Pricing the Commonality Across Alternative Measures of Liquidity

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Abstract

We estimate latent factor models of liquidity, aggregated across a variety of liquidity measures. Shocks to assets' liquidity have a common component across measures which accounts for most of the explained variation of the individual liquidity measures. We find that across-measure systematic liquidity is a priced factor while winthin-measure systematic liquidity does not exhibit additional pricing information. Controlling for across-measure systematic liquidity risk, there is some evidence that liquidity, as a characteristic of assets, is priced in the cross-section. Our results are robust to the inclusion of other equity characteristics and risk factors, such as market capitalization, book-to-market, and momentum.

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I. Introduction

There is a substantial market microstructure literature that has extensively investigated the properties of equity market liquidity on an asset-by-asset basis. Single-period models with non-stochastic levels of liquidity (e.g., Amihud and Mendelson (1986)) suggest that assets with low liquidity/high transactions costs will command a return premium. However, in multi-period models, static cross-sectional differences in liquidity might not lead to large liquidity premia since investors can structure their portfolios to trade in liquid assets while pursuing a buy-and-hold policy on the illiquid assets (Constantinides (1986), Heaton and Lucas (1996)). These models of optimizing agents that predict a small premium, however, also predict counterfactually low levels of trading volume.

Even if the absolute level of liquidity commands a small premium, the risk of common, systematic shocks to liquidity might lead to economically important liquidity risk premiums. Acharya and Pedersen (2005) derive a model with stochastic liquidity in which investors effectively behave like one-period agents. In equilibrium, the absolute level of liquidity and several dimensions of systematic liquidity risk are priced. As in the constant-liquidity case above, a multi-period model might imply smaller liquidity risk premiums than the single-period results if systematic shocks to liquidity are transitory. In that case investors can "wait-out" the transitory liquidity shocks. Gârleanu and Pedersen (2004) derive a multi-period model in which returns are related to adverse selection caused by asymmetric information. In their model, the effect on expected returns depends on the distribution of private information. There are situations in which adverse selection leads to compensation in the form of higher expected returns. While the model in Acharya and Pedersen (2005) is a single-period model, it allows for stochastic liquidity. Adverse selection in the multi-period model in Gârleanu and Pedersen (2004) does not vary through time. One might expect liquidity premia are more likely to be substantial when liquidity is stochastic, non-diversifiable, and when systematic liquidity shocks are persistent.

A number of papers have studied the empirical evidence on whether liquidity risk is systematic and whether that systematic risk is priced in equity markets. Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001) demonstrate that liquidity has a common systematic factor. Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Chen (2005), and Sadka (2006) provide evidence of a premium for systematic liquidity risk (measured as return covariation with particular measures of aggregate liquidity shocks). Stocks whose returns are more sensitive to fluctuations in aggregate liquidity earn higher returns than stocks that exhibit lower sensitivity. Sadka (2006) also finds evidence that systematic liquidity shocks are persistent.

There are many alternative measures of liquidity in the literature. Measures that have appeared in the literature include quoted bid-ask spreads, effective bid-ask spreads, turnover, the ratio of absolute returns-to-volume, and adverse-selection and market-making cost components of price impact. Each of these measures may have systematic and asset-specific components. Also, the systematic components of different liquidity measures may be correlated. This may be due to the fact that the alternate measures are error-prone estimates of the same facet of liquidity or it may be due to the fact that alternate measures actually measure different facets of liquidity that are correlated. For example, the adverse-selection and market-making cost components of price impact are different facets of liquidity that should be correlated, in equilibrium (Glosten (1987)). While some studies compare different measures of liquidity, our study focuses on combining information from various measures to form a common facet of asset liquidity.

Most papers which study liquidity premiums choose either a particular measure of liquidity or a particular measure of liquidity risk and test whether either the level of assets' liquidity or asset's liquidity risk is priced in the cross-section. For example, Amihud and Mendelson (1986) test whether stocks with high spreads have higher average returns than stocks with lower spreads. Brennan and Subrahmanyam (1996) find that there is a return premium for both the fixed and variable components of a price impact model. Hasbrouck (2006) tests for the pricing of the effective spread and finds weak evidence for a premium. Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Hasbrouck (2006), and Sadka (2006) each test whether liquidity risk is priced. In Pástor and Stambaugh (2003), liquidity is measured by the reversal of the price impact of trading volume. Acharya and Pedersen (2005) measure liquidity using the ratio of average absolute returns to trading volume, as suggested in Amihud (2002). Hasbrouck (2006) uses several measures of the effective spread. Sadka (2006) measures liquidity using the conponents of the price impact model of Glosten and Harris (1988). Most of these authors find evidence for pricing of liquidity as a characteristic or as a risk factor. From these studies, it is impossible to tell, however, whether the pricing of these disparate measures is evidence for multiple liquidity premiums, or whether each measure is a noisy estimate of a single underlying fundamental liquidity charateristic or risk. We estimate a global measure of systematic liquidity risk across a set of eight liquidity measures. We test (a) whether the across-measure liquidity risk factor is priced in the cross-section of stock returns (b) whether there is any independent pricing of systematic liquidity risk for the eight measures, after controlling for the across-measure systematic risk, and (c) whether any of the liquidity characteristics is priced after controlling for liquidity risk.

We extract the common, systematic, components of liquidity across a large sample of equities and across a set of eight measures of liquidity. With n assets ($n = 4,055$) and eight measures, we extract latent factors from a cross-sectional sample of $n \times 8$ (= 32,440). We call these systematic factors "across-measure" systematic liquidity factors. We also do factor decompositions individually for each separate measure of liquidity. We call these systematic factors "within-measure" systematic liquidity factors. The factor decomposition is performed using the asymptotic principal-components (APC) method of Connor and Korajczyk (1986) and the EM-algorithm based method of Stock and Watson (1998).

We use these factor decompositions to explore the following sets of questions.

I. What is the size of the systematic versus the idiosyncratic component of liquidity for each measure of liquidity? What is the extent of commonality across measures of liquidity?

II. How persistent are liquidity shocks? What is the lead-lag relation across liquidity measures?

III. What are the time-series relations between asset returns and liquidity? Can shocks to liquidity predict asset returns and order imbalances? Can shocks to asset returns and order imbalances predict liquidity?

IV. Is there a return premium for illiquidity? If so, is the return premium compensation for the absolute level of liquidity and/or the size of systematic liquidity risk? If systematic liquidity risk is priced, is it the across-measure systematic risk or particular within-measure systematic risks?

While most of these questions have been investigated in the literature using individual measures of liquidity, our approach allows us to look at the question of whether there is pricing of liquidity risk or liquidity characteristics apart from the pricing of the across-measure, global systematic liquidity factor. That is, are the results in the literature indicative of multiple liquidity risk premiums or is there a priced global liquidity risk factor that is related to the various measures use in the literature.

We use 18 years of intraday data from the Institute for the Study of Security Markets (ISSM) Transactions File Database and the New York Stock Exchange (NYSE) Trade and Quotation (TAQ) Database to estimate a monthly time series of a panel of liquidity measures for NYSE-listed firms. Our sample includes 4,055 firms over the period 1983-2000. The set of liquidity measures includes quoted and effective spreads, share turnover, components of price impact (fixed versus variable and temporary versus permanent), and the ratio of absolute returns-to-volume. We also study the relation of these liquidity measures to order imbalances (signed volume) and asset returns.

Our results show that there exist common factors to liquidity. This is especially exhibited in spreads (both quoted and effective) and the fixed components of price impact. For example, on average, the first three principal components (factors) can explain over 50% of the time-series variation of firm-level quoted and effective spreads. In addition, a pair-wise canonical correlation analysis between the common factors of the liquidity measures indicates that the changes in the liquidity measures are correlated and that they are contemporaneously correlated with returns and order imbalances.

To investigate the persistence of changes in liquidity, we calculate the autocorrelation structure of the first principal component of each liquidity measure. The analysis suggests that all of the liquidity measures have systematic factors that are highly autocorrelated (for more than 12 lags), which means that changes in these liquidity levels are relatively persistent. Asset returns and order imbalances do not exhibit high serial correlations. We use the residuals from a univariate AR(2) model as the estimates of shocks to liquidity. The cross-serial correlation between returns and univariate liquidity shocks indicates that changes in liquidity lag returns.

Last, we investigate the pricing of systematic liquidity risk and the premium for the absolute level of liquidity. Using cross-sectional regressions of individual stock returns on systematic risks and asset characteristics, we show that across-measure systematic liquidity risk carries a significant premium while there is little evidence for a premium for within-measure systematic risk. This does not necessarily mean that within-measure liquidity risk is unpriced, since its pricing may be reflected in the pricing of across-measure systematic risk. The results consistently support a premium for the absolute level of liquidity characteristics for two, out of eight, liquidity measures. We also include market capitalization and book-to-market equity ratios in the cross-sectional regressions. They are statistically insignificant while the significant premium for across-measure liquidity risk is unaffected by their inclusion.

The remainder of this paper is organized as follows. Section II describes the data and the measures of liquidity employed in this study. Section III describes the principal-component analysis. The persistence of liquidity shocks is discussed in Section IV, and their canonical correlation in Section V. Section VI analyzes the implications of liquidity in predicting returns, and Section VII analyzes the role of liquidity risk in the cross-section of expected returns. Section VIII concludes.

II. Data and Liquidity Measures

The empirical analysis in this paper utilizes several different databases: intraday data for the estimation of asset liquidity and daily/monthly/annual data for the asset-pricing analysis. The intraday data are obtained from two databases. The ISSM database includes tick-by-tick data for trades and quotes of NYSE- and AMEX-listed firms for the period January 1983 through December 1992 (it also includes NASDAQ-listed stocks for part of the sample). Similarly, the New York Stock Exchange Trades and Automated Quotes (TAQ) database includes data for NYSE, AMEX, and NASDAQ for the period January 1993 through December 2000. The CRSP daily/monthly stock return database is also used.

We focus on NYSE-listed stocks since NASDAQ uses a different trading mechanism (also see Chordia, Roll, and Subrahmanyam (2001, pp. 504)). Since the trading characteristics of ordinary equities might differ from those of other assets, we retain only assets whose CRSP share codes are 10 or 11, i.e. we discard certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks, and REITs.

It is important to note that prior to using the raw data stored on the intraday databases, one must clean the data. As in Chordia, Roll, and Subrahmanyam (2001, 2002), we use only BBO (best bid or offer)-eligible primary market (NYSE) quotes. Trades that are out of sequence, that are recorded before the opening or after the closing time, or that have special settlement conditions are discarded. Negative bid-ask spreads and transaction prices are also eliminated from the dataset. Trades are classified as buyer-initiated (trade direction $D = 1$) or seller-initiated (trade direction $D = -1$) using the position of the transaction price relative to the quote midpoint where the quote is the most recent quote posted at least five seconds prior to the trade (Lee and Ready (1991)). To avoid after hours liquidity effects (see, e.g., Barclay and Hendershott (2004)), the opening trade is ignored.

Quotes with implausibly large spreads are discarded. Only quotes that satisfy the following filter conditions are retained: the bid-ask spread is positive and below five dollars, and the bid-ask spread divided by the midpoint of the quoted bid and ask (henceforth defined as quoted spread) is less than 25% if the midpoint is less than or equal to \$20. These conditions assure the use of reasonable quotes in our analysis. Finally, we exclude stocks whose prices are below \$1 and above \$1000.

After preparing both intra- and inter-day datasets, they are merged by matching the firms on ISSM with CRSP by their ticker symbols, and firms on TAQ with CRSP by their CUSIPs (this approach induces the highest matching rate, as discussed in Hvidkjaer (2006)). The final dataset includes only firms with at least 24 monthly observations of asset returns and all liquidity measures listed below. Our universe includes 4,055 NYSE-listed stocks for the period 1983-2000.

We construct a monthly time series for eight different measures of liquidity used in recent studies:

1. $A_{i,t}$ - the daily average of absolute value of return divided by dollar volume for asset i in month t.

$$A_{i,t} = \sum_{j=1}^{d_t} \frac{|r_{i,j}|}{dvol_{i,j}} \tag{1}$$

   where $r_{i,j}$ is the return on asset i on day j of month t; $dvol_{i,j}$ is the dollar volume traded in asset i on day j of month t; and d_t is the number of trading days in month t. This measure is based on the measure proposed in Amihud (2002) and is further used in Acharya and Pedersen (2005). We require asset i have at least 15 days on which $\frac{|r_{i,j}|}{dvol_{i,j}}$ is observed in month t, in order to be included in the sample. As in Acharya and Pedersen (2005), we scale $A_{i,t}$ by the ratio of market capitalization of the CRSP NYSE market index at $t-1$ and at a reference date, which in our case is December 1982. An alternative measure of liquidity that has been proposed is the average of the inverse of $\frac{|r_{i,j}|}{dvol_{i,j}}$, $\frac{dvol_{i,j}}{|r_{i,j}|}$. Hasbrouck (2005) finds that $A_{i,t}$ is better behaved than the alternative measure.

2. Turnover - the ratio of monthly volume and shares outstanding.

$$Turnover_{i,t} = \frac{\sum_{j=1}^{d_t} vol_{i,j}}{SO_{i,t}} \tag{2}$$

   where SO_t is the shares outstanding at the end of month t.

3. Qspread - the quoted percentage spread is measured for each trade as the ratio of the quoted bid-ask spread and the bid/ask midpoint. Monthly estimates are obtained as a simple average through the month.

$$Qspread_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \frac{Ask_{i,j} - Bid_{i,j}}{m_{i,j}}$$

   where $m_{i,j} = (Ask_{i,j} + Bid_{i,j})/2$; $Ask_{i,j}$ and $Bid_{i,j}$ are the ask and bid quotes prevailing at the time of the j^{th} trade of asset i in month t; and $n_{i,t}$ is the number of eligible trades of asset i in month t.

4. Espread - the effective percentage half-spread is measured for each transaction as the absolute value of the difference between the transaction price and the quote midpoint, divided by the

bid/ask midpoint. Monthly estimates are obtained as simple average of all transactions in the month.

$$Espread_{i,t} = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \frac{|p_{i,j} - m_{i,j}|}{m_{i,j}}$$

where $p_{i,j}$ is the transaction price for the j^{th} trade of asset i in month t.

The next four measures of liquidity are components of price impact, that is, the reaction of transaction price to trading. The components are obtained through the regression (described in detail in the appendix):

$$\Delta p_{i,j} = \Psi_{i,t}\varepsilon_{\Psi,i,j} + \lambda_{i,t}\varepsilon_{\lambda,i,j} + \overline{\Psi_{i,t}}\Delta D_{i,j} + \overline{\lambda_{i,t}}\Delta(D_{i,j}V_{i,j}) + y_{i,j} \tag{3}$$

for $j = 1, 2, ..., n_{i,t}$ and where $D_{i,j}$ is the direction of the j^{th} trade of asset i in month t; $\varepsilon_{\Psi,i,j}$ is the unexpected direction of trade, $D_{i,j} - E_{j-1}(D_{i,j})$; $D_{i,j}V_{i,j}$ is the signed volume of the j^{th} trade of asset i in month t; $\varepsilon_{\lambda,i,j}$ is the unexpected signed volume of trade; and Δ is the first difference operator.

