Tarun Chordia
Goizueta Business School
Emory University

Richard Roll
Anderson Graduate School of Management
University of California at Los Angeles

Avanidhar Subrahmanyam
Anderson Graduate School of Management
University of California at Los Angeles

Common Determinants of Liquidity and Trading

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Mission

The Research Foundation's mission is to identify, fund, and publish research that is relevant to the AIMR Global Body of Knowledge and useful for AIMR member investment practitioners and investors.

Biographies

Tarun Chordia is an associate professor at the Goizueta Business School at Emory University in Atlanta. Previously, he was an assistant professor at Vanderbilt University. Professor Chordia also worked for Citibank as a relationship manager in the Financial Institutions Group in Mumbai, India, and served as a credit officer for Indian banks and development institutions. His theoretical and empirical research spans a diverse area of financial economics, including asset pricing, market microstructure, and financial institutions. Professor Chordia's paper with Bhaskaran Swaminathan was a finalist in the Chicago Quantitative Alliance's Institutional Brokers Estimate System (IBES) competition in 1996. His paper with Michael Brennan and Avanidhar Subrahmanyam won second place in the Fama-Dimensional Fund Advisors (DFA) competition for best paper published in the *Journal of Financial Economics* on capital markets and asset pricing in 1998, and his paper with Richard Roll and Avanidhar Subrahmanyam won the Fama-DFA prize on capital markets and asset pricing in 2000. Professor Chordia holds a Ph.D. in finance from the University of California at Los Angeles.

Richard Roll is Allstate Professor of Finance at the Anderson Graduate School of Management, University of California at Los Angeles, and a principal of Roll and Ross Asset Management Corporation. His business experience includes two years as a vice president at Goldman, Sachs & Company, where he founded and directed the mortgage securities research group, and three years with the Boeing Company. Professor Roll has served on the faculty of Carnegie-Mellon University, the European Institute for the Advanced Study of Management in Brussels, and the École des Hautes Études Commerciales near Paris. He has also served as a consultant for many corporations, law firms, and government agencies. Professor Roll is the author or co-author of two books and more than 70 articles on a variety of financial topics in refereed journals. His 1968 doctoral thesis won the Irving Fisher Prize as the best U.S. dissertation in economics. Professor Roll has twice received the Graham and Dodd Award for financial writing in the *Financial Analysts Journal*, has received the Leo Melamed Award for the best financial research by a U.S. business school professor, and was awarded *Docteur Honoris Causa* degrees from universities in France and Germany. He is past president of the American Finance Association and is a fellow of the Econometric Society. Professor Roll is or has been an associate editor of numerous journals in finance and economics. He holds a Ph.D. from the University of Chicago.

Avanidhar Subrahmanyam is professor of finance at the Anderson Graduate School of Management, University of California at Los Angeles. Previously, he was an assistant professor at Columbia University and a visiting associate professor at the Anderson Graduate School of Management. Professor Subrahmanyam has served as a consultant to the Nasdaq Stock Exchange, the National Stock Exchange of India, the *San Jose Mercury News*, and Irwin/McGraw-Hill. He is the author or co-author of numerous refereed journal articles in finance and economics on the relationship between the trading environment of a company's stock and the company's cost of capital, behavioral theories of asset-price behavior, empirical determinants of the cross-section of equity returns, and other subjects. Professor Subrahmanyam has received awards from the *Journal of Finance*, *Journal of Financial Economics*, Western Finance Association, and International Conference of Finance in Taiwan. He is also a co-editor of the *Journal of Financial Markets* and is serving or has served on the boards of several journals. Professor Subrahmanyam is a member of the Working Research Group on Market Microstructure, which was recently established by the National Bureau of Economic Research. He holds a Ph.D. in finance from the Anderson Graduate School of Management.

Foreword

It is an inescapable mathematical truth that, in aggregate, investors cannot outperform the total market, and it is an equally inescapable practical reality that, in aggregate, investors must underperform the total market by the extent to which trading costs dilute their performance. Moreover, the degree to which the market is efficient prevents even individual investors from outperforming the market by means other than chance. Therefore, any edge that will help investors overcome these inherent obstacles is a welcome contribution to the profession. Tarun Chordia, Richard Roll, and Avanidhar Subrahmanyam provide just such an edge in this comprehensive and insightful analysis of liquidity and trading.

Although market liquidity is a popular topic of research, especially because the impact of trading costs has become painfully transparent to investors, most of the research on liquidity addresses the issue from the perspective of individual securities. Chordia, Roll, and Subrahmanyam, instead, explore liquidity from a macroperspective. Specifically, they provide statistical documentation that liquidity has common determinants, which fluctuate through time, and they offer evidence of the identity of the factors that determine liquidity. Investors will be most pleased to learn that this research is not merely an academic exercise. The authors describe clearly and thoroughly its implications for those responsible for executing investment strategies.

Chordia, Roll, and Subrahmanyam's research is based on a diligently cleansed database comprising all eligible transactions on the New York Stock Exchange in the 1988–98 period. They construct several measures of liquidity, including quoted spread, effective spread, and depth, which they use in a variety of ways:

- They test the two predominant theories of liquidity—inventory risk and asymmetrical information—and find evidence to support both theories.
- They compare common influences with individual determinants of liquidity and find that common influences prevail—even after adjusting for individual attributes, such as volatility, volume, and price.
- They analyze the time-series properties of liquidity and find evidence of reversals.
- They identify the factors that influence liquidity and trading activity—equity market returns, volatility, short-term interest rates, long-term spreads, calendar regularities, and macroeconomic announcements.

Finally, Chordia, Roll, and Subrahmanyam prescribe specific guidelines for reducing transaction costs, to which many readers will, no doubt, be tempted to skip ahead. I encourage you to read every page of this monograph, however, to appreciate the cleverness and thoroughness of the authors' research and to understand its implications for such important issues as exchange design, regulation, and investment management. The Research Foundation is especially pleased to make available *Common Determinants of Liquidity and Trading*.

Mark Kritzman, CFA
Research Director
The Research Foundation of the
Association for Investment Management and Research

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Common Determinants of Liquidity and Trading

When portfolios turn over frequently, transaction expenses can accumulate to a relatively large decrement in total return. Because money managers often trade several securities simultaneously, knowing whether trading costs are correlated across securities would be important to them. Research on trading costs, however, has focused almost exclusively on individual securities. Typically, researchers and investors do not think of illiquidity in a marketwide context, and the classic models of market microstructure involve a dealer in a single stock who provides immediacy at a cost that arises because of inventory-holding risk (see Stoll 1978a) or because of the specter of trading with an investor with superior information (see Glosten and Milgrom 1985). Empirical work also has dealt solely with the trading patterns of individual assets, most often equities sampled at high frequencies (see, for example, Wood, McInish, and Ord 1985).

Illiquidity-induced trading costs should be correlated across securities for a variety of reasons. For example, if trading volume exhibits correlated changes in response to broad market movements, a corresponding correlation in liquidity costs should appear. Similarly, the cost of holding inventory could be correlated across securities because it depends, in part, on market interest rates. Within the asymmetric information view, certain types of information might be pertinent for most companies in an industry sector that, if revealed, could influence the liquidity of several securities simultaneously.

Sudden changes in systemwide liquidity appear to have been important in some well-known financial episodes. The international stock market crash of October 1987 was associated with no identifiable major news event (see Roll 1988) but was characterized by a temporary reduction in liquidity. During the summer of 1998, a liquidity crisis appears to have simultaneously affected several mid-grade and low-grade bonds and, as a result, apparently precipitated financial distress in certain highly levered trading firms.[1]

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[1] An article in the *Wall Street Journal* (1998) commented, "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 investment grade, high-yield (or junk), emerging market, and asset-backed bonds. . . . The sharp reduction in liquidity has preoccupied the Fed [U.S. Federal Reserve Board] because it is the lifeblood of markets."

In our ongoing research, we are trying to shift the focus from the notion of liquidity as a fixed attribute of an individual security to the idea that time-series movements in liquidity have common underlying determinants. This monograph concentrates on documenting common components of liquidity fluctuations and on identifying common liquidity drivers, but the shift in focus we are pursuing has important implications for such issues as the effect of liquidity fluctuations on asset prices, the effect of monetary policy on stock market liquidity, and co-movement between stock and bond market liquidity.

We began this study by using a sample of transaction data for a single year to document that time-series movements in liquidity have significant market-related and industry-related components. We then expanded the sample to cover 11 years of data (1988–1998 inclusive) to reliably uncover sources of commonality in liquidity.

In the following section, we describe the initial sample used to document commonality in liquidity and explain empirical procedures that verify that liquidity has a strong common component. Next, we describe our complete sample and present time series descriptions of the evolution of liquidity and trading variables over the full 1988–99 sample period. We then explain how we arrived at candidates for determinants of liquidity. Finally, we present results from regression analyses carried out to measure the relative influence of each determinant. In the concluding section, we summarize the implications for practitioners and discuss some intriguing paths for future research

Initial Data Sample

We obtained transaction data for New York Stock Exchange stocks from the Institute for the Study of Securities Markets (ISSM) for 1992, the latest available calendar year in the ISSM database at the time of our initial research. To be included in the sample, a stock had to (1) be continually listed throughout 1992 on the NYSE and (2) have traded at least once on at least 10 of the 254 trading days that year.

We deleted assets in the following categories: certificates, American Depositary Receipts (ADRs), shares of beneficial interest, units, companies incorporated outside the United States, Americus Trust components, closed-end funds, and real estate investment trusts (REITs). To avoid price-scaling problems in interpreting bid–ask spreads, we excluded stocks that split or paid a stock dividend during the year. This process of elimination left 1,169 securities. To remove any undue influence by the minimum tick size, we deleted a stock on a day when its average price fell below $2. We also excluded opening batch trades and transactions with special settlement conditions because they differ from normal trades and might be subject to distinct liquidity considerations. For obvious reasons, we did not include transactions reported out of sequence or after closing.

Corresponding to every transaction, we computed the following five liquidity measures:

Liquidity Measure	Variable Name	Definition	Unit
Quoted spread	*QuotedSpread*	$P_A - P_B$	$
Proportional quoted spread	*%QuotedSpread*	$(P_A - P_B)/P_M$	None
Depth	*Depth*	$0.5(Q_A + Q_B)$	Shares
Effective spread	*EffectiveSpread*	$2\lvert P_t - P_M \rvert$	$
Proportional effective spread	*%EffectiveSpread*	$2\lvert P_t - P_M \rvert / P_t$	None

With P denoting price and Q denoting quantity guaranteed available, the variables P_A and P_B denote, respectively, the specialist's ask and bid quotes guaranteed valid for Q_A and Q_B quantity of shares; $P_M \equiv 0.5(P_A + P_B)$ denotes the quote midpoint; and P_t is the actual transaction price.

We averaged each liquidity measure across all daily trades for each stock. Panel A of **Table 1** presents descriptive statistics for the five liquidity measures. Consistent with intuition, the effective spread is somewhat smaller than the quoted spread, reflecting trades within the posted quotes. Panel B shows that all the measures of spread are positively correlated with each other and negatively correlated with depth. **Table 2** documents descriptive statistics for

Table 1. Summary Statistics for Liquidity Variables, 1992

A. Cross-sectional statistics for time-series means

Variable	Mean	Median	Standard Deviation
QuotedSpread	0.32	0.27	1.36
%QuotedSpread	1.60	1.15	1.36
Depth	3,776	2,661	3,790
EffectiveSpread	0.23	0.18	1.31
%EffectiveSpread	1.11	0.77	1.32

B. Cross-sectional means of time-series correlations between liquidity measure pairs for an individual stock

	QuotedSpread	*%QuotedSpread*	*Depth*	*EffectiveSpread*
%QuotedSpread	0.844			
Depth	–0.396	–0.303		
EffectiveSpread	0.665	0.549	–0.228	
%EffectiveSpread	0.555	0.699	–0.156	0.871

Table 2. Absolute Daily Proportional Changes in Liquidity Variables, 1992
(cross-sectional statistics for time-series means)

Variable	Mean	Median	Standard Deviation
$\lvert\Delta QuotedSpread\rvert$	0.2396	0.2373	0.0741
$\lvert\Delta\% QuotedSpread\rvert$	0.2408	0.2386	0.0742
$\lvert\Delta Depth\rvert$	0.7828	0.6543	0.4533
$\lvert\Delta EffectiveSpread\rvert$	0.3148	0.2976	0.1367
$\lvert\Delta\% EffectiveSpread\rvert$	0.3196	0.2977	0.1811

daily percentage changes, denoted by Δ, in our liquidity variables. For the absolute value of the percentage change in the quoted spread, the time-series cross-sectional mean is high, about 24 percent a day. Depth is far more volatile than spreads.

