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by

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What Captures Liquidity Risk? A Comparison of Trade and Order Based Liquidity Factors

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Abstract

Is the effect of liquidity risk on asset prices sensitive to our choice of liquidity proxy? In addressing this fundamental question, we achieve two main results. First, when we estimate factor models on a broad range of liquidity measures we uncover a profound distinction between trade and order based liquidity. Second, although the order based factor provides a better signal of available liquidity, we find that only the factor related to information risk explains expected returns both in a theoretical liquidity-CAPM model and in a linear pricing framework. Our results suggest a surprising fragility of liquidity-based asset pricing.

JEL Codes: G12; G14

Keywords: CAPM; Liquidity Risk; Liquidity Factor; Order Based Measure; Trade Based Measure; Information Risk

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1 Introduction and Motivation

Does it matter how we measure liquidity? This question is important for individuals and institutional investors as well as central banks. There is some evidence that various liquidity measures tend to move together.[1] However, the results are mixed.[2] If different liquidity measures yield different predictions about the investment climate, it is crucial to distinguish which "liquidity" is most reliable. This distinction is vital during times of market stress, when accurate liquidity assessment is most valuable.

Our paper adds to the growing literature on liquidity along two important dimensions. First, we suggest a practical method for measuring liquidity. This is important because there is still no consensus liquidity measure: existing research uses more than a dozen distinct liquidity measures, all with different properties (see Aitken and Comerton-Forde [2003], Holl and Winn [1995], and Roll [2005].) In particular, we advocate using factor analysis, in conjunction with economic interpretation of the factors.[3] Moreover, an important empirical challenge is that different liquidity measures capture different aspects of the trading climate. Hence it is possible to have mixed signals. For example, during financial crises one may observe signals of both low liquidity (high spreads) and high liquidity (large volume), simultaneously.

Second, we take steps to reconcile key theoretical and empirical contradictions, by exploring a natural distinction between trade and order based liquidity. We briefly summarize the major theoretical and empirical contradictions. Regarding theoretical contradictions, classic papers conclude that in many situations there may be no trade, and that liquidity costs have small effects (see, for example, Milgrom and Stokey [1982]), and Constantinides [1986], respectively.) However, financial markets exhibit large volumes of trade, and recent research finds significant effects due to liquidity risk (see Pastor and Stambaugh [2003] and Acharya and Pedersen [2005].) Regarding empirical inconsistency, some liquidity measures exhibit strong commonality, while others do not. This inconsistency is important to resolve because commonality is the basis of liquidity-based asset pricing work: without evidence of systematic liquidity comovements, the bedrock of liquidity-based asset pricing would turn to quicksand.

[1] See, for example, Chordia et al. [2000] and Huberman and Halka [2001].

[2] See Aitken and Comerton-Forde [2003], Hasbrouck and Seppi [2001], and Roll [2005].

[3] We are aware of two papers that use a similar methodology; Chen [2005] and Korajczyk and Sadka [2007]. However, these papers do not distinguish between the type of liquidity measures, nor do they appear to provide an economic interpretation of the factors.

1.1 Overview of the paper

Our paper proceeds in three basic steps. First, we pool a set of 14 distinct measures that cover different liquidity dimensions, and extract and interpret the three most significant common factors. These factors reflect order based considerations, trade based considerations, and a mixture of return volatility and information risk. For simplicity, we call the first two factors order and trade factors, respectively. The third factor has significant loadings on both trade and order based liquidity variables. Because of its strong correlation with Amihud's [2002] illiquidity measure, we denote the third factor the Amihud factor. Second, we find supporting evidence for the conjecture that different liquidity measures point in conflicting directions during important events. We also provide an economic interpretation of our liquidity factors. Third, using our liquidity factors, we examine pricing implications in both theoretical and atheoretical models. The theoretical model is the liquidity-adjusted CAPM of Acharya and Pedersen [2005]. In this model, we document that only the Amihud factor is related to stock returns. Consequently, the risk premium found for liquidity may reflect a compensation for information risk. This is important since many studies on the role of liquidity risk in asset pricing use versions of Amihud's illiquidity measure. The atheoretical model is a simple factor model in the Fama-French tradition. In a cross section of stocks listed at the Oslo Stock Exchange, the CAPM augmented with the Amihud factor prices out the SMB and HML factors. However, the "pure" trade and order factors are less effective. Moreover, the Amihud factor is the one to receive significant premia.

The remainder of the paper is organized as follows. Section 2 summarizes the relevant literature. Section 3 describes the data, presents descriptive statistics, and documents the results of our common factor analysis. We then investigate the relationship between the common liquidity factors and asset returns in section 4. Section 5 concludes.

2 Summary of Related Literature

There is a vast and growing empirical literature on liquidity's role in asset pricing.[4] Before selectively summarizing this literature, we may bear in mind two key distinctions that impinge on analysis of liquidity. The first distinction is between trade and order based liquidity. Trade based measures such as trading volume and turnover reflect ex post liquidity, and therefore do

[4]For a more comprehensive literature review, see the surveys of Amihud et al. [2005], O'Hara [2003], and Stoll [2000].

not always give a good picture of the ease of transferring financial assets into cash. Order based measures such as spreads and order-book depth are *real time* measures of available liquidity, and although imperfect, give a better idea of an investor's current ability and cost to transfer assets into cash.[5] As can be seen in Table 1, empirical research on liquidity uses a variety of trade and order based measures, sometimes separately, sometimes together in the same study. Therefore the results could reflect dominance of either trade or order measures, making it difficult to speak definitively about pricing properties of liquidity. The second distinction concerns the four dimensions of liquidity, namely cost, resiliency, time and quantity. The cost dimension relates to the cost of transacting. In this dimension, an asset is liquid if its transaction cost is low, for example if it has a small bid-ask spread. The resiliency (or price impact) dimension relates to the ability to trade without affecting prices a lot. The time dimension relates to the speed of transacting. Accordingly, in this view, an asset is liquid if it can be traded quickly. An example of a measure that captures the time dimension is the measure of Liu [2006].[6] Finally, the quantity dimension relates to the amount of trading that can be absorbed. According to this dimension, an asset is liquid if large amounts of it can be traded.[7]

Now, in a selective survey of the literature on liquidity and asset pricing, we focus on two areas of research: those concerned with distinguishing liquidity measures, and those that attempt to construct and test *comprehensive* liquidity factors.[8] With regard to distinguishing liquidity measures, two papers are relevant.[9] Holl and Winn [1995] calculate the correlation structure for 25 measures of liquidity using transactions data from the Australian Stock Exchange (ASE) in 1995. Only those measures that are similar by design are found to be correlated, indicating that different measures of liquidity capture different characteristics of assets. In another study, Aitken and Comerton-Forde [2003] use data from the Jakarta Stock Exchange (JSE), and divide liquidity measures into trade and order based measures. They find a low correlation between the two categories. By examining changes in the liquidity measures within each category before and after an economic crisis on the JSE, the authors provide evidence that order based measures provide a better proxy for liquidity than trade based measures. Neither one of these studies considers liquidity in an asset pricing perspective, and they both stop short of constructing

[5]For more on this distinction, see Aitken and Comerton-Forde [2003], Holl and Winn [1995], and Roll [2005].

[6]Liu [2006] proposes a new liquidity measure for individual stocks, which is defined as the standardized turnover-adjusted number of zero daily trading volumes over the prior 12 months. Although this measure captures several dimensions of liquidity the study put particular emphasis on the time dimension.

[7]For more details, and an exploration of interaction of these dimensions, see Hodrick and Moulton [2006].

[8]In the interests of space, we do not discuss a number of other related issues such as commonality and the liquidity premium. Some of these papers are summarized in Table 1.

[9]Roll [2005] has discussed this issue in presentations, although not in a written research paper.

liquidity factors. Our paper is similar to these two in that we believe it is crucial to consider the differential signals from different types of liquidity. We differ in that, building on this belief, we actually construct liquidity factors and examine their performance in asset pricing models.

With regard to constructing comprehensive liquidity, three papers are relevant, namely Hasbrouck and Seppi [2001], Chen [2005], and Korajczyk and Sadka [2007]. Hasbrouck and Seppi [2001] analyze liquidity measures, returns, and order flows using a factor analysis, and find little evidence of a common factor in liquidity. Chen [2005] constructs a common liquidity factor from a few different liquidity measures using principal components analysis. She finds that exposure to the first principal component is priced. She also distinguishes liquidity effects from volatility effects, and documents that stock market liquidity is priced in bond markets. Korajczyk and Sadka [2007] construct common liquidity factors both within single liquidity measures (similar to the Hasbrouck and Seppi [2001] approach) and across different liquidity measures. They document that common liquidity across different measures is a robust priced factor, while common liquidity factors within single measures are not. Our work is similar to these papers in that we attempt to extract fundamental liquidity from a set of factors. We differ in at least three significant ways. First, a major difference is that we do not accept prima facie comovement as evidence of commonality; we examine the economic meaning of each common factor, and consider the potential for mixed signals from trade and order based liquidity. Second, we investigate whether the relationship between liquidity factors and asset prices is different for trade and order based factors. A final difference is that we test the pricing properties of our liquidity factors in both theoretical and atheoretical pricing frameworks.

[Table 1 about here.]

3 Empirical Liquidity Measures

In this section we provide a short description of our data set, and present summary statistics. We then present the results from our common factor analysis and discuss the interpretation of our liquidity factors.

