Commonality in Liquidity

by

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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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I. Motivation

I.A. The Single-Asset Focus.

The literature of market microstructure has heretofore focused almost exclusively on individual securities. Topics such as transactions costs and liquidity naturally pertain to the repeated trading of a single homogeneous asset. Typically, we do not think of them 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 were modeled with an isolated market maker in the pivotal role, providing immediacy at a cost determined by either inventory risks, (i.e., 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 concerned an individual stock, the insider serving as prototype privilegee (Kyle [1985], Admati and Pfeiderer [1988]).

Empirical work also dealt solely with the trading patterns of individual assets, most often equities sampled at high frequencies, (Wood, McInish, and Ord [1985], Harris [1991]), or examined micro questions such as the price impact of large trades, (Kraus and Stoll [1972], Keim and Madhavan [1996], Chan and Lakonishok [1997]).

Even the strand of literature about market design, (Garbade and Silber [1979], Madhavan [1992]), examined the influence of various trading mechanisms on the costs of individual transactions. Studies of such topics as intermarket competition or the contrast between dealer and auction markets devolved to predictions about **individual** liquidity and transaction costs.

The single-asset focus of the literature is exemplified by a prominent recent paper (Easley, Kiefer, and O'Hara [1997]) whose empirical work was devoted to a single common stock, Ashland Oil, on thirty trading days.

We do not imply even the slightest criticism. The microstructure literature has become a very impressive body of knowledge. But we aspire by this paper to direct some attention toward unexplored territory, toward 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.

Commonality in liquidity could play a key role in otherwise puzzling market episodes. For example, during the summer of 1998, credit sensitive bonds seemed to undergo a global liquidity crisis. This precipitated financial distress in certain highly-levered trading firms who 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 identifiable noteworthy event, (Roll [1988]), yet was characterized by a ubiquitous temporary reduction in liquidity.

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.

I.B. Theoretical Intimations of Commonality in Liquidity

There **have** been some suggestive theoretical developments about common liquidity in a multi-asset context. For example, Hagerty [1991] and Gehrig and Jackson [1998] study competition among market makers, or the lack thereof, and its effect on trading costs. Subrahmanyam

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[1] See the *Wall Street Journal*, [1998], "Illiquidity means it has become more difficult to buy or sell a given amount of any bond but the most popular treasury issue. The spread between prices at which investors will buy and sell has widened, and the amounts in which Wall Street firms deal have shrunk across the board for

[1991a] argues that basket trading is less exposed to asymmetric information than individual security trading, which implies, *inter alia*, that the existence of basket trading can influence individual liquidity. Although these papers imply interdependence among asset liquidities during a single period, none goes on to derive implications for intertemporal co-movements in liquidity; the empirical literature also has ignored such possibilities.

Within the framework of **inventory-theoretic** microstructure theory, covariation in liquidity could arise simply because trading activity displays market-wide intertemporal variation in response to general price swings (a fact well appreciated by brokers seeking employment after crashes). Program trading of simultaneous large orders might put common pressure on individual inventories. Similarly, institutional funds with similar styles might exhibit correlated trading patterns, thereby inducing changes in inventory pressure across broad sectors. Whatever the source, if inventory fluctuations were correlated across individual assets, liquidity could be expected to exhibit similar co-movement.

Within the **asymmetric information** microstructure framework, one might at first expect little covariation since few traders (aside, perhaps from Alan Greenspan) could conceivably possess privileged information about broad market movements. In the prototypical case of the 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, say fraudulent accounting statements. However, there might be other types of secret information, say a revolutionary new technology, which could influence many firms, not necessarily all in the same direction. Similarly, within an industry there are probably occasional outbreaks of asymmetric information pertinent for most firms in that sector.

Microstructure explanations of **individual price formation** include the discrete order framework (Glosten and Milgrom [1985]) and the pooled order flow framework (Kyle [1985]). Exogenous liquidity determinants in both paradigms are likely to covary over time.

investment grade, high-yield (or junk), emerging market and asset-backed bonds… The sharp reduction in liquidity has preoccupied the Fed because it is the lifeblood of markets."

In a discrete order model with both inventory and asymmetric information effects, Chordia and Subrahmanyam [1995] derive a closed-form expression for liquidity; Spread depends on (a) the probability of an order emanating from an informed trader, (b) return volatility, (c) the size of order flow, and (d) the carrying costs of the market maker, (which are assumed to increase quadratically in the level of inventory.) Each of these elements is probably time varying. All might be correlated across individual assets.