5. $\lambda_{i,t}$ is the permanent variable component of price impact since it measures how much the valuation of the asset changes given a shock to signed trading volume, $\varepsilon_{\lambda,i,j}$.

6. $\overline{\lambda_{i,t}}$ is the transitory variable component of price impact since the effect of signed volume for this trade, $D_{i,j}V_{i,j}$, has an effect of $\overline{\lambda_{i,t}}D_{i,j}V_{i,j}$ on the price of trade j, an effect of $-\overline{\lambda_{i,t}}\ D_{i,j}V_{i,j}$ on the price of trade $j+1$, and no effect on subsequent prices.

7. $\Psi_{i,t}$ is the permanent fixed component of price impact.

8. $\overline{\Psi_{i,t}}$ is the transitory fixed component of price impact.

The evidence in Glosten and Harris (1988) is that the most significant components are the permanent variable component, $\lambda_{i,t}$, and the transitory fixed component, $\overline{\Psi_{i,t}}$.

In addition to these eight measures of liquidity, we also construct a time series of monthly order imbalances:

$$OI_{i,t} = \frac{\sum_{j=1}^{n_{i,t}} D_{i,j}V_{i,j}}{SO_{i,t}} \tag{4}$$

In order to reduce the effects of outliers, we "Winsorize" the data using the 1st and 99th percentiles each month. For example, let $A_t^{1\%}$ and $A_t^{99\%}$ be the 1st and 99th percentiles $A_{i,t}$. The winsorized observations are defined as $WA_{i,t} = A_t^{1\%}$ if $A_{i,t} < A_t^{1\%}$, $WA_{i,t} = A_t^{99\%}$ if $A_{i,t} > A_t^{99\%}$, and $WA_{i,t} = A_{i,t}$, otherwise.

We have an unbalanced panel of eight measures of liquidity plus the monthly order imbalance series and the monthly return series for NYSE-traded equities.[1] We now turn to a decomposition of each measure into (within-measure) systematic and idiosyncratic components and to a measure of systematic liquidity aggregated across the disparate measures of liquidity (across-measure systematic factors).

III. Factor Decomposition of Liquidity

In some factor decompositions, the units across cross-sections are comparable. This is the case for each of our eight liquidity measures individually as well as for asset returns and order imbalances. However, when we perform a factor decomposition across our eight liquidity measures, the units across measures can vary by several orders of magnitude. This can lead to over-weighting some measures simply because their scale makes then seem much more variable than other measures. Because of this, we choose to standardize our liquidity measures. We standardize using the sample mean and standard deviation of the cross-sectional average liquidity measure, using all available data prior to month t. Define L^{i*} to be the $n \times T$ matrix of observations on the i^{th} liquidity measure ($i = 1, 2, ..., 8$). Define $\widehat{\mu}_{t-1}^i$ and $\widehat{\sigma}_{t-1}^i$ to be the time-series mean and standard deviation of the cross-sectional average of liquidity measure i, estimated from the data sample up to time $t-1$. Let L^i be the $n \times T$ matrix of observations on the i^{th} standardized liquidity measure where $L_{j,t}^i = (L_{j,t}^{i*} - \widehat{\mu}_{t-1}^i)/\widehat{\sigma}_{t-1}^i$. We assume that the data generating process for $L_{j,t}^i$ is an approximate factor model:

$$L^i = B^i F^i + \varepsilon^i \tag{5}$$

where F^i is a $k \times T$ matrix of shocks to liquidity measure i that are common across the set of n assets, B^i is a $n \times k$ vector of factor sensitivities to the common liquidity shocks, and ε^i is an $n \times T$ matrix of asset-specific shocks to liquidity measure i. Systematic, or undiversifiable, shocks are those affecting most assets while diversifiable shocks are those which have weak commonality across assets. Define $V = E(\varepsilon^i \varepsilon^{i\prime})$. Chamberlain and Rothschild (1983) characterize an approximate factor model with k systematic factors as one for which the minimum eigenvalue of $B^{i\prime} B^i$ approaches infinity and the maximum eigenvalue of V remains bounded as n approaches infinity.

[1] Pástor and Stanbaugh (2003, p. 679) caution against using their measure at the individual firm level. Therefore, as in Hasbrouck (2006), we do not include their measure.

In an approximate factor-model setting for a balanced panel (complete data), Connor and Korajczyk (1986) show that n-consistent estimates (up to a linear transformation) of the latent factors, F^i, are obtained by calculating the eigenvectors for the k largest eigenvalues of

$$\Omega^i = \frac{L^{i\prime} L^i}{n}. \tag{6}$$

They refer to these estimates as Asymptotic Principal Components (APC). Note that Ω is a $T \times T$ matrix so that the computational burden of the eigenvector decomposition is independent of the cross-sectional sample size, n. This implies that factor estimates can be obtained for very large cross-sectional samples. Standard approaches to principal component or factor analysis are often unimplementable on large cross-sections since they require eigenvector decompositions of $n \times n$ matrices.

We apply two alternative estimators of the factor model that accommodate missing data. The first, from Connor and Korajczyk (1987), estimates each element of Ω by averaging over the observed data. Let L^i be the data for liquidity measure i with missing data replaced by zeros. Define N^i to be an $n \times T$ matrix for which $N^i_{j,t}$ is equal to one if $L^i_{j,t}$ is observed and is equal to zero if $L^i_{j,t}$ is missing. Define

$$\Omega^{i,u}_{t,\tau} = \frac{(L^{i\prime} L^i)_{t,\tau}}{(N^{i\prime} N^i)_{t,\tau}}. \tag{7}$$

$\Omega^{i,u}$ is the unbalanced panel equivalent of Ω^i in which the (t, τ) element is defined over the cross-sectional averages over the observed data only. While Ω^i in a balanced panel is guaranteed to be positive semi-definite, $\Omega^{i,u}$ is not. However, in large cross-sections $\Omega^{i,u}$ we have not encountered cases in which $\Omega^{i,u}$ is not positive definite. The estimates of the latent factors, $\widehat{F}^i$, are obtained by calculating the eigenvectors for the k largest eigenvalues of $\Omega^{i,u}$.

An alternative approach is derived by Stock and Watson (1998). With an unbalanced panel, quasi-MLE estimates are obtained through an iterative procedure which maximizes, at each step, the expected complete-data likelihood. Under the assumption that $\varepsilon^i_{j,t}$ is i.i.d. $N(0,\sigma^2)$ this is done by replacing missing data by the fitted value of the factor model from the previous iteration. That is $L^{i,*}_{j,t} = L^i_{j,t}$ when the data are observed and $L^{i,*}_{j,t} = \widehat{B}^i \widehat{F}^i$ when the data are missing. The factor estimates are obtained from the eigenvectors of

$$\Omega^{i,*} = \frac{L^{i,*\prime} L^{i,*}}{n}. \tag{8}$$

The process is iterated until we reach a fixed point, $\widehat{F}^i$ (up to a k-dimensional rotational indeterminacy). The Stock and Waston (1998) estimator maximizes the objective function using the EM algorithm. The results of our analyses using APC and EM methods are very similar, and thus in most cases we only report the APC results throughout the paper.

For each liquidity measure we extract the first three principal components. To illustrate the amount of commonality, across assets, for each liquidity measure, we calculate the time-series regression for each stock's liquidity on the three extracted factors, and record the p-values of the factor loadings, the R^2 value, and the adjusted-R^2 value. The regression estimated is:

$$L^i_{j,t} = B^i_{j,\bullet}\widehat{F}_t^{\,i} + \widehat{\varepsilon}^i_{j,t} \tag{9}$$

where $\widehat{F}_t^{\,i}$ is the $k \times 1$ vector of factor estimates for month t.

The cross-sectional average R^2 and adjusted-R^2 values for $k = 1, 2, 3$ are reported in Table 1 for both the Connor and Korajczyk (Panel A) and Stock and Watson (Panel B) methods. The APC-based results indicate there is commonality across assets for most liquidity measures. The strongest commonality is observed for quoted spreads, effective spreads, and transitory fixed components of price impact, $\overline{\Psi}$. The R^2 values for the liquidity measures range from 4.2% to 26.7% for a one-factor model (using the APC method). These R^2 values increase as we increase the number of factors. For a three-factor model the R^2 range from 12.2% to 51.7%. Stock returns and order imbalances have slightly smaller R^2 values (17.2%/6.3% for one factor and 23.9%/13.0% for three factors). The variable components of price impact have the lowest level of commonality. The EM-based results are similar to the APC results.

These results are consistent with the results of Chordia, Roll, and Subrahmanyam (2000) who find commonality among quoted and effective spreads, as well as Hasbrouck and Seppi (2001) who document commonality in the order imbalances of the 30 Dow stocks. The difference is that these studies use a shorter, one-year sample period, i.e. Chordia, Roll, and Subrahmanyam (2000) utilize daily data for 1992 and Hasbrouck and Seppi (2001) utilize intraday data for 1994, while we perform the analysis on a monthly frequency over 18 years. The longer time period may allow us to test for liquidity premia in the cross-section of stock returns.

Applying our principal-component analysis to stock returns produces similar results to those reported in Hasbrouck and Seppi (2001). They also find that using three principal components they can explain roughly 20% of the variability of returns. They also find similar results when analyzing order imbalance. Our results indicate only 13% of the variability of order imbalance can be explained by three principal components, which could be possibly explained by the larger set of firms that we employ.

In addition to estimating common factors for each measure of liquidity individually, we also estimate common factors across all eight measures of liquidity. This is done by stacking the liquidity measures into $L' = [L^{1\prime}, L^{2\prime}, .., L^{8\prime}]$, forming Ω^u using L, and extracting the eigenvectors of Ω^u (with equivalent modifications for the EM version of the estimator).We refer to the systematic factors extracted across the liquidity measures as "across-measure" factors.

There is a sign indeterminacy in statistically estimated factors. We choose the sign so that the factors represent liquidity, rather than illiquidity. That is, we choose the sign of each within-measure factor to be negatively correlated with the time series of the cross-sectional mean of that measure (positively correlated for turnover). Similarly, the sign of the across-measure factor is chosen to be negatively correlated with the time series of the cross-sectional mean liquidity pooled across the eight liquidity measures (turnover is included in the mean with a negative sign). This sign convention implies that positive values of each liquidity factor, within-measure and across-measure, are associated with increasing liquidity.

IV. The Time-Series Properties of Systematic Liquidity Factors

Only systematic and long-lasting shocks to liquidity are likely to lead to large liquidity premiums. To investigate the persistence of the liquidity factors, we first plot the autocorrelation function of each of the three factors for each liquidity measure, along with confidence intervals, in Figure 1, for APC factor estimates. We also plot the autocorrelation function for the return and order imbalance factors. Most liquidity factors exhibit significant autocorrelations. As one would expect, the return and order imbalance factors do not exhibit much autocorrelation.

We fit AR(2) models for the liquidity factors. From the time series model we can calculate an estimate of how long lasting are liquidity shocks. The model also allows a decomposition of the factors into anticipated changes and unanticipated shocks, which we estimate using the residuals from the AR(2) model. This is similar to the approach of Pástor and Stambaugh (2003), and Acharya and Pedersen (2005), who use a (modified) second order autoregression to calculate unexpected innovations of liquidity. The residuals from our AR(2) regressions show little autocorrelation.

We measure persistence by calculating, from the AR(2) model, the fraction of a shock at month t that we expect to impact liquidity at month $t+12$. The results are shown in Table 2. The variable components of price impact, λ and $\bar{\lambda}$, are not persistent. Turnover also shows only mild persistence. The other measures demonstrate much more persistence. The fraction of a time t shock to the first systematic factor that persists after twelve months is 91% for the effective spread, 46% and 69% for the permanent (Ψ) and transitory ($\bar{\Psi}$) fixed components of price impact, 34% for the Amihud measure, $A_{i,t}$, 70% for the quoted spread, and 61% for the systematic liquidity factor extracted from all eight measures of liquidity.

Figure 2 plots the time series of realizations of the pre-whitened first common factor extracted for each of the eight individual liquidity measures as well as the across-measure systematic factor (using the APC method). We use a rolling AR(2) specification, whose residuals are plotted in Figure 2. The factors are signed so that positive changes are associated with increasing liquidity. There are large changes in the liquidity factors in early 1984 and around the stock market crash in late 1987. Generally, the volatility of the shocks to the standardized liquidity has declined over time. The decline in liquidity factor variance is partially due to the non-anticipatory scaling of the liquidity measures by $\widehat{\sigma}^i_{t-1}$, which is high early in the sample period due to the 1987 crash (unreported results indicate that $\widehat{\sigma}^i_{t-1}$ generally exhibits a significant increase over the entire sample period for all liquidity measures except for the effective spread, and two of the price-impact components, TF and PF).

To study some important events in the less volatile half of the sample period, we have plotted the factor shocks over shorter intervals in Figures 3 and 4. Figure 3 looks at the liquidity factors over the period January 1998 through December 1999, which includes the Russian and LTCM crises in August and September 1998. There is a decline in liquidity, as measured by the Amihud measure, the quoted spread, and the permanent/variable price impact (the data are signed such that a negative observation represents a decline in liquidity). There is a smaller decline in liquidity when measured by the effective spread, but it is not as pronounced as for the quoted spread. These lead to a decline in liquidity measured by the across-measure liquidity factor.

Figure 4 covers the period from October 1996 through March 1998. This includes the beginning of the Asian Crisis (in July 1997). The period also includes the NYSE switch from a minimum price increment of $\frac{1}{8}$ dollar to $\frac{1}{16}$ dollar on June 24, 1997. June and July of 1997 show large improvements in liquidity, as measured by quoted and effective spreads, the Amihud measure, and the transitory fixed component of the price impact model.

V. Contemporaneous Canonical Correlations of Liquidity Shocks

Most previous papers that study commonality in liquidity have done so either with a single measure (e.g., Acharya and Pedersen (2005) use $A_{i,t}$), or with several measures, each investigated separately (e.g., Chordia, Roll, and Subrahmanyam (2000) study the commonality, across assets, for each of five measures of liquidity). Hasbrouck and Seppi (2001) study the commonality across returns and order imbalances by calculating canonical correlations between the two. They find that there is significant commonality across returns and order imbalances. They also study whether price impact, the sensitivity of returns to order imbalances, is related to systematic or asset-specific measures of liquidity. They find that the most of the explanatory power is due to asset-specific liquidity rather than common factors in liquidity.