Our data set comprises roughly five years of high-frequency data from the Oslo Stock Exchange (OSE), containing every single order and trade for all listed firms. The sample period is February 1999 through 2004. Norway is a member of the European Economic Area, and its equity market is among the 30 largest world equity markets by market capitalization.[10] At the

[10]The source of information on market capitalization is FIBV (International Federation of Stock exchanges).

end of 2005, 219 companies were listed at the OSE with a total market value of NOK 1,403 billion (roughly US$230 billion). Since January 1999, the OSE has operated a fully automated computerized trading system similar to the public limit order book systems in Paris, Stockholm, and Toronto. Our data sample is unique in that it enables us to construct a wide range of liquidity measures in "real time" from the actual sequence of trades and orders. We know every order and trade that occurred during the sample period. The order data include all order submissions, deletions and amendments of existing orders. We also know whether an order is a buy or a sell order. Thus, for each security in the data, we are able to reconstruct the entire order book at any point in time. Every trade is linked to the underlying orders through an order ID. Thus, if a large order is executed against many smaller orders resulting in several smaller trades, we can trace each executed part back to the initial order.[11]

3.1 Descriptive statistics

Liquidity is often defined as "an ability to trade large quantities quickly at low cost with little price impact". This definition suggests four aspects of perfect liquidity. The aspects comprise a cost dimension, a resiliency dimension (how good is one's ability to trade with minimal price impact), a quantity dimension (how much can you trade at a given cost), and a time dimension (how quickly can you trade a given quantity at a given cost). A major problem in estimating the effects of liquidity on asset prices has been to find empirical measures that can capture all of these aspects. We try to overcome this problem in the following way. First, we calculate a large set of liquidity variables that according to the literature should capture the different dimensions of liquidity. Second, for practical implementation, we use common factor techniques to extract a small number of factors.

The selected panel of liquidity measures comprises five trade measures and nine order measures. The trade measures include the number of trades, the trading volume in shares, turnover, the number of seconds between trades, and Amihud's [2002] illiquidity ratio. Order based measures include quoted spread, relative quoted spread, depth at the inner quotes, the number of submitted limit orders, the fraction of all orders that are limit orders, the time between sub-

[11] To remove very illiquid securities and securities that only have a short listing period in the data sample, we filter the sample as follows. First, each firm is required to have been listed for the entire data sample period. In addition, the firm must have been traded on at least 80 percent of the days when the Oslo Stock Exchange is open for trading (1539 days). This reduces the sample to a total of 42 securities. To remove outliers from the reduced data sample, we check for erroneous order submissions. This is done for the largest orders submitted across all firms on each day. If we see that a large order is immediately canceled or amended to a significantly lower volume, we correct the volume in the initial submission. In addition, we remove all odd-lot trades and orders and all trades reported as off market trades.

mitted limit orders, order book symmetry, and two measures of the order book slope.[12] All variables are first calculated for each security on each trading date.[13] Then, a cross sectional average is calculated for each day. The cross sectional average represents the market wide realization of the liquidity variable on each date. Table 2 provides descriptive statistics for the liquidity measures, which we quickly summarize.[14] Over the sample period, there were on average 4494 trades in the firms each day, and the average depth at the inner quotes was 8893 shares. Measured by the quoted spread, the average cost of trading over the period was NOK 1.37, or 2.28 percent of the midpoint prices. A median number of seconds between trades of 2718 (over 45 minutes) reflects infrequent trading by some firms in the sample. However, since this is the distribution of the daily average, it does not capture considerably more frequent trading by many firms.

[Table 2 about here.]

3.2 Constructing Liquidity Factors

In preparation for our factor analysis, one important criterion is that the variables be sufficiently correlated. A rule of thumb is that a substantial number of the correlation coefficients should exceed 0.30. Table 3 helps us in this regard, since it presents correlation matrices. In particular, correlations greater than 0.30 are in grey cells. Visual inspection of the matrix indicates that a factor analysis is appropriate. Interestingly, most order and trade measures in the same liquidity dimensions exhibit fairly high correlations.

We now turn to the results of our factor analysis, which reduces our large set of liquidity variables into a manageable number of liquidity factors.[15] Table 4 summarizes the main results. The table shows rotated factor loadings for three extracted factors as well as the final estimates of shared variance among the variables. A rule of thumb frequently used is that factor loadings greater than 0.30 in absolute value are significant. These loadings are marked gray in the table. We also report Kaiser's Measure of Sampling Adequacy (MSA), both overall and for individual

[12]We do not include the effective spread since it is actually a hybrid between a trade based and an order based measure. Moreover, effective spreads are highly correlated with quoted spreads, especially in a limit order market where there are no price improvements.

[13]To avoid biases from intra-day trading patterns, we divide each trading day into 6 hourly intervals. Except for the trading frequency, the share volume and the illiquidity ratio, all measures are first averaged within each interval and then averaged over the 6 intervals to get a daily average.

[14]Some background information not in the tables: At year-end 2004, the average market cap of the sample firms was NOK 7.46 billion, with a maximum and minimum of NOK 124 billion and NOK 104 millions, respectively. Regarding the liquidity measures, a detailed description of their calculation is provided in the Appendix.

[15]A short discussion of the main design issues involved in the analysis and some robustness tests of the results from the analysis are provided in Appendix B.

variables.[16] In general, values of MSA greater than 0.8 are considered good, while values less than 0.5 are unacceptable. We find an overall MSA of 0.78, and individual MSA between 0.61 and 0.89. Hence, the set of liquidity variables seems well suited to factor analysis.

We extract 3 common factors, denoted Factors 1, 2, and 3, respectively. Factor 1 explains 39% of total shared variance among the variables, while Factors 2 and 3 explain 36% and 25%, respectively. Factor 1 is mainly an order based quantity measure, although it also has significant negative loadings on quoted spread and the illiquidity ratio. Factor 2 captures both trade and order measures related to the dimensions of quantity and immediacy. Factor 3 has significant loadings on all liquidity dimensions from both trade and order measures. There are three prominent variables; Amihud's price impact measure (largest significant split loading), the relative spread (only significant loading), and symmetry of the order book (only significant loading).[17] The first two variables are typically related to private information.

[Table 3 about here.]

[Table 4 about here.]

Since we are interested in differential properties of trade and order measures, we also estimate two separate common factor models, including only trade measures (model B), and only order measures (Model C). The results from these estimations are summarized in Table 12. Model B has one common factor, which is related to the quantity and immediacy dimensions of liquidity. Model C has two common factors. The first factor explains 68 percent of the shared variance and is mainly related to quantity variables. The second factor is a bit hard to interpret because it is loaded from variables representing three different liquidity dimensions. Based on the factor analysis, we extract daily score series that represent the daily realizations of the common factors in the three models. The correlation matrix for the factor scores is presented in Table 5, which we now discuss.

[Table 5 about here.]

Some interesting patterns emerge from the factor score correlation matrix. Factor 1 in Model A has a correlation coefficient of 0.96 with the first factor in the order based model and

[16] The underlying assumption of factor analysis is that there exists a number of unobserved latent variables that account for the correlations among the observed variables, such that if the latent variables were held constant, the partial correlations among the observed variables would be small. Kaiser's Measure of Sampling Adequacy is a summary measure of how small the partial correlations are relative to the ordinary correlations.

[17] A split loading means that a variable has multiple significant loadings. Ideally, we would like to see a single significant loading for each variable on only one factor.

Factor 2 in Model A has a correlation coefficient of 0.93 with the factor in the trade based model. Thus, even when we pool all the liquidity variables together in Model A, we extract one order based factor and one trade based factor. The order based factor reflects the quantity (or depth) dimension of liquidity, while the trade based factor is related to both quantity and immediacy. The third factor in Model A is negatively related to the "hard to interpret" factor in the order based model (Factor 2 in Model C).[18] Note that Factors 1 and 2 measure liquidity, since they increase with liquidity. By contrast, Factor 3 measures illiquidity, since it decreases with liquidity.

3.3 Economic interpretation of the liquidity factors

The factor model results indicate that there is an important distinction between order based and trade based liquidity variables. The main difference between the two classes of measures is that order measures reflect pre-trade liquidity while trade measures reflect post-trade liquidity. Aitken and Comerton-Forde [2003] argue that this difference makes order measures better proxies for liquidity, since they more accurately indicate currently available liquidity than do trade measures. This point is illustrated empirically by data for the two classes of measures during an economic crises. We find similar patterns for our liquidity variables during important events, both at the firm and aggregate levels. Figure 1 depicts the behavior in two order measures (spread and depth) and one trade measure (volume) for a specific firm event. Panel A indicate that there was an increase in liquidity, as measured by the increase in trading volume. However, Panel B shows that, exactly at the same time, there was an increase in spreads and decrease in depth, indicating reduced liquidity and increased costs. This type of discrepancy may also exist at the aggregate level, as depicted in Figure 2. In this case, aggregate trading volume in Panel A indicates increased liquidity, while average depth and spreads again signal the opposite, decreased liquidity and higher transaction costs.

[Figure 1 about here.]

[Figure 2 about here.]

Figure 3 shows the behavior of our factor scores over the same event period as in Figure 2. The major pattern is that the liquidity factors all track each other closely before the event,

[18] As a robustness test of the factor analysis, we split the sample in two and re-estimate all three models. The interpretation of the factors is similar for all models in all three sample periods. The correlations between the factors are also quite robust to the choice of sample period. This analysis is available from the authors on request.

and then diverge. Once again, there are mixed signals: the order based factor indicates reduced liquidity while the trade based factor suggests enhanced liquidity.

[Figure 3 about here.]