An inventory-specific element such as order flow is probably subject to broad market perturbations in trading such as heavy selling or buying pressure. Carrying costs respond to market interest rates, among other things. Market- or industry-wide informational events or market sentiment could affect the probability of informed trading. Individual volatilities could co-move if for no reason beyond sensitivity to market activity.

Similar implications arise in the pooled order flow framework with a risk-averse market maker and risk-neutral informed traders (Subrahmanyam [1991b]). Assuming the presence of both asymmetric information and inventory effects, the market maker sets a linear price schedule with a slope λ, where λ depends on the volatility of returns, the variability of liquidity trading, and the number of informed traders. Once again, portfolio trading or simultaneous information about many assets could easily induce covariation in each element of λ.

In summary, while microstructure theory has made impressive advances, there are no explicit models of time-series variation in liquidity for multiple assets. Plausible theory does, however, at least hint at the likelihood of such co-movement.

I.C. Implications of Commonality.

Covariation in liquidity and the associated comovements in trading costs have interesting ramifications and pose immediate questions. A key research issue is the relative importance of the two potential causes of covariation, inventory risks 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?

Trading costs must be cross-sectionally related to gross-of-cost expected return 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 trading cost **shocks** constitute a source of non-diversifiable priced risk. If covariation in trading costs is partly unanticipatable and has a varying impact across individual securities, the more sensitive an asset 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 (average cost) and one dynamic (risk.) Future work will have to determine whether the second channel is material and, if so, its relative importance.

This paper is almost entirely empirical and 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. The next section (II) describes the data. Section III reports a progression of empirical findings about commonality in liquidity. Section IV provides some interpretations, makes suggestions for additional empirical research, calls on theorists for help, and concludes.

II. Data

Transactions data for New York Exchange (NYSE) stocks during the calendar year 1992 were obtained from the Institute for the Study of Securities Markets (ISSM). 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 were rarely traded and would not have provided reliable samples. To be included here, we resolved that a stock had to be continually listed throughout 1992 on the NYSE and to trade at least once on at least ten of the 254 trading days that year. To circumvent any possible problems with trading units, stocks were excluded if they split or paid a stock dividend during the year. Because their trading characteristics might differ from ordinary equities, assets in the following categories were also expunged: certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, and REITs. This left 1,169 individual unalloyed equities in our sample.

[2]Transactions were 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 five second delay.

There were 29,655,629 transactions in the 1,169 stocks on the 254 trading days during 1992. Not all stocks traded every day. To finesse any contaminating influence of the minimum tick size, a stock was deleted on a day its average price fell below \$2. Opening batch trades and transactions with special settlement conditions were 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 were not used. After all this filtering, 289,612<296,926=1169(254) total stock-days remained, an average of 102.4 transactions per stock-day or about 99.9 transactions averaged over the 1,169 stocks and 254 trading days. All but 13 of the 1,169 stocks had transactions on more than 100 days. 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 were computed as follows:

Liquidity Measure	Acronym[3]	Definition
Quoted Spread	QSPR	$P_A - P_B$
Proportional Quoted Spread	PQSPR	$(P_A - P_B)/P_M$
Depth	DEP	$\frac{1}{2}(Q_A + Q_B)$
Effective Spread	ESPR	$2\lvert P_t - P_M \rvert$
Proportional Effective Spread	PESPR	$2\lvert P_t - P_M \rvert / P_t$

where P_A and P_B denote, respectively, the specialist's ask and bid quotes guaranteed valid for Q_A and Q_B shares, $P_M \equiv \frac{1}{2}(P_A + P_B)$ denotes the quote mid-point, and P_t is the actual transaction price.

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 was devised to measure **actual** trading costs, recognizing that (a) many trades occur

[3] A "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.

within the quoted spread and (b) if the proposed transaction exceeds the quoted depth, NYSE specialists are allowed, though not obligated, to execute that portion of the order in excess of the quoted depth at an altered price.

To reduce these multitudinous data to a manageable level and promote greater synchroneity, each liquidity measure was averaged across all daily trades. This also served to smooth out intra-day peculiarities. Thus, for each of the 1,169 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 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 in spreads over time. 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 revealing that substantial time series variability is shared by many stocks. Depth is even more volatile across time than spread.

III. Commonality in Measures of Liquidity

III.A. Some Basic Empirical Evidence.

