Commonality in Liquidity in Pure Order-Driven Markets*

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Abstract

This paper extends previous research on commonality in liquidity to pure limit order markets. Using data over three months on the order book of 19 stocks traded at the Swiss Stock Exchange (SWX), we perform a principals components analysis and find evidence of the existence of three to four common factors affecting the variation in various proxies for liquidity. The fraction of this variation explained by the common factors is higher than what has been found by other studies for quote driven markets, such as Chordia et al. (2000a) or Hasbrouck and Seppi (2001). This fraction of variation of liquidity explained by common factors varies throughout the trading day. We further find evidence of an important common factor in market activity. Liquidity demand is more subject to common variation than liquidity supply. It is found that individual stocks' liquidity is sensitive to market liquidity and market volatility, as measured by realized volatility.

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1 Introduction

Recent research in finance has focused on the question whether there exist common factors that jointly affect liquidity in different assets. The empirical evidence on the existence of such systematic factors is ambiguous. While Chordia et al. (2000a), Huberman and Halka (2001) and Amihud (2002) find supportive evidence, Hasbrouck and Seppi (2001) find that the common factors in liquidity are relatively small.

This paper has two main goals: Firstly, we use data that give more precise information on liquidity on the market to investigate the issue of commonality. Instead of the quote driven markets which have been studied before, we use data on a limit order market. Most of previous empirical work on commonality in liquidity has so far focused on markets in which market makers guarantee a minimal liquidity, in addition to the liquidity provided by limit order books. Therefore, the proxies for liquidity used in these studies are mostly related to the best quoted prices and quantities and actual trades. Recently, data on fully automated markets has become available on which liquidity is solely provided by participants placing limit orders. Research on the existence of commonality in order driven markets is interesting for the following reasons: On one hand, data on the limit order book provide much finer information on the liquidity offered on the market. In addition to the best prices and quantities offered and the actual trades, the traders' intention to trade can be observed. In view of the ambiguous evidence on the existence of commonality, the goal of this paper is to investigate whether the additional information provided by the order book yields support for the existence of common factors. And on the other hand, since the sources of commonality of liquidity are not clear, it is far from obvious that the (in addition mixed) results on commonality can be extended from quote driven to limit order markets. Yet, this is an important issue given the large number of stock exchanges that are organized as pure limit order markets and recent considerations by the NYSE to reduce the importance of market makers in favor of an electronic limit order system. In addition, this is the first study on commonality in liquidity using data on the Swiss stock exchange (SWX).

Based on the supportive evidence that we find for the existence of common factors, our second goal is to identify these common factors. We therefore try to find some financial variables that affect liquidity of all individual stocks.

Previous academic research on commonality in liquidity has been based on partial information on the supply of liquidity: For quote driven markets, only the quoted bid and ask prices and quantities could be used (Chordia et al., 2000a, Hasbrouck and Seppi, 2001, Huberman and Halka, 2001). Hansch (2003) had only access to the best fifteen orders and, in addition, the market he studies is not a pure order driven market on its own, but functions in addition to the largest quote driven market of the world, the NYSE.

We have access to the complete history of all limit and market orders submitted as well as trades carried out on stocks over a three months period at the Swiss Stock Exchange (SWX) which is a purely order driven market (Ranaldo (2000, 2001, 2004), Buhl (2003) have also analyzed this market). Given that liquidity is difficult to measure, we use different proxies to analyze the existence of commonality in liquidity. We first analyze whether there is evidence of factors that affect the liquidity of stocks jointly. We find evidence of the existence of three to four factors; these affect liquidity measures for all possible sizes of trades, not only for relatively small quantities that have been analyzed before. The explanatory power of the factors found is higher than what has been found in comparable studies on quote driven markets. This could be evidence that commonality not only exists under the different market structure of limit order markets, but also that it is of higher importance. Further, we find that the proportion of the variation of liquidity explained by the common factors varies throughout the day. This new finding adds to the intraday seasonalities found in previous research. It is also a hint that results might be misleading when liquidity proxies are used that are sampled at a certain time of the day. A further finding is that a large proportion of variation in market activity, as measured by the arrival rate of new limit and market orders and trades, is explained by a common factor.

The statistical procedure we use does not shed light on the nature of the common factors. Therefore, we analyze in a next step the effect that several financial variables have on the liquidity of individual stocks. Average market liquidity explains a larger fraction of the variation of liquidity for the limit order market than for quote driven markets studied before (see e.g. Chordia et al. (2000a)), thus confirming the finding in the principal components analysis of a higher degree of commonality. Further, we analyze several additional financial variables on their effect on stocks' liquidity. We find that market volatility has a strong impact.

The remainder of this paper is organized as follows. Section 2 gives a review of the related literature. Section 3 describes the market structure of the SWX and the data used. Section 4 discusses the proxies for liquidity used. In section 5, the commonality in liquidity is analyzed. In section 7, we analyze financial variables having a market wide impact on stocks liquidity. Section 8 concludes.

2 Related literature

Liquidity is '...a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets' (Kyle, 1985, p. 1316). Black (1971) mentions the following properties of a liquid market:

- There are always bid and asked prices for the investor who wants to buy or small amounts of stock immediately.
- The difference between the bid and asked prices (spread) is always small.
- An investor who is buying or selling a large amount of stock, in the absence of special information, can expect to do so over a long period of time at a price not very different, on average, from the current market price.
- An investor can buy or sell a large block of stock immediately, but at a premium or discount that depends on the size of the block. The larger the block, the larger the premium or discount.

Based on these properties, Kyle (1985) defined the following aspects of a liquid market:

- Tightness: The cost of turning around a position over a short period of time.
- Depth: The size of an order flow innovation required to change prices a given amount.
- Resiliency: The speed with which prices recover from a random, uninformative shock.

2.1 Liquidity in quote driven markets

Among the first contributions to the field of research on liquidity is the work on market microstructure (for on an overview on the market microstructure literature, see for example O'Hara (1995), Biais et al. (2002)). O'Hara (1995) defines market microstructure as the study of the process and outcomes of exchanging assets under explicit trading rules. Among the properties of liquidity investigated by this literature are the bid-ask spread and the depth that market makers post.

Most of the empirical studies on liquidity have used data on quote driven markets such as the NYSE. On such a market, market makers quote prices and the quantities up to which they are willing to buy and sell at the quoted prices. Market makers thus provide a minimum level of liquidity to the market. Other market participants demand liquidity by placing market orders or provide additional liquidity by placing limit orders. Order driven markets, on the other hand, function without market makers; liquidity is solely provided by investors placing limit orders.