In sum, these examples support the notion that trade and order measures give different signals of liquidity during critical periods. In order to interpret these signals we need to know what aspects of a liquid market that are important for investors. As emphasized by O'Hara [2003], financial markets have two closely related functions; coordinating buyers and sellers and price discovery. The coordination role is carried out by liquidity providers, either designated market makers or traders utilizing a limit order book. The term price discovery describes the mechanism by which prices come to reflect relevant information. The coordination role of the market is what is commonly referred to as "liquidity". However, liquid markets also require a high quality of price discovery. Consequently, there is a *confounding* effect of price discovery on liquidity. Thus, we cannot know whether a prima facie relation between asset prices and liquidity indicates liquidity risk or information risk. For an example of this confounding effect, consider the spread, a widely used measure of liquidity. The spread is a good measure of liquidity in that it is low when the market functions well, and high when the market functions poorly. The size of the spread is, however, determined by both a coordination cost component and an adverse selection cost component.

The figures above suggest that order measures more accurately indicate the current coordination quality of the market than do trade measures. Evidently, trade measures also contain information about the efficiency of the coordination process, since when coordination is poor one would also expect the trading activity to be low. However, it could be that trade measures are more closely related to price discovery. The reason is that they reflect ex post realizations of liquidity demands from impatient traders, where the impatience can be related to both private information and funding needs. Trade measures should therefore give more information about the current direction of liquidity demand (and potentially the direction of information) than order measures. Thus, one possible interpretation of the distinction found between trade and order measures is that the confounding effect of price discovery on liquidity is more reflected in trade measures than in order measures.

To investigate this interpretation empirically, we need a proxy variable for information arrivals. A natural candidate is net order flow.[19] Table 6 shows the correlation structure between

[19] The market microstructure literature on foreign exchange shows a strong relationship between returns and net order flow, see for example Evans and Lyons (2001), Bjonnes and Rime (2004).

returns, volatility, net order flow, and absolute net order flow for our firms, as well as the correlations between these and our liquidity variables. The absolute net order flow is meant to capture the information intensity regardless of direction.

[Table 6 about here.]

We find a strong contemporaneous relation between returns and net order flow, and also between volatility and absolute net order flow. These results indicate that the strong explanatory power of net order flow on returns which is documented for foreign exchange markets may also apply for stock markets. Note also that the illiquidity ratio is almost perfectly correlated with daily volatility. Last, the trade and order measures diverge sharply in their relation with net order flow: all the trade measures have a notable correlation with absolute net order flow, while most order measures do not.[20] We do a similar exercise for our estimated liquidity factors in table 7. The table shows how the score series for the three factors are correlated with volatility, net order flow, market return and relative spread. The correlation coefficients provide further support to our factor interpretation. Factor 1 has a low correlation with net order flow, as was the case for most of the order based liquidity variables. Factor 2 has a fairly high correlation with the absolute value of order flow, as was the case for most of the trade based liquidity variables. Factor 3 is highly correlated with volatility and relative spread. The high correlation with volatility comes from the significant loading to Amihud's illiquidity measure. Since this factor exhibits high correlation with relative spread and a moderate correlation with absolute net order flow, it seems more related to information risk than factor 2. To summarize, our common factor analysis has provided us with three orthogonal liquidity factors; one order based factor, one trade based factor, and one factor that reflects return volatility and information risk.

[Table 7 about here.]

As we saw from table 1 the research outcomes of studies examining the question of whether liquidity is important for asset prices are ambiguous. Our results suggest that this may be related to an important difference between the various variables used in the various studies. More specifically, if order- and trade-based measures contain different information about liquidity and price discovery, it is important to be aware of this difference when selecting proxies for liquidity. By using our common liquidity factors, we will now examine whether the different types of liquidity variables yield differential results in asset pricing tests.

[20] The correlation coefficients between liquidity measures and net order flow are much lower because net order flow frequently changes its sign.

4 Asset Pricing Results

Existing empirical evidence on the role of liquidity risk in asset pricing largely supports the existence of a liquidity risk premium.[21] The main aim of this section is to examine the sensitivity of this result to the choice of empirical liquidity proxy. We first describe how time-series for market-wide and firm specific liquidity are created from the liquidity factors found in section 3. We then employ two different frameworks to explore the relationship between these liquidity variables and asset returns. The first empirical framework is based on the theoretical liquidity-CAPM of Acharya and Pedersen [2005]. In this model liquidity risk affect asset prices through three different channels reflecting the covariances between firm specific return, firm specific illiquidity, market return, and market illiquidity. By estimating the liquidity-adjusted CAPM, we can study the liquidity factors within the context of a theoretical model where the implications of liquidity on asset prices are exactly derived and easy to interpret. To investigate differences between the liquidity factors, we estimate the model separately for each of them.

The second empirical framework is a factor model in the style of Fama and French [1992], augmented with our liquidity factors. Specifically, we try to explain the cross-section of stock returns by different multi-factor models that includes liquidity factors as well as traditional risk factors (market, size, and value). This framework is similar to the one used by, for example, Pastor and Stambaugh [2003] and Liu [2006]. The atheoretical approach allows us to study possible joint effects of the liquidity factors, and to explore the relationship between the liquidity factors and other potential risk factors from the empirical asset pricing literature. These models are empirical in nature and make no attempt to explain why different factors should affect returns. This is the approach followed by much empirical work in this field.

4.1 Liquidity variables

In accordance with our factor analysis from the previous section, we wish to use three time series liquidity measures for our asset pricing tests. In keeping with most applied factor analysis, we use the factor scores, for both the market and individual liquidity measures. Specifically, for the market-wide liquidity we use the score realizations from the factor analysis,

$$s_t^M(j) = \sum_{k^M} \omega(j)^{k^M} k_t^M, \tag{1}$$

[21] The empirical evidence is substantial, see for example Chordia et al. [2000], Hasbrouck and Seppi [2001], Pastor and Stambaugh [2003], Acharya and Pedersen [2005], and Liu [2006].

where $s_t^M(j)$ is the market-wide score realization of liquidity factor $j \in \{1,2,3\}$ at time t, k^M are the normalized market-wide liquidity variables underlying the factor analysis, and $\omega(j)^{k^M}$ are the standardized scoring coefficients of the liquidity variables k^M for factor j. Similarly, for the firm specific liquidity variables, we use the standardized scoring coefficients from the factor analysis and normalized firm specific liquidity variables,

$$s_t^i(j) = \sum_{k^i} \omega(j)^{k^M} k_t^i, \tag{2}$$

where $s_t^i(j)$ is the score realization of liquidity factor j for firm i at time t, and k_t^i are the normalized firm specific liquidity variables.

4.2 Testing a Theoretical Liquidity Model

Acharya and Pedersen [2005] argue that in an economy with illiquidity costs, the benchmark CAPM shifts to account for three additional risk sources. First, investors require compensation for holding stocks that become illiquid when the market becomes illiquid. Second, investors accept a lower return on an asset that yields higher returns during periods of market illiquidity. Third, investors accept a lower return on a stock that is liquid during down markets. To estimate and test the model, Acharya and Pedersen [2005] derive an unconditional version, assuming constant conditional covariances of innovations in illiquidity and returns:

$$E(r_t^i - r_t^f) = E(c_t^i) + \lambda\beta^{1i} + \lambda\beta^{2i} - \lambda\beta^{3i} - \lambda\beta^{4i} \tag{3}$$

where the β variables reflect traditional market risk as well as the three types of liquidity risk described above.[22] Moreover, r^f is the risk free return, r^i (r^M) is the return of firm i (the market), c^i (c^M) is a measure of the illiquidity of firm i (the market) and $\lambda_t = E_t(r_{t+1}^M - c_{t+1}^M - r_t^f)$ is the risk premium.

[22]Specifically, the betas satisfy

$$\beta^{1i} = \frac{cov(r_t^i, r_t^M - E_{t-1}(r_t^M))}{var(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}, \tag{4}$$

$$\beta^{2i} = \frac{cov(c_t^i - E_{t-1}(c_t^i), c_t^M - E_{t-1}(c_t^M))}{var(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])}, \tag{5}$$

$$\beta^{3i} = \frac{cov(r_t^i, c_t^M - E_{t-1}(c_t^M))}{var(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])} \tag{6}$$

$$\beta^{4i} = \frac{cov(c_t^i - E_{t-1}(c_t^i), r_t^M - E_{t-1}(r_t^M))}{var(r_t^M - E_{t-1}(r_t^M) - [c_t^M - E_{t-1}(c_t^M)])} \tag{7}$$

Estimation

We estimate three versions of this model. We adjust for liquidity using the order based, trade based, and Amihud factors that we extracted before. Our estimation follows the procedure described in Acharya and Pedersen [2005].[23] It comprises four stages. In the first stage, we translate our liquidity variables into measures of illiquidity cost. In the model, illiquidity is defined as the per share cost of selling. We therefore scale the liquidity variables with the relative half spread. More specifically, we first run the regression,

$$S_t^i = \hat{\alpha}^i + \hat{\beta}^i s_t^i \tag{8}$$

where S_t^i is the daily percentage half spread of firm i averaged over week t and s_t^i is the score realization of firm i for week t. We then construct firm i's illiquidity, c_t^i, based on the estimate of the average cost of trading from the regression model (α^i), the coefficient relating changes in the liquidity variable to changes in the cost of trading (β^i), and the ratio of the volatility between the half spread and the score realization:

$$c_t^i = (\hat{\beta}^i s_t^i + \hat{\alpha}^i)\frac{\sigma(S^i)}{\sigma(s^i)} \tag{9}$$

where $\sigma(S^i)$ is the volatility of the half spread and $\sigma(s^i)$ is the volatility of the score realization. Hence, α is used to match the liquidity variable to the first moment of the half spread, while the volatility ratio $\frac{\sigma(S^i)}{\sigma(s^i)}$ is used to match the variable to the second moment of the half spread. Finally, β is used to convert variations in the liquidity variable into variations in illiquidity cost. The market illiquidity, c_t^M, is constructed similarly.