To begin the investigation of commonality, we report simple "market model" time series regressions; daily percentage changes in liquidity variables for an individual stock regressed on market averages of the same variables; i.e.,

$$DL_{j,t} = \alpha_j + \beta_j DL_{M,t} + \varepsilon_{j,t}, \qquad (1)$$

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, either equal-weighted or value-weighted by 1991 year-end market capitalization.

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 <u>squared</u> return were included as additional regressors. The leads and lags were designed to capture any lagged adjustment in commonality while the market return was intended to remove spurious dependence induced by an association between returns and spread measures. This could have had 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 was 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 was 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,

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[4] Because the tables are already voluminous, we do not report coefficients for the nuisance variables: the market return and squared stock return. Details will be provided to interested readers.

when the market liquidity measure in an equal-weighted average of **all** stocks, the cross-sectional mean of β would be 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 casts doubt on small sample inferences from any single equation. However, a well-known version of the Central Limit Theorem, (Judge, *et. al.* [1985, ch. 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 depicts evidence of co-movement. For example, in panel B, which employs equal-weighted market liquidity measures, the change in the percentage quoted spread, DPQSPR, displays an average value of 0.791 for the contemporaneous β_j in (1). 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.

[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) <u>does</u> 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-sectional dependence.

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 but one instance (DPESPR with value-weighted market liquidity.) 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-square 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.

The contemporaneous slope coefficient from (1) is larger when the market spread measure is equal-weighted (compare panels A and B of Table 3), 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 is exactly the opposite pattern of market model regressions involving individual and market <u>returns</u>. 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, Table 3 reveals that smaller stocks are <u>less</u> sensitive to market-wide shocks in spreads.

[6]Measurement error might be a problem with effective spreads; e.g., Lightfoot, et al. [1999] document biases up to 32% in effective spreads computed with the Lee and Ready [1991] algorithm (which we have adopted.)

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

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].

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 mean "Sum" 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 with equal-weighted liquidity is an 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

[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. Only a few stocks in the sample experienced no trading at all on a substantial number of days. In the larger four size quintiles, about 82% of the stocks traded every day, yet the same pattern is observed in the coefficients.

market and an industry component; industry actually has larger coefficients for three of the five liquidity measures.

Since industry represents something of a mid-station between the individual firm and the broad market, its significance could reflect private information at the industry level. Alternatively, trading activity might exhibit more within- than across-industry commonality and hence inventory risks depend to some extent on industry-specific price swings.

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 1,169 individual regressions are arranged randomly (alphabetically) by stock name so we simply ran 1,168 time series regressions between adjacent residuals; i.e.,

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

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 altogether 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 make little, if any, difference in the t-statistics reported in Table 5.

Breaking the sample into separate industry groups and estimating (2) for each group, Table 7 further verifies the significance of industry liquidity. Industry has a cross-sectional t-statistic exceeding 2.0 in 24 out of 40 cases while the market liquidity's t-statistic exceeds 2.0 in only 14 cases. However, because of multi-collinearity between market and industry liquidity, it seems quite possible that their separate influences have not been properly disentangled.

III.B. 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 occassion.

Previous work by Jones, Kaul, and Lipson [1994] suggests that the <u>number</u> 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 8. If, as seems likely, some of this commonality is <u>not</u> 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 dichotomize the two effects, Table 9 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

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

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 suggest 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 effects. 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, even though market trading frequency affects individual frequency strongly (Table 8). Industry volume, which one might have thought *a priori* could represent trading by both informed and uninformed entities, displays mostly positive coefficients, thereby suggesting the dominance of informed traders.

Dollar volume depends on both the number of transactions and the average size of a transaction. Table 9 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 large orders, a notion consistent with Jones, Kaul, and Lipson [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 rather 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-value. 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 9. In contrast, industry volume has an insignificant (negative) influence on depth. Perhaps the no-information marginal influence of industry trading beyond market-wide trading is just offset by the caution induced in the specialist by a higher probability of encountering an insider.

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 did, however, conduct a simple exercise with the available data; we ran a regression analogous to (4) except that the dependent variable was 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.

III.C. 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 $1,000 stock provided that they have otherwise similar attributes. Depth should decrease with price, *ceteris paribus*. 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 10 documents the separate marginal influences on liquidity of such <u>individual</u> 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 <u>negative</u> 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[8].

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.[9] This spurious effect would disappear only when the price reached a level high enough to support occasional spreads larger than the minimum.

[8]The method reported in Table 10 was adopted in an effort to enhance power. We could have simply averaged all the variables across time and then calculated a single regression with the averages. Instead, we decided to estimate a cross-sectional regression daily, then average the cross-sectional coefficients over time, correcting for auto-correlation. If daily estimation errors are not excessively time-dependent, this method should improve statistical precision.

