocks display more market return sensitivity. In contrast, smaller stocks are less sensitive to market-wide shocks in spreads.

The size effect is demonstrated explicitly in Table 4, which stratifies the sample into size quintiles. For the spread measures of liquidity, the slope coefficient in Eq. (1) generally increases with size; large firm spreads have greater response to market-wide changes in spreads, although large firms have smaller average spreads.

[6] Measurement error might be endemic in *effective* spreads, reducing explanatory power. Lightfoot et al. (1999) document biases up to 32% in effective spreads computed with the Lee and Ready (1991) algorithm (which we have adopted). Also, since PESPR depends on the transaction price, an additional source of noise is introduced by the bid–ask bounce.

Table 4
Market-wide commonality in liquidity by size quintile 1169 stocks (≈ 234 per quintile), calendar year 1992, 253 daily observations

Daily proportional changes in an individual stock's liquidity measure are regressed in time series on proportional changes in the equal-weighted average liquidity for all stocks in the sample (the 'market'). QSPR is the quoted spread. PQSPR is the proportional quoted spread. DEP is quoted depth. ESPR is the effective spread. PESPR is the proportional effective spread. '*D*' preceding the acronym, e.g., DQSPR, denotes a proportional change in the variable across successive trading days; i.e., for liquidity measure L, $DL_t \equiv (L_t - L_{t-1})/L_{t-1}$ for trading day t. In each individual regression, the market average excludes the dependent variable stock.

Cross-sectional averages of time series slope coefficients are reported with t-statistics in parentheses. 'Sum' aggregates coefficients for concurrent, previous, and next trading day observations of market liquidity. The 'p-value' is a sign test of the null hypothesis, H_0: Sum Median = 0. The lead, lag and the concurrent values of the equal-weighted market return and the proportional daily change in individual firm squared return (a measure of change in return volatility) were additional regressors; coefficients not reported. R^2 is the cross-sectional mean adjusted R^2.

		Size quintile				
		Smaller ($N = 233$)	2 ($N = 234$)	3 ($N = 234$)	4 ($N = 234$)	Largest ($N = 234$)
DQSPR	Sum	0.498	0.745	0.903	1.080	1.101
		(4.41)	(6.83)	(12.06)	(13.82)	(16.47)
	Median	0.501	0.639	0.844	1.031	1.135
	p-value	0.00	0.00	0.00	0.00	0.00
	R^2	0.008	0.012	0.016	0.017	0.033
DPQSPR	Sum	0.632	0.823	1.053	1.155	1.382
		(5.07)	(7.95)	(12.33)	(15.37)	(18.20)
	Median	0.580	0.732	1.028	1.276	1.477
	p-value	0.00	0.00	0.00	0.00	0.00
	R^2	0.010	0.013	0.015	0.017	0.033
DDEP	Sum	1.163	1.839	2.105	1.776	1.426
		(3.32)	(4.94)	(7.76)	(5.57)	(10.08)
	Median	0.942	1.266	1.369	1.081	1.211
	p-value	0.00	0.00	0.00	0.00	0.00
	R^2	0.003	0.009	0.013	0.010	0.017
DESPR	Sum	0.314	0.183	0.389	0.375	0.636
		(2.22)	(1.70)	(5.19)	(5.50)	(8.26)
	Median	0.110	0.125	0.304	0.338	0.512
	p-value	0.12	0.00	0.00	0.00	0.00
	R^2	0.005	0.011	0.011	0.013	0.027
DPESPR	Sum	0.510	0.370	0.520	0.435	2.167
		(2.64)	(2.65)	(5.34)	(5.60)	(1.66)
	Median	0.244	0.299	0.431	0.346	0.655
	p-value	0.24	0.00	0.00	0.00	0.00
	R^2	0.004	0.011	0.011	0.015	0.027

We can only speculate on the reason for this large/small firm pattern; perhaps it has something to do with the greater prevalence of institutional herd trading in larger firms. It seems unlikely to be caused by more prevalent asymmetric information specific to small firms. That would promulgate a lower level of explanatory power in the small firm regressions but not necessarily smaller slope coefficients.[7] Alternatively, perhaps there is a 'size factor' in spreads analogous to the small minus big (SMB) factor documented for returns by Fama and French (1993). Though beyond the scope of our present paper, that possibility would indeed be an interesting issue for future research.

Although depth also exhibits commonality, it has little if any relation to size. In contrast to the spread measures, the largest firm size quintile has a smaller average coefficient than intermediate quintiles, but there is really no perceptible pattern. Evidently, market makers respond to systematic changes in liquidity by revising spreads and depth, but only the former is revised to a greater extent in larger firms. Notice too the evidence in Table 3 that depth's coefficients are quite a bit more right-skewed than many of the spread coefficients. For depth, the 'Sum' mean is larger than the median by around 0.4 while the mean-median difference for most of the spreads is no larger than 0.2 (DPESPR is the exception).