We analyze several different measures of liquidity and study the extent to which liquidity shocks are systematic across measures. We study the correlation of the systematic factors extracted across each pair of liquidity measures as well as their correlation with stock returns and order imbalances. We begin by calculating pair-wise canonical correlations between the common factors of each of the eight liquidity measures, asset returns, and order imbalances. We compute the first three canonical correlations (i.e., the maximum correlation between linear combinations of the factors) of the first three extracted factors across each pair of variables. Table 3 contains the results for unadjusted factors. In Table 4 the factors are prewhitened (using an AR(2) specification) before the canonical correlations are calculated.

The results suggest that the changes in the liquidity are correlated across measures, with the correlations being higher for the raw factors than for the pre-whitened factors. The exceptions are the correlations between the liquidity measures and returns, which tend to be higher after pre-whitening with the AR(2) process. The analysis using factors extracted with the EM method (not reported in detail here) shows similar patterns to those found in Tables 3 and 4, although the canonical correlations are generally lower using the EM approach.

The canonical correlations between the individual-liquidity-measure factors and the across-measure factors are given in the bottom row of Tables 3 and 4. The evidence indicates that there are strong correlations between the factors for each individual liquidity measure and the across-measure systematic factors. Thus, there appear to be important commonalities across the various measures of liquidity. If so, the across-measure liquidity factors may give us a more precise estimate of the truly systematic shocks to liquidity than the factors for each individual measure.

The evidence here suggests that the changes in the liquidity measures are contemporaneously correlated with each other and with stock returns. This is consistent with recent studies that suggest liquidity risk as a priced factor (see, e.g., Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Sadka (2006)).

VI. The Temporal Relation Between Liquidity and Asset Returns

Later in the paper we study if there is a relation between liquidity risk and expected returns. In this section we study whether shocks to liquidity can predict future stock returns or whether shocks to returns help us predict future liquidity. To answer this question, we perform a pair-wise canonical correlation analysis similar to the contemporaneous correlations analysis, with the exception that one of the variables is lagged. The results are reported in Tables 5 (raw common factors) and 6 (pre-whitened factors).

In contrast to the findings in the previous section, here the AR(2) fitted factors produce significantly different results. Tables 5 and 6 (Column 1) show that there seems to be very weak evidence for lagged liquidity shocks being able to predict returns. However, shocks to returns do seem to predict most of the liquidity measures, especially when pre-whitened factors are used.

The analysis above includes only a one-month lag as means of detecting predictability. Yet, predictability can be further expanded to more than one lag. This is the focus of Figures 5 and 6. These figures utilize the pre-whitened factors. The figures plot the pair-wise lead-lag correlations between the first principal components of the liquidity measures (Figure 5) and the canonical lead-lag correlations using all three factors of each measure (Figure 6).

Our conclusion from the analysis in this section is that the cross-serial correlation between returns and liquidity shocks indicates that liquidity can be predicted by historical returns. However, the opposite does not hold: liquidity shocks appear uncorrelated with future returns.

VII. The Pricing of Liquidity Risk and Liquidity Characteristics in the Cross-Section

Having looked at the time-series properties of the different liquidity factors, this section investigates whether liquidity risk or the absolute level of liquidity are priced in the cross-section. An interesting question is whether the different liquidity measures are priced, and if so, do they measure different aspects of liquidity or do they all really represent the same aspect of liquidity. One way to answer this question is to include all the liquidity factors in the same regression and conduct a "horse race." Although plausible, this might lead to difficulties in drawing inferences because of lack of power in the tests. Therefore, we apply a decomposition of liquidity shocks into those driven by the common, across-measure shocks and those driven by shocks to a specific liquidity measure.

A. Constructing Across-Measure and Measure-Specific Liquidity Factors

The across-measure liquidity factor estimates shocks to liquidity that are common across all measures of liquidity. We use the first across-measure principal component, $\widehat{F_{1,t}}$, as our overall liquidity factor. In order to study whether there is additional information in the individual liquidity factors, we orthogonalize each of the individual liquidity factors (first principal component), $\widehat{F_{1,t}}^i$, to the across-measure liquidity factor—we refer to these orthogonalized factors as measure-specific liquidity factors. That is, in the regression

$$\widehat{F_{1,t}}^i = b_0^i + b_1^i \widehat{F_{1,t}} + \widehat{u}_{1,t}^i, \tag{10}$$

$\widehat{F_{1,t}}$ is the across-measure systematic factor estimated from Ω^u, $\widehat{F_{1,t}}^i$ is the within-measure unorthogonalized systematic factor estimated from $\Omega^{i,u}$, and $\widehat{u}_{1,t}^i$ is the within-measure orthogonalized systematic factor. Both $\widehat{F_{1,t}}$ and $\widehat{F_{1,t}}^i$ are prewhitened, using the AR(2) procedure, described above, before estimating (10).

The relative importance of the across-measure liquidity factor versus the measure-specific liquidity factor in explaining the time variation of firm-level liquidity is shown in Table 7. For each liquidity measure, we regress the time series of firm liquidity on the across-measure and within-measure factors. Table 7 shows the fraction of assets that have statistically significant regression coefficients at four different levels of type-I error, or size, (1% through 20%), as well as the R^2 of the regression. Individually, the across-measure and within-measure factors are statistically significant at frequencies much greater than the test size. Rejection rates of the joint null that both the across- and within-measure factors have zero explanatory power, are much higher than the level of the test size.

We calculate the proportion of R^2 that is due to the across-measure liquidity as well as the proportion due to the within-measure liquidity. As shown in Table 8, roughly 60% of the R^2 is explained by the overall liquidity measure, while 40% by the measure-specific liquidity. This results holds for all liquidity measures, and using both APC and EM methods.

B. Liquidity Risk, Liquidity Characteristics, and Average Returns

We estimate systematic liquidity risk of assets in a five-factor model that includes the across-measure liquidity portfolio, the three Fama and French (1993) factors (the CRSP value weighted market (MKT) portfolio, high-minus-low (HML) book-to-market equity portfolios, and small-minus-big (SMB) market capitalization portfolios), plus the momentum portfolios (UMD) of Carhart (1997).[2] Factor betas are estimated through a first-stage multiple time-series regression

$$R_{i,t} = \beta_{0,i} + \beta_i' f_t + \varepsilon_{i,t} \tag{11}$$

where f_t is a vector of factors (either traded or non-traded). Every month we rank stocks according to their liquidity risk, measured by its beta relative to the across-measure liquidity factor using the past 36 months of data. We require 24 months of data out of the past 36 months in order to include an asset. Based on this past liquidity beta, using data from $t-36$ to $t-1$, the asset is allocated to one of twenty portfolios. The beta of liquidity risk portfolio j is then estimated in a second-stage regression using the entire time series of returns for that portfolio. While liquidity risk portfolio j's beta vector is assumed constant, an asset's beta vector can change on a monthly basis as its portfolio assignment changes.

Table 9 shows the average portfolio return, in excess of the one-month risk-free return and the Jensen α relative to a four-factor asset pricing model, where the factors are MKT, HML, SMB, and UMD. The standard errors are calculated using the procedure of Newy and West (1987) with five lags. Both the excess returns and α increase from the lowest liquidity beta portfolio to the highest liquidity beta portfolio. However, the relations between portfolio ranking and average excess returns and α are non-monotonic. The last row shows the average excess return and α for a portfolio that is long the high liquidity beta portfolio and short the low liquidity beta portfolio. The excess return and α are positive and significant at the 5% level (with t-statistics of 1.98 and 2.14, respectively). Figure 7 shows a plot of the four-factor α against the portfolio systematic liquidity beta of the twenty porfolios. If liquidity risk is nor priced independently of the four-factors in the asset pricing model (MKT, HML, SMB, and UMD) there should be no relation between α and the liquidity beta. There is a significant relation between α and the liquidity beta, which is consistent with pricing of liquidity risk in the cross-section. We test explicitly for pricing liquidity risk in the cross-section in the next section.

[2] The market, book-to-market, size, and momentum portfolio excess returns are obtained from Ken French's web site: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

C. Cross-Sectional Regressions

The asset-pricing models tested here are of the form

$$E\left[R_i\right] = \gamma_0 + \gamma' \beta_i + \delta' Z_i \tag{12}$$

where $E\left[R_i\right]$ denotes the expected return of portfolio i (excess of risk-free rate); β_i are factor loadings of asset i relative to several different risk factor portfolio returns and the across-measure and within-measure liquidity factors; γ is a vector of factor premiums; Z_i are characteristics, such as the raw liquidity measures, size, and the book-to-market equity ratio; and δ is a vector of characteristic premiums. The coefficients of (12) are estimated for each month, $t = 1, 2, ..., T$, in the cross-sectional regression:

$$R_{i,t} = \gamma_{0,t} + \gamma_t' \beta_{i,t} + \delta_t' Z_{i,t-1} + \upsilon_{i,t} \tag{13}$$

where $R_{i,t}$ is the return on asset i for month t, β_i is the vector of betas for the portfolio to which asset i is assigned in month t, and $Z_{i,t-1}$ is a vector of characteristics for asset i observed at time $t-1$. Since loadings are unobservable, they are estimated through a first-stage multiple time-series regression, as in (11). We estimate (13) using the cross-sectional regression method of Fama and MacBeth (1973) using individual asset returns, $R_{i,t}$, and characteristics, $Z_{i,t}$. However, since the factor loadings in (11) are likely to be estimated with much error for individual assets, we estimate β_i used in (13) from portfolios. As in the previous section, each month, we rank stocks according to their liquidity risk, measured by its beta relative to the across-measure liquidity factor from (11) using the past 36 months of data. As before, we require 24 months of data out of the past 36 months in order to include an asset. Based on this past liquidity beta, using data from $t-36$ to $t-1$, the asset is allocated to one of fifty "liquidity risk" portfolios. The beta of liquidity risk portfolio j is estimated using the entire time series of returns for that portfolio. While a liquidity risk portfolio's beta vector is held constant, an asset's beta vector can change on a monthly basis as its portfolio assignment changes. This is the same type of procedure as used in Fama and French (1992).

The cross-sectional regression (13) is estimated using individual stock data every month, resulting with time series $\widehat{\gamma}_t$ and $\widehat{\delta}_t$. The time-series means and standard errors of $\widehat{\gamma}_t$ and $\widehat{\delta}_t$ are calculated and used for hypothesis testing, using the Newey-West correction for autocorrelation. The model in Equation (13) is tested for several factor specifications. First, the CAPM is examined using the Center for Research in Security Prices (CRSP) value-weighted market portfolio, denoted MKT, as a single factor plus the unstandardized level of the liquidity measure itself, $L^{i*}_{j,t-1}$, is added as a characteristic (top left panel of Table 10). The second model specification includes non-traded factors which are our systematic, across-measure liquidity factor and measure-specific factors, but excludes the illiquidity characteristic (middle left panel). The bottom left panel includes MKT, the liquidity factors and the illiquidity characteristic. These three specifications are repeated with the addition of the SMB, HML, and UMD factors in the right-hand set of panels. Finally, we add two additional characteristics, the logarithm of the stocks' market capitalization (size) in month $t-1$ and its ratio of book-to-market equity, in the bottom right panel. The book-to-market equity ratio is constructed as in Cohen, Polk, and Vuolteenaho (2003).

The results of the cross-sectional regressions in Table 10 indicate that the premiums on MKT, SMB, HML, and UMD are insignificant. The overall across-measure liquidity factor consistently earns a statistically significant premium regardless of the specification, with one exception. The estimated premiums for measure-specific factors are generally statistically insignificant. This does not necessarily mean that measure-specific liquidity risk is unpriced, since its pricing may be reflected in the pricing of across-measure systematic risk. The premium for illiquidity as a characteristic (rather than for systematic liquidity risk), measured by δ, is significant for the Amihud measure and for turnover. In the final specification, which includes the size and book-to-market characteristics, two spread-related characteristics also become significant. Those are the quoted spread and the transitory fixed component of the price impact model. The factor risk pricing results are unchanged by adding the size and book-to-market characteristics. The premiums of size and book-to-market equity characteristics are insignificant.

The cross-sectional pricing results show a statistically significant premium for a global measure of systematic liquidity risk extracted across a sample of measures of liquidity. This result is robust to a number of alternative specifications. There is little evidence for the pricing of systematic liquidity risk restricted to each individual measure of liquidity, after controlling for the across-measure systematic risk. Some non-risk (il)liquidity characteristics are priced, but the size, and book-to-market equity characteristics are not priced in the cross-section.

The evidence ponts to a conclusion that the significant pricing of a number of liquidity risk factors found in the literature are related in that they are measuring the pricing of underlying liquidity risk for which the disparate measures are noisy proxies.

VIII. Conclusions

A number of papers in the literature test for a premium for liquidity and a characteristic or as a risk factor and find evidence consistent with liquidity premiums. Since authors have chosen a number of different measures of liquidity, it is difficult to determine from the previous results whether a number of different liquidity premiums exist or whether there is a single liquidity premium. We estimate latent factor models for each of a set of measures of liquidity and a measure of global, across-measure systematic liquidity by estimating a latent factor model pooled across all eight measures. We find that there is commonality, across assets, for each individual measure of liquidity and that these common factors are correlated across measures of liquidity. Return shocks are contemporaneously correlated with liquidity shocks and lead changes in liquidity. Additionally, shocks to liquidity tend to die out slowly over time.

We estimate assets' systematic risk to the aggregate, across-measure liquidity factor as well as assets' loading on each separate liquidity measure. We find that aggregate systematic liquidity is a priced factor. The within-measure liquidity factors that are orthogonalized to the across-measure factor, do not seem to be priced separately. This does not mean that these liquidity factors are not priced in isolation, but that their priced component is picked up by the common element in the across-measure factor. This result seems robust to a number of specifications, such as using a CAPM benchmark or a four-factor benchmark. There is mixed evidence about the relation of the absolute level of assets' liquidity characteristics and their expected returns. The pricing of the Amihud measure and turnover is consistently significant when they are included as characteristics. In one, out of several, specifications the pricing of spread characteristics (Qspread, Espread, and $\overline{\Psi}$) is significant. Size and book-to-market equity characteristics are not priced, after controlling for liquidity risk, the Fama-French factors, and the Carhart momentum factor. Thus, the commonality in different measures of liquidity seems to give us sufficient power to extract a common, underlying liquidity factor and detect a liquidity premium even though our time-series sample is relatively short due to our use of extant intra-day data. The significant pricing results found in the literature for different measures of liquidity seem to be consistent with an underlying common liquidity factor.