[9] A similar point is made by Harris [1994].

Finally and most important, note in Table 10 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.

III.D. Measures of Commonality in Liquidity for Diversified Portfolios.

Earlier tables have revealed that common influences significantly influence individual asset liquidity measures, but these influences have low explanatory power, adjusted R-squares rising to around four percent in only a few regressions[10]. See Tables 3, 4, 5 and 7. Explanatory power improves when individual liquidity measures are included as explanatory variables, (Tables 9 and 10), but there is still much unexplained variation.

Whether the unexplained variation is noise or omitted variables, diversification might eliminate much of the cross-sectional variation in individual liquidity, thereby leaving a more palpable trace of commonality. By analogy to returns, diversification dramatically increases the correlation between a portfolio and common market factors. Perhaps the same effect will be found for liquidity.

Table 11 presents some evidence about this question by co-relating liquidity measures for well-diversified portfolios. We first divided the sample into size quintiles based on the market capitalization at the end 1991. Then an equal-weighted average of each liquidity measure was calculated for each quintile on every trading day during 1992. The daily change from trading day t-1 to trading day t is our diversified liquidity construct.

Table 11 reports regressions of each daily liquidity change on a market-wide equal-weighted liquidity change for all stocks <u>not</u> in the subject quintile. The results could be compared to

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

those reported for individual stocks in Table 3. In Table 11, 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-squares of .552 and .811, respectively[11]. Effective spreads, however, still exhibit only modest explanatory power; though larger for these portfolios than for individual stocks, the R-squares are still below four percent.

The results in Table 11 reveal that a considerable portion of the cross-sectional variation in liquidity is diversifiable, particularly for the quoted spreads and for depth. When underlying market-wide forces impinge on liquidity, portfolio managers are likely to confront a substantially altered ability to liquidate their average holding.

IV. 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.

Recognizing the existence of commonality in liquidity has allowed us to uncover evidence that inventory risks **and** asymmetric information 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, Kaul, and Lipson [1994]). Although commonality is the instrument used here to reveal asymmetric information effects on liquidity, there is no direct evidence that asymmetric information itself has common determinants.

[11] The corresponding individual R-squares were 0.017 and 0.010; (Cf. Table 3, Panel B.)

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 scientific 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?

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 a relatively large decrement in total return when portfolios undergo high turnover. If liquidity shocks are indeed non-diversifiable, 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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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 was calculated for every transaction during calendar year 1992 using all NYSE stocks with at least one transaction on at least ten trading days, 1,169 stocks. Transaction observations were then averaged within each day to obtain a sample of 254 trading days.

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	$½(Q_A+Q_B)$	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

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

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

Table 2

Absolute daily proportional changes in liquidity variables

Liquidity Variables are defined in Table 1. "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. 1,169 stocks, calendar year 1992.

Cross-sectional statistics for time-series means

	Mean	Median	Standard Deviation
|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

Table 3
Market-Wide Commonality in Liquidity
1,169 stocks, calendar year 1992, 253 daily observations

Daily proportional changes in an individual stock's liquidity measure were regressed in time series on proportional changes in the value-weighted (Panel A) and the equal-weighted (Panel B) liquidity measure for all stocks in the sample (the "market"). Liquidity measures are defined in Table 1. Market averages exclude 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. "% 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 value-weighted market return (Panel A), the equal-weighted market return (Panel B) and the proportional daily change in individual firm squared return (a measure of change in return volatility) were additional regressors; coefficients not reported.

A. Value-weighted Market Liquidity

	DQSPR	DPQSPR	DDEP	DESPR	DPESPR
Concurrent	0.204	0.493	0.836	0.040	0.207
	(17.32)	(24.68)	(13.70)	(4.19)	(1.17)
% positive	74.25%	82.89%	78.02%	58.68%	53.21%
% +significant	20.02%	31.14%	25.41%	7.53%	8.13%
Lag	0.073	0.089	0.183	0.008	0.043
	(5.61)	(5.05)	(3.92)	(1.48)	(0.92)
% positive	57.40%	57.57%	55.09%	48.16%	43.03%
% +significant	8.98%	7.87%	7.70%	5.90%	5.73%
Lead	0.046	0.061	0.271	0.001	0.011
	(4.61)	(3.22)	(5.55)	(0.11)	(0.65)
% positive	57.49%	57.06%	56.63%	47.56%	42.94%
% +significant	7.27%	7.61%	7.87%	5.47%	6.33%
Sum	0.323	0.643	1.290	0.049	0.262
	(13.59)	(21.34)	(12.27)	(3.47)	(1.10)
Median	0.275	0.653	0.871	0.016	0.006
p-value	0.00	0.00	0.00	0.00	0.11
Adjusted R^2 mean	0.015	0.020	0.010	0.012	0.013
median	0.009	0.012	0.002	0.003	0.002

