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SYSTEMATIC LIQUIDITY

Gur Huberman and Dominika Halka
Columbia University

Abstract

Most of the market microstructure literature focuses on the liquidity of individual securities, whereas much of the asset pricing literature examines the association between systematic risk and return. We document the presence of a systematic, time-varying component of liquidity. At the moment, neither the inventory nor the asymmetric information-based approach to liquidity explains the systematic, time-varying component of liquidity.

JEL classification: G10, G12

I. Introduction

A market is liquid if one can trade a large quantity shortly after the desire to trade arises at a price near the prices of the trades before and after the desired trade. Liquidity indicates the speed and ease at which one can trade, but it is not directly observable. Two quantities are related to liquidity, however: spread and depth. Spread is the difference between the bid and ask prices. Depth is the number of units offered at the ask price plus the number of units bid at the bid price. Each security has its own liquidity, which may vary over time. One would expect liquidity to be correlated across securities if there was a common component of the cost of providing liquidity or if securities were substitutes. We study time-series properties of the liquidity proxies—spread and depth—with special interest in documenting the presence of a marketwide component of liquidity.

Existing explanations of the presence of a spread are based on asymmetric information and inventory considerations of market makers—the providers of liquidity. Under both approaches market makers are compensated by the spread between the price at which they are willing to buy and the price at which they are willing to sell a risky security. The reasons for their ability to maintain a spread in a competitive environment vary across these approaches.

Asymmetric-information-based explanations view the market as consisting of three types of traders: those with superior information, those with life-cycle needs to trade (liquidity traders), and market makers. Market makers possess no superior information, but perform a crucial function of providing liquidity to the market;

hence, they should earn a fair return on their capital. They trade with both informed and uninformed traders who are indistinguishable from the market makers' vantage point. To avoid losing money consistently, market makers are ready to buy the securities at lower prices than those for which they are sold. Hence, spreads are positive. On average, market makers lose on trades with the informed and profit on trades with the uninformed. Glosten and Milgrom (1985) and Kyle (1985) are the first to formulate and analyze such models.

Inventory-based models, first articulated by Amihud and Mendelson (1980, 1982) and Ho and Stoll (1981), focus on a market maker's exposure to risk through the inventory of the security. The market maker either has bounds on the amount of inventory held (Amihud and Mendelson) or a desired inventory level and a cost of deviating from it (Ho and Stoll). Bid and ask prices determine the stochastic arrival rates of sellers and buyers, and market makers adjust these prices dynamically to optimize their inventory levels. The spread is a source of profit to compensate the dealer for exposure to risk and administrative costs; it reflects the dealer's market power.

Theories of depth are extensions of asymmetric information models of the spread. They allow trades of variable quantities of the security. The dealers are prepared to trade only limited quantities to protect themselves against the better informed traders who may be interested in supplying or demanding arbitrarily large quantities at the dealers' prices (see Charoenwong and Chung (2000), Kavajecz (1996, 1999), and Rhodes-Kropf (1998)).

Although market makers seem central to current models of spread and depth, the effect of their presence on spread or depth in actual markets is not obvious. For instance, the bid and ask prices and quantities shown by New York Stock Exchange (NYSE) specialists are not necessarily their own, but often are those of other traders with no special status in the market.

The aforementioned models say little about temporal variations in liquidity. They do not tell us why liquidity would change over time; they do not characterize stocks with liquidity, which is more sensitive to such variations; and they do not suggest variables that are likely to be correlated with such variations. Moreover, because current theories focus on trading of individual stocks, they provide little guidance about systematic variations in liquidity, that is, variations in liquidity that affect many stocks simultaneously.

A few empirical studies deal with time-series behavior of liquidity proxies. Most concentrate on intraday patterns and seasonality in liquidity proxies, trading volume, and price volatility. Lockwood and Linn (1990) document a U-shaped pattern of intraday return volatility. McInish and Wood (1992) show that spreads vary during the day: they decrease from a high spread/price ratio of about 1.28 percent shortly after the 9:30 a.m. open to a low of about 1.11 percent around 2:30 p.m., and they rise again in the last hour and a half of trading to about 1.13 percent. That pattern holds even after controlling for risk and trading volume. It suggests that within a day spreads are correlated across stocks. Foster and Viswanathan (1993) examine the intraday and interday behavior of volume, volatility, and fixed and adverse-selection-related components of trading costs. They find that adverse-selection costs and return volatility are higher in the first half hour of a trading day. Trading volume is lower, and adverse selection costs tend to be higher on Monday than on other days.

Clark, McConnell, and Singh (1992) study seasonal patterns of end-of-the-month absolute and relative spreads of NYSE-traded stocks from 1982 to 1987 and show that both decline from the end of December to the end of the following January. Fortin, Grube, and Joy (1989) document seasonalities in Nasdaq dealer spreads, finding that relative spreads tend to be higher in the second half of the year and peak in December. Amihud, Mendelson, and Wood (1990) study marketwide changes in liquidity around the October 1987 crash and find that the mean spread for securities included in the S&P 500 index increases from 27 cents to 37 cents.

Popular press and commercial providers of financial data have long mentioned systematic liquidity as an established phenomenon. For instance, Wallace (1988)[1] refers to the estimates of systematic liquidity provided by Bridge Information Systems that asserts "the market's liquidity" to be "at its lowest point in two years" although still "at greater levels than five years ago."