Evidence of Common Variation in Liquidity

This section documents the empirical fact that liquidity has strong common components.

Basic Evidence. We regressed daily proportional changes in an individual stock's liquidity measure 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. We used the following equation:

$$\Delta L_{j,t} = \alpha_j + \beta_{j,M}\Delta L_{M,t} + \beta_{j,I}\Delta L_{I,t} + \varepsilon_{j,t}, \tag{1}$$

where

$\Delta L_{j,t}$ = percentage change for stock j from trading day $t-1$ to day t in liquidity variable L (where L is one of the variables—*QuotedSpread*, *EffectiveSpread*, or so on)

$\Delta L_{M,t}$ = concurrent change in a cross-sectional average of the same variable

$\Delta L_{I,t}$ = change in industry-specific average liquidity measure

$\varepsilon_{j,t}$ = regression disturbance

We examined percentage changes rather than levels for two reasons. First, our interest is fundamentally in discovering whether liquidity movements are correlated across firms, and second, time series of liquidity levels are more likely to be plagued by econometric problems (e.g., nonstationarity) than are changes in liquidity. In both the market liquidity index and the industry liquidity index, we excluded company *j* when computing the industry average.

Table 3 reports cross-sectional averages of time-series slope coefficients (the β_j's) from these regressions. Included as additional regressors (and not listed explicitly in Equation 1) are one lead and one lag of the market and industry average liquidity plus the contemporaneous leading and lagged market return and the contemporaneous change in the individual-stock squared return. "Concurrent," "Lag," and "Lead" refer, respectively, to the same, previous, and next trading day observations of market liquidity. "Sum" is the concurrent + lag + lead coefficients. We included the leads and lags to capture any lagged adjustment in commonality. Including the market return was intended to remove spurious dependence induced by an association between returns and spread measures. Such dependence could have particular relevance for the effective spread measures because they are functions of the transaction price. Their changes are thus functions of individual returns, which are known to be significantly correlated with broad market returns. Finally, we included the squared stock return to proxy for volatility, which from our perspective is a nuisance variable that may possibly influence liquidity.[2]

Table 3 provides evidence of co-movement. For example, the contemporaneous coefficient for the proportional quoted spread is consistently significant for both the market and industry average. Although the leading and lagged terms are usually positive and often significant, they are small in magnitude.

The explanatory power of the typical individual regression, however, is not impressive: The mean adjusted R^2 is about 2 percent. Clearly, either a large component of noise and/or other influences on daily changes in individual-stock liquidity constructs are present.

Except for the proportional effective spread (*%EffectiveSpread*), the liquidity measures seem to be influenced by both a market and an industry component. Indeed, the industry component actually has larger coefficients than does the market for three of the five liquidity measures. If trading activity and volatility exhibit more within-industry than across-industry commonality, inventory risks would be industry specific, a phenomenon consistent with these empirical patterns.

Commonality and Theories of Liquidity. Although the evidence strongly favors the existence of common underlying influences on liquidity

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

Table 3. Market and Industry Commonality in Liquidity, 1992
(*t*-statistics in parentheses)

	ΔQuotedSpread		*Δ%QuotedSpread*		*ΔDepth*		*ΔEffectiveSpread*		*Δ%EffectiveSpread*	
Measure	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	0.000	0.000	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	
R^2 median	0.019		0.016		0.005		0.009		0.008	

Note: The eight industry classifications follow Roll (1992) and Chalmers and Kadlec (1998). 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 are not reported. R^2 denotes the cross-sectional adjusted R^2.

variations, the identities of these influences remain to be determined. Microstructure literature suggests two possible (and not mutually exclusive) influences—inventory risk and asymmetric information. *A priori*, it seems reasonable that broad market activity would exert more influence on inventory risk than would individual trading activity, whereas individual trading would more likely be associated with asymmetric information. The industry component would represent an intermediate position—possibly influenced by both effects on occasion.

Previous work by Jones, Kaul, and Lipson (1994) suggests that the *number* of trades, not the dollar volume of trading, is an indicator of asymmetric information for individual companies. These authors showed that volume has little impact on volatility once trading frequency is taken into account. This rather puzzling result can perhaps be explained by the propensity of truly informed traders to hide their activities by splitting orders into small units, which increases the number of transactions. In other words, large, uninformed traders, such as institutions, might dominate the determination of dollar volume whereas 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.

Somewhat in conflict with the thrust of this idea, **Table 4** shows that individual-stock trading frequency is strongly influenced by both market and industry, which have similar coefficients and significance. If, as seems likely, some of this commonality is *not* caused by 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, we estimated marginal influences of individual, market, and industry transaction frequencies on our five liquidity measures. The individual time-series regressions had the general form

$$\Delta L_{j,t} = \alpha_j + \beta_{j,S}\Delta S_{j,t} + \beta_{j,T}\Delta T_{j,t} + \beta_{j,M}\Delta V_{M,t} + \beta_{j,I}\Delta V_{I,t} + \varepsilon_{j,t}, \tag{2}$$

where:

$S_{j,t}$ = average dollar size of a transaction in stock j

$T_{j,t}$ = number of trades in stock j

$V_{M,t}$ = aggregate dollar trading volume for the entire market (excluding stock j)

$V_{I,t}$ = dollar volume in stock j's industry (again excluding stock j itself)

And, as before, Δ denotes the percentage change from trading day $t-1$ to day t and L is the liquidity measure.

Table 4. Commonality in Transaction Frequency, 1992
(t-statistics in parentheses)

Coefficient	Market Alone	Together		Industry Alone
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
R^2 median	0.057	0.070		0.057

Note: Daily percentage changes in the number of transactions for 1,169 stocks when individually regressed in time series on the daily percentage change in the average number of transactions for all stocks in the sample and in the same industry. See note for Table 3.

The results, given in **Table 5**, are striking. The inventory explanation for liquidity suggests that more trading should bring about smaller spreads because inventory balances and risks for each 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. Number of individual trades, or trading frequency, $T_{j,t,}$ has a strong positive influence on the spread measures, and marketwide volume has a negative marginal influence on quoted spread, even though market trading frequency strongly affects individual frequency (as shown in Table 4). Industry volume, which intuitively could arise from both informed and uninformed trading, displays mostly positive coefficients, which suggests the dominance of informed traders.

Dollar volume depends on both the number of transactions and the average size of a transaction, and Table 5 discloses that an individual company's trade size has a strong positive influence on quoted spreads and depth. Perhaps this influence 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, make large transactions for liquidity or rebalancing reasons.

Table 5. Commonalities in Trade Size, Transaction Frequency, and Trading Volume, 1992
(t-statistics in parentheses)

Measure	ΔQuotedSpread (× 100)	Δ%QuotedSpread (× 100)	ΔDepth	ΔEffectiveSpread (× 100)	Δ%EffectiveSpread (× 100)
Own stock					
Trade size	0.643	0.597	0.166	–0.314	–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
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)
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
R^2 median	0.013	0.012	0.037	0.016	0.017

Note: 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, and (4) the trading volume for all stocks in the same industry. See note for Table 3.

To accommodate them, the specialist must maintain larger balances than during less intense periods. Informed institutions may attempt to conceal their trading by splitting up what would otherwise have been large orders (Jones et al.). If so, then smaller orders may actually be more likely than large orders to come from informed institutional traders. The trade size coefficients for the effective spread measures, which are likely to be influenced more by informed than by liquidity trading, are consistent with such an effect because they are negative, albeit insignificant.

A few outliers might have caused the puzzling pattern of market and industry coefficients for the proportional effective spread. 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 marketwide volume brings reduced spreads and greater industry volume increases spreads (presumably because of informed traders).

Based on inventory arguments, larger market volume might be expected to induce specialists to quote greater depth (but tighter spreads). Indeed, Table 5 reports this empirical result. In contrast, industry volume was found to have an insignificant (negative) influence on depth, which 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; the depth regressions produced positive and significant $\beta_{j,S}$ and $\beta_{j,T}$, whereas the asymmetric information theory suggests that the specialist should quote less depth when he or she is more fearful of informed traders. Perhaps the explanation lies, 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. If so, then depth is being established almost exclusively for uninformed traders. Hence, depth is determined by inventory risks and increases with either the number of (uninformed) trades or the average (uninformed) trade size.

The relationship between depth and either the average trade size or number of transactions 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 naturally increases depth on the ask side to encourage buying and decreases depth on the bid side to discourage selling, and vice versa when inventory is deficient. The specialist's mandate to maintain a fair and orderly market, however, might make the specialist reluctant to decrease depth on either side. In that case, the *average* bid–ask depth would be higher when inventories are abnormal, either higher or lower than normal. And inventories are likely to be abnormal when volume is greater. This possibility could account for positive correlation (although not necessarily causation) between changes in depth and either trade size or frequency.

Because we have neither access to inventory levels nor a foolproof method with which to identify buyer- and seller-originated trades, we could not fully test this idea. We did, however, conduct a simple exercise with the available data. We ran a regression analogous to Equation 2 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 but fail 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. The mean coefficient for trade size, $\beta_{j,S}$, was found to be 0.398 with a *t*-statistic of 2.93 and the coefficient for the number of transactions, $\beta_{j,T}$, was found to be 0.323 with a *t*-statistic of 2.90. This issue promises to be an interesting line of future research.

Commonality Compared with Individual Determinants of Liquidity. Previous microstructure literature has argued that *individual-stock* trading volume, volatility, and price are influential determinants of liquidity (e.g., Benston and Hagerman 1974; Stoll 1978b). From an inventory perspective, individual-stock dollar volume should reduce spreads and increase depth; individual-stock volatility should have the opposite effect. If information is possessed monopolistically by traders who have no competitors, rampant asymmetric information should increase both volatility and spreads, inducing correlation but not causation. Also, if informed traders earn greater profits than uninformed traders, as seems plausible, then spreads should increase in response to generally high volatility.

The influence of market price on quoted or effective spread levels is empirically obvious. Clearly, a $10 stock will not have the same bid–ask spread as a $1,000 stock if the two have otherwise similar attributes. All else being equal, depth should decrease with price.[3] There is less reason to anticipate

[3] Depth decreases with price because it is measured in shares. If it were measured in value, perhaps a more economically relevant construct, no obvious relationship would exist between depth and price. But a share measure of depth mitigates return "contamination"; that is, 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's value depth change on a marketwide value depth change might display significance induced by return co-movement even with no liquidity co-movement. The use of share depth is consistent with the prevailing practice in market microstructure literature; see, for example, Lee, Mucklow, and Ready (1993).

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 being equal.

Table 6 documents the separate marginal influences on liquidity of such *individual-stock* attributes as volatility, price, and trading volume. It also compares the magnitude of the individual attributes with commonality, measured in this case by industry liquidity. To produce the results in Table 6, we regressed individual-stock liquidity measures (levels) cross-sectionally for each trading day on the standard deviation of individual daily returns from the preceding calendar month, the concurrent day's mean price level, the day's dollar trading volume, and an equally weighted liquidity measure of all stocks in the same industry. We used natural logarithmic transformations for all variables. We then averaged cross-sectional coefficients across the 254 trading days in the sample.[4] As expected, Table 6 indicates that 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, but 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. This finding suggests that price should have a *negative* marginal impact on the proportional spreads, which was indeed the result. Moreover, the price coefficients for the proportional quoted spread and the proportional effective spread had the largest *t*-statistics in Table 6.