Table 3, (Continued)

B. Equal-weighted Market Liquidity

	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

Table 4
Market-Wide Commonality in Liquidity by Size Quintile
1,169 stocks (≈234 per quintile), calendar year 1992, 253 daily observations

Daily proportional changes in an individual stock's liquidity measure were regressed in time series on proportional changes in the value-weighted (Panel A) and the equal-weighted (Panel B) liquidity measure for all stocks in the sample (the "market"). Liquidity measures are defined in Table 1. Market averages excluded the dependent variable individual 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 value-weighted market return (Panel A), the equal-weighted market return (Panel B) 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-square.

A. Value-weighted Market Liquidity

		Smallest (N=233)	2 (N=234)	3 (N=234)	4 (N=234)	Largest (N=234)
		Size Quintile				
DQSPR	Sum	0.121	0.326	0.333	0.409	0.430
		(2.17)	(4.21)	(8.48)	(8.56)	(13.41)
	Median	0.034	0.215	0.282	0.343	0.408
	p-value	0.69	0.00	0.00	0.00	0.00
	R^2	0.008	0.011	0.013	0.015	0.026
DPQSPR	Sum	0.396	0.568	0.647	0.747	0.855
		(4.44)	(7.71)	(11.30)	(14.21)	(16.00)
	Median	0.353	0.478	0.651	0.773	0.902
	p-value	0.00	0.00	0.00	0.00	0.00
	R^2	0.010	0.012	0.015	0.021	0.042
DDEP	Sum	0.951	1.372	1.457	1.438	1.228
		(3.64)	(4.80)	(7.09)	(5.42)	(10.42)
	Median	0.627	0.890	0.907	0.822	0.934
	p-value	0.00	0.00	0.00	0.00	0.00
	R^2	0.003	0.007	0.010	0.006	0.022
DESPR	Sum	0.026	0.004	0.045	0.026	0.142
		(0.69)	(0.17)	(2.35)	(1.58)	(3.01)
	Median	-0.031	-0.021	0.037	0.006	0.055
	p-value	0.12	0.56	0.03	0.32	0.00
	R^2	0.005	0.013	0.011	0.010	0.024
DPESPR	Sum	0.011	0.015	0.031	0.004	1.275
		(0.20)	(0.51)	(1.81)	(0.32)	(1.18)
	Median	-0.013	-0.014	0.002	0.008	0.017
	p-value	0.19	0.08	0.85	0.85	0.00
	R^2	0.008	0.007	0.011	0.011	0.024

Table 4, (Continued)

B. Equal-weighted Market Liquidity

		Smallest (N=233)	2 (N=234)	3 (N=234)	4 (N=234)	Largest (N=234)
		Size quintile				
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

Table 5
Market and Industry Commonality in Liquidity

Daily proportional changes in an individual stock's liquidity measure were 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[12]. Liquidity measures are defined in Table 1. 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) were additional regressors; coefficients not reported. R^2 denotes the cross-sectional adjusted R-square.

	Market	Industry	Market	Industry	Market	Industry	Market	Industry	Market	Industry
	DQSPR		DPQSPR		DDEP		DESPR		DPESPR	
Concurrent	0.264 (9.86)	0.467 (16.65)	0.505 (14.06)	0.287 (11.08)	0.721 (6.17)	0.614 (7.28)	0.164 (5.26)	0.414 (7.51)	-0.172 (-0.60)	0.970 (1.81)
Lag	0.070 (2.90)	0.059 (2.12)	0.096 (2.85)	0.065 (2.74)	-0.058 (-0.60)	0.022 (0.28)	0.057 (2.64)	0.028 (0.43)	-0.138 (-0.84)	0.307 (1.37)
Lead	0.073 (2.91)	0.005 (0.22)	0.042 (1.18)	0.034 (1.40)	0.368 (4.22)	-0.040 (-0.57)	0.040 (1.75)	-0.014 (-0.57)	-0.158 (-0.92)	0.007 (0.12)
Sum	0.409 (7.49)	0.530 (9.63)	0.642 (9.13)	0.386 (6.99)	1.030 (4.99)	0.596 (3.49)	0.260 (4.79)	0.429 (3.67)	-0.468 (-0.75)	1.285 (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	

[12] The eight industry classifications follow Roll [1992] and Chalmers and Kadlec [1998].