Moreover, changes in liquidity are easily observed even for index-based securities, which are less likely to be affected by adverse selection and market maker inventory-management problems. Figure I presents an example of such shifts in the daily average bid-ask spread for SPDR, a unit investment trust replicating the S&P 500 index and traded on the American Stock Exchange. We observe a similar picture when looking at the daily spread/price ratio for SPDR.

Our goal is to document the presence of a systematic component of liquidity and to explore variables that may be correlated with it. We wish to abstract from time-of-day effects; hence, we sample liquidity proxies once a day, at noon. Moreover, because liquidity proxies are highly autocorrelated, we control for the expected component so we can concentrate on the cross-sectional correlations of the innovations in liquidity proxies.

We consider four proxies of liquidity: spread, spread/price ratio, quantity depth (i.e., depth measured as number of shares), and dollar depth (i.e., depth measured in dollars). We divide our 240-stock sample into two mutually exclusive subsets and compute the series of daily averages of the four liquidity proxies for each of the two subsets. Each of these series exhibits a high degree of autocorrelation. We estimate their autoregressive structure, thereby deriving the series of innovations for each of the four liquidity proxies, for each of the two mutually exclusive subsets.

The innovations of the time series of liquidity proxies are positively correlated for each liquidity proxy, which indicates the presence of a common

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[1]Wallace, A., 1988, Volume cut worrying Wall Street, *New York Times*, May 23, p. D1.

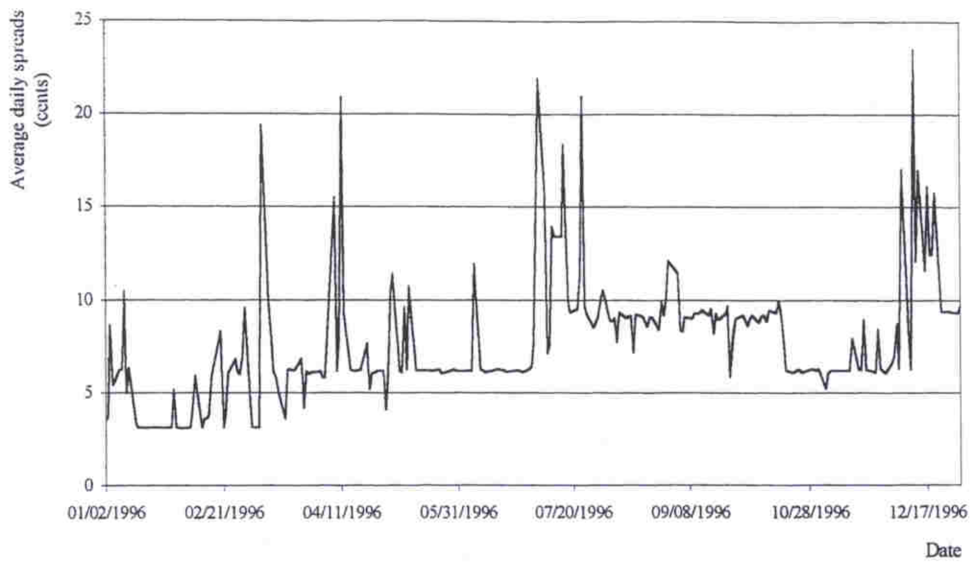

Figure I. Average Daily Bid-Ask Spreads for the SPDR in 1996.

liquidity factor. The results hold when we control for returns, volatility, trading volume, interest rates, and other variables that we think could be correlated with common movements in liquidity. Moreover, they seem similarly valid across a wide spectrum of firm sizes and betas.

As we were putting finishing touches on an earlier draft of this article, two studies addressing a similar issue came to our attention. Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001) document a common component in liquidity using different data and statistical techniques. The results of Chordia, Roll, and Subrahmanyam concur with our finding that a significant common component in liquidity exists. They estimate a "market model" for liquidity, that is, a regression model of daily percentage changes in liquidity variables for individual stocks as a function of the market averages of the same variables. They find the resulting "betas" to be positive for 85 percent of all stocks in their sample, and almost 42 percent exceed the 5 percent one-tailed critical value. These results remain fairly robust after controlling for well-known individual liquidity determinants such as volatility, volume, and price. Hasbrouck and Seppi use principal components and canonical correlation analyses to identify common factors in time variation of several liquidity proxies for the thirty stocks making up the Dow Jones Industrial Average. In contrast to Chordia, Roll, and Subrahmanyam and this study, they do not find conclusive evidence of the existence of such common factors.

II. The Data

Our primary data source is the 1996 Trade and Quotes (TAQ) Database provided by the NYSE, which reports all trades and quotes, time-stamped. We sort all NYSE stocks by size and select a random sample of 60 stocks from each size-based quartile. We use prices from the Center for Research in Securities Prices (CRSP) and numbers of shares from Standard & Poor's Compustat at the end of 1995 to compute market capitalization (size). For each stock in the sample we record the most recent bid and ask prices with corresponding depths before noon everyday. Only stocks for which we have the bid and the ask every trading day before noon are included in the sample. In addition, we record the trading volume during the twenty-four hours preceding the trading day. Thus, our basic series consist of 254 daily observations for each of the 240 stocks in the sample, 60 in each size-based group.

We consider both the absolute bid-ask spread and the spread/price ratio as proxies for liquidity, where price is taken as the midpoint of the bid and ask. Two additional proxies are derived from the depth: the sum of the number of shares bid and offered (quantity depth) and the sum of the dollar value of the shares bid and offered (dollar depth). Dollar depth is the sum of the number of shares bid times the bid price and the number of shares offered times the offer price. Thus, we have four proxies for liquidity.