IX. Appendix

This appendix contains a short summary of the estimation procedure which we use here to measure the components of price impact. The method is an extension of the specification in Glosten and

Harris (1988) developed in Sadka (2006). Let m_t denote the market maker's expected value of the security, conditional on the information set available at time t (t represents event time of a trade)

$$m_t = E_t \left[\widetilde{m}_{t+1} | D_t, V_t, y_t \right] \tag{A1}$$

where V_t is the absolute order flow; D_t is an indicator variable that receives a value of (+1) for a buyer-initiated trade and (-1) for a seller-initiated trade; and y_t is public, non-trade related information. To determine the sign of a trade we classify a trade whose price is above the midpoint of the quoted bid and ask as buyer-initiated, and below the midpoint—seller-initiated (trades whose price equals the midpoint are discarded from the estimation). As suggested by Lee and Ready (1991), we define the current quote to be the most recent quote that is at least 5 seconds old.

The literature distinguishes between two main effects, permanent and transitory, that trades may have on prices. The permanent effects are attributed to the revelation of valuation-relevant private information through the trading process. Market makers will also require compensation for the pure costs of making a market, such as inventory carrying costs and order processing. These non-adverse selection costs are recovered through the bid-ask spread and induce temporary, rather than permanent, changes in the price of assets. Sadka (2006) assumes price impacts have linear functional forms, and therefore, distinguishes between fixed costs per trade, which are independent of the order flow, and variable costs per share traded, which depend on the order flow. Therefore, there are four components of price impacts, which are denoted as follows. The fixed effects are Ψ and $\overline{\Psi}$ (permanent and transitory, respectively), and the variable costs are λ and $\overline{\lambda}$ (permanent and transitory, respectively).

To estimate the permanent price effects, we follow the formulation proposed by Glosten and Harris (1988) and assume that m_t takes a linear form such that

$$m_t = m_{t-1} + D_t \left[\Psi + \lambda V_t \right] + y_t \tag{A2}$$

where Ψ and λ are the fixed and variable permanent price-impact costs, respectively. Equation (A2) describes the innovation in the conditional expectation of the security value through new information, both private (D_t, V_t) and public (y_t). Notice that information induces a permanent impact on expected value.

Assuming competitive risk-neutral market makers, the (observed) transaction price, p_t, can be written as

$$p_t = m_t + D_t \left[\overline{\Psi} + \overline{\lambda} V_t \right] \tag{A3}$$

Notice that $\overline{\Psi}$ and $\overline{\lambda}$ are temporary effects, as they only affect p_t, and are not carried on to p_{t+1}. Taking first differences of p_t (Eq. (A3)) and substituting Δm_t from Eq. (A2) we have

$$\Delta p_t = \Psi D_t + \lambda D_t V_t + \overline{\Psi}\Delta D_t + \overline{\lambda}\Delta(D_t V_t) + y_t \tag{A4}$$

where y_t is the unobservable residual due to non-trade related information.

The formulation in Eq. (A4) assumes that the market maker revises expectations according to the total order flow observed at time t. However, the literature has documented predictability in the order flow (see, e.g., Hasbrouck (1991 a, b), Foster and Viswanathan (1993)). For example, to reduce price impact costs, traders may decide to break up large trades into smaller trades, which would create autocorrelation in the order flow. Thus, following Brennan and Subrahmanyam (1996), Madhavan, Richardson, and Roomans (1997), and Huang and Stoll (1997), Eq. (A4) is adjusted to account for the predictability in the order flow. In particular, the market maker is assumed to revise the conditional expectation of the security value only according to the *unanticipated* order flow rather than the entire order flow at time t. The unanticipated order flow, denoted by $\varepsilon_{\lambda,t}$, is calculated as the fitted error term from a five-lag autocorrelation regression of the order flow $D_t V_t$ (after computing $\varepsilon_{\lambda,t}$, the unanticipated sign of the order flow, $\varepsilon_{\Psi,t}$, is calculated while imposing normality of the error $\varepsilon_{\lambda,t}$—see Sadka (2006) for more details). Therefore, Eq. (A4) translates to

$$\Delta p_t = \Psi \varepsilon_{\Psi,t} + \lambda \varepsilon_{\lambda,t} + \overline{\Psi}\Delta D_t + \overline{\lambda}\Delta(D_t V_t) + y_t \tag{A5}$$

The literature documents different price effects induced by block trades (see, e.g., Madhavan and Smidt (1991), Keim and Madhavan (1996), Nelling (1996), and Huang and Stoll (1997)). In light of this, large/block trades (trades above 10,000 shares) are separated from smaller trades in the estimation using dummy variables. The model in Eq. (A5) is estimated separately for each stock every month using OLS (including an intercept) with Newey-West (1987) correction for serial correlation in the error term.

REFERENCES

Acharya, Viral V., and Lasse Heje Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics*, 77, 375-410.

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223-249.

Barclay, Michael J., and Terrence Hendershott, 2004, Liquidity externalities and adverse selection: evidence from trading after hours, *Journal of Finance* 58, 681-710.

Black, Fischer, Michael C. Jensen, and Myron Scholes, 1972, The capital asset pricing model: some empirical tests, in Michael Jensen, Ed.: Studies in the theory of capital markets (Praeger, New York), pp. 79-121.

Brennan, Michael J., and Avanidhar Subrahmanyam, 1996, Market microstructure and asset pricing: On the compensation for illiquidity in stock returns, *Journal of Financial Economics* 41, 441-464.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Chamberlain, Gary, and Michael Rothschild, 1983, Arbitrage, factor structure, and mean variance analysis on large asset markets, *Econometrica* 51, 1281-1304.

Chen, Jing, 2005, Pervasive liquidity risk and asset pricing, Working paper, Columbia University.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2000, Commonality in liquidity, *Journal of Financial Economics* 56, 3-28.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2001, Market liquidity and trading activity, *Journal of Finance* 56, 501-530.

Chordia Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2002, Order imbalance, liquidity and market returns, *Journal of Financial Economics* 65, 111-130.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *Journal of Finance* 58, 609-641.

Connor, Gregory, and Robert A. Korajczyk, 1986 Performance measurement with the arbitrage pricing theory: A new framework for analysis, *Journal of Financial Economics* 15, 323-346.

Connor, Gregory, and Robert A. Korajczyk, 1987, Estimating pervasive economic factors with missing observations, Working Paper No. 34, Department of Finance, Northwestern University.

Constantinides, George M., 1986, Capital market equilibrium with transaction costs, *Journal of Political Economy* 94, 842-862.

Domowitz, Ian, Oliver Hansch, and Xiaoxin Wang, 2005, Liquidity commonality and return comovement, *Journal of Financial Markets* 8, 351-376.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section expected stock returns, *Journal of Finance* 48, 427-465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and James MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Foster , F. Douglas, and S. Viswanathan, 1993, Variation in trading volume, return volatility, and trading costs: evidence on recent price formation models, *Journal of Finance* 48, 187-211.

Gârleanu, Nicolae, and Lasse Heje Pedersen, 2004, Adverse selection and the required return, *Review of Financial Studies* 17, 643-665.

Glosten, Lawrence R., 1987, Components of the bid-ask spread and the statistical properties of transaction prices, *Journal of Finance* 42, 1293-1307.

Glosten, Lawrence R., and Lawrence E. Harris, 1988, Estimating the components of the bid/ask spread, *Journal of Financial Economics* 21, 123-142.

Hasbrouck, Joel, 1991a, Measuring the information content of stock trades, *Journal of Finance* 46, 179-207.

Hasbrouck, Joel, 1991b, The summary informativeness of stock trades: An econometric analysis, *Review of Financial Studies* 4, 571-595.

Hasbrouck, Joel, 2005, Trading costs and returns for US equities: The evidence from daily data, Working paper, New York University.

Hasbrouck, Joel, 2006, Trading costs and returns for US equities: Estimating effective costs from daily data, Working paper, New York University.

Hasbrouck, Joel, and Duane J. Seppi, 2001, Common factors in prices, order flows, and liquidity, *Journal of Financial Economics* 59, 383-411.

Heaton, John, and Deborah J. Lucas, 1996, Evaluating the effects of incomplete markets on risk sharing and asset pricing, *Journal of Political Economy* 104, 443-487.

Huang, Roger D., and Hans R. Stoll, 1997, The components of the bid-ask spread: a general approach, *Review of Financial Studies* 10, 995-1034.

Hvidkjaer, Soeren, 2006, A trade-based analysis of momentum, forthcoming, *Review of Financial Studies* 19, 457-491.

Keim, Donald B., and Ananth Madhavan, 1996, The upstairs market for large-block transactions: analysis and measurement of price effects, *Review of Financial Studies* 9, 1-36.

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance* 46, 733-754.

Madhavan, Ananth, Matthew Richardson, and Mark Roomans, 1997, Why do security prices change? A transaction-level analysis of NYSE stocks, *Review of Financial Studies* 10, 1035-1064.

Madhavan, Ananth, and Seymour Smidt, 1991, A Bayesian model of intraday specialist pricing, *Journal of Financial Economics* 30, 99-134.

Nelling, Edward F., 1996, The price effects of 'shopping the block,' Working paper, Georgia Institute of Technology.

Newey, W., and K. West, 1987, A simple, positive-definite, heteroscedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Pástor, Ľuboš, and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy 111*, 642-685.

Sadka, Ronnie, 2006, Momentum and post-earnings announcement drift anomalies: The role of liquidity risk, *Journal of Financial Economics* 80, 309-349.

Stock, James H. and Mark W. Watson, 1998, Diffusion indices, Working paper 6702, National Bureau of Economic Research.

Table 1
Diagnostics of Within-Measure Common Factors

This table reports distribution statistics of time-series regressions. Within-measure common factors are extracted separately for returns and different measures of liquidity using the APC method (Panel A) and the EM method (Panel B). Then, for each variable and each stock, a time-series regression of the variable on its common factors is executed. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, order imbalance measured as the ratio of the net sum of signed trading volume through the month scaled by the number of shares outstanding (the sign of each trade is determined by the classification scheme introduced by Lee and Ready (1991)), and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors and regression analysis, for each stock, each variable (excluding return and order imbalance) is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The table reports the average R^2 and the average adjusted-R^2 of these regressions using 1, 2, and 3 factors. The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

Panel A: APC method

Variable	Statistic	Factor 1	Factor 2	Factor 3
Return	R^2	17.2	20.7	23.9
	Adjusted R^2	16.1	18.6	20.9
Amihud	R^2	17.9	36.7	44.5
	Adjusted R^2	16.9	35.0	42.2
Turnover	R^2	6.8	15.4	23.1
	Adjusted R^2	5.6	13.2	20.0
Qspread	R^2	25.2	34.4	51.7
	Adjusted R^2	23.9	32.1	49.2
Espread	R^2	26.7	46.1	54.6
	Adjusted R^2	25.4	44.2	52.1
PV (λ)	R^2	4.2	8.9	12.2
	Adjusted R^2	2.7	5.9	7.7
PF (Ψ)	R^2	14.3	18.0	21.6
	Adjusted R^2	12.8	15.3	17.5
TV ($\overline{\lambda}$)	R^2	5.8	9.9	12.9
	Adjusted R^2	4.2	6.9	8.5
TF ($\overline{\Psi}$)	R^2	23.4	31.8	47.6
	Adjusted R^2	22.1	29.4	44.9
Imbalance	R^2	6.3	10.0	13.0
	Adjusted R^2	4.8	7.0	8.6

Panel B: EM method

Variable	Statistic	Factor 1	Factor 2	Factor 3
Return	R^2	17.1	21.0	24.1
	Adjusted R^2	16.0	18.9	21.1
Amihud	R^2	22.4	39.7	46.9
	Adjusted R^2	21.4	38.1	44.7
Turnover	R^2	7.0	16.6	24.6
	Adjusted R^2	5.8	14.5	21.6
Qspread	R^2	26.6	46.2	54.5
	Adjusted R^2	25.4	44.5	52.3
Espread	R^2	22.5	46.9	59.6
	Adjusted R^2	21.3	45.1	57.4
PV (λ)	R^2	6.7	12.3	15.3
	Adjusted R^2	5.2	9.4	11.1
PF (Ψ)	R^2	8.4	17.2	28.2
	Adjusted R^2	6.9	14.5	24.5
TV ($\overline{\lambda}$)	R^2	7.5	12.1	15.8
	Adjusted R^2	6.0	9.2	11.6
TF ($\overline{\Psi}$)	R^2	26.6	39.7	50.6
	Adjusted R^2	25.4	37.7	48.1
Imbalance	R^2	6.9	11.1	15.4
	Adjusted R^2	5.4	8.2	11.1

Table 2

Persistence of Aggregate Liquidity

Within-measure common factors are extracted separately for different measures of liquidity using the APC method. In addition, across-measure common factors are extracted for all the liquidity measures jointly. Then, for each first principal component we apply an AR(2) model (coefficients Ro1 and Ro2 along with *t*-statistics in brackets below). The 6-month and 12-month values of the impulse response function applied to each a time series are also reported. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors and time-series analysis, for each stock, each variable is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

Variable	Ro1	Ro2	Shock after 12 months
Amihud	0.43	0.49	0.34
	[7.18]	[8.19]	
Turnover	0.48	0.33	0.12
	[7.57]	[5.12]	
Qspread	0.92	0.05	0.70
	[13.52]	[0.73]	
Espread	1.10	-0.12	0.91
	[16.18]	[-1.72]	
PV (λ)	0.47	0.28	0.06
	[7.16]	[4.31]	
PF (Ψ)	0.68	0.27	0.46
	[12.07]	[5.08]	
TV ($\bar{\lambda}$)	0.41	0.27	0.03
	[6.17]	[3.99]	
TF ($\bar{\Psi}$)	0.92	0.05	0.69
	[13.41]	[0.75]	
Across-measure	0.69	0.29	0.61
	[10.50]	[4.41]	

Table 3
Canonical Contemporaneous Correlations (Raw time series)

Three common factors are extracted separately for returns and different measures of liquidity using the APC method. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, order imbalance measured as the ratio of the net sum of signed trading volume through the month scaled by the number of shares outstanding (the sign of each trade is determined by the classification scheme introduced by Lee and Ready (1991)), and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each variable (excluding order imbalance) is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The table reports the first three canonical correlations (contemporaneous) between each two groups of common factors. The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months). Statistical significance of 5% and 1% correspond to correlations of 0.13 and 0.18, respectively.