Several studies have shown that proxies for liquidity vary over time: In addition to deterministic variation such as intradaily or intraweekly variation of liquidity of individual stocks (Wood et al., 1985, Jain and Joh, 1988, Foster and Viswanathan, 1990, Engle and Lange, 1997), Chordia et al. (2001) also found unpredictable variation of market liquidity. Chordia et al. (2000b) have also found considerable cross-sectional heterogeneity in liquidity.

As mentioned above, the empirical evidence on the existence of a stochastic factor that drives this variation over time of liquidity of all assets is ambiguous. Chordia et al. (2000a) look at quoted spreads, quoted depth and effective spreads of 1169 stocks traded on the NYSE throughout 254 trading days. Using transaction data, daily averages are calculated and market wide as well as industry wide averages are formed. Chordia et al. regress the first differences of the liquidity proxies against these market and industry averages and find that these aggregate quantities have a significant effect on the liquidity proxies in individual stocks, even after controlling for individual liquidity determinants, such as volatility, volume and price. They also find that the effect of market and industry averages is stronger on liquidity proxies calculated for portfolios.

Huberman and Halka (2001) use as sample of 240 stocks traded at the NYSE over 254 days, selecting 60 stocks randomly from each size quartile. They consider the absolute and relative bid-ask spread as well as the quantity and dollar depth at noon. These liquidity proxies are averaged for each of the 4 portfolios of 60 stocks. Autoregressive processes are fitted to the resulting time-series. The authors interpret the presence of positive correlation in the residuals as evidence of a common factor affecting liquidity in different stocks.

Hasbrouck and Seppi (2001) use liquidity proxies such as the spread, log spread, log size, quote slope and log quote slope, averaged over time intervals of 15 minutes length for 252 trading days for 30 Dow stocks. They perform a principal components analysis and find only little evidence of a common factor, the first common factor explaining 13 % of total variation of the log quote slope.

If a common factor affects liquidity of all assets, it should be a priced factor. Various papers have investigated this question. Amihud and Mendelson (1986), Datar et al. (1998), Brennan and Subrahmanyam (1996), Brennan et al. (1998) find empirical evidence that cross-sectional differences in liquidity help to explain differences in expected returns. Amihud (2002) and Pástor and Stambaugh (2003) find that expected stock returns are cross-sectionally related to the sensitivities of returns to fluctuations in aggregate liquidity. Sadka (2003) finds that systematic liquidity risk, rather than the level of liquidity, is priced for individual stocks. Acharya and Pedersen (2003) find that both the level and the risk of liquidity are priced. Gibson and Mougeout (2004) and Jones (2002) find that aggregate risk premia contain a premium for aggregate liquidity risk.

2.2 Liquidity in order driven markets

A number of studies have investigated the properties of liquidity on limit order markets. Various studies have found that the order flow on such markets where traders face the choice between providing liquidity by placing a limit order or demanding liquidity by placing a market order react on changing market conditions (Biais et al., 1995, Harris and Hasbrouck, 1996, Al-Suhaibani and Kryzanowski, 2000, Griffiths et al., 2000, Ahn et al., 2001, Coppejans et al., 2001, Bae et al., 2003, Bloomfield et al., 2003, Ellul et al., 2003, Hollifield et al., 2003, Ranaldo, 2004).

Irvine et al. (2000) have proposed a measure of illiquidity of a stock based on the order book, which they call the cost of a round trip, and investigated its ability to predict subsequent trading activity. The cost of a round trip is the cost of buying and selling immediately a position of a given size.

As mentioned in the introduction, little work has been done on commonality in liquidity for order driven markets. Domowitz and Wang (2002) have used a measure of liquidity similar to the cost of a round trip proposed by Irvine et al. (2000). Their focus is on the relationship between order-type (market versus limit order), order-flow (buy versus sell orders) and their impact on commonality in liquidity and returns. They conjecture that liquidity commonality is related to co-movement of order-type, whereas return co-movement is due to co-movement of order-flow. In an empirical study, they look at the liquidity of 19 stocks from the ASX-20 index (Australian stock exchange) where six snap shots are taken on each trading day throughout 2000. They test the hypothesis whether order-type co-movement indeed leads to liquidity co-movement, and whether order-flow co-movement leads indeed to return co-movement by regressing for all pairs of stocks the correlations of returns (liquidity) on order flow and order type correlations. Their results support these hypotheses.

Hansch (2003) has a different focus: He analyzes data on 100 stocks for August 2001 from the limit order book of Island, an electronic trading platform. On this platform, secondary trading takes place for stocks which are listed on AMEX, Nasdaq and NYSE; it is therefore an additional market place, but cannot be regarded as a pure limit order market, since the fact that the stocks are traded on other stocks exchanges where the stocks are listed will have a significant impact. Hansch uses a liquidity measure related to the cost of a round trip, based only on the fifteen best orders on each side of the book.

Similar to Hasbrouck and Seppi (2001), he performs a principal components analysis of this liquidity measure. He finds that the first principal component already explains 43% of the variance for the top volume stocks, which is orders of magnitude above what Hasbrouck and Seppi (2001) have found.

In contrast, we use the complete order book of 19 stocks trade on the Swiss Stock Exchange (SWX) to analyze whether there are common factors affecting the liquidity of these stocks. Further, we also try to find financial variables that could explain this co-movement of liquidity.

3 Description of the market and data set

3.1 The market structure of the Swiss Stock Exchange

SWX has the world's first fully automated trading platform (Swiss Stock Exchange, 2004e). It is a pure order driven market where all listed securities are permanently traded, with the option of voluntary market making (Swiss Stock Exchange, 2004d). The blue chips of the Swiss Market Index (SMI) which are the object of interest in this study are traded in the electronic virt-x system, based in London. The virt-x market, launched in June 2001, is based on an integrated trading, clearing and settlement model that allows to trade transnationally stocks from different European countries (Swiss Stock Exchange, 2004a). Electronic trading begins with the investor: participant banks investment advisors register incoming orders from their customers in their trading system. These data are forwarded to the trader and checked, or fed directly into the trading system by the trader. From here they go to the central exchange system of SWX, which acknowledges receipt of the order, assigns a time stamp to it and verifies its formal correctness. Depending on the type of transaction, the data are also transmitted to data vendors (Reuters, Telekurs, etc.). Trading orders are executed on a price/time priority, i.e. in the order of price (first priority) and time received (second priority) (Swiss Stock Exchange, 2004e).