The negative influence of price on proportional spread is a puzzle that cannot yet be explained. One piece of the puzzle could be discreteness. Because 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.[5] This spurious effect would disappear only when price reached a level high enough to support occasional spreads larger than the minimum.

Finally and most importantly, note in Table 6 that industry liquidity retains a strong influence on individual-stock liquidity, even after accounting for volatility, volume, and price. All the liquidity coefficients are positive and significant. Commonality is indeed a ubiquitous characteristic of liquidity.

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[4] This method was adopted to enhance power. We could have simply averaged all the variables across time and then calculated a single regression with the averages. Instead, we adopted the approach Fama–MacBeth (1973) used for returns—that is, estimating a cross-sectional regression daily, then averaging the cross-sectional coefficients over time while correcting for autocorrelation. This method should improve statistical precision.

[5] Harris (1994) makes a similar point.

Table 6. Individual Liquidity Determinants and Industry Commonality, 1992
(t-statistics in parentheses)

Explanatory Variable	Dependent Variable				
	QuotedSpread	*%QuotedSpread*	*Depth*	*EffectiveSpread*	*%EffectiveSpread*
Standard deviation	0.1268	11.71	–0.1372	0.1295	12.18
	(45.41)	(35.54)	(–17.45)	(32.49)	(27.98)
Price	0.3738	–62.15	–0.9010	0.3296	–66.69
	(108.8)	(–164.8)	(–103.2)	(54.96)	(–101.9)
Daily trading volume	–0.0669	–6.70	0.4127	–0.0523	–5.25
	(–33.17)	(–33.99)	(129.4)	(–42.06)	(–43.23)
Industry	0.3333	18.71	0.2737	0.2428	14.13
	(30.75)	(29.49)	(13.11)	(29.63)	(30.36)
R^2 mean	0.290	0.810	0.432	0.216	0.735
R^2 median	0.288	0.806	0.422	0.208	0.733

Note: t-Statistics were corrected for first-order autocorrelation. Because the coefficients in the cross-sectional regressions are not returns, nothing keeps them from being correlated across time. Indeed, their first-order autocorrelations across adjacent trading days range between 0.22 to 0.72; *all* are positive. Assuming that the coefficient's estimation error volatility, σ, is constant and that only first-order autocorrelation, 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 autocorrelation, 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) t-statistics 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.

Commonality in Liquidity for Portfolios. In the previous subsection, we documented that commonality contributes cross-sectional explanatory power for liquidity in addition to such individual-stock attributes as trading volume, volatility, and price level. Here, we report evidence of empirical covariation between portfolio liquidity and marketwide liquidity. Our findings are especially relevant for investment managers who turn their holdings over frequently.

Table 7 provides evidence of covariation in liquidity measures for size-based portfolios. To obtain the results, we first divided the sample into size quintiles based on market capitalization at the end of 1991. Then, we calculated an equal-weighted average of each liquidity measure for each quintile on every trading day in 1992. The daily change from trading day $t-1$ to trading day t is our portfolio construct. Table 7 reports regressions of each daily liquidity

Table 7. Portfolio Commonality in Liquidity by Size Quintile, 1992
(t-statistics in parentheses)

Measure	Smallest (N = 233)	2 (N = 234)	3 (N = 234)	4 (N = 234)	Largest (N = 234)
ΔQuotedSpread (system-weighted R^2 = 0.152)					
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)
Δ%QuotedSpread (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)
ΔDepth (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)
ΔEffectiveSpread (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)
Δ%EffectiveSpread (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)

Note: Five size groups (≈ 234 stocks per quintile); 253 daily observations.

change on a marketwide, equal-weighted liquidity change for all stocks *not* in the subject quintile. To allow for error correlations across quintiles, the system was estimated as a set of seemingly unrelated regressions.

As Table 7 reports, the proportional quoted spreads and depth regressions had average R^2s of, respectively, about 55 percent and 81 percent. Effective spreads, however, exhibited only modest explanatory power (R^2 below 4 percent). The low explanatory power for the effective spread regressions is puzzling; we speculate that it is caused by noise in the effective spread measures that may arise from using the midpoints of stale quotes in order to calculate these quantities.

Overall, the results in Table 7 indicate that simultaneous trades of several securities are likely to incur correlated trading costs. Furthermore, the trading costs of broadly diversified portfolio managers are likely to co-move significantly through time. The results also suggest that the risks of unexpected changes in average liquidity contain a strong common component.

Common Determinants of Liquidity

We have shown that time-series movements in liquidity have a significant common component. Now, we explore the common influences that underlie movements in liquidity and trading activity. The exploration is valuable for several reasons: Exchange organization, regulation, and investment management could all be improved by knowledge of factors that influence liquidity and trading activity. A better understanding of these determinants would increase investor confidence in financial markets and thereby enhance the efficacy of corporate resource allocation.

To investigate common determinants of liquidity, we constructed time series of marketwide liquidity measures and marketwide trading activity over the 11-year period 1988 through 1998, almost 2,800 trading days. We averaged the data for a comprehensive sample of NYSE stocks on each trading day. For the most part, we studied equal-weighted, cross-sectional averages. For completeness and as a check on robustness, however, we also provide results obtained with value-weighted averages. As in the previous sections, we used quoted and effective spreads plus market depth to measure liquidity, and we used volume and the number of daily transactions to measure trading activity.

In choosing explanatory variables for liquidity and trading activity, we were guided by prior paradigms of price formation and by intuitive *a priori* reasoning. The *inventory* paradigm (Demsetz 1968; Stoll (1978a); Ho and Stoll 1981) suggests that liquidity depends on (1) the costs of financing dealer inventories, (2) factors that influence the risk of holding inventory, and (3) extreme events that provoke order imbalances and thereby cause inventory overload. Therefore, our first set of candidates for explanatory factors consisted of short- and long-term interest rates, default spreads, market volatility, and contemporaneous market moves. The *informed speculation* paradigm (Kyle 1985; Admati and Pfleiderer 1988) suggests that marketwide changes in liquidity may closely precede informational events, such as scheduled U.S. federal government announcements about the state of the economy. Furthermore, trading activity may vary—in a weekly cycle, for example—because of systematic variations in the opportunity cost of trading over the week; it may vary also around holidays. We thus included indicator variables to represent days around major macroeconomic announcements, day of the week, and major holidays.

Many authors, starting with Banz (1981), Reinganum (1983), and Gibbons and Hess (1981), documented regularities in asset returns on a monthly or daily basis but did not consider the time-series behavior of liquidity. In work that is more directly related to ours, Draper and Paudyal (1997) carried out an analysis of seasonal patterns in liquidity on the London Stock Exchange but were able to obtain monthly data for only 345 companies. Ding (1999) analyzed time-series variations of the spread in the foreign exchange futures market, but his data span less than a year. Jones et al. studied stock returns, volume, and transactions for a six-year period but did not attempt to explain why trading activity varies over time. Pettengill and Jordan (1988) analyzed seasonalities in volume, and Lo and Wang (2000) analyzed commonality in share turnover (both works used data spanning more than 20 years), but they did not analyze the behavior of market liquidity. Finally, Hiemstra and Jones (1994) and Karpoff (1987) analyzed the relationship between stock returns and volume over several years but, again, did not consider market liquidity.

Foster and Viswanathan (1993) used intraday data from a single year, 1988, to examine patterns in stock market trading volume, trading costs, and return volatility. For actively traded companies, they found that trading volume is low and adverse-selection costs are high on Mondays. Lakonishok and Maberly (1990) used more than 30 years of data on odd-lot sales/purchases to show that the propensity of individuals to sell is particularly high on Mondays. Harris (1986, 1989) documented various patterns in intraday and daily returns using transaction data over a period of three years. He did not have data on spreads, depths, or trading activity, however, and consequently was unable to directly analyze the behavior of liquidity. Thus, to our knowledge, no analysis has been made of the time-series behavior of liquidity over a long time span and its relationship, if any, with macroeconomic variables.

Comprehensive Sample. The sources for our data are the ISSM and the NYSE TAQ (trades and quotes) system database.[6] The ISSM data cover 1988 through 1992, and the TAQ data cover 1993 through 1998. Stocks were included or excluded during a calendar year on the basis of the following criteria:

- To be included, a stock had to be present at the beginning and at the end of the year in both the Center for Research in Security Prices (CRSP) database and the ISSM or TAQ database.
- If the company changed exchanges from the Nasdaq to the NYSE during the year (no companies switched from the NYSE to the Nasdaq during our sample period), it was dropped from the sample for that 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 United States, Americus Trust components, closed-end funds, preferred stock, and REITs.
- To avoid the influence of stocks priced unduly high, if the price at any month-end during the year was greater than $999, the stock was deleted from the sample for the year.
- Intraday data were purged of trades out of sequence, trades recorded before the open or after the closing time,[7] and trades with special settlement conditions (because they might be subject to distinct liquidity considerations).[8]

Our preliminary investigation revealed that autoquotes (passive quotes by secondary-market dealers) were eliminated in the ISSM database but not in TAQ, causing the quoted spread to be artificially inflated in TAQ. Because we had no reliable way to filter out autoquotes in TAQ, we used only BBO (best bid or offer)-eligible primary market (NYSE) quotes. Quotes established before the opening of the market or after the close were discarded, as were quotes with negative bid–ask spreads, transaction prices, and quoted depths. Following Lee and Ready (1991), we ignored any quote less than five seconds prior to the trade and retained the first one at least five seconds prior to the trade.

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6 We used only NYSE stocks to avoid any possibility of the results being influenced by differences in trading protocols in different trading venues.

7 The last daily trade was assumed to occur no later than 4:05 p.m. Transactions are commonly reported up to five minutes after the official close of 4:00 p.m.

8 These settlement conditions typically excluded dividend-capture trades. This exclusion should not have had any material impact on our results.

For each stock, we defined the following variables:

- *QuotedSpread*: quoted bid–ask spread associated with the transaction,
- %*QuotedSpread*: quoted bid–ask spread divided by the midpoint of the quote (in percent),
- *EffectiveSpread*: effective spread (i.e., the difference between the execution price and the midpoint of the prevailing bid–ask quote),
- %*EffectiveSpread*: effective spread divided by the midpoint of the prevailing bid–ask quote (in percent),
- *Depth*: average of the quoted bid and ask depths,
- $*Depth*: average of the ask depth times ask price and bid depth times bid price, and
- *CompositeLiq*: %*QuotedSpread/*$*Depth*—spread and depth combined in a single measure. *CompositeLiq* was intended to measure the average slope of the liquidity function (in percent per dollar traded).

In addition to these averages, we calculated the following measures of trading activity on a daily basis:

- *Volume*: total share volume during the day,
- $*Volume*: total dollar volume (number of shares multiplied by the transaction price) during the day, and
- *NumTrades*: total number of transactions during the day.

Our initial scanning of the intraday data revealed a number of anomalous records that appeared to be keypunching errors. We thus applied filters to the transaction data by deleting records that satisfied the following conditions:

- *QuotedSpread* > $5,
- *EffectiveSpread/QuotedSpread* > 4.0,
- %*EffectiveSpread/*%*QuotedSpread* > 4.0, and
- *QuotedSpread*/Transaction Price > 0.4.

These filters removed fewer than 0.02 percent of transaction records, out of more than 3 billion records in the sample.

After we had used the screening procedure, our investigation focused on daily cross-sectional averages of the liquidity and trading activity variables (for convenience, we retain the same variable names).