In the second stage, we form a market portfolio for each week t over our entire sample period based on all sample stocks. We also form four test portfolios for each week w during the sample period based on each stock's illiquidity in month $w-1$, computed as the average over month $m-1$ of the stock's daily illiquidities.

Similarly, we form four liquidity risk portfolios by ranking the stocks each month based on the average daily standard deviation of illiquidity over the previous month. We then compute returns and illiquidity costs for each portfolio for each week and the weekly returns on the market portfolio. In the third stage, we estimate innovations in market illiquidity, market

[23] Some differences follow from the limitations of our data sample. To reduce the problem with a short time period, we use weekly instead of monthly observations when we estimate the betas and test the model. This gives us 301 time series observations. In addition, when we form our test portfolios, we sort on the average daily illiquidity over the previous month (not previous year).

returns and in illiquidity for the four test portfolios. This is done using an ARMA modelling strategy, and ends up being an AR(4) specification. In the fourth and final stage, we run cross section regressions to estimate equation (3).

Properties of liquidity sorted portfolios

Table 8 shows some properties of the four illiquidity portfolios for each of the liquidity factors.[24] The four betas are computed using all weekly return and illiquidity observations for each portfolio and for an equally weighted market portfolio.

[Table 8 about here.]

It is instructive to compare our results based on the Amihud factor, since Acharya and Pedersen use a version of this same measure. The magnitude of the beta estimates is in fact quite similar to the results of Acharya and Pedersen. However, since their sample is larger and from a more liquid stock exchange, the variation in their estimates is larger. Reassuringly, our portfolios match best the most illiquid half of their portfolios. We also find, for all models, that the most illiquid stocks (based on previous illiquidity) have the highest variation in illiquidity and the smallest market cap. An interesting finding in Acharya and Pedersen [2005] is that illiquid stocks also have higher return volatility and higher liquidity risk, as measured by all three liquidity betas. Using the Amihud factor, we obtain similar results for β^2 and β^4 but not for β^3. An unsystematic pattern for β^3 (and β^1) risk may be explained by the relationship between illiquidity and return volatility in our sample; the most liquid portfolio also includes the most volatile stocks. This pattern should affect β^3 since it includes firm specific returns.

Having established a good correspondence between our results and the previous research, we are interested in studying whether there are any differences across the three liquidity factors. For the order based factor, the importance of β^3 (higher return sensitivity to market liquidity) seems to be a bit lower than for the other models. Also, the negative relationship between illiquidity and β^2 (meaning that commonality in liquidity with the market is highest for the most liquid stocks) is opposite from the other two models. Based on the Amihud factor, the relationship between illiquidity and β^4 increases monotonically over the portfolios and have a much larger variation than when we base portfolio construction on the two other factors. This is also the only factor for which we find a monotonically increasing relationship between illiquidity and weekly returns. As emphasized in Acharya and Pedersen [2005], there is an inherent severe

[24] We find very similar results when we sort the portfolios by the variation in illiquidity.

collinearity problem in their model caused by high correlations between the betas. This means that we cannot use the empirical results to distinguish separate effects of the individual betas.

Results

To determine whether the choice of liquidity variable is important for the existence of a liquidity risk premium, we estimate the Acharya and Pedersen [2005] model by a cross-sectional regression with the excess returns of our test portfolios on pre-estimated betas that are re-estimated each year. Since the sample period is relatively short, the results are not used as a formal test of the model. Instead, the main purpose of the exercise is to examine whether the order-based, trade-based and Amihud variables contain similar or differential information about expected returns. Table 9 provides the results from the cross sectional regressions on portfolios that differ in their liqudity attributes. The betas are estimated for each year and for each portfolio.

In bringing the theoretical model to the data, we have two issues to address. The first issue is that, in the theoretical model the liquidity cost is incurred once every period such that κ=1. However, since we are estimating the model for weekly periods, this is much shorter than a typical investor's holding period. Thus, following Acharya and Pedersen, in the models where the $E(c_t^p)$ has a superscript ^{a}, we scale the liquidity cost by the average turnover for all stocks in the sample, which is equal to 19 months (or 76 weeks). Since the average investor only incur the illiquidity cost once during his holding period, we proxy the estimation period cost to be 1/76th of the average cost of a trade. To accomodate a fixed κ, we treat the net return in models 1, 4 and 7 as $E(r_t^p - r^f) - \kappa E(c_t^p)$. In models 2, 5 and 8 we estimate κ as a free parameter, and in models 3 and 6 we ignore transaction costs. The second issue is that the theoretical model restricts the risk premia related to each beta to be the same, $\lambda^1 = \lambda^2 = \lambda^3 = \lambda^4$. To facilitate this constraint, we follow Acharya and Pedersen [2005], and construct a net beta which is the sum of the estimated betas for each portfolio. In particular, in all three panels, Model 1 estimates the liquidity adjusted CAPM with the model restriction of a single λ and a fixed transaction cost scaled to match the weekly estimation period. This is the estimation that is the most consistent with the theoretical model, and avoids severe collinearity issues associated with estimating the different risk premia separately.

[Table 9 about here.]

Examining the estimation results for Model 1 across the three liquidity variables, we see that the liquidity adjusted beta is significant and positive only in model 1c. This setup uses portfolios based on the Amihud factor. The R-squared suggests that the model is a poor fit to the data, but it is difficult with the small sample size to ascribe this to the model or noise. However, comparing the fit to the unadjusted CAPM which is estimated in model 3c, we see that the liquidity-adjusted CAPM in model 1c improves the explanatory power a great deal. Thus, although the unadjusted CAPM manages to explain some of the cross sectional return differences across portfolios, the liquidity adjusted CAPM does better. The results in models 1a and 1b shows no systematic relationship between the portfolio returns and the liquidity adjusted beta. This suggests that there is no priced liquidity risk connected to order-based and trade-based liquidity variables, in the context of the Acharya and Pedersen [2005] model.

If we believe the estimated coefficient in Model 1c, we can calculate the return premium associated with portfolios with the highest liquidity risk. Our estimate in model 1c suggests that λ=2.30. By using the β-estimates for portfolio 1 and 4 in table 8 we can calculate the annualized expected return differential between the two portfolios attributed to differences in their liquidity betas. For β^2 the model estimate of λ suggests that the return premium between portfolio 1 and 4 associated with β^2 risk is about 0.56% per year. The expected return difference related to β^3 is about 1% and the return difference associated with β^4 is almost 6%. This is somewhat higher than corresponding results for the US, although it is plausible when we consider the much higher market return: over this period the market return on the OSE averaged in excess of 20% per year. Importantly, the ranking of the return premiums associated with the liquidity betas are the same as in Acharya and Pedersen [2005].[25]

4.3 Atheoretical Liquidity Models

A limitation of the theoretical model above is its restriction to only one liquidity factor. In that setting, although we can estimate which liquidity factor performs best in the model, we cannot use information on other risk factors. This limitation is evidently at odds with a large empirical asset pricing literature on alternative risk factors. To accommodate this latter perspective, we now estimate factor models in the style of Fama and French [1993]. This approach enables us to ask whether the cross section of stock returns can be explained by one or more of our liquidity factors in *addition* to the CAPM beta and other standard risk factors. We construct test-assets and risk factors for each of our three liquidity factors using both the variance of the firm specific liquidity variables $var(s_t^i)$, and the level of the firm specific liquidity s_t^i. By utilizing a similar

[25] Acharya and Pedersen [2005] calculate the premium associated with β^2 to be 0.08% per year, β^3 to 0.16% per year and β^4 to be about 0.8% per year for the US market over a much longer sample period.

cross sorting method as is used for the construction of the Fama-French factors, we reduce the collinearity problem discussed above among the liquidity risk measures.

Constructing Test Assets and Risk Factors

The risk factors are "factor-mimicking" portfolios, constructed to have different degrees of liquidity risk. We create the mimicking portfolios by sorting firms into quartiles based on our three liquidity risk measures. Then, based on the factor-mimicking portfolios, we construct liquidity risk factors by computing the difference in the risk adjusted return between the high liquidity risk (mimicking) portfolio and the low liquidity risk (mimicking) portfolio. The test assets are 10 portfolios of firms constructed based on the market capitalization at the beginning of each year.

How does liquidity compare to standard suspects?

We now consider the second question from above, and compare the pricing performance of our liquidity factors to that of other factors. For this purpose, we use publicly traded firms from the Oslo Stock Exchange.[26] Table 10 shows estimated risk premia when we construct the risk factors from portfolios sorted on the variance of firm specific liquidity. Table 11 shows estimated risk premia when we construct the risk factors from portfolios sorted on the level of the firm specific liquidity composites.

[Table 10 about here.]

We first discuss the premia, then the asset pricing tests. The most significant finding for premia is that the Amihud factor is the only one that is consistently priced, in both Tables. The trade factor also has a significant premium, but only in the short horizon case of Panel A. In Table 11 there is a similar finding, although this is insignificant at the 8-week lag.

We now turn to the asset pricing tests. A brief background is as follows. The HJ distance of Hansen and Jagannathan (1997) measures the maximum annualized pricing error for each model. The SupLM test of Andrews (1993) measures whether the model parameters are stable over time. The Wald test assesses whether the coefficient on all the factors is equal to zero. The delta-J test of Newey and West (1987) examines whether SMB and HML have additional ability to explain asset prices, relative to each alternative model. In all cases, a low p-value

[26] The asset pricing tests on Norwegian data have to be interpreted with care, given the relatively small sample size. The total sample is 50 stocks, comprising all the stocks that were available for the full sample period, February 1999 to December 2004.