	Return	Amihud	Turnover	Qspread	Espread	PV (λ)	PF (Ψ)	TV ($\bar{\lambda}$)	TF ($\bar{\Psi}$)	Imbalance
Amihud	0.20									
	0.08									
	0.04									
Turnover	0.28	0.84								
	0.12	0.50								
	0.08	0.35								
Qspread	0.17	0.95	0.84							
	0.11	0.90	0.70							
	0.04	0.08	0.44							
Espread	0.23	0.93	0.78	0.98						
	0.15	0.70	0.31	0.83						
	0.00	0.27	0.09	0.23						
PV (λ)	0.10	0.74	0.69	0.75	0.75					
	0.07	0.61	0.30	0.55	0.45					
	0.05	0.06	0.16	0.01	0.05					
PF (Ψ)	0.14	0.89	0.79	0.89	0.90	0.75				
	0.10	0.40	0.12	0.39	0.36	0.61				
	0.04	0.03	0.02	0.04	0.07	0.20				
TV ($\bar{\lambda}$)	0.25	0.76	0.75	0.80	0.70	0.84	0.71			
	0.07	0.41	0.09	0.33	0.43	0.76	0.36			
	0.02	0.05	0.00	0.18	0.08	0.63	0.06			
TF ($\bar{\Psi}$)	0.16	0.93	0.91	0.98	0.98	0.72	0.89	0.83		
	0.10	0.91	0.78	0.94	0.79	0.57	0.47	0.34		
	0.04	0.02	0.41	0.84	0.18	0.08	0.05	0.04		
Imbalance	0.28	0.47	0.66	0.52	0.36	0.34	0.53	0.38	0.61	
	0.16	0.33	0.23	0.40	0.20	0.16	0.12	0.07	0.32	
	0.04	0.08	0.01	0.07	0.01	0.02	0.05	0.00	0.05	
Across-	0.13	0.98	0.87	0.99	0.99	0.76	0.91	0.82	0.99	0.58
measure	0.07	0.96	0.57	0.95	0.81	0.66	0.47	0.44	0.96	0.36
	0.01	0.45	0.43	0.76	0.08	0.10	0.09	0.04	0.77	0.10

Table 4

Canonical Contemporaneous Correlations (Fitted AR(2))

Three common factors are extracted separately for returns and different measures of liquidity using the APC method. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, order imbalance measured as the ratio of the net sum of signed trading volume through the month scaled by the number of shares outstanding (the sign of each trade is determined by the classification scheme introduced by Lee and Ready (1991)), and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each variable (excluding order imbalance) is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The table reports the first three canonical correlations (contemporaneous) between each two groups of common factors. The table uses the residuals of a second order autocorrelation model for each factor (using a monthly expanding window). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months). Statistical significance of 5% and 1% correspond to correlations of 0.13 and 0.18, respectively.

	Return	Amihud	Turnover	Qspread	Espread	PV (λ)	PF (Ψ)	TV ($\bar{\lambda}$)	TF ($\bar{\Psi}$)	Imbalance
Amihud	0.35									
	0.14									
	0.01									
Turnover	0.26	0.32								
	0.18	0.08								
	0.03	0.04								
Qspread	0.39	0.33	0.18							
	0.04	0.04	0.11							
	0.02	0.01	0.03							
Espread	0.40	0.36	0.10	0.76						
	0.11	0.26	0.05	0.43						
	0.02	0.08	0.01	0.24						
PV (λ)	0.22	0.27	0.20	0.60	0.35					
	0.09	0.17	0.13	0.45	0.13					
	0.04	0.15	0.01	0.00	0.07					
PF (Ψ)	0.13	0.29	0.17	0.33	0.50	0.58				
	0.07	0.22	0.04	0.09	0.13	0.19				
	0.02	0.03	0.00	0.06	0.01	0.01				
TV ($\bar{\lambda}$)	0.24	0.30	0.15	0.72	0.38	0.93	0.36			
	0.10	0.13	0.08	0.56	0.22	0.73	0.14			
	0.00	0.05	0.00	0.17	0.01	0.33	0.05			
TF ($\bar{\Psi}$)	0.19	0.47	0.30	0.52	0.26	0.42	0.40	0.48		
	0.13	0.22	0.10	0.25	0.20	0.16	0.23	0.18		
	0.01	0.01	0.00	0.16	0.08	0.06	0.06	0.03		
Imbalance	0.21	0.43	0.21	0.25	0.16	0.15	0.20	0.21	0.18	
	0.14	0.12	0.05	0.17	0.06	0.04	0.11	0.09	0.10	
	0.06	0.02	0.03	0.03	0.00	0.00	0.01	0.01	0.02	
Across-	0.32	0.78	0.48	0.66	0.50	0.61	0.32	0.63	0.74	0.30
measure	0.19	0.57	0.26	0.43	0.37	0.23	0.24	0.31	0.64	0.09
	0.03	0.01	0.00	0.16	0.06	0.05	0.09	0.07	0.15	0.02

Table 5
Canonical Lead-Lag Correlations (Raw Time Series)

Three common factors are extracted separately for returns and different measures of liquidity using the APC method. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, order imbalance measured as the ratio of the net sum of signed trading volume through the month scaled by the number of shares outstanding (the sign of each trade is determined by the classification scheme introduced by Lee and Ready (1991)), and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each variable (excluding order imbalance) is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The table reports the first three canonical auto- and cross-correlations (one lag) between each two groups of common factors. Each column contains the canonical correlations between the common factors of the variable of that column and the lag common factors of each of the other variables (pair wise). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months). Statistical significance of 5% and 1% correspond to correlations of 0.13 and 0.18, respectively.

t-1 \ t	Return	Amihud	Turnover	Qspread	Espread	PV (λ)	PF (Ψ)	TV ($\bar{\lambda}$)	TF ($\bar{\Psi}$)	Imbalance	Across-measure
Return	0.27	0.34	0.29	0.18	0.42	0.18	0.15	0.20	0.16	0.16	0.13
	0.22	0.08	0.13	0.13	0.15	0.13	0.10	0.12	0.10	0.07	0.11
	0.07	0.07	0.04	0.01	0.00	0.06	0.08	0.01	0.02	0.04	0.03
Amihud	0.16	0.95	0.85	0.95	0.92	0.72	0.91	0.74	0.93	0.50	0.95
	0.08	0.93	0.50	0.88	0.67	0.57	0.30	0.34	0.90	0.33	0.90
	0.04	0.74	0.36	0.08	0.25	0.09	0.00	0.05	0.04	0.08	0.28
Turnover	0.17	0.84	0.98	0.83	0.77	0.68	0.78	0.73	0.89	0.80	0.86
	0.04	0.47	0.97	0.69	0.24	0.32	0.18	0.11	0.78	0.29	0.56
	0.01	0.39	0.55	0.43	0.09	0.12	0.04	0.00	0.38	0.01	0.31
Qspread	0.16	0.94	0.84	0.99	0.97	0.72	0.90	0.81	0.98	0.65	0.98
	0.07	0.90	0.72	0.97	0.80	0.58	0.39	0.36	0.96	0.38	0.95
	0.02	0.11	0.47	0.90	0.17	0.07	0.04	0.03	0.84	0.09	0.73
Espread	0.17	0.94	0.79	0.97	0.99	0.72	0.91	0.74	0.98	0.52	0.98
	0.08	0.69	0.35	0.79	0.98	0.53	0.50	0.39	0.82	0.19	0.81
	0.02	0.25	0.08	0.22	0.75	0.04	0.06	0.05	0.14	0.00	0.05
PV (λ)	0.14	0.75	0.68	0.72	0.69	0.67	0.71	0.58	0.72	0.46	0.74
	0.08	0.60	0.28	0.53	0.43	0.46	0.23	0.29	0.55	0.20	0.59
	0.00	0.05	0.16	0.17	0.02	0.10	0.06	0.04	0.13	0.03	0.16
PF (Ψ)	0.10	0.89	0.82	0.88	0.88	0.75	0.94	0.69	0.89	0.56	0.90
	0.09	0.34	0.22	0.39	0.35	0.23	0.13	0.18	0.43	0.07	0.42
	0.01	0.02	0.00	0.06	0.07	0.14	0.06	0.07	0.07	0.00	0.05
TV ($\bar{\lambda}$)	0.13	0.72	0.73	0.77	0.68	0.61	0.68	0.77	0.80	0.51	0.75
	0.08	0.43	0.06	0.30	0.38	0.29	0.16	0.27	0.32	0.09	0.36
	0.02	0.02	0.02	0.06	0.03	0.01	0.07	0.00	0.04	0.00	0.03
TF ($\bar{\Psi}$)	0.14	0.91	0.91	0.97	0.97	0.70	0.88	0.82	0.99	0.73	0.98
	0.10	0.87	0.79	0.91	0.73	0.57	0.41	0.34	0.97	0.32	0.92
	0.05	0.00	0.41	0.76	0.20	0.11	0.04	0.05	0.95	0.09	0.71
Imbalance	0.16	0.37	0.68	0.48	0.35	0.38	0.35	0.43	0.59	0.79	0.49
	0.09	0.29	0.29	0.38	0.19	0.23	0.04	0.10	0.33	0.18	0.33
	0.00	0.02	0.04	0.04	0.02	0.02	0.02	0.01	0.04	0.02	0.05
Across-	0.15	0.95	0.87	0.98	0.98	0.74	0.91	0.80	0.98	0.65	0.99
measure	0.08	0.90	0.58	0.92	0.77	0.62	0.40	0.40	0.95	0.33	0.96
	0.01	0.23	0.37	0.68	0.13	0.15	0.06	0.04	0.75	0.12	0.69

Table 6
Canonical Lead-Lag Correlations (Fitted AR(2))

Three common factors are extracted separately for returns and different measures of liquidity using the APC method. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, order imbalance measured as the ratio of the net sum of signed trading volume through the month scaled by the number of shares outstanding (the sign of each trade is determined by the classification scheme introduced by Lee and Ready (1991)), and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each variable (excluding order imbalance) is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The table reports the first three canonical auto- and cross-correlations (one lag) between each two groups of common factors. Each column contains the canonical correlations between the common factors of the variable of that column and the lag common factors of each of the other variables (pair wise). The table uses the residuals of a second order autocorrelation model for each factor (using a monthly expanding window). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months). Statistical significance of 5% and 1% correspond to correlations of 0.13 and 0.18, respectively.

t-1 \ t	Return	Amihud	Turnover	Qspread	Espread	PV (λ)	PF (Ψ)	TV ($\bar{\lambda}$)	TF ($\bar{\Psi}$)	Imbalance	Across-measure
Return	0.21	0.39	0.19	0.20	0.29	0.15	0.12	0.25	0.35	0.23	0.27
	0.08	0.17	0.11	0.10	0.14	0.08	0.11	0.13	0.13	0.12	0.13
	0.06	0.07	0.03	0.02	0.03	0.05	0.08	0.03	0.05	0.04	0.08
Amihud	0.17	0.44	0.30	0.21	0.28	0.22	0.35	0.22	0.38	0.34	0.31
	0.14	0.10	0.18	0.12	0.21	0.15	0.07	0.12	0.09	0.23	0.13
	0.01	0.05	0.05	0.01	0.07	0.01	0.06	0.02	0.01	0.05	0.05
Turnover	0.23	0.33	0.32	0.20	0.16	0.23	0.19	0.11	0.24	0.22	0.30
	0.10	0.15	0.23	0.10	0.13	0.11	0.10	0.07	0.16	0.12	0.16
	0.02	0.04	0.11	0.02	0.05	0.00	0.01	0.01	0.05	0.00	0.05
Qspread	0.29	0.57	0.25	0.28	0.56	0.40	0.27	0.54	0.56	0.19	0.67
	0.12	0.20	0.10	0.15	0.11	0.23	0.17	0.33	0.23	0.17	0.24
	0.03	0.01	0.03	0.09	0.04	0.06	0.06	0.06	0.16	0.03	0.03
Espread	0.18	0.42	0.28	0.29	0.66	0.32	0.48	0.40	0.47	0.20	0.55
	0.14	0.19	0.12	0.19	0.52	0.12	0.34	0.21	0.12	0.06	0.23
	0.01	0.05	0.02	0.05	0.06	0.09	0.05	0.03	0.02	0.01	0.01
PV (λ)	0.14	0.23	0.21	0.36	0.30	0.59	0.22	0.84	0.33	0.16	0.25
	0.06	0.19	0.13	0.10	0.28	0.23	0.12	0.46	0.20	0.04	0.20
	0.01	0.08	0.01	0.10	0.04	0.02	0.04	0.10	0.14	0.00	0.05
PF (Ψ)	0.12	0.19	0.24	0.33	0.38	0.35	0.37	0.42	0.27	0.11	0.26
	0.03	0.15	0.08	0.16	0.20	0.18	0.19	0.16	0.20	0.06	0.17
	0.00	0.10	0.05	0.00	0.10	0.12	0.07	0.03	0.03	0.01	0.05
TV ($\bar{\lambda}$)	0.29	0.24	0.19	0.43	0.41	0.61	0.17	0.80	0.25	0.17	0.24
	0.05	0.17	0.12	0.19	0.21	0.21	0.15	0.44	0.21	0.07	0.21
	0.00	0.03	0.04	0.07	0.02	0.12	0.07	0.12	0.06	0.00	0.02
TF ($\bar{\Psi}$)	0.13	0.27	0.22	0.32	0.35	0.22	0.24	0.30	0.38	0.14	0.21
	0.10	0.09	0.09	0.22	0.24	0.02	0.06	0.08	0.15	0.14	0.10
	0.04	0.04	0.01	0.01	0.05	0.00	0.02	0.04	0.09	0.09	0.03
Imbalance	0.16	0.14	0.19	0.16	0.13	0.17	0.11	0.14	0.17	0.68	0.12
	0.12	0.04	0.04	0.10	0.03	0.07	0.03	0.07	0.11	0.37	0.04
	0.05	0.02	0.02	0.03	0.01	0.03	0.01	0.02	0.03	0.08	0.02
Across-measure	0.24	0.32	0.24	0.23	0.43	0.27	0.43	0.36	0.39	0.25	0.38
	0.10	0.20	0.11	0.14	0.06	0.13	0.20	0.18	0.16	0.15	0.23
	0.04	0.10	0.02	0.01	0.05	0.04	0.01	0.01	0.13	0.07	0.10

Table 7

Percent of Firms with Significant Exposure to Across-Measure and Within-Measure Factors

This table reports distribution statistics of time-series regressions. Within-measure common factors are extracted separately for different measures of liquidity using the APC method (Panel A) and EM method (Panel B). In addition, across-measure common factors are extracted for all the liquidity measures jointly. Then, for each liquidity measure of each stock, a time-series regression of the variable on the across-measure common factor (the first principal) and the within-measure common factor (the first principal) of the particular liquidity measure is executed (the within-measure common factor is first projected on the across-measure common factor to orthogonalize the two factors). The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each variable is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The table reports the percentage of firms in the sample that exhibit significant coefficients at the 1%, 5%, 10%, and 20% statistical significance levels, as well as the joint significance (F-statistic). The average R^2 and the average adjusted-R^2 of these regressions are also reported below. The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