We calculated trading activity averages using all stocks present in the sample throughout the year as a divisor. (Stocks that did not trade were assigned a value of zero for trading volume, which is their actual volume on a day they did not trade.) We could not use the same method for spread or depth averages because a nontrading stock does not really have a spread or depth of zero. One possibility for dealing with this problem is to use only stocks trading on each day to calculate averages. Infrequently trading stocks probably have higher-than-average spreads (and lower depths), however, so daily changes in a liquidity measure could be unduly influenced by such stocks moving in and out of the sample. An alternative is to use the last recorded value for a nontrading stock, but the averages will then, of course, contain some stale data. We have done all the calculations both ways but report the results for only the latter method—that is, filling in missing data from the past 10 trading days *only* in order to limit the extent of staleness. The two methods yielded virtually identical results.

Levels of Liquidity and Trading Activity. Summary statistics of the basic market liquidity and trading activity measures are in **Table 8**. All variables displayed substantial intertemporal variation, but trading activity showed more variability than spreads, as indicated by the higher coefficients of variation. This finding might be attributable to the discrete nature of bid–ask spreads, which could serve to attenuate volatility through clustering. As Table 8 shows, the effective spread was considerably smaller than the quoted spread—a reflection, evidently, of within-quote trading. None of the variables exhibited any significant skewness; means were quite close to the medians.

Figures 1–5 graphically present the liquidity and trading activity levels for the entire sample period. Dollar depth and dollar trading volumes were plotted in real terms after scaling by the U.S. Consumer Price Index (all items) interpolated daily.[9] The effective spread (Figure 1) and the proportional effective spread (Figure 2) appear to have steadily declined in the latter half of our sample. This decline is consistent with a concomitant increase in trading activity, as shown in Figure 4.

According to Figures 1 and 3, depth and spread show an abrupt decline around June 1997, which coincides with the reduction of the minimum tick size from 1/8 to 1/16 on the NYSE.[10] Average dollars per trade (shown in Figure 5) increased from 1991 through 1996 as the level of stock prices (not plotted) and the number of transactions increased, but the trend reversed in 1997 and 1998, perhaps reflecting the increased volume of Internet trades and their smaller size per trade.

As **Figure 6** shows, we found sudden one-day changes in the number of stocks traded, especially in the period covered by ISSM. Many such changes occurred around the turn of the year, which was to be expected because we reformulated the sample at the beginning of each year, but anomalous

[9] If $g = CPI_T/CPI_{T-1} - 1$ is the reported monthly inflation rate for calendar month T, which consists of N days, the interpolated CPI value for the tth calendar day of the month is $CPI_{T-1}(1 + g)^{t/N}$.

[10] These decreases in spread and depth were predicted by Harris (1994).

Table 8. Market Liquidity and Trading Activity Variables, 1988–98

Statistic	Number of Companies	Quoted Spread ($)	Quoted Spread (%)	Effective Spread ($)	Effective Spread (%)	Depth (shares)	Price ($)	Volume (000)	Volume ($ million)	Number of Daily Trades	Depth ($ 0000)	Dollars/ Trade (00)
Mean	1,326	0.208	1.497	0.137	1.033	6,216	28.31	183.48	7.12	109.63	13.85	634.0
Standard deviation	126	0.026	0.412	0.017	0.278	1,195	2.84	75.76	3.74	47.94	2.95	104.7
Coefficient of variation[a]	0.0954	0.125	0.276	0.126	0.269	0.192	0.100	0.413	0.525	0.437	0.213	0.165
Median	1,344	0.217	1.490	0.138	0.993	6,478	27.97	162.21	5.72	95.84	13.77	627.1
Minimum	252	0.142	0.691	0.099	0.480	3,224	20.88	30.93	0.83	16.77	6.21	244.6
Maximum	1,504	0.282	2.819	0.203	2.052	8,584	36.52	613.95	27.76	379.22	21.77	1,814.2

[a]Standard deviation/Mean (dimensionless).