Trading hours are on business days from 09:00 to 17:30. Trading takes place continuously. Rules for trading halts are defined, similar to the circuit breakers at the NYSE, to avoid extreme market movements. Trading stops for 15 minutes (5 minutes for stocks priced less than CHF 10) if the potential follow up price deviates by 2% (25%) or more from the previous trade's or closing price (Swiss Stock Exchange, 2003b). During the last 10 minutes of the trading day, no orders are executed. Rather, they are matched in an auction at 17:30 when official closing prices are determined (Swiss Stock Exchange, 2004b). From 17:30 until 22:00 and again between 06:00 and 09:00, the so-called pre-opening takes place. Orders (bids and offers) may be entered or deleted in the electronic order book during pre-opening times, but no actual trades are made. A theoretical opening price is continuously calculated and displayed for the guidance of traders (Swiss Stock Exchange, 2004c). At the opening at 09:00, the opening price is determined and the orders are executed according to the matching rules of SWX. In order to establish the opening price at the start of trading (or upon resumption of trading after an interruption), the highest-execution principle is used; in other words, the price is fixed in such a manner as to achieve the largest possible turnover. If the potential opening price deviates by 2% (25% for stocks priced less than CHF 10) or more from the reference price (which equals essentially the previous traded price), opening is delayed by 15 minutes (5 minutes) (Swiss Stock Exchange, 2003b).

All equity orders with a size of less than CHF 200'000 must be executed within official trading hours through the SWX trading system, whereas orders above this size limit may be traded off-exchange. However, all off-exchange transactions must be reported within 30 minutes of their conclusion (Swiss Stock Exchange, 2004d).

The tick size varies with the stock price (Swiss Stock Exchange, 2003b) according to the rules summarized in Table 1. This implies that when large changes in the stock price take place, tick sizes will change and hence also the observed spreads. This is different from other markets such as the NYSE where the tick size remains fixed.

Besides limit and market orders, there are three further types of orders (Swiss Stock Exchange, 2003a):

- The hidden size order is a large order whose size is in the order book is only partially visible; all participants see that this order is of hidden size.
- The accept order is executed immediately against all orders in the book, either fully or partially. The remaining order is cancelled immediately and the order is never entered in the order book.
- The fill or kill order is like an accept order which is only executed if full matching is possible.

3.2 Description of the data set

The data set consists of all orders that have been submitted on the SWX between May and July 2002 together with all trades during this period. For each order, the time of submission is given, the state of the order book at the time of submission (trading, opening, stop trading, etc.), the original size and price of the order, the type and direction (buy or sell) of the order, the quantity and time at which part of the order was executed, the expiry period, the time and reason of actual deletion and the state of the order book at the time of deletion.

Only stocks that are part of the Swiss Market Index (SMI) are considered.[1] Table 2 gives an overview of the stocks in the sample. The data available

[1] The SMI is a capital-weighted, non-dividend-corrected index (see `http://www.swx.com/products/indices/products_smi_en.html`). It comprises at maximum 30 of the most significant equity-securities issues included in the Swiss performance index (SPI) which is a dividend-corrected index including all equity traded at the SWX of companies domiciled in Switzerland or Liechtenstein. The SMI is adjusted on the basis of the free float market capitalization. An issuer's market capitalization is adjusted to reflect the number of shares in fixed ownership, whereas only the freely tradable portion of the outstanding shares is taken into account.

cover 66 trading days from May 3rd to July 31st 2002. The sample only covers about 45% of the market capitalization of the SMI.[2] It includes with NOVN the stock with the highest market capitalization traded on the SWX.

As for the market environment during the observation period, the Swiss market experienced during the second quarter 2002 a significant downturn. Unfortunately, this is likely to have an impact on our results and it would be very interesting to have additional data on a different time period. The total market value of the stocks in the sample declined from 349 BCHF to 289 BCHF (see Table 2). This downturn affected all stocks in the sample: The closing price of each stock on July 31st is below its level on May 3rd. Also the mean daily return is negative for all stocks and zero for a single stock. Another indication of the turbulences during the sample period are the large daily standard deviations of the returns, ranging from 1.2% to 4.4%.

The data set comprises 1'157'196 trades. 99% of the trades have been carried out on the exchange. The percentage of trades on exchange does not vary across stocks. The trades on the exchange make up only 76% of the 1.3 billion shares traded. The importance of off exchange trading varies considerably across stocks, it ranges between 5.4% and 66.0% of the total traded volume. The variation across stocks of the median turnover of off exchange trades is relatively small, while the variation of the mean turnover is considerable. This indicates that stocks with a very low on exchange trading volume experienced during the observation period a small number of off exchange trades of large volume.

Further, the data set comprises 2'524'580 orders. 90.3% of all orders are limit orders, 8.2% are market orders and 1.5% are special orders, that is hidden, accept or fill or kill orders. Stocks are quite homogeneous with respect to the distribution of order types. 50.7% of all orders are sell orders. This imbalance reflects the downward pressure on the stock prices. Limit orders are evenly split into buy and sell orders. Yet, several stocks show a very high fraction of market orders being sell orders. The contrary is true for the special orders where a higher fraction are buying orders.

The chances that a limit order would be executed at least partially amounts to 48.6% on average, ranging between 33.6% and 56.6% for the different stocks. From these limit orders with at least partial execution, 19.0% have been fully executed at the instant of submission, like market orders, and have never been entered in the book as open orders. Another part of the limit orders, 25.5%, have held for some time the status as open orders and have eventually been fully executed. Only 3.8% of all limit orders were deleted upon request of the trader and 0.2% of all orders were only partially executed before their expiry date.

[2] The data on the remaining stocks in the SMI still needs to be produced by the SWX.

The majority of the orders were not traded against. 46.9% were deleted upon request of the trader, where this fraction varied between 37.3% and 63.2% among stocks. A further 4.5% of all limit orders expired without any trade. The vast majority, 84.0%, of all orders were only valid for a single day, that is, they expired on the same day as they were submitted on.

Most of the 37'148 special orders in the sample are accept orders (86.8%) and 11.3% are of the type fill or kill. Almost all (75.6%) accept orders got fully or partially matched. This suggests that accept orders are very similarly used as market orders. The same is true for fill or kill orders: 10.2% out of the total of 11.3% of all special orders that were of this type got matched.