We test whether innovations in the liquidity proxies are correlated across stocks. To gain statistical power, we consider the average liquidity proxies for groups of stocks instead of for individual stocks. We thereby circumvent the technical challenge posed by the discreteness of bid-ask spreads.

Table 1 reports summary statistics for the four liquidity proxies for each of the four size-based groups of 60 stocks as well as for the full sample. A comparison between Panels A and B suggests the bid-ask spread does not vary across size categories, but the spread/price ratio increases as firm size decreases. For firms in the largest quartile the bid-ask spread is on average 0.43 percent of price, whereas for firms in the smallest quartile it is on average 2.32 percent of price. The depth shows a similar feature: the dollar depth increases with firm size (Panel D), whereas the quantity depth exhibits no pattern when moving across firm sizes (Panel C).

Table 2 reports price, return, and trading volume attributes of the sample stocks. Panel A shows that on average share price increases more than four-fold when moving from the lowest to the highest quartile. Panel B shows that the stocks of the larger firms were more volatile than those of the smaller firms, at least in 1996. Panel C shows that the daily volatility estimated using the GARCH (1,1) model increases with size, and Panel D shows that the average number of shares traded increases with size. (Note that the depth does not vary with size—Panel C of Table 1.) Interest rate data are taken from the Datastream Database.

TABLE 1. Summary Statistics of the Four Liquidity Proxies for Equally Weighted Portfolios of the Whole Sample and the Four Size-Based Quartiles (where Quartile 1 is the smallest).

		Market Capitalization Quartiles			
	Whole Sample	1	2	3	4
Panel A. Spread (cents)					
Mean	18.2	17.7	18.0	19.0	18.1
Std. dev.	0.7	0.9	1.2	1.2	1.1
Median	18.2	17.6	17.9	19.0	18.1
Maximum	20.8	19.8	21.9	22.7	21.3
Minimum	16.1	15.4	15.0	16.0	15.6
Panel B. Spread/Price Ratio (%)					
Mean	1.27	2.32	1.37	0.95	0.43
Std. deviation	0.06	0.17	0.08	0.06	0.03
Median	1.26	2.31	1.37	0.95	0.43
Maximum	1.48	3.03	1.67	1.13	0.53
Minimum	1.14	1.95	1.21	0.84	0.36
Panel C. Depth (hundreds of shares)					
Mean	257	238	323	250	217
Std. deviation	32	35	55	33	33
Median	253	238	320	252	216
Maximum	327	320	449	325	337
Minimum	183	128	169	150	111
Panel D. Depth (thousands of dollars)					
Mean	419	184	323	355	814
Std. deviation	51	33	58	49	117
Median	416	185	321	354	811
Maximum	582	284	456	487	1,267
Minimum	291	82	157	254	449

III. Analysis

The statistical analysis seeks to detect the presence of a common factor that is correlated with the liquidity proxies of different stocks. To this end, it should control for serial correlation of liquidity proxies and for discreteness when considering the absolute bid-ask spread as a liquidity proxy. To gain statistical power and to avoid direct modeling of spread discreteness, we look at average liquidity proxies over a sample of stocks. We model the time-series properties of the average liquidity proxies by decomposing them into expected and unexpected components. The Appendix provides the econometric justification of such an approach.

TABLE 2. Summary Statistics for the Prices, Daily Returns, Squared Daily Returns, Trading Volume, and Stock Size for the Equally Weighted Portfolios of the Whole Sample and the Four Size-Based Quartiles (where Quartile 1 is the smallest).

		Market Capitalization Quartiles			
	Whole Sample	1	2	3	4
Panel A. Price ($)					
Mean	25.97	11.68	17.46	25.81	48.92
Std. deviation	0.72	0.35	0.58	0.76	1.66
Median	26.07	11.80	17.52	25.83	48.95
Maximum	27.49	12.26	18.52	27.46	52.19
Minimum	24.15	10.88	16.36	24.06	44.52
Panel B. Daily Return (%)					
Mean	0.07	0.06	0.07	0.07	0.08
Std. deviation	0.48	0.43	0.50	0.58	0.68
Median	0.11	0.07	0.09	0.16	0.16
Maximum	1.22	1.40	1.32	1.51	2.02
Minimum	-2.40	-1.93	-2.24	-2.55	-2.96
Panel C. Volatility of Return (%^{2})					
Mean	0.49	0.52	0.55	0.61	0.70
Std. deviation	0.11	0.03	0.08	0.10	0.10
Median	0.45	0.50	0.53	0.59	0.67
Maximum	1.06	0.65	0.90	1.10	1.27
Minimum	0.38	0.48	0.47	0.50	0.59
Panel D. Daily Trading Volume (thousands of shares)					
Mean	216	25	73	207	559
Std. Deviation	41	11	21	63	115
Median	217	22	70	200	553
Maximum	361	111	167	568	967
Minimum	71	8	23	66	164
Panel E. Daily Trading Volume As a Fraction of Shares Outstanding (%)					
Mean	0.030	0.021	0.030	0.035	0.033
Std. deviation	0.006	0.006	0.009	0.010	0.007
Median	0.030	0.021	0.028	0.034	0.033
Maximum	0.054	0.047	0.071	0.113	0.060
Minimum	0.010	0.007	0.010	0.012	0.010
Panel F. December 31, 1995, Market Capitalization (millions of dollars)[a]					
Mean	2,445	85	292	927	8,475
Std. deviation	5,778	42	86	330	9,242
Median	507	75	273	843	5,292
Maximum	44,092	165	496	1,684	44,092
Minimum	10	10	174	517	1,775

[a]The numbers for December 31, 1995, market capitalization are for stocks in the whole sample and the respective size-based quartiles, not for portfolios.