Turning now to a more detailed examination of the sources of commonality in liquidity, Table 5 reports regressions with both market and industry liquidity measures, both equal-weighted:

$$DL_{j,t} = \alpha_j + \beta_{j,M} DL_{M,t} + \beta_{j,I} DL_{I,t} + \varepsilon_{j,t}, \tag{2}$$

where the additional regressor, $DL_{I,t}$, is an industry-specific average liquidity measure. As with market liquidity, firm j was excluded when computing the industry average. Perhaps surprisingly, except for DPESPR the liquidity measures seem to be influenced by *both* a market and an industry component; industry actually has larger coefficients for three of the five liquidity measures. If trading activity and volatility exhibit more within- than across-industry commonality, inventory risks would be industry-specific, a phenomenon consistent with these empirical patterns.

The reliability of the t-statistics in Table 5 (and in other tables) depends on estimation error being independent across equations, a presumption tantamount to not having omitted a material common variable. To check this, we conducted a simple investigation of the residuals from (2). The 1169 individual

[7] Some readers have conjectured that the smaller coefficients for small firms could be attributable to non-synchronous trading. We doubt, however, that this can be the sole explanation. Few stocks in our sample were inactive for many days. Thus, in the larger four size quintiles, about 82% of the stocks traded every day, yet the same pattern is observed in the coefficients.

Table 5

Market and industry commonality in liquidity

Daily proportional changes in an individual stock's liquidity measure are regressed in time series on proportional changes in the equal-weighted liquidity measures for all stocks in the sample (the 'market') and sample stocks in the same industry. [a]QSPR is the quoted spread. PQSPR is the proportional quoted spread. DEP is quoted depth. ESPR is the effective spread. PESPR is the proportional effective spread. '*D*' preceding the acronym, e.g., DQSPR, denotes a proportional change in the variable across successive trading days; i.e., for liquidity measure L, $DL_t \equiv (L_t - L_{t-1})/L_{t-1}$ for trading day t. Market and Industry averages excluded the dependent variable individual stock. Cross-sectional averages of time series slope coefficients are reported with t-statistics in parentheses. 'Concurrent', 'Lag', and 'Lead' refer, respectively, to the same, previous, and next trading day observations of market liquidity. 'Sum' = Concurrent + Lag + Lead coefficients. The '*p*-value' is a sign test of the null hypothesis, H_0: Sum Median = 0. The lead, lag and concurrent values of the equal-weighted market return and the proportional daily change in individual firm squared return (a measure of change in return volatility) are additional regressors; coefficients not reported. R^2 denotes the cross-sectional adjusted R^2.

	DQSPR		DPQSPR		DDEP		DESPR		DPESPR	
	Market	Industry	Market	Industry	Market	Industry	Market	Industry	Market	Industry
Concurrent	0.264	0.467	0.505	0.287	0.721	0.614	0.164	0.414	– 0.172	0.970
	(9.86)	(16.65)	(14.06)	(11.08)	(6.17)	(7.28)	(5.26)	(7.51)	(– 0.60)	(1.81)
Lag	0.070	0.059	0.096	0.065	– 0.058	0.022	0.057	0.028	– 0.138	0.307
	(2.90)	(2.12)	(2.85)	(2.74)	(– 0.60)	(0.28)	(2.64)	(0.43)	(– 0.84)	(1.37)
Lead	0.073	0.005	0.042	0.034	0.368	– 0.040	0.040	– 0.014	– 0.158	0.007
	(2.91)	(0.22)	(1.18)	(1.40)	(4.22)	(– 0.57)	(1.75)	(– 0.57)	(– 0.92)	(0.12)
Sum	0.409	0.530	0.642	0.386	1.030	0.596	0.260	0.429	– 0.468	1.285
	(7.49)	(9.63)	(9.13)	(6.99)	(4.99)	(3.49)	(4.79)	(3.67)	(– 0.75)	(1.76)
Median	0.238	0.527	0.784	0.259	0.749	0.480	0.022	0.307	0.030	0.259
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.03	0.00
R^2 mean	0.024		0.022		0.014		0.020		0.018	
Median	0.019		0.016		0.005		0.009		0.008	

[a]The eight industry classifications follow Roll (1992) and Chalmers and Kadlec (1998).

Table 6
Check for cross-equation dependence in estimation error

After estimating 1169 time series regressions of individual liquidity measures on equal-weighted market and industry liquidity, Eq. (2), residuals for stock $j+1$ are compared with residuals for stock j, where j is ordered alphabetically. From these 1168 pairs, the table reports the average correlation coefficient. Also reported from pair-wise regressions (3) are the sample mean and median t-statistic of the regression slope coefficient and the frequency of absolute t-statistics (for the slope) exceeding typical critical levels, 5% and 2.5%. Because there are two tails, double these critical percentages (i.e., 10% and 5%, respectively), should be found just by chance if, in fact, there is no dependence. QSPR is the quoted spread. PQSPR is the proportional quoted spread. DEP is quoted depth. ESPR is the effective spread. PESPR is the proportional effective spread. '*D*' preceding the acronym, e.g., DQSPR, denotes a proportional change in the variable across successive trading days; i.e., for liquidity measure L, $DL_t \equiv (L_t - L_{t-1})/L_{t-1}$ for trading day t.