The trading activity is subject to large daily variation. Both the number of limit and market orders submitted on a day vary considerably. Also the daily turnover of the submitted limit orders displays large variation, the minimal turnover ranging between 0.4% and 3% and the maximal turnover ranging between 2.3% and 14%. As for the turnover of the submitted market orders, the minimal turnover is between 0.004% and 0.05% and the maximal turnover is between 0.38% and 1.1%.

3.3 Selection of the sample and construction of the order book

The database contains information on the time of the order submission, its original size and price, all the partial executions of the order and the time of deletion. It contains all orders submitted between May 3rd and July 31st 2002. In order to construct the order book for any time period, we need to know the orders which have been submitted before this period and that have not been executed before the start of this relevant period. We therefore start only to build the order book as per May 10th, thus allowing orders to be submitted between May 3rd and May 9th without execution. This initial period of five trading days is sufficiently long, given that a large fraction of the orders expires at the end of the trading day of their submission: As discussed above, 84.0 % of all orders were only valid a single day. After 24 hours, more than 98% of all orders have been removed from the book. From this, we consider for the analysis a time period starting May 10th and ending July 31st 2002, spanning 59 trading days.

To reconstruct the order book, only orders that have been visible in the book are used, that is, hidden, accept and fill or kill orders are omitted. These special orders only make up 1.5% of all limit orders, thus the loss of sample size is not severe. Further, 87% of the special orders were accept orders that function like market orders: They are executed against all orders in the book and then immediately deleted. They are therefore not part of the liquidity supply.

The order book is known at each instant. As customary in much of the literature on high-frequency data, we use snapshots taken at time intervals of 5 minutes, between 09:05 and 17:15. This gives 99 observations a day, $T = 5841$ in total. Observation times are denoted by $t_i, i = 1, 2, \ldots, T$, at these intervals of 5 minutes, between 09:05 and 17:15, starting May 10th and ending July 31st 2002. At various times, trading in one or several of the stocks in the sample has been stopped according to the rules of the SWX described in section 3.1. The trading halts lasted typically for 15 minutes, some up to an hour. Table 4 shows an overview how on number of trading halts of the different stocks. For such trading halts, the liquidity proxies defined in the section were set equal to the their value at the nearest time at which trading took place. It appears to be likely that this interpolation will not have a significant effect on the analysis, given that for most stocks, less then 50 trading halts were observed out of a total number of $T = 5841$ observations.

For each point of time t_i, the total amount of shares on offer for buying or selling defines supply curves of liquidity, such as the example shown in Figure 1, as follows: At any time t_i, $N^A_{t_i}$ orders are open on the ask side and $N^B_{t_i}$ on the bid side. The $n-th$ order on side $s \in \mathcal{S} \equiv \{A, B\}$ open at time t is characterized by its price $p^s_{t,n}$ and quantity $q^s_{t,n}$. The orders are sorted from 'best to worst', that is, such that $p^A_{t,n} \leq p^A_{t,n+1}$, $n = 1, 2, \ldots, N^A_t - 1$ on the ask side and $p^B_{t,n} \geq p^B_{t,n+1}$, $n = 1, 2, \ldots, N^B_t - 1$. The total depth of any side of the book is then the sum of all quantities offered,

$$\bar{Q}^s_t \equiv \sum_{n=1}^{N^s_t} q^s_{t,n}. \tag{1}$$

The quantity offered by the n best orders is defined as

$$Q^s_{t,n} \equiv \sum_{m=1}^{n} q^s_{t,m},\ s \in \mathcal{S}. \tag{2}$$

Based on the orders, two forms of the liquidity supply curve can be derived. The first is the supply curve such as shown in Figure 3(b),

$$\begin{aligned}
&Q^s_t(p) \equiv Q^s_{t,N^s(p)}, 0 \leq p \leq p^s_{t,N^s_t}, s \in \mathcal{S}, \text{ where}\\
&N^A(p) \equiv \sup\{n \leq N^A_t : p^A_{t,n} \leq p\},\\
&N^B(p) \equiv \sup\{n \leq N^B_t : p^B_{t,n} \geq p\}.
\end{aligned}$$

For any price p, $Q^s_t(p)$ equals the total number of shares offered at this price.

Alternatively, the supply curve can also be defined in its inverse form, such as shown in Figure 3(a):

$$P_t^s(Q) \equiv p^s_{t,N^s(Q)}, 0 \le Q \le \bar{Q}_t^s \text{ where}$$
$$N^s(Q) \equiv \inf\{N \le N_t : \sum_{n=1}^{N} q^s_{t,n} \ge Q\}.$$

$P_t^s(Q)$ gives the price that a market order of size Q has to pay/receives for the last unit.

The price per share for an order of size Q is then given by

$$p_t^s(Q) \equiv \left(\sum_{n=1}^{N^s(Q)-1} p^s_{t,n} q^s_{t,n} + (Q - Q_{t,N^s(Q)-1}) p_{t,N^s(Q)} \right) /Q, \ 0 \le Q \le \bar{Q}_t^s.$$

When an order of size Q is to be matched, the offer 'walks up the book' for the first $N^s(Q) - 1$ orders; the remaining quantity $Q - Q_{t,N^s(Q)-1}$ is then executed at the price $p_{t,N^s(Q)}$.

From the price schedules on the ask and bid side, the mid-price is defined as the average of the best bid price p_t^B and best ask price p_t^A,

$$p_t^{mid} \equiv \frac{1}{2}\left(p^A_{t,1} + p^B_{t,1}\right).$$

The spread is defined as the difference between the best bid and ask price,

$$\text{Spread}_t = p^A_{t,1} - p^B_{t,1}.$$

In order to attain comparable quantities, quantities are always expressed as a fraction of the free float of the respective stock. Since it is only the market capitalization of the free floating stocks that is relevant for the stocks' weighting in the SMI, SWX has to collect the information on the free float. 'Free float describes that portion of a given joint-stock company's shares that is not closely held as measured against the total number of issued shares' (Swiss Stock Exchange, 2004). Holdings by a group of persons of five percent or more of the outstanding shares is considered as being closely held. The numbers on freefloat published by the SWX on the stocks in the sample are given in Table 2. We standardize quantities by the number of shares free floating, given by the product of the total number of outstanding shares NO and the fraction of free float $FFl(t)$ at time t,

$$\frac{Q}{FFl(t)NO}.$$

Both of these quantities are given in Table 2. This way of standardizing is motivated by the large differences in the free float as shown in Table 2: Some stocks, such as the former state owned Swisscom (SCMN), have a ratio of free float as little as one third of all shares while other stocks have a free float of 100%. The figures on the number of outstanding securities reported in Table 2 further show that standardization of quantities is essential since these numbers display large variation across stocks. Price levels of the stocks in the sample vary considerably, as shown in Table 2. Therefore, wherever the structure of the order book is of interest and not the intertemporal behavior of prices, prices are expressed as multiples of the mid-price. Figures 1(b) and 1(d) show an example of such a standardized order book, both the supply curve and the inverse supply curve.