We first estimate a time-series model of the average liquidity proxy for mutually exclusive groups of stocks and examine whether the residuals from the time-series model are correlated for the different groups of stocks. We interpret positive correlations as evidence of the presence of a common liquidity factor. The common liquidity factor could be associated with variables known to move together and to be associated with liquidity, namely, the last twenty-four-hour return, volatility, trading volume, and interest rates. We add these as explanatory variables in the time-series models and re-examine the residuals. They are still positively correlated.

We select the time-series models that best capture the dynamic properties of each of the four liquidity proxies based on the Akaike information criterion (AIC) as described in Harvey (1989). The AR models that maximize AIC are: (1) for the average spread, an AR(5) process; (2) for the average spread/price ratio, an AR(6) process; (3) for the average quantity depth, an AR(3) process; and (4) for the average dollar depth, an AR(4) process.

We further study a systematic component of liquidity by randomly splitting each of the four size-based groups of 60 stocks into two subgroups of 30 stocks. Then we select one size-based subgroup for each size and pool them into two mutually exclusive and size-balanced subsets consisting of 120 stocks. (Huberman and Kandel (1987, 1990) use a similar sample-splitting technique.)

Table 3 reports estimates of the time-series models that capture the dynamic properties of each of the four liquidity proxies of the 120 stocks in each subset and of the 30 stocks in the subsets of each quartile. The estimation is under the efficiency-improving constraint that the coefficients for the two subsets are equal. The symmetric and random construction of the two subsets justifies the constraint. The residuals of the time-series model estimates reported in Table 3 are positively correlated. The correlation estimates are .32 for the spread, .25 for the spread/price ratio, .50 for the quantity depth, and .28 for the dollar depth. All the correlations are significantly different from zero.

The time-series regression estimates reported in Table 3 produce eight series of residuals, two corresponding to each size-based quartile. We examine but do not report the correlations among those residuals. Because size-based groups contain fewer stocks than do the two original subsets of the full sample, the size-based subsample correlations are smaller. Under the null hypothesis these correlations should have an arbitrary sign. Yet, most have positive signs, which lends further support to the presence of systematic liquidity. For each liquidity proxy, the correlations are on average positive and a few standard errors away from zero.

We observe that the correlations of the innovations in depth and dollar depth seem higher for smaller stocks. We detect no such pattern for correlations of innovations in spread, or spread-price, but those are weaker statistically, to the extent that the correlations of innovations in spread and spread/price ratio for the largest stocks are insignificant at conventional significance levels.

TABLE 3. Estimates of the Time-Series Models for the Four Liquidity Proxies for the Equally Weighted Portfolios (*t*-statistics in parentheses).

		Market Capitalization Quartiles			
	Whole Sample	1	2	3	4
Panel A. Spread ($)					
a	5.11	8.01	8.84	3.59	8.45
	(4.98)	(6.48)	(6.93)	(4.08)	(6.31)
b_1	0.15	0.20	0.17	0.10	0.13
	(3.49)	(4.49)	(3.77)	(2.41)	(2.89)
b_2	0.11	0.12	0.07	0.11	0.07
	(2.56)	(2.63)	(1.61)	(2.63)	(1.51)
b_3	0.15	0.03	0.11	0.17	0.03
	(3.46)	(0.73)	(2.34)	(4.15)	(0.79)
b_4	0.18	0.08	0.10	0.21	0.17
	(4.00)	(1.73)	(2.27)	(5.03)	(3.95)
b_5	0.12	0.11	0.06	0.22	0.13
	(2.83)	(2.51)	(1.26)	(5.07)	(2.93)
ρ	0.32	0.10	0.15	0.16	0.11
p-value	0.00	0.10	0.02	0.01	0.08
Panel B. Spread/Price Ratio (%)					
a	0.03	0.09	0.17	0.06	0.11
	(1.24)	(1.56)	(3.13)	(1.95)	(4.41)
b_1	0.32	0.35	0.22	0.09	0.18
	(7.28)	(8.03)	(5.08)	(1.97)	(4.11)
b_2	0.13	0.13	0.20	0.06	0.09
	(2.93)	(2.75)	(4.55)	(1.29)	(1.96)
b_3	0.15	0.12	0.05	0.19	0.10
	(3.25)	(2.67)	(1.15)	(4.71)	(2.32)
b_4	0.14	0.04	0.13	0.25	0.18
	(2.99)	(0.96)	(2.79)	(6.14)	(4.02)
b_5	0.05	0.10	0.09	0.17	0.12
	(1.13)	(2.10)	(2.10)	(3.93)	(2.66)
b_6	0.18	0.22	0.18	0.17	0.08
	(4.13)	(4.99)	(3.99)	(3.99)	(1.80)
ρ	0.26	0.13	0.20	0.18	0.05
p-value	0.00	0.04	0.00	0.01	0.39
Panel C. Quantity Depth (× 10,000)					
a	0.01	0.01	0.03	0.03	0.06
	(2.46)	(2.43)	(4.54)	(4.77)	(6.24)
b_1	0.40	0.52	0.82	0.73	0.32
	(9.17)	(12.05)	(19.86)	(18.67)	(7.69)
b_2	0.38	0.29	−0.07	−0.09	0.15
	(8.51)	(6.09)	(−1.27)	(−1.92)	(3.39)
b_3	0.18	0.15	0.15	0.25	0.24
	(4.12)	(3.53)	(3.71)	(6.25)	(5.62)
ρ	0.50	0.26	0.24	0.09	0.14
p-value	0.00	0.00	0.00	0.16	0.02

(Continued)

TABLE 3. Continued.