Figure 1. Average Quoted and Effective Bid–Ask Spreads, 1988–98

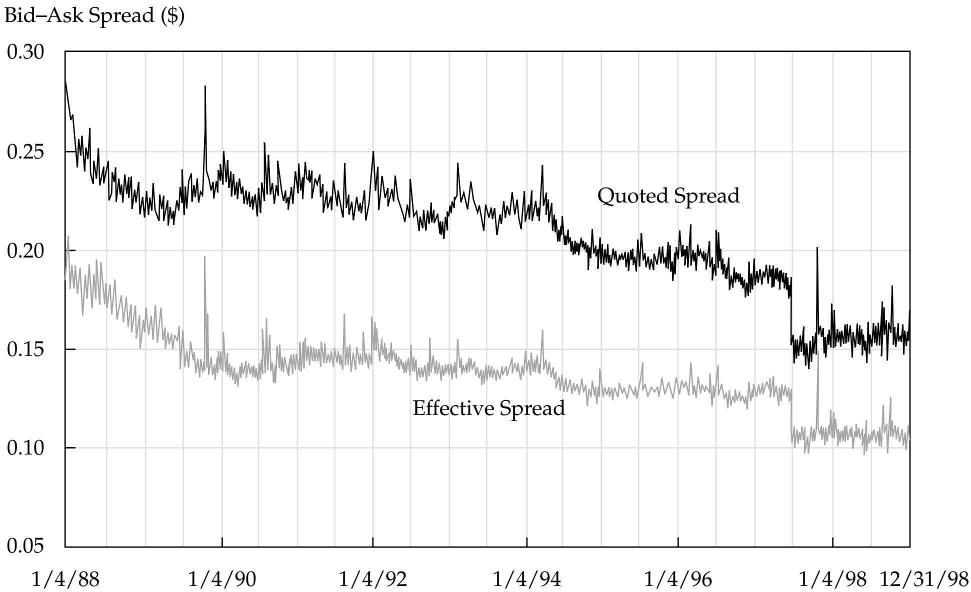


Figure 2. Average Percentage Quoted and Effective Bid–Ask Spreads, 1988–98

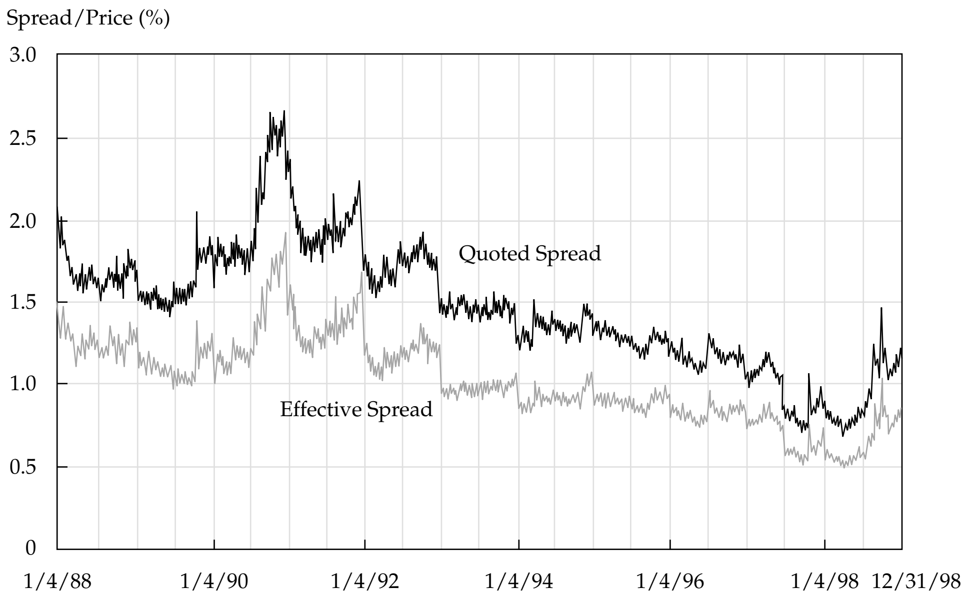


Figure 3. Bid–Ask Average Quoted Dollar and Share Depth, 1988–98

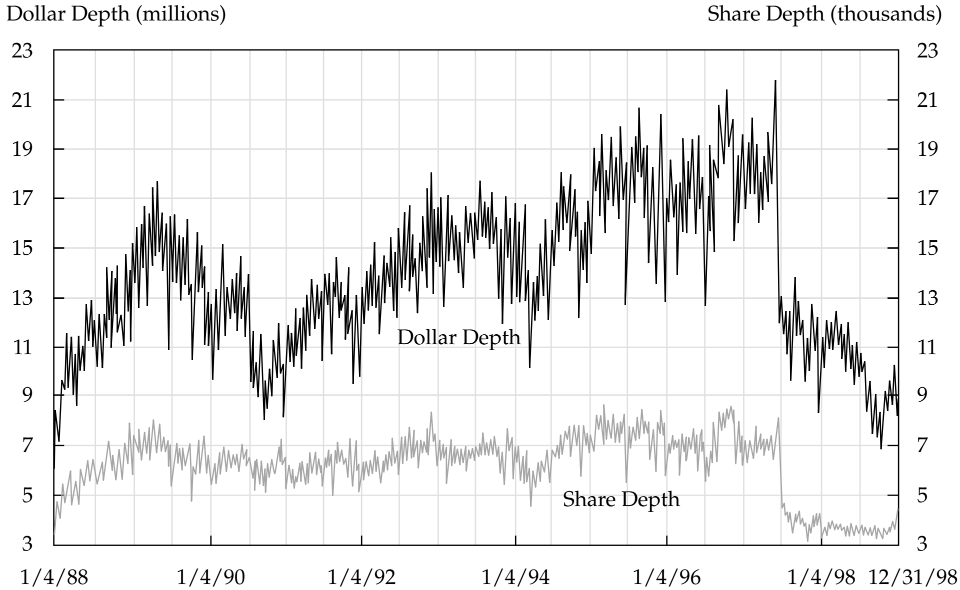


Figure 4. Average Daily Trading Volume per Stock, 1988–98

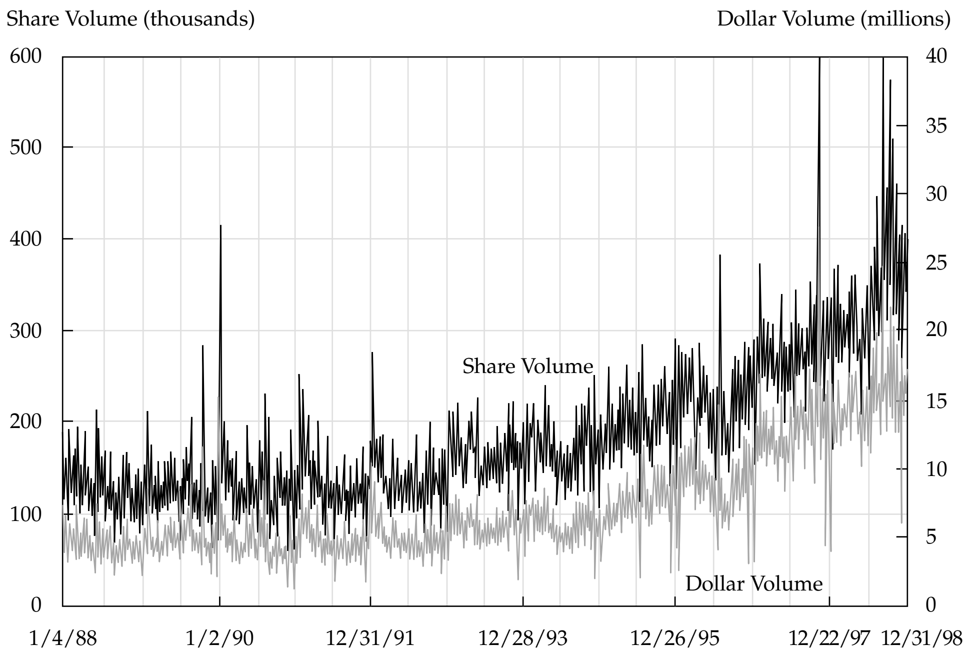


Figure 5. Average Number and Size of Daily Transactions, 1988–98

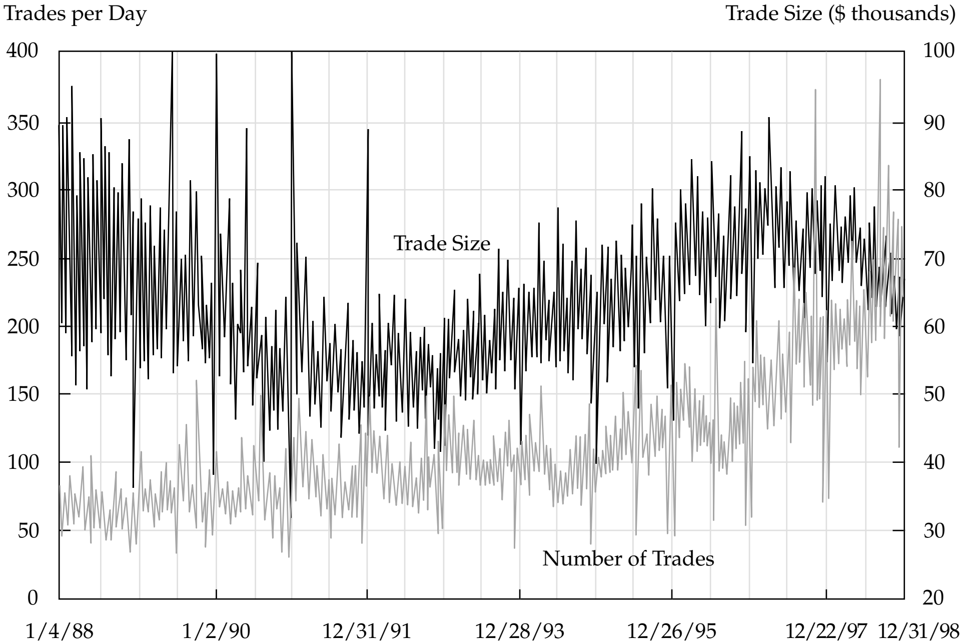
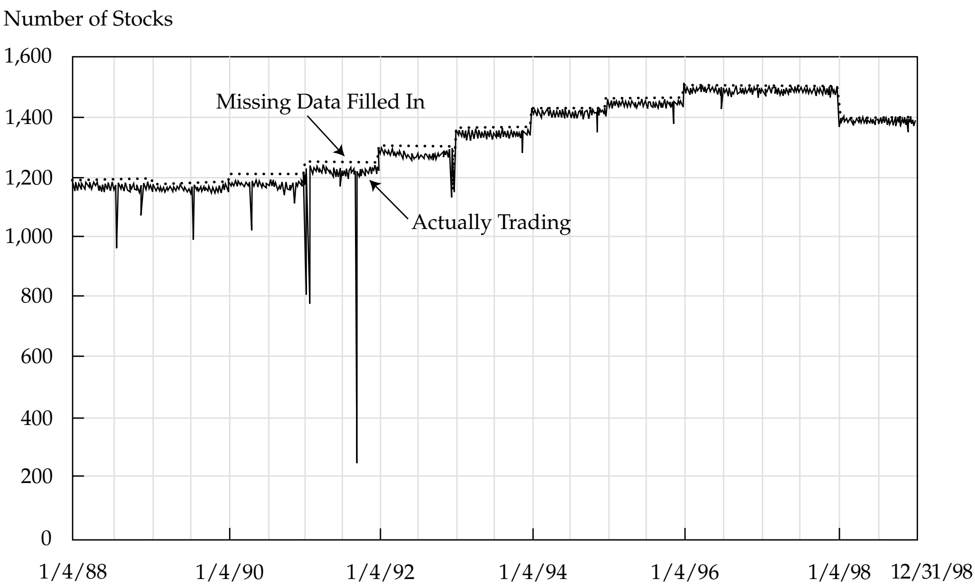


Figure 6. Number of Stocks in Daily Sample, 1988–98



changes also occurred on other dates. An extreme example is Monday, September 16, 1991, when only 248 companies were recorded in the ISSM database as having traded, even though 1,219 traded on the preceding Friday and 1,214 on the immediately following Tuesday. We believe that some of these cases are simply data-recording errors, although other cases could have been caused by unusually sluggish trading (for example, on days preceding or following major holidays).

Figure 6 also plots the number of stocks for each day after we filled in missing spreads and depths from previous values (up to a maximum of 10 past trading days). The number is almost constant within each calendar year, which implies that going back even further to fill in missing data would add virtually no additional stocks to each day's average. Filling in missing data, however, mitigates concerns about the results being influenced by fluctuations in the number of traded stocks.[11] Moreover, despite sizable variation in the number of stocks actually trading, we found a correlation of more than 0.98 between quoted spreads averaged over trading stocks and averaged over trading and back-filled nontrading stocks. This finding explains why the results were not sensitive to the specific method used to construct the liquidity index. We present a robustness check of this procedure later.

Daily Changes in Liquidity and Trading Activity. The pairwise correlations between changes in the liquidity variables and the trading activity variables are in **Table 9**. *A priori*, from reasoning at the individual-stock level, one might have anticipated a positive relationship between volume and liquidity and thus a negative (positive) relationship between volume and spreads (depth). But although correlations between changes in the marketwide quoted and proportional quoted spreads and share or dollar volume were negative, they were quite low. And the effective spread measures were actually positively correlated with each measure of volume. Furthermore, the correlations between various spread changes and the number of transactions were also positive. In contrast, share depth and dollar depth displayed strong and, as anticipated, positive correlations with volume.[12]

[11] After filling in missing observations with data no more than 10 days old, the average absolute change in the sample size was 0.13 companies a day. In contrast, the average absolute change in the number of *trading* companies was 7.0 a day.

[12] The correlation between (changes in) the quoted spread and the proportional quoted spread was only about 0.75, which might appear surprisingly low. But the proportional quoted spread was calculated by averaging the stock-by-stock ratios of quoted spread to price, and we found substantial cross-sectional variation in prices. The correlation between (changes in) the average quoted spread and the ratio of average quoted spread to average price was much higher, about 0.95.

Table 9. Correlations of Simultaneous Daily Percentage Changes in Marketwide Liquidity and Trading Activity

	Liquidity Variables							Trading Activity Variables		
	ΔQuoted Spread	*Δ%Quoted Spread*	*ΔEffective Spread*	*Δ%Effective Spread*	*ΔDepth*	*Δ$Depth*	*ΔCompositeLiq*	*ΔPrice*	*ΔVolume*	*Δ$Volume*
Δ%QuotedSpread	0.749									
ΔEffectiveSpread	0.782	0.581								
Δ%EffectiveSpread	0.492	0.568	0.686							
ΔDepth	–0.464	–0.355	–0.323	–0.181						
Δ$Depth	–0.460	–0.375	–0.316	–0.213	0.923					
ΔCompositeLiq	0.623	0.628	0.458	0.362	–0.882	–0.948				
ΔPrice	–0.150	–0.293	–0.192	–0.273	0.183	0.247	–0.303			
ΔVolume	–0.051	–0.138	0.091	–0.018	0.310	0.347	–0.308	–0.052		
Δ$Volume	–0.039	–0.142	0.095	–0.028	0.273	0.322	–0.290	–0.024	0.975	
ΔNumTrades	–0.034	–0.059	0.151	0.112	0.241	0.256	–0.204	–0.066	0.838	0.834

Note: Correlations between daily percentage changes in the variables described in Table 1 with changes at the turn of each year were omitted.

Not surprisingly, spread changes were negatively correlated with depth changes. Correlations between the number of transactions and either share or dollar volume were greater than 0.80.

Time-Series Properties of Market Liquidity and Trading Activity. **Table 10** records autocorrelations for percentage changes in each series out to a lag of five trading days (roughly one week, the exception being weeks with holidays). Every series except price exhibits statistically significant negative first-order autocorrelation. We even found evidence, albeit weaker, of negative second-order autocorrelation. Negative autocorrelation might be expected, because most of these series are likely to be stationary; for example, bid–ask spreads probably will not wander off to plus or minus infinity.[13] Notice also that the fifth-order coefficients were uniformly positive and about half of them were significant. This result reveals the presence of a weekly seasonal effect.

Negative first-order serial dependence in spreads could arise also from discreteness. Imagine, for instance, that most stocks have quoted spreads of

Table 10. Autocorrelations of Liquidity and Trading Activity Variables (order = lag in daily observations)

Variable	1	2	3	4	5
Liquidity variables					
Δ*QuotedSpread*	**–0.295**	**–0.131**	–0.048	–0.032	**0.081**
Δ%*QuotedSpread*	**–0.221**	**–0.127**	–0.002	–0.018	0.047
Δ*EffectiveSpread*	**–0.306**	**–0.093**	–0.072	–0.017	0.035
Δ%*EffectiveSpread*	**–0.291**	–0.075	–0.031	–0.021	0.046
Δ*Depth*	**–0.188**	**–0.212**	**–0.117**	–0.015	**0.229**
Δ$*Depth*	**–0.218**	**–0.179**	**–0.106**	0.001	**0.140**
Δ*CompositeLiq*	**–0.198**	**–0.178**	**–0.096**	–0.005	**0.130**
Trading activity variables					
Δ*Price*	0.006	0.019	0.013	0.025	–0.030
Δ*Volume*	**–0.266**	**–0.107**	–0.042	–0.017	**0.095**
Δ$*Volume*	**–0.268**	**–0.099**	–0.038	–0.020	**0.097**
Δ*NumTrades*	**–0.259**	**–0.097**	–0.036	–0.007	0.033

Note: Autocorrelation coefficients for the variables are after omitting the changes at the turn of each year. Numbers in bold indicate a p-value less than 0.0001 for an asymptotic test that the autocorrelation coefficient is zero.

[13] Formal unit root tests (not reported) strongly implied that daily changes of all variables are stationary.

either 1/8 or 1/4, that some stocks oscillate between these discrete points daily, and that they tend to oscillate as a correlated group. This arrangement would produce negative first-order autocorrelation in the percentage change of the *average* spread. Table 6 does show that the four spread measures have absolutely larger negative first-order autocorrelation coefficients than other variables.

Data-recording errors are another possible source of negative serial correlation, but we do not believe they are the main cause for two reasons. First, errors are as likely to appear in the average recorded price series, but its first-order coefficient is positive and insignificant. Second, we found that the negative serial correlation is just as strong for the quintile of largest companies, and actively traded large companies are unlikely to be as influenced by data-recording errors. Overall, the evidence suggests that negative serial correlation is a basic feature of the true time-series process of liquidity.

Determinants of Liquidity and Trading Activity. We report in this section the time-series regressions of liquidity and trading activity measures on various potential determinants. First, we offer some justification for the explanatory variables.

■ *Explanatory variables.* The inventory paradigm introduced by Demsetz and developed further both by Stoll and by Ho and Stoll suggests that liquidity depends on dealer financing costs, inventory turnover rates, and inventory risks. By reducing the cost of margin trading and decreasing the cost of financing inventory, a decrease in short rates could stimulate trading activity and increase market liquidity. An increase in long-term U.S. T-bond yields could cause investors to reallocate wealth between equity and debt instruments and thus stimulate trading activity and affect liquidity. An increase in default spreads could increase the perceived risk of holding inventory and thereby decrease liquidity. Consequently, as plausible candidates for determinants of liquidity, we nominated the daily overnight federal funds rate, a term-structure variable, and a measure of default spread.[14]

Equity market performance is another plausible causative candidate. Recent stock price moves could trigger changes in investor expectations and also prompt changes in optimal portfolio compositions. In addition, the direction of stock market movements could trigger asymmetric effects on liquidity. For example, sharp price declines could induce relatively more-pronounced changes in liquidity, to the extent that market makers would find adjusting

[14] We repeated all calculations using the one-year T-bill rate as a proxy for dealer financing costs but found that the federal funds rate is a better determinant of daily liquidity variations. The results were otherwise essentially identical.

inventory more difficult in falling markets than in rising markets. We thus considered the signed concurrent daily return on the CRSP index.