4 Proxies of liquidity

4.1 Spread of best bid-ask prices

In quote driven markets, tightness of the market can only be observed at the quoted prices and quantities as spread between the best bid and ask price; depth is only observable as the quantities up to which the quoted prices of the market maker are valid. Since a large part of the literature has focused on these measures, we will briefly discuss them.

Table 5 shows descriptive statistics on the observed spreads. Relative spreads lend themselves better for comparison across stocks that are traded at very different price levels and therefore have different tick sizes and thus minimal spreads. The average spread across all stocks was 0.28%.

4.2 Depth related liquidity measures

A defining feature of market liquidity is the degree to which large quantities can be traded. Therefore, the depth of the book measures the quantity dimension of liquidity: A large depth is necessary but not sufficient for market to be liquid. We discuss three different depth measures in this section that will be used in the empirical analysis. In order to have comparable units, depth is always measured in millionths of the total free float.

4.2.1 Depth of best orders

Depth of the best bid and ask orders, denoted by $Q^s_{t,1}$ $s \in \mathcal{S}$ as defined in (2), are widely used measures of depth in quote driven markets. The market maker guarantees to buy or sell any quantity up to the quoted depth. In the sense of Kyle (1985), this is the trade size required to change the price, because up to the quoted depth, market makers trade at the quoted prices.

In a pure limit order driven market, the economic significance of the depth at the best orders is less clear: It can happen, that an order has been partially executed up to a single share and that this order happens to be the best order on its side of the book. The depth of the best order will then be only one share, while large quantities might be offered by the next best orders at the next tick. The depth of the best orders will thus be an incomplete measure of the depth right at the mid-price.

A further problematic consequence of this fact is that the depth is highly volatile. Figure 2 shows in the upper (lower) panel the maximum (minimum) of the number of shares available at the best bid and ask offer on a single day, averaged across all stocks. It can be seen that the depth of the best bid and ask offers, even for the sample average, undergoes dramatic changes within a day, moving from its minimum to its maximum. On May 27th 2002, for example, the minimum depth was 37 shares, while the maximum was attained at 6441 shares.

Given that the quantity of the currently best offers on both sides of the book vary tremendously, previous research has used different measures of depth, such as the depth at the best 5 quotes (Biais et al., 1995, Al-Suhaibani and Kryzanowski, 2000, Ahn et al., 2001) or depth at a number of ticks away from the current mid-price (Coppejans et al., 2001). We follow the literature and calculate the depth $Q^s_{t,5}$ that the best five orders on each side of the book offer (see the definition (2)).

Table 5 reports the descriptive statistics for the depth $Q^s_{t,5}$. The mean depth is 0.008% averaged over all stocks. Interestingly, the averages reported for the quantiles are very similar on both sides of the book. Thus, the depth provided on the buying and selling side behave very similarly.

4.2.2 Total depth of the book

Another measure of liquidity is the total amount of stocks that are in the limit book available, i.e. the total depth $\bar{Q}^s_t$, $s \in \mathcal{S}$ of the book, as defined in (1). Table 5 reports some descriptive statistics on the total depth of either side of the book. On average, the open orders correspond to about 0.2% of the free float on the ask side and to about 0.1% on the bid side. This surplus of selling orders reflects the general downward tendency of the market during the given period. In contrast, the best five orders, considered above, provide on average only a depth $Q^s_{t,5}$ of 0.008%. Yet, the descriptive statistics on $Q^s_{t,5}$ are symmetric on both sides of the book. Thus, the order imbalance reflected by the differing total depth $\bar{Q}^s_t$, $s \in \mathcal{S}$ on each side of the book is caused by a large number of selling orders that have limit prices far away from the current price level.

The total depth of the book shows huge variation on both sides of the book: For several stocks, the maximum depth amounts to about ten to twenty times the minimal depth. This is a first indication that the quantity dimension of liquidity displays large changes over time.

To get an idea about the economic relevance of this variation in quantity offered by the book, we ask whether depth was at all times sufficient to execute the largest market orders. We therefore compare the 99% quantile of the size of the market orders with the minimal total depth of the book ever observed. We find that the minimal depth was for all but three stocks (BAER, BALN, CFR) sufficient to execute the market orders. Thus, total depth of the book varies around levels much higher than most market orders ever placed.

4.2.3 Depth at a premium around the mid-price

Kyle's 1985 original definition of depth refers to the quantity that needs to be traded to move the price by a given amount. We will consider the quantity required to change the price by 1%. To this end, we consider the depth $Q_t^A(1+1\%)$ of the book available at the mid-price plus 1% on the ask and the analogous quantity $Q_t^B(1-1\%)$ available at a 1% discount on the bid side, respectively.

Table 5 reports the descriptive statistics for the depth available at a premium of 1%. As before, we compare this depth with the size of market orders to get an idea of its economic significance. We find that very large market orders, as given by the 90% quantile of the market orders' size could be executed on both sides of the book at least 95% of the time without moving the price by more than 1%. Yet, at least 1% of the time, the 10% largest market orders had an impact on price of more than 1%. And 5% of all times, the 1% largest market orders moved prices by more than 1%. We conclude that relatively often, large orders have a significant price impact. It would be interesting to study whether the depth was especially low at times of market turmoil, and thus pose an additional risk at such a time. As for the depth $Q_{t,5}^s$ of the best five offers, both the numbers for median and mean depth are very similar, indicating similar depth on the buy and sell side under 'normal' market conditions.

4.3 Cost of illiquidity

Black (1971) has pointed out that in a liquid market, traders need to accept a premium or discount in order to trade a large order immediately. The size of this premium (for brevity, we call also the discount required on the bid side premium) will increase with order size and will be higher at times where the market is less liquid. Therefore, we use the premium for a given order size as a proxy for market liquidity. We call the difference between the price per share offered by the limit orders and the mid-price the cost of illiquidity (CIL) of the respective side of the book (see Irvine et al. (2000)),

$$l_t^s(Q) \equiv |p_t^s(Q) - p_t^{mid}|,\ s \in \mathcal{S}.$$

It is the cost that a trader faces who requires immediate trading by placing a market order of size Q. If the market was perfectly liquid, that is, the spread was zero and depth equal to all shares that are in the free float, the CIL amounted to zero for any order size. On the other hand, if the market is not perfectly liquid, the CIL for a quantity Q exceeding the total depth of the book cannot be observed and would be needed to set equal to infinity. To avoid such difficulties, the analysis in this paper will always be restricted to quantities smaller than the total depth of the book.