		Market Capitalization Quartiles			
	Whole Sample	1	2	3	4
Panel D. Dollar Depth (× 10,000)					
a	9.19	2.75	5.94	5.48	31.04
	(5.00)	(4.70)	(5.01)	(4.38)	(6.63)
b_1	0.30	0.53	0.43	0.35	0.28
	(6.58)	(11.77)	(9.67)	(8.11)	(6.37)
b_2	0.19	0.19	0.23	0.22	0.07
	(4.18)	(3.84)	(4.73)	(4.90)	(1.50)
b_3	0.21	0.06	0.08	0.10	0.19
	(4.50)	(1.15)	(1.57)	(2.31)	(4.13)
b_4	0.09	0.07	0.07	0.17	0.08
	(1.95)	(1.63)	(1.67)	(3.84)	(1.74)
ρ	0.28	0.30	0.35	0.09	0.13
p-value	0.00	0.00	0.00	0.16	0.05

Note: The estimated model is:

$$X_t^1 = a^1 + b_1^1 \cdot X_{t-1}^1 + \dots + b_n^1 \cdot X_{t-n}^1 + \varepsilon_t^1,$$

$$X_t^2 = a^2 = b_1^2 \cdot X_{t-1}^2 + \dots + b_n^2 \cdot X_{t-n}^2 + \varepsilon_t^2,$$

where X_t^i is the value of the liquidity proxy for portfolio i ($i = 1$ or 2) on day t and n is the number of lags of the liquidity proxy included in the model. Portfolios 1 and 2 are mutually exclusive and make up either the whole sample or the corresponding market capitalization quartile. The model is estimated under the following constraints: Intercept^1 = Intercept^2, $b_1^1 = b_1^2$, ..., $b_n^1 = b_n^2$; thus, there is only one set of estimates reported for the whole sample and for each of the quartiles. ρ is the coefficient of correlation between the residuals from the two estimated equations (ε^1 and ε^2). The p-value is the probability that a t-statistic is at least as extreme as the observed ρ value under H_0: $\rho = 0$.

IV. Determinants of the Common Movements in Liquidity

Because there is no established theory of time-series behavior of liquidity proxies, we must rely on our intuition in the choice of explanatory variables. We consider the two basic explanations of the existence of spread in the single security setting: the cost of holding inventory by market makers and adverse selection. Variations in depth are also commonly explained by adverse selection.

Intuitively, the costs of holding inventory for all the stocks in the market would depend on interest rates and the relative riskiness of equities at the particular time as perceived by the market makers and other traders. The other traders could depend on past volatility of equity returns, interest rate volatility, and the presence of marketwide shocks such as major shifts in the yield curve. The level of inventories that market makers would hold on average at certain times may be correlated across stocks and affect changes in liquidity.

The adverse-selection component of the spread should depend on the relative proportion of informed traders in the pool of traders. That in turn may vary over time because of the stochastic nature of new information releases.

We include the following explanatory variables in our regression model:

Rpos = daily return on the portfolio measured from noon on the preceding day to noon on the observation day when that return is positive, and 0 otherwise;
Rneg = daily return when the return is negative or zero, and 0 otherwise;
Vol = volatility of portfolio return measured by fitting returns with a GARCH (1,1) model;
EV = expected volume;
UV = unexpected volume from a decomposition of trading volume into expected and unexpected components;
YldVol = two-day volatility of yields on the one-year Treasury note;
BaaSpread = daily change in the spread between the Baa corporate bond yield and the one-year Treasury note yield; and
TenSpread = daily change in the spread between yields on ten-year and one-year Treasury bonds.

In Table 4 we report estimates of the coefficients for the regressions of our four liquidity proxies on the explanatory variables. Rneg, which captures negative daily returns on the portfolio of 240 stocks, is negatively correlated with the spread variables (absolute spread and spread/price ratio) and positively correlated with the depth variables (quantity depth and dollar depth). We do not obtain a similar result for Rpos. The estimated coefficient suggests the common component of liquidity decreases following a negative return, but does not increase following a positive return.

Variables related to volume (EV, UV) exhibit a significant relation only with depth. The unexpected component of volume (UV) is positively correlated with depth. Variables capturing changes in the relative riskiness of equities exhibit significant relations with the liquidity proxies. Both daily volatility of returns (Vol) and two-day volatility of yields on the one-year Treasury note (YldVol) are positively correlated with spread variables and negatively correlated with depth variables. As the relative riskiness of equities increases, liquidity decreases. Daily change in spreads between the yield on Baa corporate bonds and one-year Treasury notes (BaaSpread) do not exhibit significant relations with the liquidity proxies, except for depth with which they are positively correlated. Daily changes in spread between yields on ten-year and one-year Treasury bonds (TenSpread) are positively correlated with the spread variables and negatively correlated with the depth variables.

TABLE 4. Estimates for Regressions of the Four Liquidity Proxies on Their Own Lagged Values and Explanatory Variables for the Equally Weighted Portfolios (*t*-statistics in parentheses).