Table 6

Check for Cross-Equation Dependence in Estimation Error

After estimating 1,169 time series regressions of individual liquidity measures on equal-weighted market and industry liquidity, equation (2), residuals for stock j+1 were compared with residuals for stock j, where j was ordered alphabetically. From these 1,168 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.

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

Table 7
Market and Industry Commonality in Liquidity, By Industry

Daily proportional changes in an individual stock's liquidity measure were 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. Liquidity measures are defined in Table 1. Market and Industry averages excluded the dependent variable individual stock. The eight industry classifications follow Roll [1992] and Chalmers and Kadlec [1998].

Cross-sectional averages of time series slope coefficients are reported by industry with t-statistics in parentheses. "Sum" aggregates coefficients for concurrent, previous, and next trading day observations. The number of stocks by industry is reported in parentheses in the column heading. 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 returns, 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-square.

Table 7, (Continued)

		Finance (178)		Energy (61)		Utilities (131)		Transportation/Storage (32)	
		Market	Industry	Market	Industry	Market	Industry	Market	Industry
DQSPR	Sum	0.045	0.820	0.041	0.781	0.071	0.935	-0.130	0.968
		(0.83)	(8.35)	(0.41)	(5.25)	(0.61)	(7.38)	(0.52)	(1.85)
	Median	0.049	0.710	0.144	0.673	-0.031	1.053	0.022	0.455
	p-value	0.33	0.00	0.61	0.00	0.72	0.00	0.60	0.00
	Mean R^2	0.021		0.030		0.026		0.035	
DPQSPR	Sum	0.524	0.512	0.559	0.462	0.498	0.604	0.285	0.443
		(3.80)	(5.39)	(2.63)	(3.45)	(2.81)	(5.16)	(0.75)	(4.13)
	Median	0.701	0.263	0.634	0.362	0.594	0.447	0.568	0.390
	p-value	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.01
	Mean R^2	0.020		0.030		0.021		0.028	
DDEP	Sum	0.953	1.075	0.244	0.707	1.514	0.500	1.975	-0.082
		(2.19)	(2.87)	(0.41)	(1.11)	(1.80)	(1.02)	(2.12)	(-0.19)
	Median	0.607	0.750	0.350	0.664	0.773	0.504	0.702	0.186
	p-value	0.02	0.00	0.44	0.02	0.01	0.02	0.22	0.11
	Mean R^2	0.021		0.011		0.011		0.028	
DESPR	Sum	-0.017	0.837	0.045	0.672	-0.024	0.681	-0.179	0.861
		(-0.46)	(4.43)	(0.61)	(2.27)	(-0.46)	(4.55)	(-1.35)	(1.48)
	Median	-0.015	0.695	-0.027	0.282	-0.013	0.566	-0.043	0.155
	p-value	0.12	0.00	0.31	0.00	0.60	0.00	0.59	0.02
	Mean R^2	0.016		0.028		0.020		0.019	
DPESPR	Sum	-0.045	1.062	-0.086	0.525	-0.065	0.652	0.035	0.531
		(-0.40)	(1.71)	(-0.69)	(2.78)	(-0.91)	(4.89)	(0.21)	(1.29)
	Median	-0.010	0.265	0.006	0.572	-0.022	0.612	0.045	0.130
	p-value	0.41	0.00	1.00	0.00	0.38	0.00	0.38	0.11
	Mean R^2	0.012		0.025		0.016		0.018	

Table 7, (Continued)