(less than 0.05, for example) indicates evidence against the model.[27] For Table 10 we examine first the HJ distance. In all cases the HJ distance has large p-values, and therefore cannot reject the models. The Wald test has small p-values in 3 cases, in both panels. These cases correspond to models with significant factor loadings being Fama-french, CAPM plus Factor 2, and CAPM plus Factor 3. The delta J test only has a p-value beneath 0.05 for one model in panel A, namely, the CAPM plus Factor 1. This indicates that HML and SMB potentially add information, for this model. For other models, there is no extra information from HML and SMB. In panel B, HML and SMB are priced out by all alternative models. Now we turn to Table 11, which gives similar estimates for the factors based on the level of liquidity. Here the HJ distance has large p-values, indicating that we cannot reject any model, in both panels. The Wald test has small p-values only in the Fama-French model, in both panels, indicating significant factor loadings. The delta J test in Panel A has low p-values for CAPM plus Factor 1, and CAPM plus Factor 2. A similar pattern exists in Panel B. Therefore HML and SMB add information in the presence of the first 2 factors, but not for the Amihud factor.

[Table 11 about here.]

5 Conclusion

Our research addresses the fundamental question, "Is the effect of liquidity risk on asset prices sensitive to our liquidity proxy?" There is currently little research on how best to define and test liquidity. This makes it difficult to agree on asset pricing implications, since many liquidity measures in use are only modestly correlated with each other. With this background in mind, our paper proceeds to address our leading question, in three steps.

First, we construct comprehensive liquidity factors from a panel of 14 diverse liquidity measures. We subsequently document "mixed signals" from both raw liquidity and liquidity factors – during critical events, order based measures correctly indicate diminished liquidity, while trade based measures erroneously suggest enhanced liquidity. This finding supports a dichotomy between trade and order measures, as alluded to by Roll [2005]. Second, unlike previous studies, we interpret our liquidity factors economically, and find that they reflect trade based, order based, and information considerations. Third, we use our liquidity factors to estimate both theoretical and atheoretical asset pricing models. With regard to asset pricing, we document that a theoretical liquidity CAPM outperforms the traditional CAPM only if we use

[27]These tests are standard in asset pricing literature. For more details on these tests, see Cochrane [2001].

a liquidity proxy related to information risk and return volatility, the Amihud factor. Moreover, in the atheoretical factor model, we find that although the Fama-French model sometimes does well relative to order-based and trade-based factors, it is usually outperformed by a model with the Amihud factor.

In summary, to the best of our knowledge, we are the first to construct and systematically interpret a comprehensive set of liquidity factors. Using a natural distinction between trade and order based factors, we document that the effect of liquidity on asset prices is sensitive to the choice of liquidity proxy. What are the relevance and importance of our results? These results are interesting and important, since our liquidity factors capture all dimensions of liquidity and are nonetheless easy to interpret. Furthermore, there is substantial practical value, since our portfolios can be easily utilized by moderately sophisticated investors. Consequently, investors may, in principle, be able to hedge specific types of liquidity risk by holding our factors. At a deeper level, our findings suggest great caution when deciding which types of liquidity to use in asset pricing. The reason is that research using trade based liquidity might only capture effects related to information risk or funding needs.

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A Calculation of liquidity variables

The appendix describes how the various liquidity measures used in the common factor estimation are calculated. To make the data discrete and have a common time frame we use hourly windows, starting from 10:00 am until 16:00 pm. Thus, we have 6 one hour intervals during each trading day. If not otherwise stated, the measures are first average within each interval, and then averaged over these intervals to get a daily average. For simplicity, summing and averaging operators as well as security and time indicators are suppressed in the equations. The variables are presented in alphabetical order.

`Depth at the inner quotes` is defined as the average share volume at the best quotes. The measure is calculated as $\frac{v^a+v^b}{2}$, where v^a is the share-volume at the best ask price and v^b is the share-volume at the best bid price.

`Frequency of limit orders` is measured as the number of limit orders submitted during the day excluding marketable limit orders. Thus, by only using the "passive" limit orders we measure only the liquidity provision in the market since the marketable limit orders are executed immideately and are the same as the trade frequency.

`Fraction of limit orders` is the number of limit orders providing liquidity in percentage of the total number of orders submitted into the market.

`Illiquidity ratio` measures how much the price moves per unit trading volume and was proposed by Amihud [2002]. The measure is calculated per day for each firm, using close to close returns as $\frac{|r|*100)}{\log(V)}$, where V is the total daily share volume, and r is the open to close return.

`Interquote time` measures the number of seconds between new limit orders.

`Order book symmetry` measures the symmetry of the limit order book. It is calculated as the difference between the ask and bid slopes over the first 6 ticks of the order book divided by the added 6 tick slopes (to ensure that the measure is equal to 1 and -1 if one side in the order book is empty),

$$(\frac{v_6^a - v_0^a}{p_6^a - p_0^a} - \frac{v_6^b - v_0^b}{p_0^b - p_6^b})/(\frac{v_6^a - v_0^a}{p_6^a - p_0^a} + \frac{v_6^b - v_0^b}{p_0^b - p_6^b}),$$

where v_0^b is the share volume at the best bid quote, v_6^b is the cumulative share volume 6 ticks away from the best bid quote, v_0^a is the share volume at the best ask quote, v_6^a is the cumulative share volume 6 ticks away from the best ask quote, p_0^b and p_0^a are respectively the best bid and ask quotes, and p_6^b and p_6^a are respectively the bid and ask quotes 6 ticks away from the best quotes.

`Price slope` is defined as the average of bid and ask slopes over the first 6 ticks of the order book computed relative to the price levels in the book,

$$\left\{\frac{v_6^a - v_0^a}{p_6^a - p_0^a} + \frac{v_6^b - v_0^b}{p_0^b - p_6^b}\right\}/2,$$

where v_0^b is the share volume at the best bid quote, v_6^b is the cumulative share volume 6 ticks away from the best bid quote, v_0^a is the share volume at the best ask quote, v_6^a is the cumulative share volume 6 ticks away from the best ask quote, p_0^b and p_0^a are respectively the best bid and ask quotes, and p_6^b and p_6^a are respectively the bid and ask quotes 6 ticks away from the best quotes.

`Quoted spread` is the difference between the best ask and bid quotes, $p^a - p^b$ where p^a is the best ask quote and p^b is the best bid quote.

`Relative quoted spread` is calculated as the quoted spread divided by the bid-ask midpoint price, $\frac{p^a - p^b}{(p^a + p^b)/2}$, where p^a is the best ask price, and p^b is the best bid price.

`Seconds between trades` is defined as the average number of seconds between trade executions.

`Tick slope` is defined as the average slope of the bid and ask side of the order book, where the slopes are measured over the 6 first ticks of the book and computed relative to the number of ticks away from the best quotes,

$$\left\{\frac{v_6^a - v_0^a}{6} + \frac{v_6^b - v_0^b}{6}\right\}/2$$

where v_0^b is the share volume at the best bid quote, v_6^b is the cumulative share volume 6 ticks away from the best bid quote, v_0^a is the share volume at the best ask quote, v_6^a is the cumulative share volume 6 ticks away from the best ask quote.

`Trade frequency` is measured as the total number of trade executions across all firms during the day.

`Trading volume` is measured as the total number of shares traded in the security during the day.

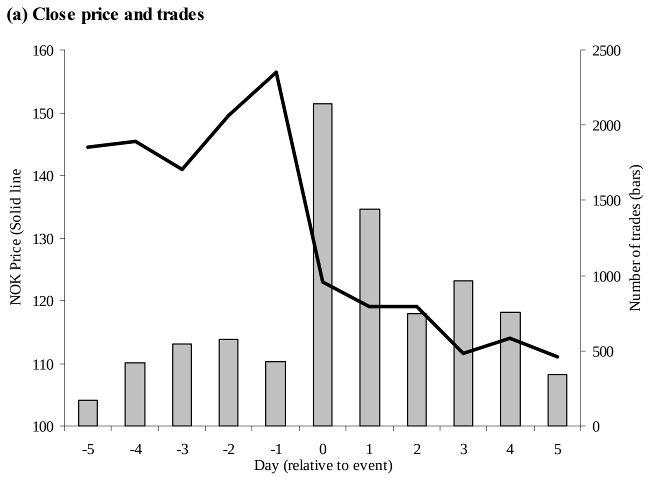
`Turnover` is measured as the trading volume divided by the number of issued shares in the company.

B Additional factor analysis results

Separate factor models for trade based and order based measures In panel A of table 12 (model B), we extract one common factor from a set of only trade based liquidity measures. The overall MSA of 0.71 indicate that the model is acceptable. Expect for the illiquidity ratio, the indiviual MSA numbers are also within the acceptable range. The factor is related to the quantity and immediacy dimensions of liquidity. In panel B of table 12 (model C) we extract two common factors for the set of only order based variables. Factor 1 explains 68 percent of the total shared variance among the variables, and is mainly driven by variables related to the quantity dimension of liquidity. Factor 2 is driven by variables related to the cost and immediacy dimensions of liquidity. The model is acceptable based on the MSA criterion. The overall MSA is 0.74, and the individual MSA numbers varies from a minimum of 0.56 for relative spread to a maximum of 0.82 for the NOK spread.

[Table 12 about here.]

Figure 1: Trade and order variables during an individual firm event
The figures show the developement in various liquidity measures in the days around an important event for a single Norwegian company, Tomra, which produces equipment for recycling bottles and cans. The event is 13 June 2001, when the German Bundesrat chose not to vote on a amendment that would have been beneficial for Tomra's earnings in Germany if it had been voted in favor of. This resulted in an increased uncertainty about the future of Tomra's products in Germany. Figure (a) shows the daily close prices and average number of trades for each day around the event. Figure (b) shows the average spread and depth on the dates at and around the event day.