Panel A. Spread (cents)

		Market Capitalization Quartiles			
	Whole Sample	1	2	3	4
a	5.65	8.23	9.84	5.12	9.57
	(5.38)	(6.63)	(7.21)	(4.55)	(6.34)
b_1	0.12	0.20	0.15	0.09	0.12
	(2.82)	(4.29)	(3.48)	(2.04)	(2.59)
b_2	0.11	0.12	0.07	0.10	0.05
	(2.53)	(2.60)	(1.58)	(2.41)	(1.07)
b_3	0.15	0.03	0.09	0.16	0.03
	(3.59)	(0.71)	(2.09)	(3.86)	(0.60)
b_4	0.17	0.08	0.10	0.19	0.16
	(3.96)	(1.67)	(2.20)	(4.61)	(3.73)
b_5	0.13	0.11	0.06	0.20	0.13
	(2.98)	(2.34)	(1.42)	(4.62)	(3.04)
c_1	0.08	0.45	0.34	0.17	0.03
	(0.55)	(2.28)	(1.63)	(0.84)	(0.17)
c_2	−0.27	−0.22	−0.30	−0.14	−0.27
	(−2.16)	(−1.19)	(−1.40)	(−0.73)	(−1.56)
c_3	0.28	−0.03	−0.08	0.04	−0.03
	(2.21)	(−0.42)	(−0.92)	(0.40)	(−0.43)
c_4	−0.22	−2.87	−9.25	−1.91	−0.80
	(−0.22)	(−0.48)	(−1.54)	(−2.08)	(−1.51)
c_5	−1.19	−0.76	0.01	−0.86	−0.19
	(−1.41)	(−0.24)	(0.00)	(−0.92)	(−0.38)
c_6	0.02	0.01	0.04	0.03	0.03
	(3.06)	(1.28)	(2.78)	(2.23)	(2.04)
c_7	−3.20	−8.79	−14.10	0.21	7.26
	(−0.93)	(−1.77)	(−2.17)	(0.03)	(1.17)
c_8	2.82	3.17	5.65	1.39	1.68
	(2.35)	(1.86)	(2.50)	(0.60)	(0.78)
R^2	0.29	0.14	0.14	0.06	0.10
ρ	0.27	0.08	0.11	0.15	0.09
p-value	0.00	0.22	0.09	0.02	0.14

Panel B. Spread/Price Ratio (%)

a	0.03	0.08	0.18	0.11	0.11
	(0.88)	(1.37)	(3.07)	(3.17)	(4.42)
b_1	0.32	0.35	0.21	0.06	0.16
	(7.22)	(8.00)	(4.93)	(1.44)	(3.45)
b_2	0.14	0.14	0.22	0.05	0.08
	(3.14)	(2.94)	(4.89)	(1.12)	(1.91)
b_3	0.15	0.12	0.05	0.18	0.09
	(3.28)	(2.66)	(1.19)	(4.30)	(2.08)
b_4	0.13	0.03	0.11	0.24	0.17
	(2.90)	(0.68)	(2.49)	(5.63)	(3.82)

(Continued)

TABLE 4. Continued.

	Market Capitalization Quartiles				
	Whole Sample	1	2	3	4
Panel B. Spread/Price Ratio (%)					
b_5	0.05	0.09	0.10	0.15	0.12
	(1.14)	(2.00)	(2.32)	(3.47)	(2.72)
b_6	0.18	0.22	0.17	0.16	0.07
	(4.06)	(4.97)	(3.89)	(3.68)	(1.71)
c_1	−0.01	−0.01	0.01	0.00	0.00
	(−0.97)	(−0.38)	(0.95)	(0.23)	(−0.11)
c_2	−0.02	−0.03	−0.03	−0.02	−0.01
	(−1.60)	(−0.89)	(−2.04)	(−1.83)	(−3.21)
c_3	0.03	0.01	0.00	0.00	0.00
	(2.35)	(0.56)	(−0.06)	(−0.45)	(−0.19)
c_4	−0.02	0.71	−0.24	0.16	0.04
	(−0.20)	(0.59)	(−0.57)	(2.98)	(2.83)
c_5	−0.02	−0.41	0.12	0.04	0.00
	(−0.24)	(−0.67)	(0.69)	(0.84)	(0.17)
c_6	0.00	0.00	0.00	0.00	0.00
	(0.75)	(−0.49)	(1.90)	(2.18)	(1.43)
c_7	−0.42	−1.66	−0.67	0.26	0.25
	(−1.44)	(−1.84)	(−1.47)	(0.83)	(1.68)
c_8	0.19	0.58	0.30	−0.10	0.00
	(1.86)	(1.85)	(1.91)	(−0.93)	(−0.06)
R^2	0.46	0.40	0.19	0.16	0.24
ρ	0.22	0.13	0.15	0.15	0.01
p-value	0.00	0.04	0.02	0.02	0.90
Panel C. Quantity Depth (× 10,000)					
a	0.28	0.09	0.44	0.37	0.57
	(4.01)	(2.03)	(3.37)	(5.18)	(5.26)
b_1	0.38	0.52	0.47	0.37	0.27
	(9.28)	(11.88)	(10.67)	(8.92)	(6.19)
b_2	0.39	0.27	0.29	0.21	0.15
	(9.41)	(5.81)	(6.11)	(4.71)	(3.42)
b_3	0.17	0.16	0.12	0.22	0.21
	(4.16)	(3.70)	(2.74)	(5.25)	(4.89)
c_1	−0.04	0.02	−0.03	−0.03	−0.11
	(−1.06)	(0.41)	(−0.55)	(−0.51)	(−2.19)
c_2	0.19	0.03	0.23	0.18	0.12
	(5.89)	(0.79)	(4.18)	(3.74)	(2.55)
c_3	0.02	0.02	0.07	0.04	0.01
	(0.74)	(1.07)	(3.27)	(1.53)	(0.45)
c_4	−0.37	1.94	0.17	0.81	0.58
	(−1.45)	(1.15)	(0.11)	(3.22)	(3.66)
c_5	0.44	0.05	−0.14	0.42	0.44
	(2.09)	(0.06)	(−0.22)	(1.71)	(3.03)
c_6	−0.01	−0.01	−0.01	−0.01	0.00
	(−3.60)	(−3.60)	(−3.04)	(−1.91)	(−1.22)