		Consumer goods (375)		Capital goods (131)		Basic industries (179)		Technology (82)	
		Market	Industry	Market	Industry	Market	Industry	Market	Industry
DQSPR	Sum	1.144	-0. 021	0.148	0.731	-0.040	0.745	0.254	0.630
		(7.82)	(-0.17)	(1.74)	(5.03)	(-0.59)	(7.07)	(2.66)	(5.81)
	Median	1.260	-0.148	0.114	0.680	-0.69	0.800	0.301	0.732
	p-value	0.00	0.04	0.22	0.00	0.65	0.00	0.10	0.00
	Mean R^2	0.026		0.019		0.020		0.027	
DPQSPR	Sum	0.898	0.310	0.597	0.338	0.443	0.197	0.669	0.524
		(5.56)	(2.23)	(3.39)	(2.49)	(2.73)	(1.84)	(3.34)	(3.49)
	Median	1.032	0.138	0.819	0.208	0.685	0.165	0.852	0.293
	p-value	0.00	0.41	0.00	0.08	0.00	0.10	0.01	0.00
	Mean R^2	0.021		0.023		0.017		0.031	
DDEP	Sum	1.055	0.658	1.298	-0.072	0.704	0.685	0.811	0.478
		(2.94)	(1.76)	(2.84)	(-0.21)	(1.02)	(1.44)	(1.96)	(1.53)
	Median	0.639	0.613	0.932	0.055	1.016	0.267	0.933	0.454
	p-value	0.00	0.00	0.00	0.86	0.00	0.45	0.00	0.15
	Mean R^2	0.013		0.015		0.006		0.018	
DESPR	Sum	0.852	0.115	0.001	-0.020	-0.029	0.618	-0.009	0.527
		(5.31)	(1.31)	(0.02)	(-0.02)	(-0.97)	(4.70)	(-0.19)	(3.27)
	Median	0.924	0.015	-0.038	0.683	-0.007	0.607	0.002	0.524
	p-value	0.00	0.26	0.22	0.00	0.55	0.00	1.00	0.00
	Mean R^2	0.023		0.017		0.016		0.017	
DPESPR	Sum	1.371	2.655	-0.098	0.541	0.013	0.404	-0.024	0.487
		(0.71)	(1.18)	(-0.84)	(3.09)	(0.14)	(3.58)	(-0.23)	(2.03)
	Median	0.580	0.085	-0.022	0.388	-0.007	0.269	-0.012	0.392
	p-value	0.00	0.30	0.73	0.00	0.55	0.01	0.58	0.06
	Mean R^2	0.020		0.019		0.015		0.019	

Table 8
Commonality in Transactions Frequency

Daily percentage changes in the number of transactions (i.e., not volume) for 1,169 stocks were 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 were equal-weighted but excluded the individual subject stock[13] .

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

[13] The equal-weighted market return was an additional regressor, coefficient not reported. The eight industry classifications follow Roll [1992] and Chalmers and Kadlec [1998].

Table 9

Commonalities in Trade Size, Transaction Frequency and Trading Volume
1,169 Stocks, Calendar Year 1992

Daily proportional changes in individual stock liquidity variables were 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. Liquidity measures are defined in Table 1. Market and Industry averages excluded the dependent variable individual stock. The eight industry classifications follow Roll [1992] and Chalmers and Kadlec [1998].

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 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 was an additional regressor; coefficients not reported. The spread measures were 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

Table 9, (Continued)

Industry Trading Volume					
Concurrent	1.306 (2.77)	1.133 (2.39)	-0.058 (-1.94)	1.931 (1.64)	-2.634 (-0.43)
Lag	0.824 (1.63)	0.651 (1.29)	-0.029 (-1.12)	-0.543 (-0.61)	-11.410 (-1.03)
Lead	0.450 (0.89)	0.244 (0.44)	-0.009 (-0.35)	0.087 (0.09)	0.586 (0.59)
Sum	2.581 (2.86)	2.029 (2.18)	-0.097 (-1.71)	1.475 (0.70)	-13.458 (-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

Table 10
Individual Liquidity Determinants and Industry Commonality

Individual stock liquidity measures (levels) were 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)[14]. The INDUSTRY observation corresponding to an individual stock excluded that stock. Natural logarithmic transformations were used for all variables. Cross-sectional coefficients were then averaged across the 254 trading days in the sample and are reported with t-statistics in parentheses. Liquidity measure definitions are in Table 1. The R^2 is adjusted.

	QSPR	PQSPR	DEP	ESPR	PESPR
STD	0.1268	0.1171	-0.1372	0.1295	0.1218
t_0	(72.14)	(60.88)	(-30.08)	(59.01)	(51.81)
t_1	(45.41)	(35.54)	(-17.45)	(32.49)	(27.98)
PRICE	0.3738	-0.6215	-0.9010	0.3296	-0.6669
t_0	(228.3)	(-361.9)	(-208.3)	(129.0)	(-251.2)
t_1	(108.8)	(-164.8)	(-103.2)	(54.96)	(-101.9)
DVOL	-0.0669	-0.0670	0.4127	-0.0523	-0.0525
t_0	(-81.82)	(-82.94)	(257.7)	(-73.72)	(-74.81)
t_1	(-33.17)	(-33.99)	(129.4)	(-42.06)	(-43.23)
INDUSTRY	0.3333	0.1871	0.2737	0.2428	0.1413
t_0	(50.65)	(48.16)	(21.99)	(40.63)	(38.00)
t_1	(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