Liquidity measure	Average correlation	Mean t	Median t	$\lvert t\rvert > 1.645$ (%)	$\lvert t\rvert > 1.96$ (%)
DQPSR	− 0.001	− 0.006	0.014	15.92	9.33
DPQPSR	− 0.0004	0.0001	− 0.015	14.38	7.71
DDEP	− 0.003	− 0.030	− 0.125	11.73	6.08
DESPR	0.004	0.053	0.024	13.44	8.39
DPESPR	0.007	0.082	0.041	12.33	7.62

regressions are arranged randomly (alphabetically) by stock name so we simply run 1168 time series regressions between adjacent residuals; i.e.,

$$\varepsilon_{j+1,t} = \gamma_{j,0} + \gamma_{j,1}\varepsilon_{j,t} + \xi_{j,t} \quad (j = 1, \ldots, 1168), \tag{3}$$

where $\gamma_{j,0}$ and $\gamma_{j,1}$ are estimated coefficients and $\xi_{j,t}$ is an estimated disturbance. The t-statistics for $\gamma_{j,1}$ provide evidence about cross-equation dependence. Table 6 summarizes the results of this exercise by tabulating the average correlations between $\varepsilon_{j+1,t}$ and $\varepsilon_{j,t}$ and sample characteristics for the t-statistics of $\gamma_{j,1}$, the slope coefficient in (3).

There is little evidence of cross-equation dependence. The mean and median slope coefficients from (3) are near zero on average. Although there are rather more observations in the tails than would be expected by chance, the excess is too slight to overturn the very high significance levels in (2). The correlations, being very close to zero on average, imply that adjusting for cross-equation dependence would change few, if any, of the conclusions.[8]

[8] With 1168 regression, even small cross-equation correlations can have a big effect on standard errors for cross-sectional averages. For a quick, back-of-the-envelope estimate of the extent of this effect, assume that all the residual variances are equal and that every pair of residuals has the same correlation ρ. Then the ratio of the true standard error to the usual standard error is $[1 + 2(N-1)\rho]^{1/2}$, where N is the number of regressions. For negative ρ, the usual standard error is too large and thus the reported t-statistic is too small; The average correlation is, in fact, negative for DQPSR, DPQPSR, and DDEP (Table 6). For DPESPR, the reported t-statistics are too large, but they are generally not significant anyway. For DESPR, t-statistics could be overstated by a factor of about three.

3.2. Commonality, inventory risk, and asymmetric information

Although the evidence strongly favors the existence of common underlying influences on variations in liquidity, their identities remain to be determined. Microstructure literature suggests two possible influences, inventory risk and asymmetric information (which are not mutually exclusive). A priori, it seems reasonable that broad market activity would exert more influence on inventory risk while individual trading activity would more likely be associated with asymmetric information. Industry would again represent an intermediate position, possibly being influenced by both effects on occasion.

Previous work by Jones et al. (1994) suggests that the *number* of trades, not the dollar volume of trading, is an indicator of individual firm asymmetric information; they showed that volume has little impact on volatility once trading frequency has been taken into account. This rather puzzling result could perhaps be explained by the propensity of truly informed traders to hide their activities by splitting orders into small units. In other words, large uninformed traders such as institutions might dominate the determination of dollar volume while informed traders might dominate the determination of the number of transactions. Barclay and Warner (1993) suggest that informed traders do break up their orders and are most active in the medium-size trades.

However, somewhat in conflict with the thrust of this idea, individual stock trading frequency turns out to be strongly influenced by both market and industry, which have similar coefficients and significance; Table 7. If, as seems likely, some of this commonality is not the result of asymmetric information, the empirical conundrum is to separately identify that portion of individual trading frequency truly attributable to informed agents.

In an attempt to separate the two effects, Table 8 presents estimated marginal influences of individual, market, and industry transaction frequencies on our five liquidity measures. The individual time series regressions have the general form

$$DL_{j,t} = \alpha_j + \beta_{j,S} DS_{j,t} + \beta_{j,T} DT_{j,t} + \beta_{j,M} DV_{M,t} + \beta_{j,I} DV_{I,t} + \varepsilon_{j,t}\,, \qquad (4)$$

where, as before 'D' denotes the percentage change from trading day $t-1$ to day t, L is the liquidity measure, $S_{j,t}$ is the average dollar size of a transaction in stock j, $T_{j,t}$ is the number of trades in stock j, $V_{M,t}$ is the aggregate dollar trading volume for the entire market (excluding stock j), and $V_{I,t}$ is the dollar volume in stock j's industry (again excluding stock j itself).