(Continued)

TABLE 4. Continued.

	Market Capitalization Quartiles				
	Whole Sample	1	2	3	4
Panel C. Quantity Depth (× 10,000)					
c_7	2.30	1.95	2.93	1.96	1.82
	(2.53)	(1.61)	(1.66)	(1.32)	(1.06)
c_8	-1.17	-1.08	-1.64	-1.54	-0.45
	(-3.68)	(-2.55)	(-2.68)	(-2.95)	(-0.75)
R^2	0.68	0.57	0.62	0.28	0.28
ρ	0.38	0.21	0.26	0.11	0.13
p-value	0.00	0.00	0.00	0.09	0.05
Panel D. Dollar Depth (× 10,000)					
a	11.67	2.82	6.15	7.08	30.66
	(5.40)	(4.62)	(3.88)	(5.45)	(6.17)
b_1	0.29	0.52	0.41	0.30	0.25
	(6.64)	(11.61)	(9.38)	(6.93)	(5.62)
b_2	0.20	0.18	0.24	0.22	0.07
	(4.42)	(3.60)	(5.06)	(5.00)	(1.45)
b_3	0.18	0.05	0.07	0.09	0.17
	(3.95)	(1.09)	(1.49)	(1.93)	(3.84)
b_4	0.09	0.09	0.10	0.15	0.06
	(2.11)	(2.09)	(2.37)	(3.51)	(1.37)
c_1	-0.39	0.44	-0.47	-0.16	-2.27
	(-0.47)	(1.07)	(-0.79)	(-0.20)	(-1.25)
c_2	2.76	0.36	3.22	2.18	4.82
	(3.86)	(0.94)	(5.30)	(2.97)	(2.66)
c_3	-1.12	0.01	0.84	0.34	0.64
	(-1.43)	(0.04)	(3.58)	(0.82)	(0.79)
c_4	0.08	10.13	3.97	9.49	14.04
	(0.01)	(0.80)	(0.24)	(2.55)	(2.41)
c_5	9.46	1.49	-2.89	10.29	15.76
	(1.90)	(0.22)	(-0.41)	(2.76)	(2.86)
c_6	-0.10	-0.08	-0.13	-0.10	-0.09
	(-2.49)	(-3.63)	(-3.39)	(-2.19)	(-0.72)
c_7	38.73	31.04	39.03	37.52	39.17
	(1.96)	(2.81)	(2.06)	(1.61)	(0.60)
c_8	-16.17	-13.24	-20.80	-27.07	-1.34
	(-2.34)	(-3.45)	(-3.15)	(-3.31)	(-0.06)
R^2	0.47	0.60	0.60	0.28	0.16
ρ	0.19	0.24	0.23	0.06	0.11
p-value	0.00	0.00	0.00	0.32	0.09

The estimated model is:

$$X_1^t = a_1 + b_1^1 X_{t-1}^1 + \dots + b_n^1 X_{t-n}^1 + c_1 \text{Rpos}_t^1 + c_2 \text{Rneg}_t^1 + c_3 \text{Vol}_t^1 + c_4 \text{EV}_t^1$$

$$+ c_5 \text{UV}_t^1 + c_6 \text{YldVol}_t + c_7 \text{BaaSpread}_t + c_8 \text{TenSpread}_t + \varepsilon_t^1, \text{ and}$$

$$X_2^t = a_2 + b_1^2 X_{t-1}^2 + \dots + b_n^2 X_{t-n}^2 + c_1 \text{Rpos}_t^2 + c_2 \text{Rneg}_t^2 + c_3 \text{Vol}_t^2 + c_4 \text{EV}_t^2$$

$$+ c_5 \text{UV}_t^2 + c_6 \text{YldVol}_t + c_7 \text{BaaSpread}_t + c_8 \text{TenSpread}_t + \varepsilon_t^2.$$

where

X_t^i = liquidity proxy for portfolio i (i = 1 or 2) on day t;
n = number of lags;
Rpos = daily return on the portfolio measured from noon on the preceding day to noon on the observation day when that return is positive, and 0 otherwise;
Rneg = daily return when the return is negative or zero, and 0 otherwise;
Vol = volatility of portfolio return measured by fitting returns with a GARCH (1,1) model;
EV = expected volume;
UV = unexpected volume from a decomposition of trading volume into expected and unexpected components;
YldVol = two-day volatility of yields on the one-year Treasury note;
BaaSpread = daily change in the spread between the Baa corporate bond yield and the one-year Treasury note yield; and
TenSpread = daily change in the spread between yields on ten-year and one-year Treasury bonds.