t_0: t-statistic assuming no intertemporal dependence

t_1: t-statistic corrected for first-order auto-correlation

Auto-correlation correction

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 ranged between 0.22 to 0.72; <u>all</u> were 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, t_1. If intertemporal dependence actually decays more slowly because of second- or higher-order auto-correlation, the t-statistics would still have remained large. Assuming no decay at all, a grossly conservative assumption, the minimum t-statistic in the table would have been 1.99 and 18 (11) would have exceeded 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 have exceeded 2.0. By any measure, the coefficients are very significant.

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[14] The eight industry classifications follow Roll [1992] and Chalmers and Kadlec [1998].

Table 11

Portfolio Commonality in Liquidity by Size Quintile

Five size groups (≈234 stocks per quintile), calendar year 1992, 253 daily observations

Daily proportional changes in each quintile's liquidity measure were regressed in time series on proportional changes in the equal-weighted liquidity measure for all stocks in the sample (the "market"). Liquidity measures are defined in Table 1. Market averages excluded the quintile dependent variable. To allow for error correlations across quintiles the system was estimated as a Seemingly Unrelated Regression.

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) were additional regressors; coefficients not reported. T-statistics are in parenthesis.

DQSPR (System Weighted R^2=0.152)

	Smallest (N=233)	2 (N=234)	3 (N=234)	4 (N=234)	Largest (N=234)
	Size Quintile				
Concurrent	0.185 (6.05)	0.187 (4.87)	0.223 (6.82)	0.231 (6.58)	3.940 (7.66)
Lag	0.018 (0.62)	0.052 (1.46)	0.075 (2.48)	0.023 (0.71)	-0.651 (-1.27)
Lead	0.020 (0.72)	0.010 (0.29)	0.030 (0.98)	0.058 (1.79)	-0.130 (-0.25)

DPQSPR (System Weighted R^2=0.552)

	Smallest (N=233)	2 (N=234)	3 (N=234)	4 (N=234)	Largest (N=234)
	Size Quintile				
Concurrent	0.739 (12.21)	0.763 (10.35)	0.843 (12.93)	0.769 (11.74)	1.829 (8.38)
Lag	-0.037 (-0.64)	0.043 (0.61)	0.275 (4.42)	0.131 (2.09)	-0.316 (-1.46)
Lead	0.023 (0.40)	0.018 (0.25)	0.088 (1.42)	0.245 (3.93)	-0.343 (-1.61)

Table 11, (Continued)

DDEP (System Weighted R^2=0.811)

	Smallest (N=233)	2 (N=234)	3 (N=234)	4 (N=234)	Largest (N=234)
	Size Quintile				
Concurrent	0.637 (9.47)	0.835 (12.35)	1.062 (19.22)	1.110 (19.77)	1.013 (17.59)
Lag	-0.080 (-1.16)	0.208 (3.06)	0.028 (0.50)	-0.002 (-0.03)	-0.034 (-0.57)
Lead	-0.098 (-1.43)	-0.037 (-0.55)	0.015 (0.27)	0.044 (0.77)	0.143 (2.41)

DESPR (System Weighted R^2=0.036)

	Smallest (N=233)	2 (N=234)	3 (N=234)	4 (N=234)	Largest (N=234)
	Size Quintile				
Concurrent	0.015 (0.70)	0.003 (0.27)	0.016 (1.47)	0.033 (3.08)	2.477 (1.84)
Lag	0.006 (0.28)	0.010 (0.89)	-0.003 (0.32)	-0.016 (-1.54)	0.781 (0.61)
Lead	0.019 (0.94)	-0.000 (-0.00)	0.015 (1.42)	-0.006 (-0.59)	-0.611 (-0.46)

DPESPR (System Weighted R^2=0.039)

	Smallest (N=233)	2 (N=234)	3 (N=234)	4 (N=234)	Largest (N=234)
	Size Quintile				
Concurrent	0.020 (1.13)	0.011 (0.91)	0.026 (1.79)	0.033 (2.49)	5.280 (1.82)
Lag	0.015 (0.87)	0.021 (1.82)	-0.002 (-0.14)	-0.014 (-1.06)	1.631 (0.61)
Lead	0.010 (0.57)	-0.007 (-0.59)	0.009 (0.66)	0.011 (0.86)	1.802 (0.66)