Panel A: APC method

Variable	Statistical sig. level (%)	Intercept	Across-measure	Within-measure	Joint sig.	Average R^2	Average Adj. R^2
Amihud	20	18.1	39.6	63.0	89.3	35.1	32.3
	10	16.9	36.7	59.4	85.8		
	5	15.9	34.6	56.4	82.7		
	1	13.6	29.5	50.6	76.7		
Turnover	20	30.6	37.2	50.7	72.2	14.0	10.6
	10	27.4	32.4	44.9	65.6		
	5	24.8	28.8	39.4	59.8		
	1	20.7	22.8	29.3	48.7		
Qspread	20	15.8	58.2	24.9	90.8	38.6	35.4
	10	14.5	55.4	21.5	88.0		
	5	13.6	52.9	19.6	85.3		
	1	11.1	48.3	15.5	78.7		
Espread	20	17.4	58.4	32.8	89.6	38.9	35.5
	10	15.8	55.6	30.3	85.8		
	5	14.5	52.9	28.0	82.9		
	1	12.0	48.3	22.9	76.6		
PV (λ)	20	15.0	29.2	29.4	47.3	8.3	3.7
	10	12.1	22.9	22.1	38.2		
	5	9.4	18.6	16.5	30.8		
	1	6.0	12.1	9.5	20.6		
PF (Ψ)	20	16.3	36.5	32.2	70.8	20.9	16.8
	10	13.0	32.5	27.6	63.0		
	5	11.0	28.8	23.6	57.5		
	1	7.6	22.4	16.5	47.0		
TV ($\bar{\lambda}$)	20	55.1	12.2	22.5	51.7	10.7	6.2
	10	49.0	9.0	17.1	43.2		
	5	44.4	6.8	13.8	36.9		
	1	35.5	4.1	8.8	27.0		
TF ($\bar{\Psi}$)	20	11.7	56.0	26.0	83.5	31.6	28.0
	10	10.6	52.5	21.9	79.5		
	5	9.8	50.2	18.9	75.6		
	1	8.1	44.9	13.9	68.7		

Panel B: EM method

Variable	Statistical sig. level (%)	Intercept	Across-measure	Within-measure	Joint sig.	Average R^2	Average Adj. R^2
Amihud	20	22.2	39.1	22.0	90.5	33.9	31.2
	10	20.5	37.2	19.8	87.0		
	5	19.1	35.3	18.1	83.9		
	1	16.7	31.3	15.5	77.8		
Turnover	20	38.6	37.6	43.6	74.7	14.4	11.1
	10	36.2	33.7	38.0	67.6		
	5	33.9	30.7	33.1	61.7		
	1	30.4	24.4	25.0	50.0		
Qspread	20	21.6	57.5	43.5	88.9	35.7	32.3
	10	20.5	54.7	39.7	84.8		
	5	19.7	52.2	36.5	81.5		
	1	18.2	47.9	29.6	74.4		
Espread	20	21.2	56.8	43.5	91.9	42.3	39.4
	10	19.9	54.7	40.9	89.0		
	5	18.9	52.8	39.0	86.6		
	1	17.1	48.2	34.3	81.1		
PV (λ)	20	19.6	29.5	26.6	54.8	11.5	7.0
	10	16.6	23.9	21.2	45.5		
	5	14.1	20.0	17.2	38.7		
	1	10.5	13.4	11.4	28.3		
PF (Ψ)	20	26.9	33.8	24.6	71.4	20.7	16.6
	10	23.9	30.4	21.6	65.3		
	5	21.3	27.5	18.8	59.6		
	1	17.0	22.3	14.5	49.5		
TV ($\bar{\lambda}$)	20	63.5	12.5	37.4	52.8	11.9	7.5
	10	59.0	9.4	30.1	44.3		
	5	55.7	7.7	24.7	37.8		
	1	48.6	4.7	15.3	27.4		
TF ($\bar{\Psi}$)	20	16.2	58.0	42.6	88.2	34.5	31.3
	10	15.4	55.1	38.5	84.5		
	5	14.4	53.0	35.0	81.8		
	1	13.0	47.9	27.9	74.9		

Table 8

Variance Decomposition

Within-measure common factors are extracted separately for different measures of liquidity using the APC method (Panel A) and EM method (Panel B). In addition, across-measure common factors are extracted for all the liquidity measures jointly. Then, for each liquidity measure of each stock, a time-series regression of the variable on the across-measure common factor (the first principal) and the within-measure common factor (the first principal) of the particular liquidity measure is executed (the within-measure common factor is first projected on the across-measure common factor to orthogonalize the two factors). The table reports the composition of the part of the variance explained by the model. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each variable is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

Panel A: APC method

Variable	Across-measure factor	Within-measure factor
Amihud	61.9	38.1
Turnover	57.2	42.8
Qspread	58.6	41.4
Espread	59.5	40.5
PV (λ)	54.8	45.2
PF (Ψ)	57.6	42.4
TV ($\bar{\lambda}$)	55.6	44.4
TF ($\bar{\Psi}$)	66.0	34.0

Panel B: EM method

Variable	Across-measure factor	Within-measure factor
Amihud	63.1	36.9
Turnover	57.0	43.0
Qspread	64.3	35.7
Espread	58.6	41.4
PV (λ)	52.4	47.6
PF (Ψ)	59.6	40.4
TV ($\bar{\lambda}$)	54.9	45.1
TF ($\bar{\Psi}$)	63.2	36.8

Table 9

Performance of Across-Measure-Liquidity-Loading-Sorted Portfolios

Across-measure common factors are extracted jointly for different measure of liquidity measures using the APC method. Factor shocks are then proxied with AR(2) residuals calculated using a monthly expanding window. Twenty portfolios are sorted each month by the across-measure liquidity loading estimated using the past 36 months (the loading is computed while controlling for Fama-French four factors). The time-series mean return (excess of risk-free rate) and risk-adjusted returns (using Fama-French four factors) of each portfolio are presented below (Newey-West adjusted *t*-statistics in parentheses). Portfolio returns are quoted in percent. The liquidity measures used for the analysis are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each variable is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

Portfolio ranking	Excess return	T Statistic	FF4 alpha	T Statistic
1 [low]	0.53	[1.11]	-0.10	[-0.50]
2	0.79	[1.87]	0.02	[0.14]
3	0.93	[2.35]	0.09	[0.67]
4	0.79	[2.15]	0.03	[0.22]
5	0.70	[1.86]	-0.06	[-0.36]
6	0.91	[2.63]	0.10	[0.69]
7	0.77	[2.22]	-0.08	[-0.51]
8	0.69	[2.12]	-0.03	[-0.21]
9	0.62	[2.00]	-0.16	[-1.07]
10	0.61	[1.90]	-0.20	[-1.71]
11	0.64	[2.18]	-0.07	[-0.50]
12	0.60	[1.92]	-0.21	[-1.48]
13	0.62	[2.02]	-0.07	[-0.45]
14	0.68	[2.27]	-0.04	[-0.34]
15	0.63	[2.01]	0.01	[0.10]
16	0.84	[2.68]	0.12	[1.12]
17	0.85	[2.61]	0.20	[1.86]
18	0.81	[2.14]	0.17	[1.00]
19	0.91	[2.26]	0.33	[1.85]
20 [high]	1.06	[2.20]	0.59	[2.52]
20 - 1 [high - low]	0.52	[1.98]	0.69	[2.45]

Table 10
Pricing Liquidity in the Cross-Section

Within-measure factors are extracted separately for different measures of liquidity using the APC method. In addition, across-measure common factors are extracted for all the liquidity measures jointly. Factor shocks are then proxied with AR(2) residuals calculated using a monthly expanding window. Factor loadings are calculated using time-series regressions of returns to 50 portfolios on the Fama-French four factors, the across-measure common factor (the first principal) and the within-measure common factor (the first principal) of the particular liquidity measure (the within-measure common factor is first projected on the across-measure common factor to orthogonalize the two factors). The portfolios are sorted each month by the across-measure liquidity loading estimated using the past 36 months (the loading is computed while controlling for Fama-French four factors). Each month a stock is assigned the factor loadings of the portfolio to which it has assigned at the end of the prior month. The results of Fama-MacBeth regressions of individual stock returns on the factor loadings are reported below (Newey-West adjusted *t*-statistics in parentheses). The liquidity measure (estimated the previous month) of each stock (ILLIQ) is also added to the cross-sectional regressions, as well as the natural logarithm of market capitalization (in millions of dollars) (Size) and book-to-market ratio (as of the previous month) (B/M). The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each variable is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). While added to the cross-sectional regressions, the liquidity measures are not normalized; the Amihud measure, PV, and TV are multiplied by 10^5, and quoted and effective spreads, PF, and TF are multiplied by 100. The return premium estimates are reported in percent. The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

	Factor Premium			Chr. Pr.
Measure	MKT	Across-measure	Within-measure	ILLIQ
Amihud	0.63			0.79
	[0.98]			[2.15]
Turnover	0.54			0.28
	[0.87]			[2.15]
Qspread	-0.32			0.10
	[-0.60]			[0.89]
Espread	-0.25			0.23
	[-0.46]			[0.80]
PV (λ)	0.07			-0.59
	[0.11]			[-0.61]
PF (Ψ)	0.07			-0.47
	[0.12]			[-0.87]
TV ($\bar{\lambda}$)	0.00			-1.12
	[0.00]			[-0.75]
TF ($\bar{\Psi}$)	-0.25			0.58
	[-0.45]			[1.54]
Amihud	0.58	0.33	-0.16	
	[0.89]	[2.82]	[-0.82]	
Turnover	0.38	0.30	0.47	
	[0.56]	[2.72]	[2.04]	
Qspread	-0.19	0.29	0.02	
	[-0.30]	[2.37]	[0.27]	
Espread	-0.18	0.28	0.10	
	[-0.29]	[2.30]	[0.80]	
PV (λ)	0.05	0.28	0.04	
	[0.07]	[2.36]	[0.17]	
PF (Ψ)	0.00	0.26	0.31	
	[-0.01]	[2.03]	[1.22]	
TV ($\bar{\lambda}$)	-0.08	0.32	-0.74	
	[-0.12]	[2.90]	[-1.38]	
TF ($\bar{\Psi}$)	0.12	0.23	-0.07	
	[0.19]	[2.47]	[-0.69]	
Amihud	0.50	0.32	-0.12	0.78
	[0.79]	[2.74]	[-0.66]	[2.10]
Turnover	0.27	0.29	0.36	0.27
	[0.43]	[2.63]	[1.62]	[2.09]
Qspread	-0.38	0.26	0.02	0.09
	[-0.70]	[2.13]	[0.27]	[0.84]
Espread	-0.32	0.25	0.09	0.21
	[-0.57]	[2.12]	[0.68]	[0.77]
PV (λ)	0.05	0.28	0.03	-0.61
	[0.07]	[2.37]	[0.14]	[-0.63]
PF (Ψ)	0.02	0.25	0.30	-0.47
	[0.03]	[2.03]	[1.21]	[-0.88]
TV ($\bar{\lambda}$)	-0.13	0.31	-0.76	-1.03
	[-0.20]	[2.90]	[-1.41]	[-0.70]
TF ($\bar{\Psi}$)	-0.20	0.19	-0.06	0.56
	[-0.39]	[2.17]	[-0.60]	[1.49]

	Factor Premium						Characteristic Premium		
Measure	MKT	SMB	HML	UMD	Across-measure	Within-measure	ILLIQ	Size	B/M
Amihud	-0.91	0.80	-0.40	-0.74			0.78		
	[-1.24]	[1.40]	[-0.76]	[-0.96]			[2.10]		
Turnover	-0.80	0.73	-0.34	-0.60			0.27		
	[-1.09]	[1.28]	[-0.68]	[-0.78]			[2.13]		
Qspread	-0.78	-0.18	0.14	-0.94			0.10		
	[-1.08]	[-0.29]	[0.25]	[-0.97]			[0.89]		
Espread	-0.78	-0.10	0.09	-0.90			0.22		
	[-1.09]	[-0.15]	[0.16]	[-0.92]			[0.80]		
PV (λ)	-0.82	0.21	-0.18	-0.82			-0.69		
	[-1.06]	[0.29]	[-0.32]	[-0.89]			[-0.71]		
PF (Ψ)	-0.74	0.18	-0.19	-0.80			-0.50		
	[-0.95]	[0.26]	[-0.35]	[-0.87]			[-0.94]		
TV ($\bar{\lambda}$)	-0.86	0.21	-0.14	-0.86			-0.93		
	[-1.11]	[0.30]	[-0.25]	[-0.92]			[-0.63]		
TF ($\bar{\Psi}$)	-0.77	0.11	0.08	-0.53			0.57		
	[-1.01]	[0.16]	[0.13]	[-0.56]			[1.55]		
Amihud	-0.36	0.72	-0.55	-0.14	0.25	-0.05			
	[-0.53]	[1.28]	[-1.01]	[-0.19]	[2.44]	[-0.26]			
Turnover	-0.26	0.52	-0.60	-0.03	0.25	0.37			
	[-0.39]	[0.91]	[-1.10]	[-0.04]	[2.41]	[1.66]			
Qspread	-0.32	-0.20	-0.16	-0.44	0.28	0.05			
	[-0.53]	[-0.28]	[-0.27]	[-0.50]	[2.57]	[0.67]			
Espread	-0.21	-0.22	-0.22	-0.31	0.28	0.13			
	[-0.34]	[-0.31]	[-0.37]	[-0.34]	[2.56]	[1.04]			
PV (λ)	-0.12	-0.05	-0.26	-0.25	0.27	0.06			
	[-0.17]	[-0.07]	[-0.47]	[-0.28]	[2.74]	[0.24]			
PF (Ψ)	-0.21	-0.22	-0.13	-0.58	0.23	0.36			
	[-0.31]	[-0.30]	[-0.23]	[-0.62]	[2.18]	[1.33]			
TV ($\bar{\lambda}$)	-0.32	-0.11	-0.24	-0.42	0.30	-0.85			
	[-0.48]	[-0.16]	[-0.42]	[-0.49]	[3.36]	[-1.59]			
TF ($\bar{\Psi}$)	-0.03	-0.02	-0.19	-0.17	0.23	-0.08			
	[-0.06]	[-0.02]	[-0.34]	[-0.20]	[2.62]	[-0.73]			
Amihud	-0.54	0.55	-0.43	-0.14	0.24	-0.04	0.72	-0.05	0.01
	[-0.83]	[1.05]	[-0.81]	[-0.20]	[2.33]	[-0.24]	[1.96]	[-0.87]	[0.21]
Turnover	-0.28	0.21	-0.46	0.19	0.25	0.36	0.28	-0.07	0.02
	[-0.45]	[0.40]	[-0.90]	[0.25]	[2.41]	[1.63]	[2.09]	[-1.22]	[0.37]
Qspread	-0.32	-0.37	-0.03	-0.46	0.26	0.03	0.23	0.09	0.04
	[-0.55]	[-0.55]	[-0.05]	[-0.52]	[2.25]	[0.31]	[2.06]	[1.56]	[0.61]
Espread	-0.31	-0.31	-0.11	-0.36	0.25	0.11	0.53	0.07	0.04
	[-0.52]	[-0.46]	[-0.19]	[-0.40]	[2.27]	[0.87]	[1.86]	[1.26]	[0.63]
PV (λ)	-0.26	-0.06	-0.24	-0.27	0.26	0.04	-0.52	0.00	0.05
	[-0.39]	[-0.09]	[-0.43]	[-0.32]	[2.54]	[0.19]	[-0.60]	[-0.04]	[0.82]
PF (Ψ)	-0.33	-0.28	-0.05	-0.66	0.20	0.41	-0.46	-0.01	0.05
	[-0.50]	[-0.41]	[-0.10]	[-0.72]	[1.81]	[1.54]	[-0.99]	[-0.15]	[0.85]
TV ($\bar{\lambda}$)	-0.47	-0.12	-0.24	-0.44	0.29	-0.86	-0.70	0.01	0.05
	[-0.74]	[-0.18]	[-0.43]	[-0.53]	[3.08]	[-1.59]	[-0.50]	[0.20]	[0.91]
TF ($\bar{\Psi}$)	-0.10	-0.19	-0.08	-0.15	0.20	-0.07	0.96	0.07	0.05
	[-0.18]	[-0.28]	[-0.15]	[-0.18]	[2.34]	[-0.68]	[2.75]	[1.45]	[0.89]