This measure has been proposed by Irvine et al. (2000) (this measure was also used by Domowitz and Wang (2002) and Hansch (2003)) who analyzed the cost of a round trip, that is, buying and selling a quantity at the same instant. This corresponds to the sum of the CIL of the ask and bid side, $l_t^A(Q) + l_t^B(Q)$. CIL is a natural generalization of the best bid-ask spread to the situation where the complete order book is known: Where the latter amounts to twice the premium that has to be accepted, relative to the mid price, in order to trade a single unit, the CIL indicates the premium relative to the mid-price that has to be accepted when trading any desired quantity.

The measure $l_t^s(Q)$ is affected by the spread between the best bid and ask offers, since it corresponds to the premium paid relative to the mid-price: When the spread widens, the premium $l_t^s(Q)$ relative to the mid-price will increase as well. Therefore, commonality in the spread will induce commonality in the CIL measure. We therefore propose a new measure CIL$^{(2)}$ $L_t^s(Q)$:

$$L_t^s(Q) \equiv |p_t^s(Q) - p_{t,1}^s|,\ s \in \mathcal{S},$$

where $p_{t,1}^s$ denotes the price of the best order on the side $s \in \mathcal{S}$ of the book (see section 3.3 for the definition of $p_{t,1}^s$). The relationship between the spread, CIL and CIL$^{(2)}$ is then

$$l_t^s(Q) = \frac{1}{2}\text{Spread}_t + L_t^s(Q).$$

$L_t^s(Q)$ measures the liquidity on the side $s \in \mathcal{S}$ of the book without any impact of the other side of the book.

$l_t^s(Q)$ and $L_t^s(Q)$ depend on the trade size Q. Different trade sizes have been used in the literature: Irvine et al. (2000) used 5 different trade sizes, ranging from 5000 CAD up to 150'000 CAD; Hansch (2003) uses multiples of the average trade size; and Domowitz and Wang (2002) used trading quantities ranging from 1000 to 20'000 shares. We consider the following four hypothetic order sizes for which the CIL will be calculated:

- Small orders of size Q_{Sm}, corresponding to the first quartile of the size of market orders.
- Median orders of size Q_{Md}, corresponding to the median of the size of market orders.
- Order size Q_{MinD}, equal to the minimum depth that has ever been observed in a given stock on either side of the book,

$$Q_{\text{MinD}} \equiv \min(\min_{i=1,\dots T}\{\bar{Q}_{t_i}^A\}, \min_{i=1,\dots T}\{\bar{Q}_{t_i}^B\}).$$

- Order size Q_{Gmin}, equal to the minimum depth that has ever been observed for any stock (that is, the minimum of Q_{MinD} of all stocks).

Small and median orders reflect the size of actually placed market orders. The CIL and CIL$^{(2)}$ for these order sizes indicate the cost that average and below average sized orders face. Yet, observed market orders are only one part of the demand for liquidity: Since market participants will only place such orders that appear favorable to them in view of the liquidity of the market, we do not observe the largest orders because the market conditions are so unfavorable that they are not placed. Yet, we would like to measure also the liquidity for these unobservable demand for liquidity. We therefore calculate in addition CIL and CIL$^{(2)}$ for two very large hypothetic order sizes: Q_{MinD} amounts for any stock to the minimal total depth ever observed in the book for this title. This is the largest quantity for which the data allows us to calculate the CIL and CIL$^{(2)}$ for each point of time. As shown in Table 6, Q_{MinD} varies considerably across stocks. To measure the CIL for a hypothetic large order of constant size across different stocks, we use the fourth quantity, Q_{Gmin}. This quantity equals the minimum of Q_{MinD}, which is in our sample equal to the minimal depth of the stock BALN.

Table 7 reports the minimum, maximum and mean CIL and CIL$^{(2)}$ both for the ask and bid side averaged across stocks. Since the premium that a trader has to accept increases with order size, the minimum is constant for all order sizes. On average, the minimum CIL amounted to 4.7 basis points. This corresponds quite closely to one half of the average minimum spread reported in Table 5, suggesting that during the most liquid times, the only costs of immediacy faced by traders was the spread. This is confirmed by the fact that the minimum for CIL$^{(2)}$ amounts to zero. This means that there was for each stock an observation of the book where the size of the best order was larger the Q_{Sm}. Yet, both the maximum and the mean of CIL and CIL$^{(2)}$ reveal that the spread by far underestimates the costs of immediacy: The means for small and median orders are about three times as high as the half-spread. Interestingly, the mean values of CIL and CIL$^{(2)}$ are very similar on both sides of the book, suggesting similar costs of immediacy on average on both sides. Both the maximum values and the quantiles (not shown for the sake of space) suggest that the CIL and CIL$^{(2)}$ are very high at certain times. Again, it would be interesting to study whether the costs are high at times of market turmoil, and thus increase the risk of positions in the stock even further.

In general, the CIL for small and medium sized orders is below 1%, on average at a level of about 0.14%. A significant part of this cost consists of the spread, since the mean level of CIL$^{(2)}$ averaged across stocks are much smaller, around one basis point, except for the largest quantity Q analyzed, Q_{MinD}. The CIL thus constitute a second order risk compared to the market risk where standard deviations of daily returns are in the range from 1% to 4%. Yet, for trading strategies with a high trading frequency, the CIL can be of concern.

The summary statistics on the CIL for the largest stock in the sample, NOVN, confirm the higher liquidity in this stock: For small trading quantities (Q_{Sm} and Q_{Md}), the mean CIL amount to 5 basis points only on both sides of the book, while these numbers are for most other stocks above 100 basis points.

5 Commonality in liquidity

Research on commonality has proceeded mainly along three paths. Three main approaches have been used in the . Chordia et al. have regressed the liquidity proxies against market and industry averages. The significant coefficients in these regressions are interpreted as evidence for commonality.

Huberman and Halka (2001) have looked at the residuals of autoregressive processes that were fitted to the time-series of the liquidity proxies. The presence of positive correlation in these residuals is interpreted as evidence of a common factor affecting liquidity in different stocks. And Hasbrouck and Seppi (2001) have performed a principal components analysis of the liquidity proxies. We follow this last approach.