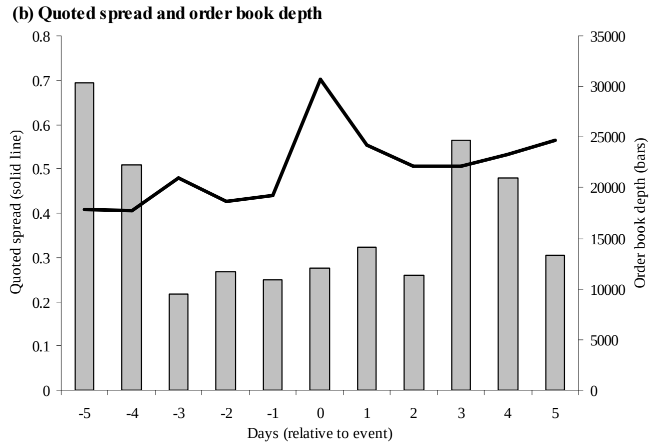
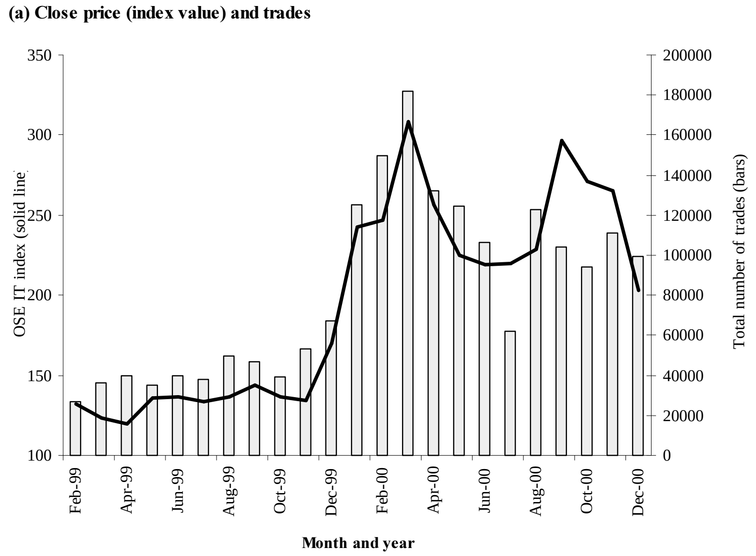


Figure 2: Marketwide liquidity variables around the burst of the internet bubble
Figure (a) shows the level of the Oslo Stock Exchange IT index and the total number of trades within each month from 1999 through 2000. Figure (b) shows the average quoted spread across companies at the OSE and the average depth in the order book within each month.



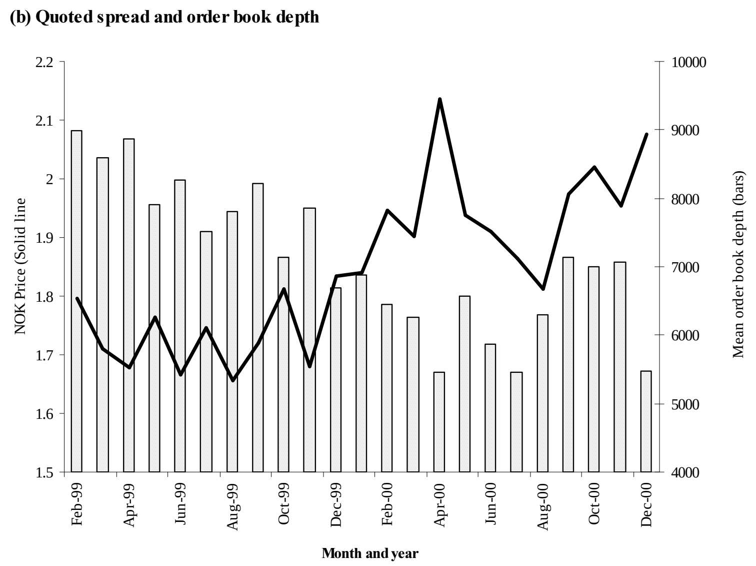


Figure 3: The common liquidity factors during the boom and burst of the internet bubble
The figure shows the time series of the three estimated common liquidity factors during the boom and the burst of the internet bubble.

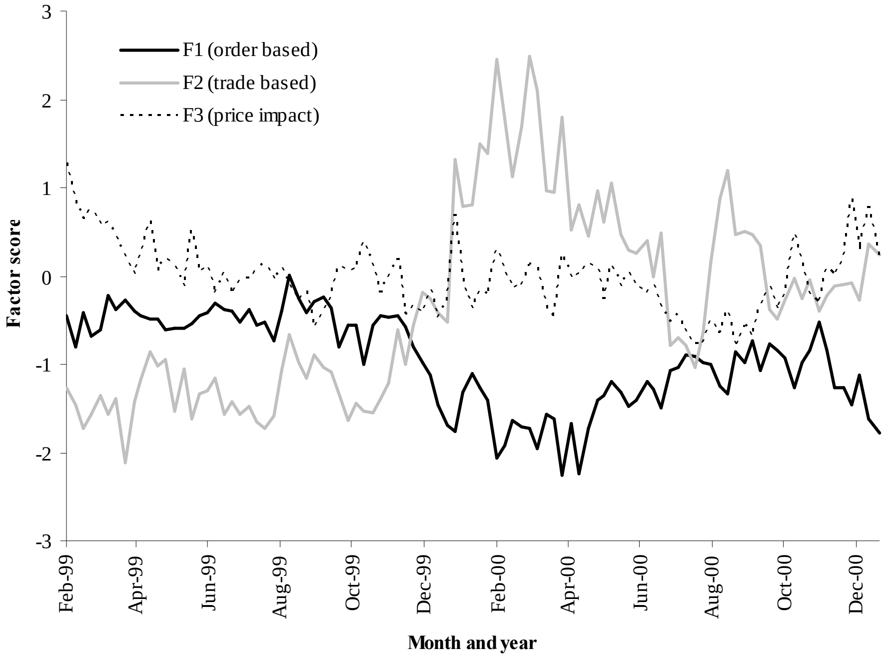


Table 1: Selective Summary of Literature

Article	**Type**	**Dimensions**	**Data**	Results	Article	**Type**	**Dimensions**	**Data**	Results
Liu [2006]	T	Quantity, Cost, Immediacy	1963-2003; daily and monthly; NYSE, AMEX, NASDAQ (1983-2003)	liquidity risk priced	Chordia et al. [2001]	T	Quantity	1966-1995; monthly data, NYSE/AMEX, NASDAQ (1984-1995)	negative relation between returns and volatility (and mean) of liquidity
Acharya and Pedersen [2005]	T	Price impact	1962-1999; daily; NYSE, AMEX	liquidity adjusted CAPM better than unadj. CAPM	Engle and Lange [2001]	T	Quantity, Immediacy	1990-1991; intraday; NYSE (TORQ)	likelihood of price adjustment increases with volume; depth negatively related to spreads
Chen [2005]	T	Quantity, Cost, Price impact	1963-2002; daily data; NYSE, AMEX	largest principal component priced (0.56% premium)	Lo and Wang [2000]	T	Quantity	1962-1996; weekly; NYSE, AMEX	evidence against 2-fund separation; a 2-factor model explains liquidity
Pastor and Stambaugh [2003]	T	Quantity, Price impact	1966-1999; monthly; NYSE, AMEX	positive liquidity premium	Korajczyk and Sadka [2007]	T,O	Quantity, Cost, Immediacy, Price impact	1983-2000; intraday data; NYSE	aggregate liquidity priced (level); large common factors
Jones [2002]	T	Quantity, Cost	1900-2000; annual; NYSE (Dow Jones)	liquidity predicts aggregate stock returns up to three years ahead	Aitken and Comerton-Forde [2003]	T,O	Quantity, Cost, Immediacy, Price impact	1996-1998; intraday data; Jakarta exchange	low correlation between trade- and order-based measures
Breen et al. [2002]	T	Price impact	1993-1997; intraday data; NYSE	predicted liquidity overestimated; especially for large and patiently executed trades	Hasbrouck and Seppi [2001]	T,O	Quantity, Cost, Price impact	1994; intraday data, NYSE	evidence of commonality in liquidity; common factors from order flow explain return variations
Amihud [2002]	T	Price impact	1963-1997; daily, monthly; NYSE	illiquidity has pos effect on returns if anticipated; neg effect if unanticipated	Huberman and Halka [2001]	T,O	Quantity, Cost	1996; Intraday data; TAQ	strong evidence of commonality; estimated residuals are correlated across portfolios
Eckbo and Norli [2002]	T	Quantity, Cost, Price impact	1963-2000, daily CRSP data for NYSE, AMEX, NASDAQ	Commonality in liquidity (except Pastor and Stambaugh [2003] measure), liquidity priced	Chordia et al. [2000]	T,O	Quantity, Cost	1992; Intraday data; NYSE	liquidity measures co-move

T=Trade-based liquidity measures, O=Order-based liquidity measures

Table 2: Descriptive statistics

The table presents means, medians, standard deviations, and maximum and minimum values for daily cross-sectional averages of our set of liquidity variables. A description of how the liquidity variables are calculated is provided in Appendix A.