Additionally, we included a measure of recent market history. The rationale is the notion that momentum or contrarian strategies and various techniques for technical analysis involve past market moves, which creates a link between trading activity and recent price trends.[15] To proxy for such activity, we included a signed five-day moving average of past returns (ending the day prior to the observation date).

Because volatility should influence liquidity and trading activity through its effect on inventory risk, as well as the risk of engaging in short-term speculative activity, we included a measure of recent market volatility. Our proxy was a five-day trailing average of daily absolute returns for the CRSP market index.

Trading activity might also be influenced by the opportunity cost of devoting time to trading decisions. Simple behavioral arguments (such as fluctuations in investor mood or sentiment over the week) suggest that trading activity could show systematic intertemporal patterns. Work by Admati and Pfleiderer (1989) and by Foster and Viswanathan (1990) implies that liquidity could exhibit predictable patterns through time.[16] To investigate such regularities, we included indicator variables for days of the week and for days preceding and following holiday closings.

The concept of information-based trading (based on the asymmetric information paradigms of Kyle and of Admati and Pfleiderer 1988) suggests another group of proximate determinants. Because company-specific inside information is a more likely source than macroeconomic announcements for information-based trades, sensible proxies would be dummies for earnings announcement dates. These dates are not well coordinated, however, among companies. Furthermore, conversations with accounting researchers indicate that information about earnings is often conveyed to the market some time before the official earnings announcement date. That is, estimates of earnings with significant information content are often prereleased by corporate managers,[17] and such prerelease dates are completely discretionary.

Because of these concerns, we decided to focus on information associated with macroeconomic announcements. We included dummy variables for

15 See Lakonishok, Shleifer, and Vishny (1994) and Chan, Jegadeesh, and Lakonishok (1996) for evidence on the performance of momentum and contrarian strategies.

16 These articles did not explicitly specify which days of the week should involve high or low liquidity.

17 See, for example, Ruland, Tung, and George (1990) and Baginski, Hassell, and Waymire (1994).

macroeconomic announcements about gross domestic product (GDP), the unemployment rate, and the Consumer Price Index (CPI). Separate dummies are provided for the day of the announcement and for the two days preceding the announcement.

We used the following explanatory variables. Appendix A reports summary statistics for these debt and equity market variables:

- *ShortRate*: daily first difference in the federal funds rate;
- *TermSpread:* daily change in the difference between the yield on a constant maturity 10-year T-bond and the federal funds rate;
- *QualitySpread*: daily change in the difference between the yield on Moody's Baa or Better Corporate Bond Index and the yield on a constant-maturity 10-year T-bond;[18]
- *MKT*+: 1.0 if the concurrent CRSP daily index return was positive and 0 otherwise;[19]
- *MKT*–: 1.0 if the concurrent CRSP daily index return was negative and 0 otherwise;
- *MA5MKT*+: 1.0 if the past-five-trading-day CRSP daily index return was positive and 0 otherwise;
- *MA5MKT*–: 1.0 if the past-five-trading-day CRSP daily index return was negative, and 0 otherwise;
- *MA5|MKT|*: past-five-trading-day average of CRSP daily absolute index returns;
- *HOLIDAY*: 1.0 if a trading day satisfied the following conditions: (1) if Independence Day, Christmas, or New Year's Day fell on a Friday, then the preceding Thursday, (2) if any holiday fell on a weekend or on a Monday, then the following Tuesday, (3) if any holiday fell on another weekday, then the preceding and following days;[20] if none of these conditions applied, *HOLIDAY* equaled 0;
- *Monday–Thursday*: 1.0 if the trading day was, respectively, a Monday, Tuesday, Wednesday, or Thursday and 0 otherwise;
- *GDP*(*1–2*): 1.0 on the two trading days prior to a GDP announcement and 0 otherwise;
- *GDP*(*0*): 1.0 on the day of a GDP announcement and 0 otherwise; and

[18] All interest rates came from the U.S. Federal Reserve Web site, www.federalreserve.gov/releases/H15/data.htm. We thank Yacine Aït-Sahalia for directing us to this site. The Fed uses the daily yield curve to calculate the yield on a constant-maturity T-bond on a daily basis.

[19] The equal-weighted (value-weighted) CRSP index was used for regressions with equal-weighted (value-weighted) liquidity and trading activity dependent variables.

[20] This circumstance was always the case for Thanksgiving.

- *UNP*(*1–2*) and *UNP*(*0*), *CPI*(*1–2*) and *CPI*(*0*): defined as for GDP but for, respectively, unemployment (*UNP*) and CPI announcements.

■ *Regression results.* In **Table 11**, we report time-series regressions for daily percentage changes, denoted by Δ, in marketwide liquidity and trading activity variables—the scaled spread measures (Δ%*QuotedSpread* and Δ%*EffectiveSpread*), the percentage quote spread divided by dollar depth (Δ*CompositeLiq*), the dollar values of depth (Δ$*Depth*) and volume (Δ$*Volume*), and the number of transactions (Δ*NumTrades*).[21]

Because ordinary least-squares (OLS) runs indicated a high Durbin–Watson test statistic in all regressions, a consequence of the previously noted negative dependence in all of the dependent variables, we applied the Cochrane–Orcutt iterative correction procedure (first order only) in the time-series regressions.[22] The Durbin–Watson statistics from the final iteration of the Cochrane–Orcutt regressions were statistically significant.

The sample size is 2,694 in the Panel A and B regressions for the full period. (The correlations between the variables in Panel A are given in Appendix B.) We started with 2,779 trading days, eliminated the first day of the calendar year for 1989 to 1998 (10 observations), and lost five days at the beginning to accommodate the lagging five-day market trend. In addition, bond market data were unavailable for 35 holidays when the stock market was open (Martin Luther King, Jr., Day, Columbus Day, and Veterans Day, although not every year); thus, our data were reduced by 70 (35 × 2) observations because the interest rate variables were first-differenced. The total reduction was 85 observations. Panel A reports regressions with equally weighted liquidity and trading activity measures; Panel B reports regressions with value-weighted liquidity and trading activity measures and value-weighted stock market indexes, for which the weights were proportional to each company's total market capitalization at the end of the previous year. Panel C reports regressions only for stocks that traded every single trading day in a shorter period (each calendar year from 1993 to 1998) with equally weighted liquidity and trading activity measures and is explained in the subsection on robustness checks.

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[21] To conserve space, we are not reporting results for the nonscaled spreads, *QuotedSpread* and *EffectiveSpread*, or for share depth and volume. These results were qualitatively similar and are available on request.

[22] The results obtained when we used OLS regression did not differ qualitatively from those obtained when we used the Cochrane–Orcutt method. The OLS results are available on request.

Table 11. Time-Series Regressions

Explanatory Variable	Δ%*QuotedSpreads*		Δ%*EffectiveSpread*		Δ$*Depth*		Δ*CompositeLiq*		Δ$*Volume*		Δ*NumTrades*	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
A. Equally weighted, full period (2,694 observations)												
MKT+	–0.486**	–3.74	–0.373*	–2.27	3.285**	9.07	–3.514**	–8.27	10.43**	7.19	8.871**	7.97
MKT–	–2.375**	–22.34	–2.855**	–21.27	2.936**	9.92	–5.821**	–16.78	–11.95**	–10.09	–12.32**	–13.56
MA5MKT+	0.052	1.36	0.010	0.22	–0.434**	–3.98	0.425**	3.33	–0.65	–1.49	–0.346	–1.03
MA5MKT–	0.036	0.72	0.210**	3.34	–0.151	–1.06	0.234	1.41	1.970**	3.46	1.910**	4.35
MA5|*MKT*|	–0.141**	–3.97	–0.124**	–2.80	–0.033	–0.33	–0.097	–0.83	–1.266**	–3.15	–1.101**	–3.56
Monday	–0.592**	–3.88	–0.573**	–2.90	0.335	0.82	–0.775	–1.61	1.484	0.90	6.656**	5.33
Tuesday	–1.400**	–10.78	–1.300**	–7.81	5.982**	16.85	–7.369**	–17.65	19.39**	13.63	11.144**	10.26
Wednesday	–0.367**	–2.75	–0.691**	–4.05	2.830**	7.74	–3.414**	–7.94	8.01**	5.47	4.555**	4.07
Thursday	–0.553**	–3.73	–0.681**	–3.54	1.460**	3.69	–2.214**	–4.74	4.81**	3.02	3.429**	2.84
Holiday	0.807**	3.40	0.161	0.54	–4.807**	–7.21	7.150**	9.16	–10.77	–4.04	–8.792**	–4.29
ShortRate	2.485**	2.63	0.461	0.39	–5.795*	–2.21	7.910**	2.57	–32.43**	–3.08	–28.724**	–3.56
TermSpread	2.092*	2.23	–0.047	–0.04	–5.466*	–2.10	7.141*	2.34	–34.60**	–3.32	–29.582**	–3.70
QualitySpread	0.959	0.61	–0.087	–0.04	3.549	0.81	–3.354	–0.65	–1.508	–0.09	–8.983	–0.67
GDP(1–2)	–0.549	–1.91	–0.216	–0.59	1.975*	2.47	–2.384**	–2.54	12.81**	4.00	7.138**	2.91
GDP(0)	–0.242	–0.84	0.022	0.06	–0.542	–0.68	0.096	0.10	–3.485	–1.08	–1.248	–0.51
UNP(1–2)	–0.293	–1.58	–0.088	–0.37	2.046**	3.97	–2.159**	–3.57	4.561*	2.21	3.865*	2.45
UNP(0)	0.135	0.72	0.118	0.49	–1.389**	–2.66	1.522*	2.48	2.549	1.22	3.457*	2.15
CPI(1–2)	–0.166	–0.97	0.014	0.06	0.672	1.41	–0.908	–1.62	–1.539	–0.81	–0.827	–0.57
CPI(0)	–0.183	–1.06	0.078	0.36	0.302	0.63	–0.416	–0.74	1.961	1.03	0.579	0.40
Intercept	0.909**	6.02	1.005**	5.08	–2.519**	–6.31	3.923**	8.32	–7.183**	–4.48	–6.283	–5.18
Adjusted R^2	0.288		0.270		0.290		0.334		0.206		0.179	
B. Value weighted, full period (2,694 observations)												
MKT+	–0.141	–1.34	0.385**	3.22	5.307**	12.89	–4.453**	–9.51	14.83**	13.98	11.27**	14.44
MKT–	–2.867**	–29.69	–3.496**	–31.80	1.992**	5.27	–5.405**	–12.58	–12.72**	–13.05	–11.94**	–16.64
MA5MKT+	0.017	0.40	0.055	1.13	–0.389*	–2.35	0.335	1.79	–0.502	–1.15	–0.115	–0.36
MA5MKT–	0.094	1.93	0.129*	2.34	–0.291	–1.53	0.435*	2.02	1.33**	2.67	1.115**	3.03

Table 11. Time-Series Regressions (continued)