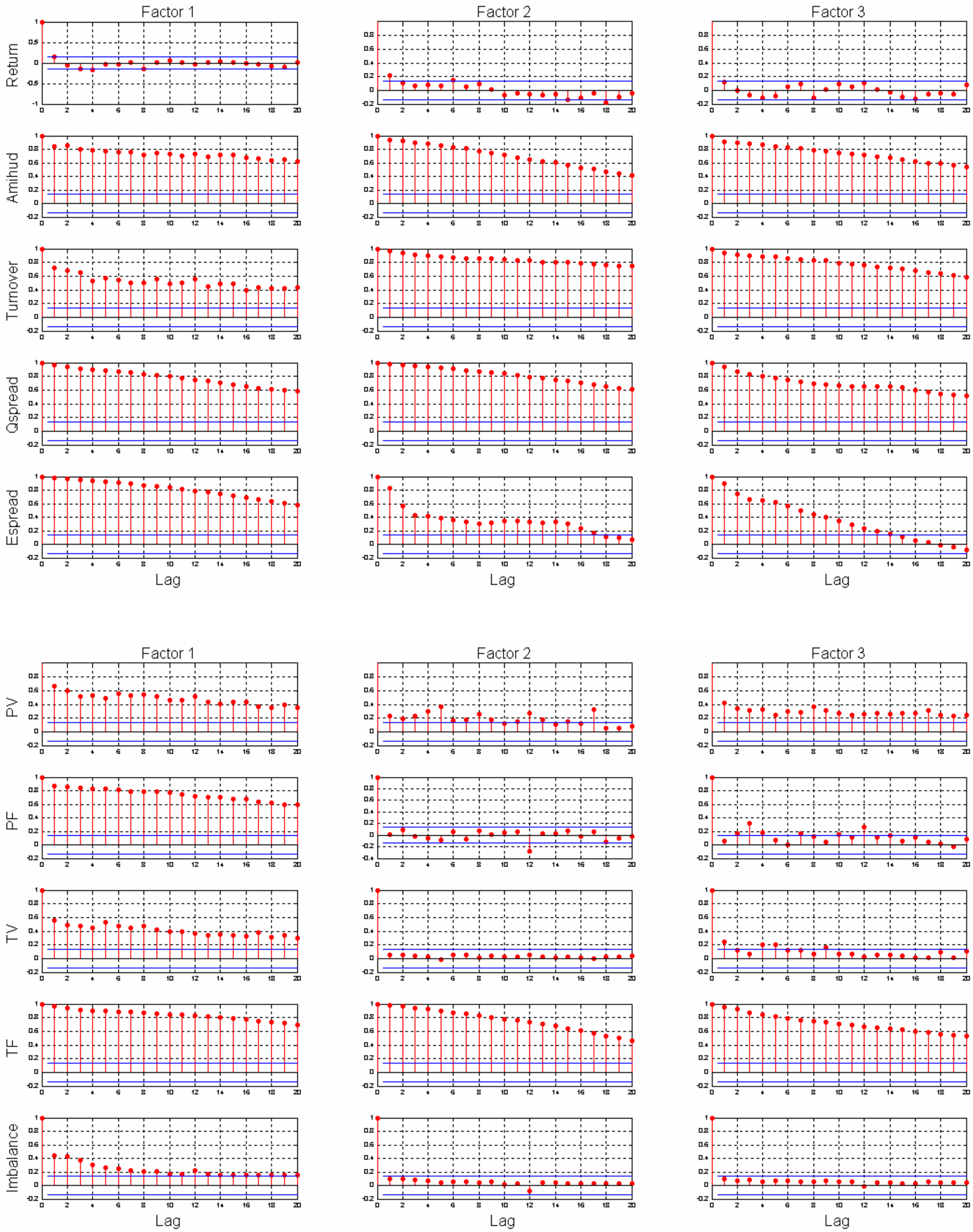

Figure 1. Autocorrelations of Liquidity Factors. Common factors are extracted separately for returns and different measures of liquidity using the APC method. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, order imbalance measured as the ratio of the net sum of signed trading volume through the month scaled by the number of shares outstanding (the sign of each trade is determined by the classification scheme introduced by Lee and Ready (1991)), and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). The figure plots the autocorrelation between of each of the first three principal components. The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

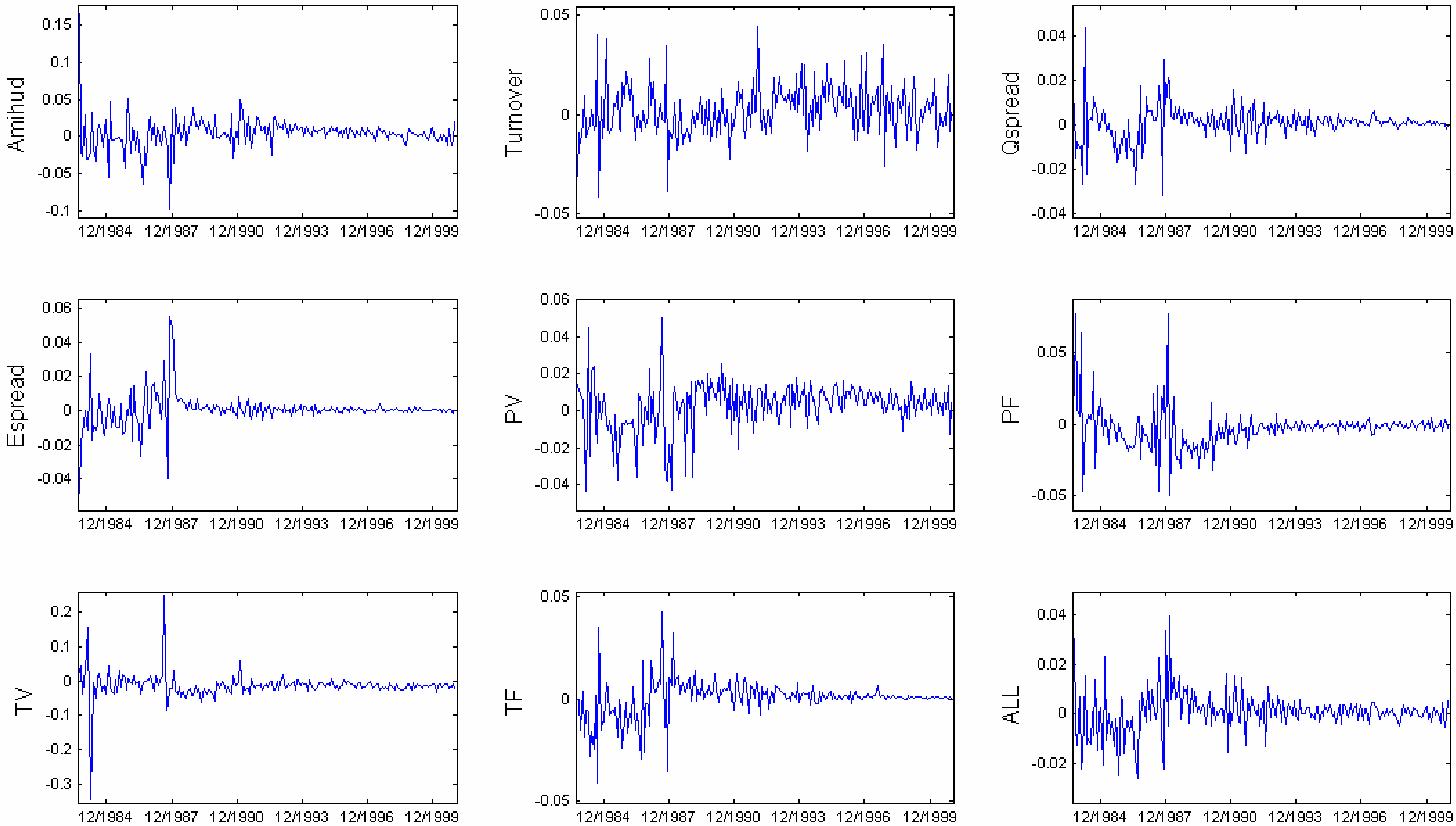

Figure 2. Time series of liquidity shocks (APC). The first common factor is extracted separately for different measures of liquidity using the APC method. In addition, an across-measure common factor is extracted for all the liquidity measures jointly (ALL). The factor shocks plotted above are calculated as the residuals of an AR(2) model (estimated using a monthly expanding window). The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each liquidity variable is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

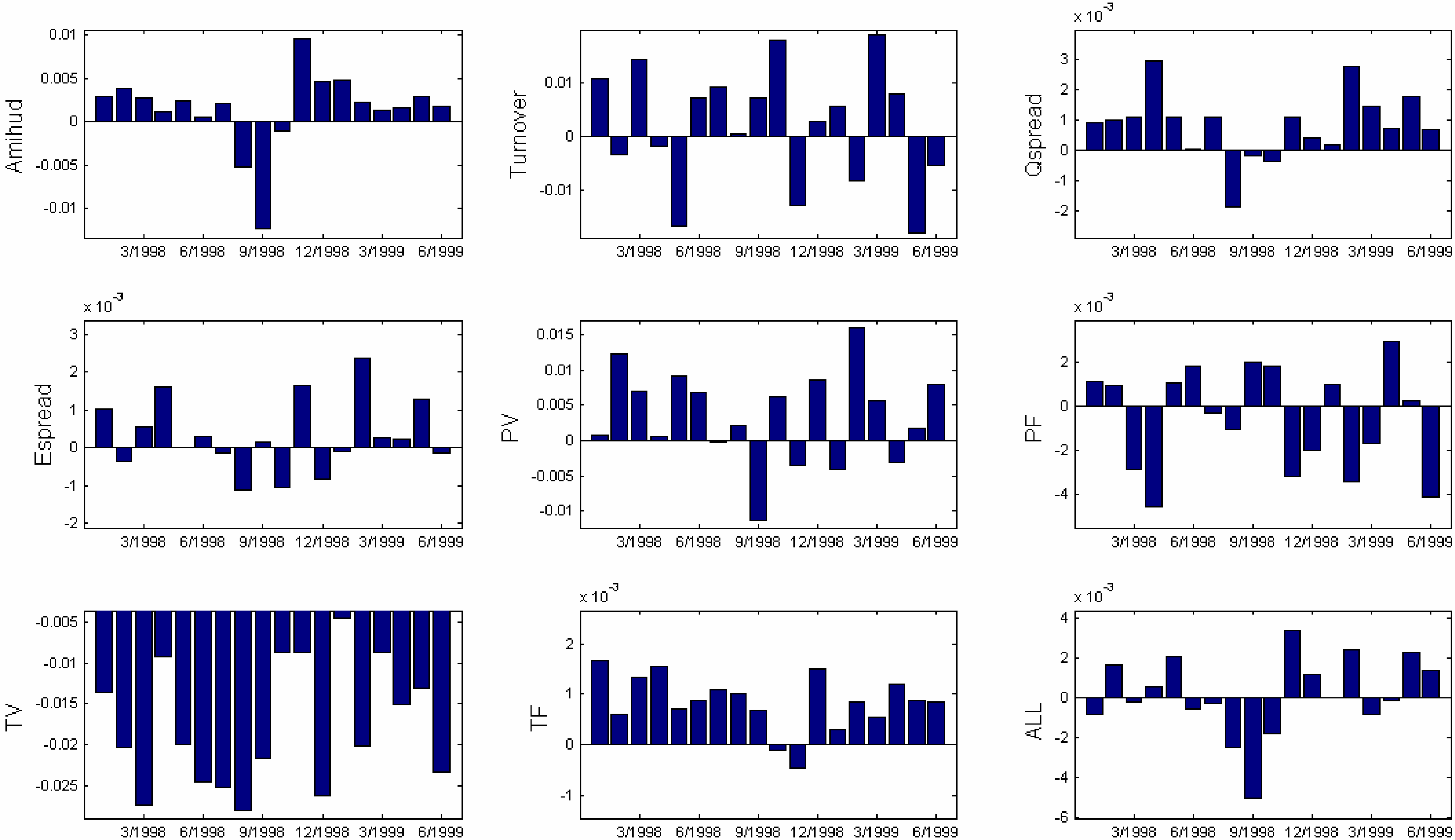

Figure 3. The time series of liquidity shocks of Figure 2 over the subperiod January 1998 through December 1999.