The results are striking. The inventory explanation for liquidity suggests that more trading should bring about smaller spreads because inventory balances and risks per trade can be maintained at lower levels. Conversely, when surreptitious informed traders become active, spreads should increase with the number of transactions. The results are consistent with both explanations. Individual trading frequency ($T_{j,t}$) has a strong positive influence on the spread measures while market-wide volume has a negative marginal influence on quoted spread,

Table 7
Commonality in transactions frequency

Daily percentage changes in the number of transactions (i.e., not volume) for 1169 stocks are individually regressed in time series on the daily percentage change in the average number of transactions for all stocks in the sample (the 'market'), and/or for all firms in the same industry (the 'industry') during 1992. Market and industry averages are equal-weighted but excluded the individual subject stock.[a]

Cross-sectional averages of time series slope coefficients are reported with t-statistic in parentheses. 'Concurrent', 'Lag', and 'Lead' refer to the same, previous, and next trading day observations of market and industry; 'Sum' aggregates the three coefficients. The 'p-value' is a sign test of the null hypothesis, H_0: Sum Median $= 0$. R^2 is adjusted.

	Alone	Together		Alone
	Market		Industry	
Concurrent	1.0486	0.6470	0.4202	0.9213
	(63.97)	(16.58)	(11.88)	(63.60)
Lag	− 0.0643	− 0.1427	0.0787	− 0.0434
	(− 5.26)	(− 3.91)	(2.37)	(− 3.88)
Lead	0.0356	0.0079	0.0305	0.0163
	(2.69)	(0.22)	(0.98)	(1.38)
Sum	1.0199	0.5121	0.5294	0.8942
	(37.71)	(7.69)	(8.65)	(36.57)
Median	1.0400	0.5243	0.4896	0.9100
p-value	0.00	0.00	0.00	0.00
R^2 mean	0.095	0.061		0.100
Median	0.057	0.070		0.057

[a]The equal-weight market return is an additional regressor, coefficient not reported. The eight industry classifications follow Roll (1992) and Chalmers and Kadlec (1998).

even though market trading frequency affects individual frequency strongly (Table 7). Industry volume, which one might have thought could arise from both informed and uninformed trading, displays mostly positive coefficients, suggesting the dominance of informed traders.

Dollar volume depends on both the number of transactions and the average size of a transaction. Table 8 discloses that the individual firm's trade size has a strong positive influence on quoted spreads and depth. Perhaps this can be explained by the obligation of specialists to maintain larger inventories during periods of intense institutional trading. When engaging in portfolio trading, institutions are presumably uninformed but nonetheless effectuate large transactions for liquidity or rebalancing reasons. To accommodate them, the specialist must maintain more substantial balances. Note that informed institutions might attempt to conceal themselves by splitting up what would otherwise have been

Table 8
Commonalities in trade size, transaction frequency and trading volume 1169 Stocks, Calendar Year 1992

Daily proportional changes in individual stock liquidity variables are regressed in time series on daily proportional changes in (1) the stock's average trade size, (2) its number of transactions, (3) the trading volume for all stocks in the sample (the 'market'), and/or (4) the trading volume for all stocks in the same industry. QSPR is the quoted spread. PQSPR is the proportional quoted spread. DEP is quoted depth. ESPR is the effective spread. PESPR is the proportional effective spread. 'D' preceding the acronym, e.g., DQSPR, denoted a proportional change in the variable across successive trading days, i.e., for liquidity measure L, $DL_t \equiv (L_t - L_{t-1})/L_{t-1}$ for trading day t, Market and Industry averages exclude the dependent variable individual stock. The eight industry classification follow Roll (1992) and Chalmers and Kadlec (1998).

Cross-sectional averages of time series slope coefficients are reported with t-statistic in parentheses. 'Concurrent', 'Lag', and 'Lead' refer to the same, previous, and next trading day observations of market or industry while 'Sum' = Concurrent + Lag + Lead coefficients. The 'p-value' is a sign test of the null hypothesis, H_0: Sum Median = 0. The lead, lag and concurrent values of the equal-weighted market return is an additional regressor; coefficients not reported. The spread measures are multiplied by 100 to suppress leading zeroes in the coefficients. R^2 is adjusted.