Explanatory Variable	Δ%*QuotedSpreads* Coefficient	Δ%*QuotedSpreads* *t*-Statistic	Δ%*EffectiveSpread* Coefficient	Δ%*EffectiveSpread* *t*-Statistic	Δ$*Depth* Coefficient	Δ$*Depth* *t*-Statistic	Δ*CompositeLiq* Coefficient	Δ*CompositeLiq* *t*-Statistic	Δ$*Volume* Coefficient	Δ$*Volume* *t*-Statistic	Δ*NumTrades* Coefficient	Δ*NumTrades* *t*-Statistic
B. Value weighted, full period (2,694 observations) (continued)												
MA5|MKT|	–0.194**	–6.14	–0.300**	–8.30	–0.470**	–3.79	0.339*	2.41	–2.172**	–6.67	–1.722**	–7.16
Monday	–1.002**	–5.41	–0.851**	–4.08	–0.193	–0.27	–0.664	–0.80	–2.828	–1.58	7.315**	5.60
Tuesday	–0.769**	–4.90	–1.091**	–6.14	3.942**	6.42	–4.926**	–7.04	15.75**	10.17	10.19**	8.98
Wednesday	–0.043	–0.27	–0.513**	–2.79	0.849	1.34	–1.323	–1.83	5.82**	3.62	4.243**	3.60
Thursday	–0.178	–0.98	–0.623**	–3.06	1.058	1.49	–1.521	–1.87	1.831	1.05	3.196*	2.51
Holiday	0.432	1.51	0.377	1.16	–2.281*	–2.04	4.393**	3.46	–9.840**	–3.38	–6.933**	–3.23
ShortRate	0.797	0.69	–0.925	–0.70	–2.522	–0.56	2.542	0.49	–17.50	–1.50	–21.00*	–2.44
TermSpread	0.801	0.70	–0.868	–0.66	–1.732	–0.39	1.749	0.34	–19.42	–1.68	–21.93**	–2.57
QualitySpread	3.069	1.60	2.601	1.19	6.339	0.84	–3.633	–0.43	4.96	0.26	–3.791	–0.27
GDP(1–2)	–0.664	–1.91	–0.739	–1.86	2.339	1.72	–3.16*	–2.04	9.243**	2.63	6.510*	2.52
GDP(0)	0.398	1.14	0.100	0.25	–0.793	–0.58	0.879	0.56	–3.097	–0.88	–0.892	–0.34
UNP(1–2)	–0.557*	–2.48	–0.446	–1.75	3.752**	4.27	–4.250**	–4.26	2.981	1.32	3.077	1.85
UNP(0)	0.482*	2.12	0.259	1.00	–2.839**	–3.19	3.109**	3.07	1.577	0.69	3.821*	2.27
CPI(1–2)	–0.359	–1.72	–0.189	–0.80	1.736*	2.13	–2.208*	–2.38	–2.174	–1.04	–0.361	–0.23
CPI(0)	–0.151	–0.72	–0.206	–0.87	1.811	2.22	–1.692	–1.82	2.498	1.19	1.218	0.79
Intercept	–0.500**	2.64	0.787**	3.71	–0.700	–0.95	2.350**	2.77	–2.806	–1.56	–6.013**	–4.59
Adjusted R^2	0.326		0.324		0.229		0.245		0.226		0.211	
C. Equally weighted, 1993 through 1998, for stocks that traded every day throughout the period (1,472 observations)												
MKT+	–0.823**	–4.48	–0.574**	–3.16	2.793**	5.76	–3.459**	–6.06	4.241*	2.21	4.205**	2.82
MKT–	–2.563**	–17.90	–2.844**	–20.07	1.919**	5.08	–4.776**	–10.74	–9.674**	–6.48	–9.967**	–8.60
MA5MKT+	0.091	1.73	0.095	1.85	–0.35*	–2.47	0.374*	2.26	–0.259	–0.45	0.070	0.16
MA5MKT–	0.068	1.03	0.128*	1.97	–0.025	–0.14	0.125*	0.60	1.680*	2.33	1.481**	2.67
MA5|MKT|	–0.121**	–2.66	–0.167**	–3.73	–0.010	–0.08	–0.081	–0.56	–0.499	–1.00	–0.616	–1.61
Monday	–0.604**	–2.68	–0.894**	–3.94	1.001	1.75	–1.437*	–2.10	3.099	1.44	9.281**	5.47
Tuesday	–1.300**	–6.88	–1.204**	–6.37	5.128**	10.51	–6.429**	–11.09	17.41**	9.22	11.51**	7.81
Wednesday	–0.276	–1.42	–0.629**	–3.23	2.067	4.09	–2.557**	–4.27	7.585**	3.86	4.963**	3.24

Table 11. Time-Series Regressions (continued)

Explanatory Variable	Δ%*QuotedSpreads*		Δ%*EffectiveSpread*		Δ$*Depth*		Δ*CompositeLiq*		Δ$*Volume*		Δ*NumTrades*	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
C. Equally weighted, 1993 through 1998, for stocks that traded every day throughout the period (1,472 observations) (continued)												
Thursday	–0.430*	–1.97	–0.778**	–3.53	1.482**	2.69	–2.175**	–3.29	4.150*	2.01	3.801*	2.33
Holiday	1.356**	3.86	0.839*	2.42	–4.195**	–4.49	7.203**	6.57	–9.711**	–2.59	–8.836**	–3.06
ShortRate	3.026*	2.44	2.568*	2.09	–7.592*	–2.33	11.72**	3.05	–38.84**	–3.02	–31.08**	–3.11
TermSpread	2.375	1.95	1.636	1.35	–6.735*	–2.10	10.07**	2.66	–43.73**	–3.46	–34.12**	–3.47
QualitySpread	–0.563	–0.19	2.002	0.69	–1.459	–0.19	1.662	0.18	–77.80**	–2.60	–57.63*	–2.47
GDP(*1–2*)	–0.656	–1.55	–0.438	–1.05	1.678	1.51	–1.867	–1.43	11.51**	2.62	8.504*	2.50
GDP(*0*)	0.023	0.06	–0.658	–1.57	–1.607	–1.44	1.431	1.09	–2.801	–0.64	–1.810	–0.53
UNP(*1–2*)	–0.347	–1.28	–0.251	–0.93	2.287**	3.20	–2.310**	–2.74	5.609*	1.99	4.782*	2.18
UNP(*0*)	0.221	0.82	0.165	0.62	–1.715*	–2.40	2.001*	2.38	3.065	1.09	4.419*	2.02
CPI(*1–2*)	0.110	0.44	0.162	0.65	0.719	1.10	–0.704	–0.91	–2.224	–0.86	–1.014	–0.51
CPI(*0*)	–0.241	–0.96	–0.199	–0.80	0.558	0.85	–0.698	–0.90	3.371	1.30	2.385	1.18
Intercept	0.773**	3.47	1.098**	4.85	–2.524**	–4.55	3.844**	5.74	–7.174**	–3.50	–7.475**	–4.60
Adjusted R^2	0.325		0.342		0.232		0.298		0.164		0.175	

Note: Dependent variables are daily percentage changes in marketwide liquidity and trading activity. The Cochrane–Orcutt method was used to correct first-order serial dependence in the disturbances.

*Significant at the 5 percent level.
**Significant at the 1 percent level.

The adjusted R^2s in Panels A and B range from 18 percent to 33 percent; that is, the explanatory variables capture an appreciable fraction of the daily time-series variation in marketwide liquidity and trading activity.

The day-of-the-week dummies for Tuesday, Wednesday, and Thursday are significantly negative in the spread regressions and significantly positive for the depth and the trading activity regressions. These results are compelling evidence that market liquidity declines and trading activity becomes sluggish on Fridays relative to the other days of the week, particularly the three midweek days. Usually, we found Tuesday to have the largest absolute coefficient, which suggests that liquidity and trading activity appreciably increase on Tuesdays relative to other days.[23] The composite liquidity measure shows a pattern that is similar to the individual liquidity and depth variables.

The regression intercepts are all strongly significant, positively for spreads and negatively for depth and trading activity. Although one cannot rule out the possibility that significant intercepts are caused by omitted explanatory variables or by a departure from linearity, the most likely explanation is decreased liquidity and trading activity on Fridays (when the four day-of-the-week dummies equal zero). If Tuesday, instead of Friday, is the zero base case for day-of-the-week dummies, the sign of every intercept is reversed and its significance actually increases (not reported, but available on request).

Trading activity also slows down around holidays, as evidenced by the negative and significant coefficient for the holiday dummy in the $\Delta\$Volume$ and $\Delta NumTrades$ in Panel A of Table 11. The reduced trading activity appears to result in decreased market depth and increased quoted spreads, as evidenced by the negative and positive coefficients, respectively, on the holiday dummy in the quoted spread and depth regressions. The holiday dummy for the composite liquidity variable is also highly significant.

A distinctly asymmetric response of spreads to up and down markets is observable in Panel A: Spreads weakly decline in up markets and strongly increase in down markets. The opposite is true for depth. This finding suggests that concerns about inventory accumulation are more important in down markets than in up markets.

Panel A indicates that depth increases significantly in up markets. One possible explanation is that market makers attempt to manage inventory by quoting higher depth on the bid side but the same or only slightly lower depth

[23] A joint test that Tuesday's coefficient is the same as Monday's, Wednesday's, and Thursday's was rejected with a p-value less than 0.0001 in all regressions except those for $\Delta CompositeLiq$.

on the ask side, so average depth increases. Note that the trading activity variables show a symmetric response: They increase in up and down markets.

A recently falling market (*MA5MKT–*), Panel A indicates, tends to be associated with increased trading activity and decreased effective spreads. A recently rising market (*MA5MKT+*) appears to cause a decrease in depth but has little effect on spreads and trading activity; this result might imply that market makers quote lower depth on the buy side, which leads to smaller overall depth.

According to Panel A, high levels of recent marketwide volatility (*MA5|MKT|*) decrease trading activity, as might have been expected, but they also, perhaps surprisingly, decrease spreads, although depth is virtually unaffected.[24] Apparently, sluggish trading following recent volatility allows dealers to reduce inventory imbalances, which then prompts them to reduce spreads.

Panel A in Table 11 reports the federal funds rate (*ShortRate*) change as negative and significant in regressions on the trading activity and depth measures but positive and significant in regressions on the quoted spread. An increase in T-bond yields relative to the short rate (*TermSpread*) is accompanied by significantly decreased trading activity, decreased depth, and increased quoted spreads. The composite (inverse) measure of liquidity, Δ*CompositeLiq*, had a positive reaction to *TermSpread* that is consistent with the coefficient sign on the depth variable. Overall, we found evidence that increases in either the long- or short-term interest rate have a significantly negative effect on both liquidity and trading activity. The default spread (*QualitySpread*) apparently has little influence on either trading activity or liquidity.

Turning to the macroeconomic variables, Panel A in Table 11 indicates that trading activity increases *prior* to GDP and unemployment announcements. Depth also rises, but we found no significant impact on bid–ask spreads. On the day of such announcements (which occur typically in the morning), depth falls back toward its normal level. This pattern is consistent with differences in anticipations about the forthcoming information and a concomitant flurry of prior uninformed trading. Increased speculative trading activity allows greater depth to be quoted. This result is also consistent with an increase in the number of informed traders as the announcement date

[24] In contrast to this result for recent marketwide volatility, it is well known that individual-stock volatility is cross-sectionally associated with higher spreads (see Benston and Hagerman), reflecting the notion that individual-stock volatility is more closely associated than market volatility with asymmetric information.

approaches. Competition among informed traders could bring additional liquidity (Admati and Pfleiderer 1988).

Overall, the evidence can be summarized as follows:

- Quoted spreads, depth, and trading activity respond to short-term interest rates, the term spread, equity market returns, and recent market volatility.
- Depth and a composite measure of liquidity respond to recent market trends.
- Effective spreads respond strongly to equity market returns, recent market trends, and recent market volatility.
- Spreads respond asymmetrically to contemporaneous market movements; they increase much more in down markets than they decrease in up markets.
- Strong evidence indicates that liquidity and trading activity fall on Fridays.
- Tuesdays tend to be accompanied by increased trading activity and increased liquidity.
- Depth and trading activity tend to decrease around major holidays.
- Both depth and trading activity increase prior to announcements of GDP and unemployment rates.
- Impending CPI announcements do not seem to influence either liquidity or trading activity. Evidently, inflation has been relatively easy to predict in the United States recently.

Panel B of Table 11, in which regressions with value-weighted liquidity and trading activity measures and value-weighted stock market indexes are reported, provides results qualitatively similar to those of Panel A, except that interest rate variables are no longer significant for the liquidity variables and the day-of-the-week effects are weaker (although mostly still significant). This finding may imply that inventory considerations are more important for small-company stocks than for large-company stocks and that weekly variations in trading have a larger impact on the liquidity of smaller companies than on larger ones. The total explanatory power (adjusted R^2) is actually slightly higher, however, in the spread regressions and for dollar volume and number of transactions in Panel B. Notice also that the unemployment announcement is statistically significant for quoted spreads in Panel B.