	Mean	Median	STD	Max	Min
Trade based measures					
Trade frequency	4494	4434	1779	12030	604
Trading volume (shares)	10455041	9352699	5432928	41891165	1397510
Turnover	0.26	0.24	0.12	0.98	0.05
Sec. between trades	2770	2718	738	5126	965
Illiquidity ratio	0.57	0.55	0.20	2.41	0.22
Order based measures					
Frequency of limit orders	4343	4273	1717	11965	734
Depth inner quotes (shares)	8893	8623	2268	25304	3811
Tick slope	4893	4546	1673	10830	1822
Price slope	53899	37859	50709	313468	6956
Fraction of limit orders	0.66	0.66	0.03	0.77	0.56
Quoted spread (NOK)	1.37	1.34	0.34	2.37	0.70
Relative quoted spread	2.28%	2.20 %	0.70 %	6.53 %	0.97 %
Inter-quote time (seconds)	1096	1071	257	2404	549
Book symmetry	0.06	0.06	0.08	0.28	-0.20

Table 3: Correlation structure

The table shows Pearson's correlation coefficients for the whole set of liquidity measures. Correlation coefficients over 0.30 are in grey cells. Trade based variables include the number of trades, the trading volume in shares, the turnover, the number of seconds between trades, and Amihud's illiquidity ratio (absolute value of returns over trading volume). Order based variables include the number of limit orders, the depth at the inner quotes in shares, the order book slope measured in ticks over the 6 first ticks, the order book slope measured by price levels over the first 6 ticks, the fraction of submitted orders that are limit orders, the quoted spread, the quoted spread in percent of the midpoint price, the number of seconds between order submissions, a measure of the symmetry of the limit order book. A detailed description of how the liquidity variables are calculated is provided in Appendix A.

	Tfreq.	Tvol.	Turnover	Ttime	ILR	LO freq.	Depth	Tslope	Pslope	LO frac.	Spread	Rel. Spr.	IQtime
Trade based													
Trading frequency	1.00												
Trading volume	0.62	1.00											
Turnover	0.72	0.67	1.00										
Sec between trades	-0.48	-0.19	-0.49	1.00									
Illiquidity ratio	0.16	0.15	0.02	0.13	1.00								
Order based													
Limit order frequency	0.80	0.62	-0.10	-0.39	-0.10	1.00							
Depth inner quotes	0.03	0.51	-0.16	0.05	-0.16	0.26	1.00						
Tick slope	0.26	0.61	-0.34	-0.17	-0.34	0.54	0.76	1.00					
Price slope	0.11	0.67	0.01	0.08	0.01	0.29	0.62	0.64	1.00				
Limit order fraction	-0.10	0.08	-0.17	0.21	-0.33	0.36	0.26	0.39	0.32	1.00			
Spread	-0.10	-0.41	-0.21	0.11	0.43	-0.50	-0.59	-0.75	-0.55	-0.57	1.00		
Relative Spread	-0.16	0.05	-0.27	0.48	0.68	-0.33	-0.06	-0.35	0.13	-0.16	0.40	1.00	
Inter-quote time	-0.42	-0.20	-0.43	0.76	0.21	-0.48	-0.02	-0.26	0.00	-0.10	0.25	0.49	1.00
Book symmetry	-0.01	-0.20	0.00	-0.15	-0.24	-0.02	-0.15	-0.03	-0.25	-0.06	0.04	-0.29	-0.11

Table 4: Results from the estimation of a common factor model on all liquidity measures

The table presents the main results from a common factor model estimated on 5 trade based liquidity variables and 9 order based liquidity variables. MSA is Kaiser's measure of sampling adequacy. The factors are rotated orthogonally using the Varimax method. Grey cells indicate a factor loading above 0.30.

Model A	**MSA**	**Shared variance**	**Rotated factor loadings** **Factor 1**	**Factor 2**	**Factor 3**
Trade based measures					
Trade frequency	0.70	0.81	0.00	0.89	0.09
Trading volume	0.72	0.89	0.53	0.67	0.41
Turnover	0.85	0.67	0.15	0.81	0.02
Sec. between trades	0.72	0.63	0.14	-0.67	0.41
Illiquidity ratio	0.76	0.62	-0.34	0.11	0.70
Order based measures					
Frequency of limit orders	0.73	0.67	0.39	0.71	-0.11
Depth inner quotes	0.82	0.58	0.75	0.09	0.12
Tick slope	0.85	0.85	0.85	0.33	-0.12
Price slope	0.80	0.69	0.74	0.14	0.34
Fraction of limit orders	0.61	0.35	0.54	-0.14	-0.19
Quoted spread	0.89	0.79	-0.84	-0.14	0.27
Relative quoted spread	0.74	0.80	-0.18	-0.27	0.84
Inter-quote time	0.75	0.55	-0.03	-0.59	0.45
Book symmetry	0.87	0.15	-0.14	0.01	-0.36
Overall MSA	0.76				
Shared variance explained			3.47	3.45	2.14
% of total shared variance			38	38	24

Table 5: Relationship between factor models

The table presents the correlation matrix between the factor scores from three factor models. The three factors in Model A are extracted from all liquidity variables. The factor in Model B is extracted from trade based liquidity variables only, and the two factors in Model C are extracted from order based liquidity variables only.

	Model B (trade based)	**Model C** (order based)	
	Factor 1 (quantity, immediacy)	Factor 1 (quantity)	Factor 2 (all dimensions)
Model A			
Factor 1 (quantity)	0.18	0.96	0.11
Factor 2 (quantity, immediacy)	0.93	0.19	-0.48
Factor 3 (information)	-0.11	0.14	-0.83

Table 6: Correlation with returns, volatility, and order flow

The table presents the correlation structure of returns, volatility, and net order flow as well as the correlation coefficients between these variables and our set of trade and order based liquidity variables.

	Return	Volatility	Net order flow	|Net order flow|
Return	1.00			
Volatility	-0.03	1.00		
Net order flow	0.64	0.11	1.00	
|Net order flow|	0.06	0.40	0.20	1.00
Trade based measures				
Trade frequency	0.06	0.28	0.15	0.44
Trading volume	0.11	0.25	0.18	0.26
Turnover	0.21	0.17	0.19	0.29
Sec. between trades	-0.08	0.00	-0.02	-0.20
Illiquidity ratio	-0.06	0.96	0.08	0.32
Order based measures				
Frequency of limit orders	0.05	0.00	0.11	0.26
Depth inner quotes	0.11	-0.14	0.05	-0.06
Tick slope	0.16	-0.29	0.09	-0.02
Price slope	0.08	0.02	0.04	0.01
Fraction of limit orders	-0.02	-0.37	-0.01	-0.17
Quoted spread	-0.08	0.40	0.00	0.09
Relative quoted spread	-0.14	0.60	-0.02	0.05
Inter-quote time	-0.12	0.09	-0.06	-0.15
Book symmetry	-0.24	-0.23	-0.29	-0.05

Table 7: Correlation between factor scores, order flow and volatility

The table shows correlations between the three score series for the market-wide factors and volatility, net order flow and absolute net order flow. We also show the correlation of the factors with market returns and relative spread. All correlations are significant at the 1 % level.

	Factor 1	Factor 2	Factor 3
Volatility	-0.34	0.27	0.70
Net order flow	0.04	0.17	0.09
|Net order flow|	-0.14	0.41	0.18
EW market return	0.09	0.13	-0.06
VW market return	0.07	0.09	-0.04
relative spread	-0.18	-0.28	0.88

Table 8: Properties of illiquidity portfolios under different measures of illiquidity

The table presents descriptive statistics for the four betas in the liquidity-adjusted CAPM derived by Acharya and Pedersen [2005]. The betas are estimated based on three different liquidity factors for a set of four portfolios sorted on firm specific illiquidity (c_t^i). The most liquid (illiquid) stocks are sorted into portfolio 1(4). Following Acharya and Pedersen [2005], the beta estimates are multiplied by 100. The table also reports the mean and standard deviation of the illiquidity measure, the mean and standard deviation of the percentage weekly portfolio return, the MCAP of the portfolios in million NOK, and the mean and standard deviation of the percentage relative half-spread.

	Portfolio 1	**Portfolio 2**	**Portfolio 3**	**Portfolio 4**
Order based factor				
β^1	95.2	79.7	67.1	69.1
β^2	0.02	0.02	0.08	0.09
β^3	-1.28	-0.90	-0.68	-0.56
β^4	-1.86	-0.97	-1.46	-3.92
Mean illiquidity (%)	0.21	0.69	1.30	3.34
σ(illiquidity) (%)	0.36	0.20	0.35	0.95
Weekly return (%)	0.62	0.35	0.38	0.61
σ(weekly return) (%)	3.66	3.24	2.72	3.14
MCAP (mill. NOK)	16523	4607	1925	1085
Relative half spread (%)	0.51	0.73	1.21	2.86
σ(relative half spread) (%)	0.16	0.28	0.39	1.15
Trade based factor				
β^1	94.4	79.0	66.6	68.5
β^2	0.41	0.20	0.26	0.59
β^3	-1.44	-1.21	-1.23	-1.26
β^4	-1.54	-1.41	-2.19	-3.50
Mean illiquidity (%)	0.26	0.73	1.32	3.38
σ(illiquidity) (%)	0.63	0.24	0.35	0.85
Weekly return (%)	0.31	0.56	0.51	0.60
σ(weekly return) (%)	3.60	3.06	2.90	3.12
MCAP (mill. NOK)	17179	4182	1874	834
Relative half spread (%)	0.46	0.70	1.24	2.93
σ(relative half spread) (%)	0.20	0.21	0.41	1.15
Amihud factor				
β^1	95.7	80.1	67.5	69.4
β^2	0.04	0.10	0.13	0.51
β^3	-1.00	-1.16	-0.82	-1.86
β^4	-0.28	-0.75	-1.76	-5.23
Mean illiquidity (%)	0.35	0.75	1.25	3.04
σ(illiquidity) (%)	0.12	0.24	0.38	1.14
Weekly return (%)	0.35	0.49	0.53	0.61
σ(weekly return)(%)	3.43	3.21	2.80	3.29
MCAP (mill. NOK)	18124	3238	1723	972
Relative half spread (%)	0.36	0.75	1.25	2.98
σ(relative half spread) (%)	0.08	0.21	0.36	1.19

Table 9: Expected returns and liquidity sorted portfolios

The table reports the estimated coefficients from various specifications of the model,

$$E(r_t^p - r_t^f) = \alpha + \kappa E(c_t^p) + \lambda^1\beta^{1,p} + \lambda^2\beta^{2,p} + \lambda^3\beta^{3,p} + \lambda^4\beta^{4,p} + \lambda\beta^{net,p}$$

We use weekly data for the period 1999-2005, and the betas are re-estimated for each year for each portfolio (p). The portfolios are constructed each week based on firms' average liquidity variable the previous week. Panel (a) shows the results when the portfolios are based on the order based factor. In panel (b) the portfolios are constructed based on the trade based factor and in panel (c) the portfolios are based on the Amihud factor. The $\beta^{net,p}$ is when we impose the model implied constraint that the risk premia of the different betas are the same. The estimated models' R^2 are in percentage terms. ** denote that the estimated coefficient is significantly different from zero at the 1% level, and superscript [a] in the $E(c_t^p)$ column denotes that the liquidity cost is scaled by the average turnover for all stocks in the sample.