	DQSPR (× 100)	DPQSPR (× 100)	DDEP	DESPR (× 100)	DPESPR (× 100)
Own trade size	0.643	0.597	0.166	− 0.341	− 0.499
	(7.72)	(7.11)	(26.41)	(− 1.70)	(− 1.37)
Median	0.359	0.361	0.125	− 0.268	− 0.268
p-value	0.00	0.00	0.00	0.00	0.00
Own number of transactions	2.807	2.820	0.126	8.088	8.406
	(17.53)	(17.27)	(11.31)	(22.01)	(14.38)
Median	2.468	2.282	0.083	6.446	6.373
p-value	0.00	0.00	0.00	0.00	0.00
Market trading volume					
Concurrent	− 2.367	− 2.569	0.165	− 2.782	− 0.871
	(− 4.10)	(− 4.438)	(4.03)	(− 2.11)	(− 0.17)
Lag	0.350	0.324	− 0.029)	1.520	11.900
	(0.58)	(0.53)	(− 0.87)	(1.41)	(1.07)
Lead	− 0.698	− 0.469	0.084	− 0.528	− 3.733
	(− 1.02)	(− 0.65)	(2.30)	(− 0.47)	(− 1.42)
Sum	− 2.715	− 2.714	0.219	− 1.790	7.296
	(− 2.43)	(− 2.41)	(2.83)	(− 0.87)	(0.47)
Median	− 2.859	2.135)	0.135	− 4.670	− 5.878
p-value	0.01	0.00	0.00	0.00	0.00
Industry trading volume					
Concurrent	1.306	1.133	− 0.058	1.931	− 2.634
	(2.77)	(2.39)	(− 1.94)	(1.64)	(− 0.43)
Lag	0.824	0.651	− 0.029	− 0.543	− 11.410
	(1.63)	(1.29)	(− 1.12)	(− 0.61)	(− 1.03)

Table 8 (*continued*)

	DQSPR (×100)	DPQSPR (×100)	DDEP	DESPR (×100)	DPESPR (×100)
Lead	0.450	0.244	−0.009	0.087	0.586
	(0.89)	(0.44)	(−0.35)	(0.09)	(0.59)
Sum	2.581	2.029	−0.097	1.475	−13.458
	(2.86)	(2.18)	(−1.71)	(0.70)	(−0.80)
Median	2.283	1.444	−0.050	3.113	2.876
p-value	0.00	0.09	0.14	0.01	0.01
R^2 mean	0.020	0.021	0.050	0.031	0.032
Median	0.013	0.012	0.037	0.016	0.017

large orders, a notion consistent with Jones et al. (1994). Suggestive evidence to support this argument are the negative but insignificant trade size coefficients for the effective spread measures, which are likely to be more influenced by informed trading.

The puzzling pattern of market and industry coefficients for DPESPR might have been caused by a few outliers. Notice that the median coefficient for market (industry) volume is negative (positive) and significant according to the sign tests' p-values. In contrast, both mean coefficients have the opposite signs from their corresponding medians but are insignificant. The medians of all the spread measures tell the consistent story that greater market-wide volume brings reduced spreads while industry volume increases spreads (presumably due to informed traders).

Based on inventory arguments, one might have anticipated that larger market volume would induce specialists to quote greater depth (though tighter spreads.) Indeed, this is the empirical result in Table 8. In contrast, industry volume has an insignificant (negative) influence on depth. This suggests that any marginal reduction in inventory costs from industry trading is offset by caution induced in the specialist by a higher probability of encountering an insider when industry volume is high.

We were surprised that individual trading frequency and the size of the average individual trade have significant positive influences on depth; $\beta_{j,S}$ and $\beta_{j,T}$ are positive and significant in the depth regressions. Asymmetric information would suggest that the specialist should quote less depth when more fearful of informed traders. Perhaps the explanation resides once again in the tendency of informed traders to split orders. If they adopt this practice regularly, depth is inconsequential because they will invariably transact in units smaller than the quoted depth. This implies that depth is established almost exclusively for uninformed traders. Hence it is determined by inventory risks and thus increases with either the number of (uninformed) trades or the average (uninformed) trade size.

The relation between depth and either the average trade size or the number of transaction could also be explained by strategic motives underlying depth quotations. Large changes in volume are likely to be accompanied by substantial fluctuations in inventory. A specialist overloaded with inventory would naturally increase depth on the ask side to encourage buying and decrease depth on the bid side to discourage selling, and vice versa when inventory is deficient. However, the specialist's mandate to maintain a fair and orderly market might make him reluctant to decrease depth on either side. It follows that the *average* bid–ask depth would be higher when inventories are abnormal, either higher or lower, and inventories are likely to be abnormal when volume is greater. This could account for positive correlation (though not necessarily causation) between changes in depth and either trade size or frequency.

Since we have no access to inventory levels, nor a foolproof method by which to sign trades, we are unable to fully test this idea. We do, however, conduct a simple exercise with the available data; we run a regression analogous to (4) except that the dependent variable is the proportional daily change in the absolute value of the difference between bid and ask depth, i.e., $L = |Q_A - Q_B|$. If specialists respond to abnormal inventory by increasing depth on one side of the market while failing to decrease depth as much on the other side, this variable should be significantly and positively related to trade size and the number of trades. It is. The mean coefficient for trade size, $\beta_{j,S}$, is 0.398 with a t-statistic of 2.93 and the coefficient for the number of transactions, $\beta_{j,T}$, is 0.323 with a t-statistic of 2.90. Further investigation promises to be an interesting line of research.