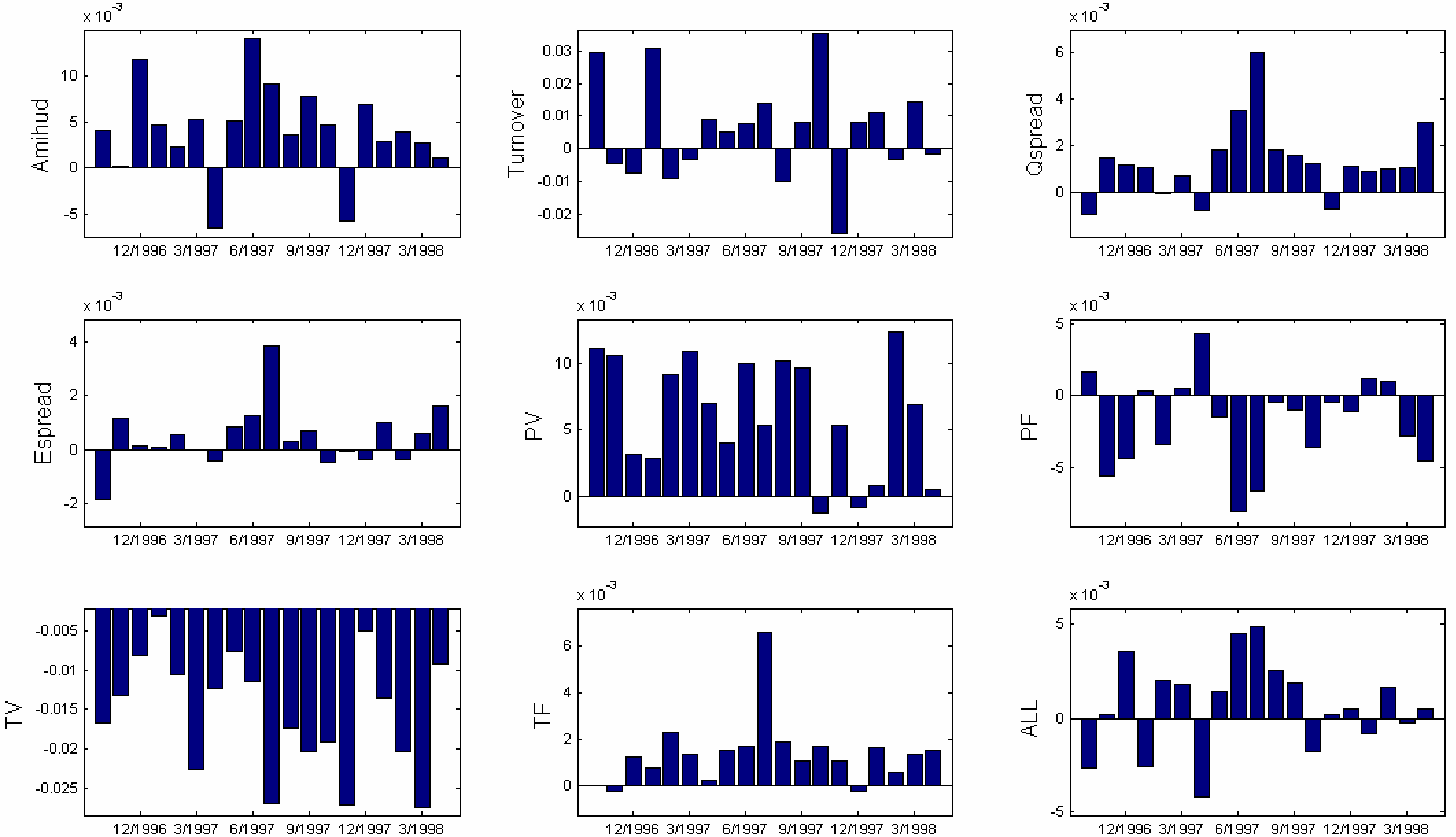

Figure 4. The time series of liquidity shocks of Figure 2 over the subperiod October 1996 through March 1998.

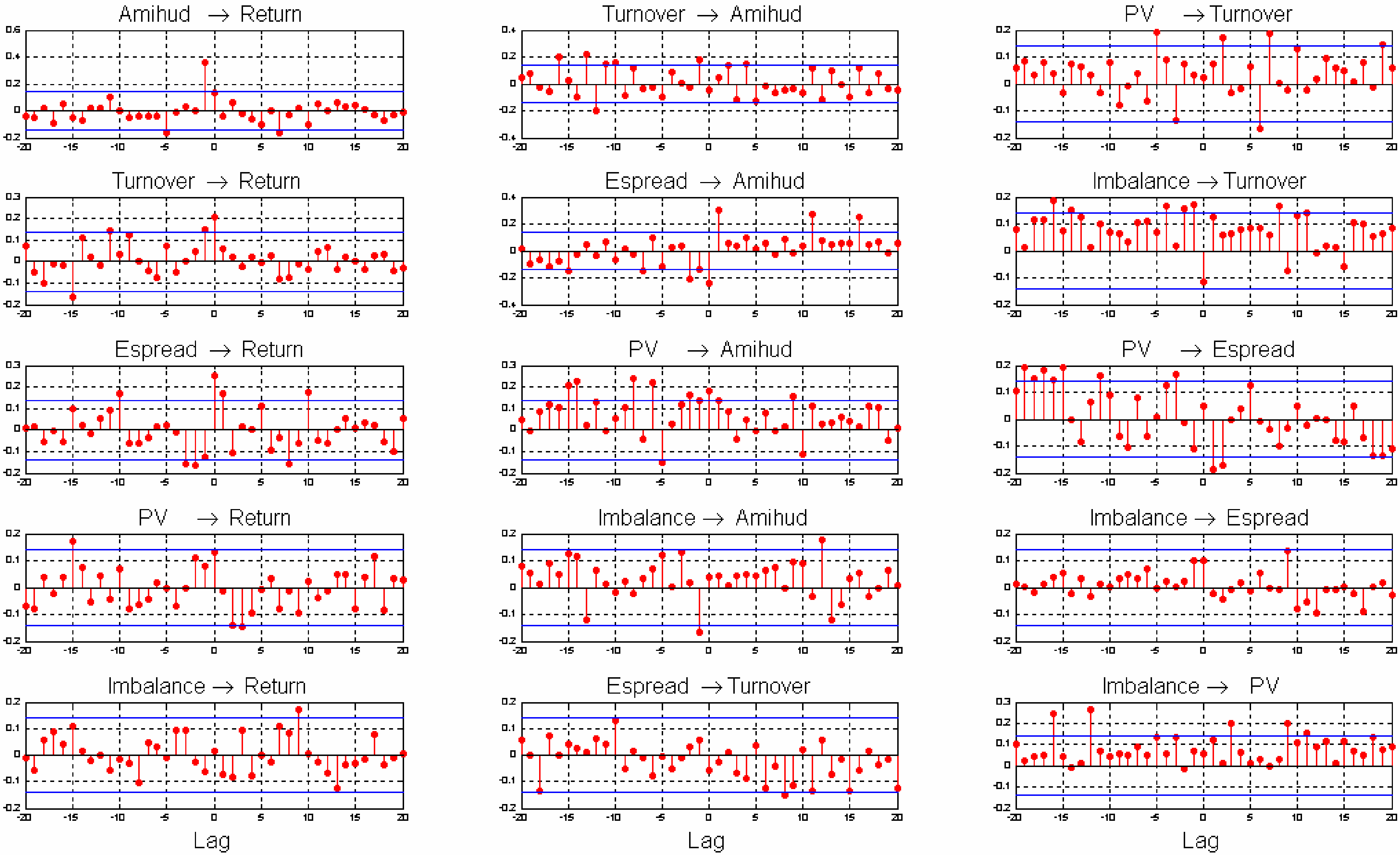

Figure 5. Lead-Lag Correlations of Liquidity Shocks (first component). Common factors are extracted separately for returns and different measures of liquidity using the APC method. Factor shocks are calculated as the residuals of an AR(2) model (estimated using a monthly expanding window). The figure plots the pairwise correlation between the leads and lags of first principal component shocks. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, order imbalance measured as the ratio of the net sum of signed trading volume through the month scaled by the number of shares outstanding (the sign of each trade is determined by the classification scheme introduced by Lee and Ready (1991)), and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each liquidity variable is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

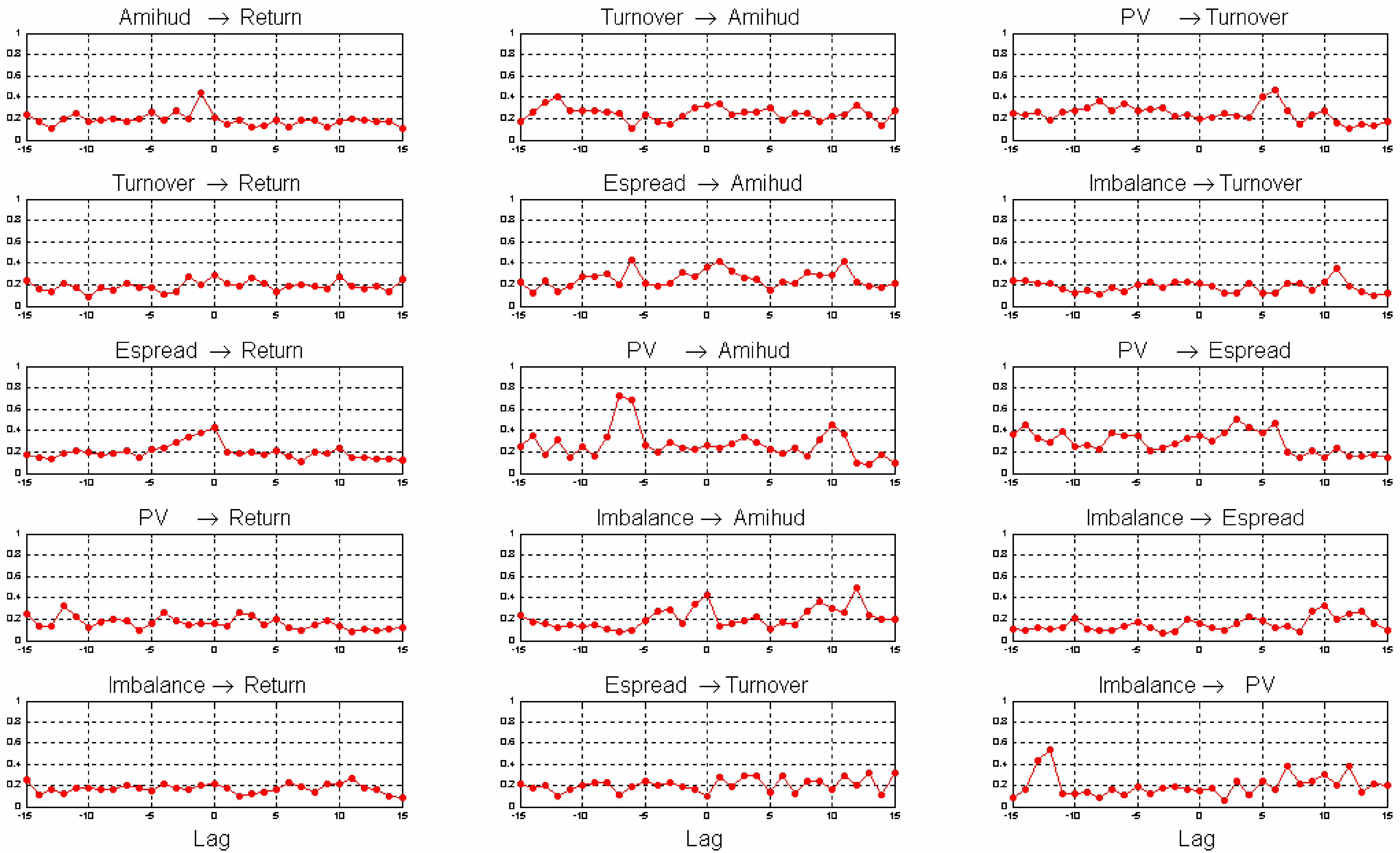

Figure 6. Lead-Lag Canonical Correlations of Liquidity Shocks. Three common factors are extracted separately for returns and different measures of liquidity using the APC method. Factor shocks are calculated as the residuals of an AR(2) model (estimated using a monthly expanding window). The table reports the first canonical correlation between the leads and lags of two groups of common factors. The liquidity measures analyzed are: The Amihud (2002) measure, defined as the monthly average of daily absolute value of return divided by dollar volume, turnover, defined as the ratio of monthly volume and shares outstanding, the average monthly quoted spread measured as the ratio of the quoted bid-ask spread and the bid/ask midpoint, the average monthly effective spread measured as the absolute value of the difference between the transaction price and the midpoint of quoted bid and ask, divided by the bid/ask midpoint, order imbalance measured as the ratio of the net sum of signed trading volume through the month scaled by the number of shares outstanding (the sign of each trade is determined by the classification scheme introduced by Lee and Ready (1991)), and four price-impact components PV, PF, TV, TF, as measured in Sadka (2006). Prior to the extraction of common factors, for each stock, each liquidity variable is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).

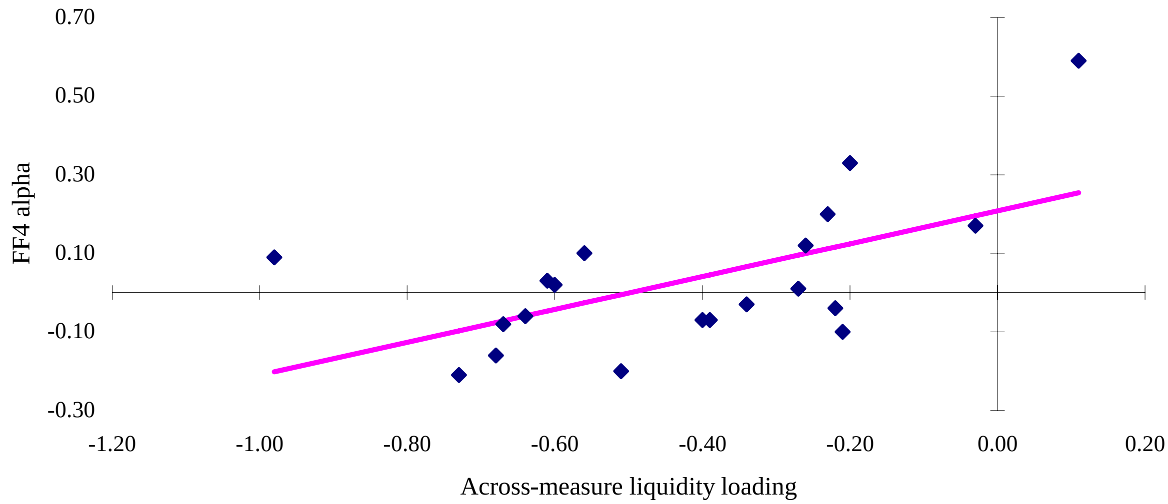

Figure 7. Risk-adjusted returns and liquidity loadings. Across-measure common factors are extracted jointly for different measure of liquidity measures using the APC method. Factor shocks are then proxied with AR(2) residuals calculated using a monthly expanding window. Twenty portfolios are sorted each month by the across-measure liquidity loading estimated using the past 36 months (the loading is computed while controlling for Fama-French four factors). The risk-adjusted returns of each portfolio *p*, α_p, are calculated using Fama-French four factors. In addition, the loading of each portfolio on the across-measure liquidity factor, $\beta_{LIQ,p}$, is calculated using a time-series regression of returns (excess of the risk-free rate) including the Fama-French four factors. The points on the graph plot the risk-adjusted returns against the liquidity loadings. The line plots the fitted regression model

$$\underset{[3.09]}{\alpha_p = 0.21} + \underset{[3.07]}{0.42}\beta_{LIQ,p} + \varepsilon_p , \qquad R^2 = 0.34$$

where ε_p is the error term (*t*-statistics are in square brackets). The sample includes 4,055 NYSE-listed stocks with available intra-day data from ISSM and TAQ for the period January 1983 until December 2000 (216 months).