The residuals of the regressions reported in Table 4 are still positively correlated after controlling for several explanatory variables. The correlation estimates are close to those reported in Table 3. Finally, we repeat the analysis by sorting the sample stocks into beta-based quartiles and treat those similarly to our size-based quartiles. The results are sufficiently similar so we do not report them here.

V. Conclusion

Informed traders are reluctant to trade with each other, and in the absence of noise traders they would not trade at all, as Milgrom and Stokey (1982) suggest. Black (1986) argues that the presence of noise traders enables liquidity to emerge. Noise traders are agents who trade on noninformation as if it were information.

According to Black (1986), noise trading can affect prices, and therefore prices of assets may deviate from their economic values. This gives rise to speculators who trade in anticipation of price changes caused by noise trading. Possibly, some noise traders trade with the illusion of possessing insights on future price changes caused by other noise traders.

We conjecture that a systematic component of the temporal variation of liquidity emerges because of the presence and effect of noise traders. Unfortunately, we cannot offer a model of the motivation, incidence, and effect of noise traders on stock returns, volatility, trading volume, and, most relevant here, liquidity. At the moment we do not know how to measure liquidity directly. Nor do we understand the costs of its provision or how they vary over time and across securities. However, we consider it useful to record empirical regularities until we develop a model of liquidity.

We focus on four proxies of liquidity and show that they vary over time and that cross-sectionally, this temporal variation has a common component. Moreover, the temporal variation in the liquidity proxies is positively correlated with return and negatively correlated with volatility. However, those variables do not capture the common component of the temporal variation.

Appendix: The Experimental Design

Liquidity is governed by

$$L_{it} = a_i + b_i f_t + \varepsilon_{it} + \eta_{it}, \quad \text{(A.1)}$$

where f_t is a common liquidity shock, ε_{it} is an idiosyncratic liquidity shock, and η_{it} is a rounding error designed to equate the stock-specific liquidity measure to the nearest acceptable integer multiple. These three random variables are assumed to be independent of each other. Moreover, the ε's and η's are cross-sectionally independent. (The rounding is important when liquidity is measured as the bid-ask spread, which is an integer multiple of 1/8, and to a lesser extent when looking at the quantity depth, because it is expressed as an integer multiple of 100.)

We assume that both the common liquidity shock and the idiosyncratic term follow AR(1) processes. (More general stationary time-series processes can also be accommodated, but for ease of exposition we confine ourselves to AR(1) processes.) Thus,

$$f_t = \rho f_{t-1} + u_t = \sum_{\tau=0}^{\infty} \rho^{\tau} u_{t-\tau}, \quad \text{(A.2)}$$

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + v_{it} = \sum_{\tau=0}^{\infty} \rho_i^{\tau} v_{it-\tau}. \quad \text{(A.3)}$$

Next, consider L_{it}, the average liquidity of a subset of stocks, I, which has $|L|$ members.

$$L_{It} = \bar{a}_I + \bar{b}_I f_t + \left[\sum_{i \in I} \left(\sum_{\tau=0}^{\infty} \rho_i^{\tau} v_{it-\tau} \right) + \eta_{it} \right] / |I|, \quad \text{(A.4)}$$

where $\bar{a}_i$ is the average a_i, and $\bar{b}_i$ is the average b_i.

The variance of the term in the square brackets of (4) converges to zero as $|I|$ approaches infinity, which by Chebychev's inequality implies this term converges to zero in probability as $|I|$ approaches infinity. Therefore, if indeed the common liquidity shock is present, it will dominate fluctuations in the average liquidity and render them approximately AR(1) processes. Moreover, the residuals from the (approximately) AR(1) processes describing the average liquidity fluctuations of mutually exclusive sets of stocks will be correlated. To see this, note that

$$L_{It} = \bar{a}_I + \bar{b}_I \sum_{\tau=0}^{\infty} \rho^{\tau} u_{t-\tau} + \left[\sum_{i \in I} \left(\sum_{\tau=0}^{\infty} \rho_i^{\tau} v_{it-\tau} \right) + \eta_{it} \right] / |I| = \bar{a}_I + \bar{b}_I \sum_{\tau=0}^{\infty} \rho^{\tau} u_{t-\tau} + \xi_t$$

$$= \bar{a}_I (1 - \rho) + \rho L_{It\text{-}1} + \bar{b}_I u_t + \xi_{It} - \rho \xi_{It\text{-}1}, \quad \text{(A.5)}$$

where the last two terms are small.

Our focus is on the residuals from the (approximately) autoregressive process, namely

$$\text{RESL}_{It} \equiv L_{It} - \rho L_{It\text{-}1}. \quad \text{(A.6)}$$

In particular, note that if the sets I and J are mutually exclusive, then

$$\text{CORR}(\text{RES}_{It}, \text{RESL}_{It}) \approx \frac{\bar{b}_I \bar{b}_J \text{VAR}(u_t)}{\sqrt{\text{VAR}(\bar{b}_I u_t + \xi_{It} - \rho \xi_{It\text{-}1}) \text{VAR}(\bar{b}_J u_t + \xi_{Jt} - \rho \xi_{Jt\text{-}1})}}. \quad \text{(A.7)}$$

The correlation is positive if there is a common liquidity component and the stocks' average exposures to it ($\bar{b}_I$ and $\bar{b}_J$) are positive. Moreover, the larger $|I|$ and $|J|$ are, the higher is the estimated correlation.

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