3.3. Commonality compared to individual determinants of liquidity

Previous microstructure literature argues that individual trading volume, volatility, and price are influential determinants of liquidity (Benston and Hagerman, 1974; Stoll, 1978b). From an inventory perspective, individual dollar volume should reduce spreads and increase depth while individual volatility should have the opposite effect. If possessed monopolistically by traders who have no competitors, more rampant asymmetric information should increase both volatility and spreads, inducing correlation but not causation; and if, as seems plausible, informed traders earn greater profits when volatility is generally high, spreads should increase in response.

The empirical influence of market price on the quoted or effective spread levels is obvious. Clearly, a \$10 stock will not have the same bid–ask spread as a \$1000 stock provided that they have otherwise similar attributes. Depth should decrease with price, ceteris paribus.[9] There is less reason to anticipate any influence of price on the proportional spreads; unless price is proxying for some other variable, the proportional spread should be roughly independent of the stock's price level, other things equal.

Table 9 documents the separate marginal influences on liquidity of such individual attributes: volatility, price, and trading volume. It also compares their magnitude with commonality, measured in this case by industry liquidity. As expected, individual volume (volatility) has a negative (positive) influence on spreads and the opposite influence on depth. Their impacts are large and highly significant for all five liquidity constructs. Also as anticipated, price and spread level are positively related while depth falls with price. In the case of spreads, however, note that the marginal influence of price is less than proportional; the coefficients are about 0.3 for both quoted and effective spreads, QSPR and ESPR. This suggests that price should have a negative marginal impact on the proportional spreads, which is indeed the result shown. Moreover, the price coefficient for PQSPR and PESPR have the largest *t*-statistics in the Table.[10]

We regard the negative influence of price on proportional spread as something of a puzzle remaining to be explained. One piece of that puzzle could be discreteness. Since the minimum quoted spread was \$1/8, all stocks liquid enough to trade at the minimum spread would display a substantial negative correlation between price and proportional quoted spread.[11] This spurious effect would disappear only when price reaches a level high enough to support occasional spreads larger than the minimum.

Finally and most important, note in Table 9 that industry liquidity retains a strong influence on individual stock liquidity even after accounting for volatility, volume, and price. All coefficients are positive and significant. Commonality is indeed a ubiquitous characteristic of liquidity.

[9] The referee points out that depth decreases with price because it is measured in shares. If it were measured in value, arguably a more economically relevant construct, there would be no obvious relation between depth and price. But a share measure of depth mitigates return 'contamination', i.e., if depth is measured in value, the change in depth from one day to another effectively includes a price change. Consequently, a regression of an individual stock change in depth on a market-wide change in depth could display significance induced by return co-movement even if there is no liquidity co-movement. The use of share depth is consistent with prevailing practice in market microstructure literature; see, for example, Lee et al. (1993).

[10] The method reported in Table 9 is adopted in an effort to enhance power. We could simply average all the variables across time and then calculate a single regression with the averages. Instead, we adopt the Fama–MacBeth (1973) approach of estimating a cross-sectional regression daily, then averaging the cross-sectional coefficients over time, correcting for auto-correlation. This method should improve statistical precision.

[11] A similar point is made by Harris (1994).

Table 9
Individual liquidity determinants and industry commonality[a]

Individual stock liquidity measures (levels) are regressed cross-sectionally each trading day on the standard deviation of individual daily returns from the preceding calendar month (STD), the concurrent day's mean price level (PRICE), the day's dollar trading volume (DVOL), and an equally-weighted liquidity measure of all stocks in the same industry (INDUSTRY).[b] The INDUSTRY observation corresponding to an individual stock excluded that stock. Natural logarithmic transformations are used for all variables. Cross-sectional coefficients are then averaged across the 254 trading days in the sample and are reported with t-statistics in parentheses QSPR is the quoted spread. PQSPR is the proportional quoted spread. DEP is quoted depth. ESPR is the effective spread. PESPR is the proportional effective spread. The R^2 is adjusted.

	QSPR	PQSPR	DEP	ESPR	PESPR
STD	0.1268	0.1171	− 0.1372	0.1295	0.1218
t	(45.41)	(35.54)	(− 17.45)	(32.49)	(27.98)
PRICE	0.3738	− 0.6215	− 0.9010	0.3296	− 0.6669
t	(108.8)	(− 164.8)	(− 103.2)	(54.96)	(− 101.9)
DVOL	− 0.0669	− 0.0670	0.4127	− 0.0523	− 0.0525
t	(− 33.17)	(− 33.99)	(129.4)	(− 42.06)	(− 43.23)
INDUSTRY	0.3333	0.1871	0.2737	0.2428	0.1413
t	(30.75)	(29.49)	(13.11)	(29.63)	(30.36)
R^2 mean	0.290	0.810	0.432	0.216	0.735
Median	0.288	0.806	0.422	0.208	0.733

[a]Note: t denotes t-statistic corrected for first-order auto-correlation.