Principal components analysis looks for linear combinations of the data that explains as much as possible of the variance of the data. The weights of the variables in the linear combination forming the first principal components correspond to the first eigenvector of the variables' covariance matrix; the weights of for the second principal components correspond to the second eigenvector of the covariance matrix and so on (for a rigorous treatment of principal components analysis, see e.g. Flury (1988), Krzanowski (1988), Rao (1996)). Since principal components analysis is sensitive to units of measurement, the data is usually standardized to unit variances. Equivalently, the correlation matrix is used. Total variance in this case is just equal to the number of variables in the analysis. The ratio of the total variance explained by the $i-th$ principal component is then given by

$$v_i \equiv \frac{\lambda_i}{n}, \tag{3}$$

where λ_i is the $i-th$ eigenvalue of the correlation matrix of n variables. We denote by

$$V_m \equiv \frac{\sum_{i=1}^{m} \lambda_i}{n} \tag{4}$$

the ratio of the total variance explained by the first m principal components jointly. Under the assumption of normality for the original variables, then the sample eigenvalues $\hat{\lambda}_i$ are asymptotically independent and normally distributed with the following $1-\alpha$ confidence interval:

$$\frac{\hat{\lambda}_i}{1+z(\alpha/2)\sqrt{2/n}} \leq \lambda_i \leq \frac{\hat{\lambda}_i}{1-z(\alpha/2)\sqrt{2/n}}. \tag{5}$$

where $z(\alpha/2)$ is the upper $\alpha/2$th percentile of a standard normal distribution (Flury, 1988). For the ratio V_m of the cumulative variance explained by the first m principal component, the $1-\alpha$ confidence interval is given by

$$\frac{1}{n}\left(\sum_{i=1}^{m}\hat{\lambda}_i - z(\alpha/2)\sqrt{\frac{2}{n}\sum_{i=1}^{m}\hat{\lambda}_i^2}\right) \leq V_m \leq \frac{1}{n}\left(\sum_{i=1}^{m}\hat{\lambda}_i + z(\alpha/2)\sqrt{\frac{2}{n}\sum_{i=1}^{m}\hat{\lambda}_i^2}\right).$$

If there is no common factor explaining the variation in the time series, then all eigenvalues will be equal to one. Thus, we will report such eigen values (and corresponding principal components) which are statistically larger than 1. For principal components belonging to smaller eigen values, the hypothesis that all variables have the same explanatory power cannot be rejected.

It is well known that high-frequency data display strong intradaily patterns. This has been found in data on returns (Wood et al., 1985), volume (Jain and Joh, 1988, Foster and Viswanathan, 1990), volatility (Foster and Viswanathan, 1990) and in various markets such as stock, fixed income (Ballocchi et al., 1999) and foreign exchange markets (Andersen and Bollerslev, 1997), just to cite a selection of important contributions. Yet, for all three methods mentioned above it is crucial that the liquidity proxies can be well described by stationary stochastic processes. Hasbrouck and Seppi (2001) have therefore standardized the intradaily data by the mean and standard deviation at the time of the day. We use three different versions of the data in order to reduce distortions due to nonstationarity: First, we use the full series of intradaily data, aggregated over time intervals of 30 minutes. To avoid the distorting effect of these intradaily seasonalities, we then analyze commonality in the liquidity proxies on a daily basis, looking at the time series of daily averages. Further, we also study the time series of each liquidity proxies at a single point of time during the day. Panel A in Table 8 summarizes the different liquidity measures used.

5.1 Commonality of intraday data and daily averages

Starting from the full time series consisting of observations every five minutes, we construct two time series to perform statistical analysis: One series consists of intradaily data, averaged over 30 minutes time intervals. The other time series consists of the daily averages of the full sample.

The following filtering procedure is applied to obtain a stationary series of intraday data. The observations for a given liquidity proxy are averaged over time intervals of 30 minutes. In order to take the above mentioned intraweekly and intradaily seasonalities into account, we subtract from each observation the mean value for this time and day of the week.

The daily time series is obtained by averaging the observations for a given liquidity proxy for a single day, thus yielding a single observation of this liquidity proxy for this day and stock.

Figure 4 shows a plot of the daily series. During the three months' sample period, liquidity has clearly dropped, as indicated by the increase in the CIL. This suggests that liquidity is sensitive to general market conditions and is reduced during market downturns. $Q_t^s(1 \pm 1\%)$, the depth on the ask and bid side at 1%, has remained relatively constant. Both time series evolve in parallel. But the total depth of the book $\bar{Q}_t^s$ has experienced several shifts of level: The depth on the ask side increases during each of the three months, and drops at the end of the month when a large number of orders expire. The depth on the bid side dropped sharply at the end of the first month and remained relatively constant afterwards.

In view of these shifts of level in liquidity, a further transformation is required to obtain stationary time series. There is evidence that taking first differences would not appropriate to remove this nonstationarity since this induces negative autocorrelation, both for the intraday and daily series. As reported in Table 9, the actual time series of the liquidity proxies display for most stocks significantly positive coefficients of first order autocorrelation, using the standard 95% confidence intervals of $\pm 2/\sqrt{T}$ implied by Gaussian white noise (Hamilton, 1994). Yet, the first order autocorrelation of the differenced time series are mostly significantly negative. Thus, instead of using first differences, we follow the standard procedure in time series analysis (Brockwell and Davis, 1991) and remove first the trend component from the time series. For the intradaily series, we estimate the trend by the Hodrick Prescott filter (Hodrick and Prescott, 1997) with a smoothing parameter of $\lambda = 100 \cdot 220^2$. For the daily series, we estimate the trend by a moving average calculated over a time window of five days.[3] The number of observations is reduced by five days and 55 days remain. For these detrended time series, we then fit autoregressive processes. The resid-

[3]Without detrending by the moving average, the autoregressive processes estimated below fit the time series a bit less well. The explanatory power of the principal components estimated from the time series without trend removal is by about 1-2% higher, but otherwise the results from the principal components analysis are robust. This effect is thus likely to be due to the downward market movement during the sample period and we choose to use the trend removal.

uals are then sufficiently stationary and the sample correlation matrices can be used as input for the principal components analysis. Hence, we estimate commonality in the unpredictable component of liquidity that can be viewed as true risk factors. The predictable variation in liquidity, due to common intradaily seasonal patterns then adds to the commonality that we report. To judge the goodness of fit of the autoregressive processes, we report in Table 10 how often the null of the Ljung-Box test for nonzero autocorrelation in the residuals could be rejected at a confidence level of 95%. We calculate the Ljung-Box test statistic for 10 lags. As an example, consider the 100% reported for $l_t^A(Q_{\mathrm{Sm}})$ in Table 10. This means that for $l_t^A(Q_{\mathrm{Sm}})$ the hypothesis that the residuals have nonzero autocorrelation could be rejected for all stocks and for each of the first 10 lags of each series of residuals. Overall, the autoregressive processes give a very good fit; only $Q_t^A(1+1\%)$ displays residuals that are still autocorrelated for about 15% of all stocks.