(a) Order based factor

	Constant	$E(c^p)$	β_1^p	β_2^p	β_3^p	β_4^p	β_{net}^p	R^2 (%)
Model 1a	-0.29	0.01[a]					0.75	0.15
Model 2a	0.21	-0.12					0.39	0.34
Model 3a	-0.13		0.58					0.09
Model 4a	-0.05	0.01[a]	-5.24				5.86	0.34
Model 5a	0.55	-0.13	-6.08				6.26	0.59
Model 6a	0.00		-5.32				5.89	0.33
Model 7a	0.52	0.01[a]	0.29	-351.66**	42.29**	-9.94		1.46
Model 8a	1.60**	-0.25**	-0.43	-305.02**	59.63**	-12.85**		2.10

(b) Trade based factor

	Constant	$E(c^p)$	β_1^p	β_2^p	β_3^p	β_4^p	β_{net}^p	R^2 (%)
Model 1b	1.21**	0.01[a]					-1.00	0.23
Model 2b	2.51**	-0.26					-2.10**	1.15
Model 3b	0.86		-0.53					0.06
Model 4b	0.31	0.01[a]	11.09**				-11.60**	1.50
Model 5b	1.66**	-0.28**	11.67**				-13.34**	2.55
Model 6b	0.37		11.12**				-11.68**	1.53
Model 7b	0.03	0.01[a]	-0.58	-53.85	-46.06**	-5.15		3.93
Model 8b	1.12	-0.23**	-1.44**	-70.21	-43.71**	-9.95		4.64

(c) Amihud factor

	Constant	$E(c^p)$	β_1^p	β_2^p	β_3^p	β_4^p	β_{net}^p	R^2 (%)
Model 1c	-1.67**	0.01[a]					2.30**	0.98
Model 2c	-1.54**	-0.02					2.21**	0.96
Model 3c	-1.26**		1.83**					0.54
Model 4c	-0.34	0.01[a]	-15.25**				16.26**	2.35
Model 5c	-0.33	0.01	-15.23**				16.23**	2.32
Model 6c	-0.30		-15.19**				16.17**	2.31
Model 7c	-0.94	0.01[a]	1.82**	27.64	48.60**	-0.04		3.38
Model 8c	-0.76	-0.13	1.73**	68.13	49.23**	-2.04		3.49

Table 10: Factor model estimation - volatility of liquidity

The table presents the estimated risk premia (with the associated t-value below each estimate) for risk factors constructed from portfolios based on the variance of the firm specific liquidity factors. Panel A shows the results for when the risk factors are constructed based on the previous week volatility of the liquidity variable. Panel B shows the results when we construct risk factors based on the previous 8 weeks daily volatility of the liquidity factors. For each model, the asset pricing tests are reported in the last four columns, with the associated p-values below each test statistic. These are the HJ-distance metric of Hansen and Jagannathan (1997), the Wald-p test of the factor coefficients being zero in the linear pricing kernel. The delta-J test of Newey and West (1987) is reported testing whether including the Fama-French factors improves the model.

Panel A: Liquidity risk based on previous week liquidity volatility							**Tests**		
	Market (VW)	SMB	HML	F1	F2	F3	HJ-dist.	Wald-p	delta J
Fama French	**0.007**	0.003	0.005				0.153	0.000	-
	2.401	1.690	1.067				0.472	0.019	-
Model 1	0.004			0.006			0.196	0.000	6.829
	1.569			1.312			0.142	0.189	0.033
Model 2	0.001				**0.013**		0.166	0.000	1.535
	0.570				**2.519**		0.418	0.018	0.464
Model 3	0.002					**0.014**	0.139	0.000	2.961
	1.074					**2.543**	0.668	0.017	0.228
Model 4	0.001			0.004	**0.011**	**0.014**	0.132	0.000	2.370
	0.560			1.000	**2.187**	**2.399**	0.543	0.052	0.306

Panel B: Liquidity risk based on previous 8 week liquidity volatility							**Tests**		
	Market (VW)	SMB	HML	F1	F2	F3	HJ-dist.	Wald-p	delta J
Fama French	**0.007**	0.003	0.005				0.153	0.000	-
	2.401	1.690	1.067				0.472	0.019	-
Model 1	0.005			0.008			0.183	0.000	3.508
	1.890			1.874			0.329	0.067	0.173
Model 2	0.003				0.009		0.194	0.000	5.614
	1.189				1.626		0.165	0.110	0.060
Model 3	0.004					**0.010**	0.168	0.000	2.800
	1.672					**2.399**	0.423	0.035	0.247
Model 4	0.004			0.006	0.004	0.010	0.166	0.000	3.417
	1.464			1.195	0.950	1.773	0.254	0.144	0.181

Table 11: Factor model estimation - level of liquidity

The table presents the estimated risk premia (with the associated t-value below each estimate) for risk factors constructed from portfolios based on the variance of the firm specific liquidity factors. Panel A shows the results for when the risk factors are constructed based on the previous week average of the liquidity variable. Panel B shows the results when we construct risk factors based on the previous 8 weeks average of the liquidity factors. For each model, the asset pricing tests are reported in the last four columns, with the associated p-values below each test statistic. These are the HJ-distance metric of Hansen and Jagannathan (1997), the Wald-p test of the factor coefficients being zero in the linear pricing kernel. The delta-J test of Newey and West (1987) is reported testing whether including the Fama-French factors improves the model.

Panel A: Liquidity risk based on previous week liquidity level							Tests		
	Market (VW)	SMB	HML	F1	F2	F3	HJ-dist.	Wald-p	delta J
Fama French	**0.007**	0.003	0.005				0.153	0.000	-
	2.401	1.690	1.067				0.472	0.019	-
Model 1	0.003			0.001			0.195	0.000	7.955
	1.258			0.223			0.124	0.450	0.019
Model 2	0.003				0.001		0.196	0.000	8.190
	1.227				0.116		0.115	0.464	0.017
Model 3	0.003					**0.009**	0.174	0.000	4.473
	1.481					**2.081**	0.302	0.058	0.107
Model 4	0.003			-0.001	0.002	**0.009**	0.168	0.000	5.011
	1.271			-0.258	0.533	**2.045**	0.201	0.175	0.082
Panel B: Liquidity risk based on previous 8 week liquidity level							**Tests**		
	Market (VW)	SMB	HML	F1	F2	F3	HJ-dist.	Wald-p	delta J
Fama French	**0.007**	0.003	0.005				0.153	0.000	-
	2.401	1.690	1.067				0.472	0.019	-
Model 1	0.003			0.003			0.196	0.000	8.302
	1.391			0.667			0.123	0.344	0.016
Model 2	0.003				-0.001		0.195	0.000	8.435
	1.261				-0.126		0.110	0.450	0.015
Model 3	0.004					0.007	0.182	0.000	5.423
	1.608					1.583	0.238	0.126	0.066
Model 4	0.003			-0.002	0.001	0.009	0.173	0.000	6.025
	1.482			-0.324	0.215	1.484	0.185	0.304	0.049

Table 12: Results from factor models for trade based and order based liquidity measures separately

Panel A presents main results from a common factor model where the variables set includes trade based liquidity measures only. Panel B shows the results from a factor model where the variable set includes order based liquidity measures only. MSA is the Kaiser's measure of sampling adequacy. The factors are rotated according to an orthogonal rotation method (Varimax in SAS).

Panel A: Trade based liquidity measures

Model B	**MSA**	**Shared variance**	**Factor loadings**
Trade frequency	0.74	0.74	0.86
Trading volume	0.70	0.50	0.69
Turnover	0.72	0.81	0.90
Sec. between trades	0.64	0.23	-0.48
Illiquidity ratio	0.40	0.01	0.09
Overall MSA/Shared variance	0.70	2.27	

Panel B: Order based liquidity measures

			Rotated factor loadings	
Model C	**MSA**	**Shared variance**	**Factor 1**	**Factor 2**
Frequency of limit orders	0.78	0.43	0.49	-0.43
Depth inner quotes	0.74	0.61	0.77	0.13
Tick slope	0.74	0.85	0.90	-0.22
Price slope	0.77	0.69	0.78	0.28
Fraction of limit orders	0.78	0.25	0.47	-0.15
Quoted spread	0.82	0.75	-0.82	0.30
Relative quoted spread	0.56	0.65	-0.16	0.79
Inter-quote time	0.71	0.39	-0.16	0.60
Book symmetry	0.70	0.13	-0.17	-0.32
Overall MSA/Shared variance	0.74	4.75		
Shared variance explained			3.22	1.53
% of total shared variance			68	32

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Liquidity factor
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