[b]This is similar to the Fama and MacBeth (1973) method for returns. The eight industry classifications follow Roll (1992) and Chalmers and Kadlec (1998).

Since the coefficients in the cross-sectional regressions are not returns, there is nothing to keep them from being correlated across time. Indeed, their first-order auto-correlations across adjacent trading days range between 0.22 and 0.72; *all* are positive. Assuming that the coefficient's estimation error volatility, σ, is constant and that only first-order auto-correlation, ρ, is present, the standard error of the time series sample mean becomes

$$\sigma\{(1 + 2\rho/(1 - \rho)]/T - 2\rho[(1 - \rho^T)/(1 - \rho)^2]/T^2\}^{1/2},$$

where T is the sample size. When $\rho > 0$, this expression exceeds the usual estimator, $\sigma/T^{1/2}$, resulting in a smaller t-statistic. If intertemporal dependence actually decays more slowly because of second- or higher-order auto-correlation, the t-statistics would still remain large. Assuming no decay at all, a grossly conservative assumption, the minimum t-statistic in the table would be 1.99 and 18 (11) would exceed 4.0 (6.0). Even assuming perfect correlation (i.e., not dividing σ by any multiple of T), 18 of the 20 t-statistics would still exceed 2.0. By any measure, the coefficients are very significant.

3.4. Measures of commonality in liquidity for portfolios

Earlier tables reveal that common influences significantly influence daily changes in individual asset liquidity measures; however, these influences have low explanatory power, adjusted R^2 rising to around four percent in only a few regressions.[12] See Tables 3–5 and 7. Explanatory power improves when changes in determinants of individual liquidity measures are included as explanatory variables (Table 8), but there is still much unexplained variation.

Whether the unexplained variation is noise or omitted variables, portfolio liquidity might exhibit a more palpable trace of commonality. By analogy, portfolio returns are much more correlated with common market factors than individual stock returns. Perhaps the same effect will be found for intertemporal changes in liquidity.

Table 10 presents some evidence about this question by co-relating changes in liquidity measures for size-based portfolios. We first divide the sample into size quintiles based on the market capitalization at the end 1991. Then an equal-weighted average of each liquidity measure is calculated for each quintile on every trading day during 1992. The daily change from trading day $t-1$ to trading day t is our portfolio construct.

Table 10 reports regressions of each daily liquidity change on a market-wide equal-weighted liquidity change for all stocks not in the subject quintile. The results could be compared to those reported for individual stocks in Table 3. In Table 10, all the contemporaneous coefficients are positive and highly significant. The explanatory power has also improved, in some cases substantially. Notice that the percentage quoted spreads (DPQSPR) and depth (DDEP) now have average R^2 of 0.552 and 0.811, respectively.[13] Effective spreads, however, still exhibit only modest explanatory power; though larger for these portfolios than for individual stocks, the R^2 are still below four percent.

The results in Table 10 reveal that when market-wide forces impinge on liquidity, portfolio managers are likely to face more challenges, on average, in altering their holdings. Though they may have different portfolios, two randomly-chosen managers are likely to find their average liquidities co-moving significantly through time.

Much of the intertemporal variation in liquidity changes is firm-specific, particularly for the quoted spread and for the depth; which is why the explanatory power is relatively low in regressions with individual securities (Tables 3 and 5). By using portfolios, Table 10 effectively expunges much of the firm-specific variation and thereby uncovers stronger co-movements in liquidity changes. The results show that the risks of unexpected changes in average liquidity contain a strong market component.

[12] Unadjusted R^2 are, of course, higher – around six percent. Many of the nuisance variables such as squared return are not significant. Consequently, the low adjusted R^2 give a somewhat misleading portrayal of the actual power of the liquidity variables.

[13] The corresponding individual R^2 squares are 0.017 and 0.010 (cf. Table 3).

Table 10
Portfolio commonality in liquidity by size quintile five size groups ($\approx$ 234 stocks per quintile), calendar year 1992, 253 daily observations

Daily proportional changes in each quintile's liquidity measure are regressed in time series on proportional changes in the equal-weighted liquidity measure for all stocks in the sample (the 'market'). '*D*' preceding the acronym, e.g., DQSPR, denotes a proportional change in the variable across successive trading days; i.e., for liquidity measure L, $DL_t \equiv (L_t - L_{t-1})/L_{t-1}$ for trading day t. Market averages exclude the quintile dependent variable. To allow for error correlations across quintiles the system is estimated as a set of Seemingly Unrelated Regressions.

The lead, lag and concurrent values of the equal-weighted market returns, the proportional daily change in individual firm squared return (a measure of change in return volatility) are additional regressors; coefficients not reported. T-statistics are in parenthesis.