The explanatory power of the regressions reported in Panels A and B of Table 1 ranges from 18 percent to 33 percent, and the number of separate significant regressors is impressive. For example, in the Δ*NumTrades* regression reported in Panel A, 12 of the 19 variables are significant at the 1 percent level and two others are significant at the 5 percent level. We found more significant determinants in the depth and trading activity regressions than in the spread regressions.

■ *Robustness checks.* Figure 6 reveals that the number of companies that are trading varies daily. Hence, average liquidity measures contain some ambiguity because spreads and depth are not available for nontrading companies. (This problem does not affect the trading activity measures because volume is properly counted as zero when a stock does not trade.) We addressed this issue by using liquidity measures from the last day the stock did trade, for which we went back a maximum of 10 trading days. To ensure that the results were not influenced by this procedure, we reran the regressions for a sample of stocks that traded every single trading day in each calendar year from 1993 through 1998, the period corresponding to the TAQ data source. The results are presented in Panel C of Table 11. (The same robustness check was not done for the 1988–92 period because of aberrant variation in the reported number of stocks trading in the ISSM data.) The resulting sample size was 1,472 days, and the results are qualitatively similar to those in Panel A. Some of the coefficients lost significance, particularly those representing day-of-the-week effects, and the effective spread also shows a significant influence from the short rate in this smaller sample. The overall pattern of significance, however, remains unchanged.

Conclusions and Suggestions for Future Research

Liquidity is more than an attribute of a single asset. Individual-stock liquidity measures 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 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 interpreted this pattern as a manifestation of two effects: (1) a diminution in inventory risk from greater marketwide trading activity, most plausibly by uninformed traders, and (2) 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. Although commonality is the instrument used here to uncover asymmetric information effects on liquidity, we have no evidence that asymmetric information itself has common determinants.

Co-movements in liquidity suggest that an opportunity exists to manage transaction expenses through appropriate timing. When spreads are low, portfolio turnover can be larger without sacrificing performance.

To ascertain the sources of commonality in liquidity, we studied liquidity and trading activity for a comprehensive sample of NYSE-listed stocks over an 11-year period. Daily changes in these variables were negatively serially correlated during this period. A secular downtrend in spreads and an upward trend in depth and volume were apparent, although major excursions around these trends and at least one important structural break occurred (when the minimum tick size was reduced from 1/8 to 1/16 in mid-1997).

Liquidity and trading activity are influenced by several factors. Based on theoretical paradigms of price formation (inventory and asymmetric information) and on intuitive reasoning, we nominated several candidates as possible determinants: short- and long-term interest rates; default spreads; market volatility; recent market movements; and indicator variables for the days of the week, for holiday effects, and for major macroeconomic announcements. We found that equity market returns and recent volatility in the market influence liquidity and trading activity. In addition, short-term interest rates and the term spread significantly affect liquidity and trading activity. Strong day-of-the-week regularities appeared in liquidity and in trading activity. A typical Friday, for example, has decreased liquidity and trading activity, as do days adjacent to major holidays.

A particularly intriguing result is the asymmetric response of bid–ask spreads to market movements. Both quoted and effective spreads increase dramatically in down markets but decrease only marginally in up markets. Indeed, the down-market variable is the most significant of all those we studied. In addition, contrary to intuition, recent market volatility tends to reduce spreads. Although one could informally speculate about these results, a formal theoretical investigation is desirable.

Trading activity and market depth increase prior to scheduled macroeconomic announcements of GDP and the unemployment rate, and they fall back toward normal levels on the announcement days themselves. This finding is consistent with increased trading induced by differences of opinion prior to the announcement, and this trading, being conducted by uninformed traders, is accommodated by dealers offering greater depth. The depth pattern is also consistent with an increase in the number of informed traders as the announcement day approaches. Competition among this larger number of informed agents would drive down asymmetric information costs to dealers and result in higher liquidity (Admati and Pfleiderer 1988).

The determinants investigated here explain 18–33 percent of daily changes in liquidity and trading activity. This result is consistent with the evidence for commonality in liquidity documented by Chordia, Roll, and Subrahmanyam (2000).

Chowdhry and Nanda (1991) and Admati and Pfleiderer (1988), among others, have pointed out that "liquidity begets liquidity." Although a return anomaly is subject to arbitrage forces, a "liquidity anomaly" is self-perpetuating; that is, as agents find out about such an anomaly, they will avoid trading in illiquid periods, which will further reduce liquidity in those periods. Thus, regularities in the time-series behavior of liquidity and trading activity should be dynamically stable.

To our knowledge, no other study has examined such a long history of spreads, depth, and trading activity, nor has any study attempted to identify their determinants. The sample period, however (1988–1998 inclusive), was a relentless bull market, and liquidity and trading activity may behave differently in a bear market. Rising markets attract investors; indeed, ample evidence exists of steadily increasing liquidity over the past decade. Prolonged bear markets, however, may be subject to falling liquidity.

Liquidity *levels* may vary with market trends, but the determinants of day-to-day *changes* in liquidity are probably the same in most environments, although their explanatory power may very well fluctuate. For example, based on recent experience with crash events, down markets may be characterized by frenzied selling (in contrast to steady buying in rising markets), so inventory could accumulate and the impact of interest rates on liquidity could become stronger in bear markets.

Macroeconomic variables should have influences over horizons longer than those examined here. If macro variables anticipate economic downturns, they may also anticipate lower liquidity and trading activity in equity markets. As a longer history of data becomes available, future studies will shed more light on this interesting issue.

Our results have the following clear and direct implications for practitioners:

- High negative serial correlation in trading costs suggests that days of spread increases are generally followed by days of spread decreases; hence, postponing trading to the day following a day of an unusually high decrease in liquidity should be beneficial.
- Investors should avoid trading on Fridays and attempt to trade on Tuesdays, if the cost of postponing trades is not too high.
- Sharp declines in the market are accompanied by significantly decreased liquidity and are to be avoided as a time for much trading.
- Days of dramatic increases in short-term interest rates should be avoided for trading purposes.
- Both depth and trading activity increase prior to announcements of GDP and unemployment rates; the days before such announcements, therefore, should produce lower trading costs.

An interesting follow-up to this research would be to investigate the cross-sectional differences in the marketwide effects found here. For example, do interest rates and equity returns influence the liquidity of large and small companies differently? Are the day-of-the-week effects more prevalent in actively traded stocks or relatively inactive ones? Do default spreads influence the liquidity of small, relatively new companies?

The general goal of our research has been to shift the focus from liquidity as a "micro" concept—a fixed property of a given stock—to a broader concept of aggregate market liquidity. Such a shift should allow us to explore frontiers hitherto unvisited, such as the effect of monetary policy on stock market liquidity and the co-movement between stock liquidity and bond yields.

An important recent change in the microstructure of U.S. markets is the adoption of decimal pricing. With the removal of the rigidity represented by the 1/16th discrete grid, liquidity could become even more sensitive to macroeconomic conditions. Thus, the results we found for a prior period could be stronger in the current regime. Unfortunately, not enough data are available at this time to reliably replicate our study for the postdecimal period. The practice of allowing limit orders to be placed within the spread and the reduction in the monopoly power of the specialist should also cause the spread to narrow in the postdecimal era. Furthermore, according to results of Harris (1994) and the results shown in Figure 3, depth might decline dramatically after decimalization. There is no reason to believe, however, that day-to-day *changes* in either spreads or depths should be influenced significantly by decimalization. The qualitative conclusions of this monograph should, we believe, remain largely unaffected.

In the work described here, trading activity was measured by aggregate volume. A measure of trading activity that is intuitively appealing and could have a stronger relationship to liquidity and returns is the imbalance between buying and selling activity. In ongoing research, we are investigating the tripartite relationships among marketwide order imbalances, liquidity, and stock market returns. This research represents a first attempt to measure order imbalance on a large scale. Initial results suggest that imbalance has a strong association with both liquidity and returns.

The implications of our results for asset pricing remain unexplored, and many interesting questions are still to be answered. For example, do weekly regularities in liquidity correspond to previously documented patterns in returns? Do unanticipated liquidity variations constitute a risk priced in the cross-section of asset returns? Such questions deserve the attention of future research.

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Appendix A. Debt and Equity Market Explanatory Variables, Summary Statistics, Daily, 1988 to 1998 Inclusive
(2,694 observations)

Measure	*ShortRate*	*TermSpread*	*QualitySpread*	Stocks (%/day)
Levels				
Mean	5.77	1.35	1.79	0.111
Standard deviation	1.87	1.35	0.29	0.570
Median	5.52	1.24	1.73	0.170
Maximum	10.71	4.24	2.77	2.760
Minimum	2.58	–2.35	1.16	–5.432
Absolute values of daily first differences				
Mean	0.1591	0.1682	0.0252	
Standard deviation	0.2411	0.2411	0.0250	
Median	0.0800	0.1000	0.0200	
Maximum	2.8300	2.8600	0.2300	
Minimum	0.0000	0.0000	0.0000	

Appendix B. Correlations of Explanatory Variables in Table 11, Panel A Regressions

	MKT+	*MKT–*	*MA5MKT+*	*MA5MKT–*	*MA5|MKT|*	*Mon.*	*Tues.*	*Weds.*	*Thurs.*	*Holiday*	*Short Rate*	*Term Spread*	*Quality Spread*	*GDP (1–2)*	*GDP (0)*	*UNP (1–2)*	*UNP (0)*	*CPI (1–2)*
MKT–	0.308																	
MA5MKT+	0.355	0.221																
MA5MKT–	–0.092	0.431	0.350															
MA5|MKT|	0.403	–0.228	0.283	–0.583														
Monday	–0.104	–0.098	–0.015	0.007	–0.003													
Tuesday	–0.096	–0.024	–0.001	–0.008	0.003	–0.011												
Wednesday	0.025	0.044	0.001	–0.014	0.001	–0.471	–0.034											
Thursday	0.076	0.040	0.015	0.000	0.001	–0.455	–0.491	–0.035										
Holiday	0.097	0.039	–0.001	0.007	0.002	–0.025	–0.017	0.051	–0.040									
ShortRate	–0.035	–0.008	–0.063	–0.001	–0.034	0.093	–0.019	0.131	–0.066	0.023								
TermSpread	–0.131	–0.176	0.046	–0.027	0.014	–0.146	–0.039	0.114	0.088	0.032	–0.973							
QualitySpread	0.111	0.021	–0.073	–0.056	0.031	–0.054	–0.009	0.027	0.028	–0.016	–0.011	–0.405						
GDP(1–2)	–0.014	–0.027	–0.038	–0.009	–0.018	0.039	0.043	0.002	–0.070	0.017	0.018	–0.041	0.001					
GDP (0)	0.048	0.005	–0.013	–0.022	0.004	–0.068	–0.021	0.047	0.032	0.095	0.045	–0.007	–0.006	–0.027				
UNP(1–2)	0.045	0.054	0.089	0.027	0.018	–0.177	0.008	0.357	–0.012	0.023	0.006	0.013	0.043	–0.048	0.042			
UNP(0)	0.032	0.010	0.083	0.041	0.007	–0.011	–0.191	–0.190	–0.001	0.001	–0.131	–0.001	0.008	–0.048	–0.048	–0.085		
CPI(1–2)	–0.030	–0.007	–0.040	–0.009	–0.011	0.029	–0.024	–0.022	–0.065	–0.049	0.029	0.017	–0.030	–0.044	–0.039	–0.083	–0.042	
CPI(0)	0.011	0.016	–0.029	–0.022	–0.016	–0.083	0.036	0.052	0.010	–0.046	0.007	–0.015	0.019	–0.030	–0.044	–0.083	–0.083	–0.087