	Smallest ($N = 233$)	2 ($N = 234$)	3 ($N = 234$)	4 ($N = 234$)	Largest ($N = 234$)
DQSPR (System Weighted $R^2 = 0.152$) size quintile					
Concurrent	0.185	0.187	0.223	0.231	3.940
	(6.05)	(4.87)	(6.82)	(6.58)	(7.66)
Lag	0.018	0.052	0.075	0.023	− 0.651
	(0.62)	(1.46)	(2.48)	(0.71)	(− 1.27)
Lead	0.020	0.010	0.030	0.058	− 0.130
	(0.72)	(0.29)	(0.98)	(1.79)	(− 0.25)
DPQSPR (System Weighted $R^2 = 0.552$)					
Concurrent	0.739	0.763	0.843	0.769	1.829
	(12.21)	(10.35)	(12.93)	(11.74)	(8.38)
Lag	− 0.037	0.043	0.275	0.131	− 0.316
	(− 0.64)	(0.61)	(4.42)	(2.09)	(− 1.46)
Lead	0.023	0.018	0.088	0.245	− 0.343
	(0.40)	(0.25)	(1.42)	(3.93)	(− 1.61)
DDEP (System Weighted $R^2 = 0.811$)					
Concurrent	0.637	0.835	1.062	1.110	1.013
	(9.47)	(12.35)	(19.22)	(19.77)	(17.59)
Lag	− 0.080	0.208	0.028	− 0.002	− 0.034
	(− 1.16)	(3.06)	(0.50)	(− 0.03)	(− 0.57)
Lead	− 0.098	− 0.037	0.015	0.044	0.143
	(− 1.43)	(− 0.55)	(0.27)	(0.77)	(2.41)
DESPR (System Weighted $R^2 = 0.036$)					
Concurrent	0.015	0.003	0.016	0.033	2.477
	(0.70)	(0.27)	(1.47)	(3.08)	(1.84)
Lag	0.006	0.010	− 0.003	− 0.016	0.781
	(0.28)	(0.89)	(0.32)	(− 1.54)	(0.61)
Lead	0.019	− 0.000	0.015	− 0.006	− 0.611
	(0.94)	(− 0.00)	(1.42)	(− 0.59)	(− 0.46)

Table 10 (*continued*)

	Smallest ($N = 233$)	2 ($N = 234$)	3 ($N = 234$)	4 ($N = 234$)	Largest ($N = 234$)
DPESPR (System Weighted $R^2 = 0.039$)					
Concurrent	0.020	0.011	0.026	0.033	5.280
	(1.13)	(0.91)	(1.79)	(2.49)	(1.82)
Lag	0.015	0.021	− 0.002	− 0.014	1.631
	(0.87)	(1.82)	(− 0.14)	(− 1.06)	(0.61)
Lead	0.010	− 0.007	0.009	0.011	1.802
	(0.57)	(− 0.59)	(0.66)	(0.86)	(0.66)

4. Summary and implications for future work

Liquidity is more than just an attribute of a single asset. Individual liquidity measures co-move with each other. Even after accounting for well-known individual determinants of liquidity such as trading volume, volatility, and price, commonality retains a significant influence.

To the best of our knowledge, commonality in liquidity has not before been empirically documented. It is a wide-open area of research with both academic and practical aspects. Future research will surely be devoted to understanding why liquidity co-moves. Is it induced by market peregrinations, political events, macroeconomic conditions, or even hysteria? A sensible next step would attempt to identify specific macroeconomic influences that correlate with time-series variation in liquidity.

Recognizing the existence of commonality in liquidity allows us to uncover evidence that inventory risks and asymmetric information both affect individual stock liquidity. A stock's spread is positively related to the number of individual transactions but negatively related to the aggregate level of trading in the entire market. We interpret this pattern as a manifestation of two effects (a) a diminution in inventory risk from greater market-wide trading activity, most plausibly by uninformed traders, and (b) an increase in asymmetric information risk occasioned by informed traders attempting to conceal their activities by breaking trades into small units, thus increasing the number of transactions, cf. Jones et al. (1994). Although commonality is the instrument used here to reveal asymmetric information effects on liquidity, we have no evidence that asymmetric information itself has common determinants.

Co-movements in liquidity also suggest that transaction expenses might be better managed with appropriate timing. When spreads are low, managed portfolio turnover can be larger without sacrificing performance. However, we do not yet know whether common variations in trading costs are associated with other market phenomena, such as price swings, which might offset the benefits of time-managed trading.

Finally, an important research issue not investigated here is whether and to what extent liquidity has an important bearing on asset pricing. Transaction expenses can accumulate to become a relatively large decrement in total return when portfolios are turned over frequently. If liquidity shocks cannot be diversified, the sensitivity of an individual stock to such shocks could induce the market to require a higher average return. Notice that a higher expected return would surely be required for stocks with higher average trading costs, but there might be an additional expected return increment demanded of stocks with higher sensitivities to broad liquidity shocks.

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