Table 17 (Table 16) reports the results from the principal components analyses of the intradaily (daily) series. For all liquidity proxies and both sides of the book as well as the total, the first three eigenvalues are always significantly different from one, for most liquidity proxies the fourth eigenvalue is also statistically significant different from one. The proportion of the total variance explained by the first three principal components is about 25% intradaily and about 40% on a daily level. This suggests that specific factors have a higher impact within the trading day. The proportion of the total variance that is explained by the first principal component varies between the different liquidity proxies: For the spread, this proportion is about 13% (27% on a daily level). The number for the CIL measures are in a similar range, the variance being explained by the first principal component varying between 11% and 14% (23% and 29% on a daily level). However, for some of the $\mathrm{CIL}^{(2)}$ measures, this proportion is much lower at about 7% (15% on a daily level). This shows that the former measures are affected by commonality in the spread. The second principal component explains an additional 7% (12% on a daily level) of the variance and about another 7% (12% on a daily level) are explained by the third principal component. Overall, this is evidence for the presence of three, possibly four factors where the second and third factor have almost the same explanatory power.

For the depth related liquidity measures, the explanatory power is generally lower on the bid side than on the ask side, both for the intradaily and daily data. This could be related to the general downturn in market conditions during the sample period during which buy orders are more likely to be motivated by stock specific information than by market wide factors.

The explanatory power of the principal components for the CIL proxies of liquidity is not sensitive with respect to the quantity Q of the hypothetic order. However, for $\mathrm{CIL}^{(2)}$, the explanatory power of the first principal component increases with order size. This is another result from the effect of the spread on the liquidity proxy CIL. The $\mathrm{CIL}^{(2)}$ liquidity measures give thus a more precise picture of the commonality across various order sizes. The results suggest that common factors affect not only the liquidity offered at small quantities, but also the whole book.

Using intradaily data, Hasbrouck and Seppi (2001) find for the liquidity proxy with the highest fraction of the variation explained by the first common factor, the log quote slope, an explanatory power of 13% of the variance for the first principal component. They find that the first three principal components jointly explain about 30% of the total variation for the NYSE. Our results based on intradaily data are similar. Yet, on a daily level, we find for most liquidity proxies a higher explanatory power of the first principal component.

5.2 Commonality at different times of the day

We now analyze whether the explanatory power of the common factors varies across the day. We use the average of the liquidity proxies during each hour of the day. This yields 9 distinct time series, for each hour from 9:00 to 17:00. Similar as for the intradaily and daily data, there is clear evidence that taking first differences is inappropriate: From the actual time series for each stock, liquidity proxy and time of the day, 68% have a significant positive coefficient of first order autocorrelation; the coefficient of first order autocorrelation of the first differences of these time series is in 92% of all cases significantly negative. We therefore use the same filtering procedure as above, that is, a five days moving average is removed first, and then autoregressive processes are fitted. The residuals are used for the principal components analysis.

For each hour of the day and liquidity proxy used, a principal components analysis is performed. Table 13 reports the average number of significant factors found (that is, the number of eigenvalues that are statistically different from 1). The results confirm the findings of the previous analysis in that there is evidence of the existence of common factors driving the liquidity proxies. The number of principal components statistically significant different from 1 ranges between 4 and 5. The various liquidity proxies display very similar degrees of commonality. Thus, we find between three and four factors affecting commonality on daily averages, and between four and five factors affecting the liquidity at different times of the day.

Figures 5 and 6 show the portion of the total variance explained by the first four principal components for different times of the day. Their explanatory power varies between 20% and 40% at the different times of the day, a bit less than for the daily averages. The two CIL measures corresponding to small ($l_t^s(Q_{\text{Sm}})$, denoted by CIL small) and median order size ($l_t^s(Q_{\text{Md}})$, denoted by CIL median) move closely together and show very similar behavior on the ask and bid side. They display a minimum at lunch time, are high in the morning and attain their maximum after 15:00. On the bid side, $l_t^B(Q_{\text{MinD}})$ and $l_t^B(Q_{\text{Gmin}})$ also show this behavior. Yet, on the ask side, $l_t^B(Q_{\text{MinD}})$ fluctuates around its mean, while $l_t^B(Q_{\text{Gmin}})$ also attains its maximum in the late afternoon.

The explanatory power of the spread plotted in Figure 6 follows closely the corresponding curve for $l_t(Q_{\text{Sm}})$. This results from the fact that $l_t(Q_{\text{Sm}})$ and the spread almost coincide, as can be seen from Figure 4(a).

For the depth measures, the explanatory power of the common factors displays only little intradaily variation. At lunch time, the effect of the common factors on liquidity on the depth $Q_{t,5}^s$ provided by the best 5 offers is the highest on the ask side, while these factors have the least effect on the bid side between 13:00 and 15:00. The explanatory power of the common factors for the quantity $Q_t^s(1 \pm 1\%)$ available at a 1% premium displays on the bid side a U-shape, characteristic for many activity related measures. Also the impact of the common factors on the total depth $\bar{Q}_t^s$ displays on the bid side the U-shape. As for the daily averages, the fraction of the variation in liquidity that can be explained by common factors is generally lower than for the CIL measures. This is evidence that changes in the number of shares offered or demanded are more subject to stock specific factors than the costs at which they are available. A hypothesis that would be interesting to test is whether stock specific factors determine market participants' decision to buy or sell, while the competitiveness of their orders are more subject to market wide factors.

Our results suggest that the CIL liquidity measures are generally most subject to common factors after 15:00 and the least during lunch time. This corresponds to the intradaily patterns found for the SWX by Ranaldo (2001) in the levels of some liquidity proxies. He explains the high liquidity in the afternoon by the preopening of the US markets. This could also explain the large fraction of variation explained by common factors since news from the US markets might be interpreted as hints on the general direction of the markets, thus giving rise to market wide buying or selling. On the other side, we find some evidence that during lunch time liquidity in stocks moves more independently.

The U-shape in the variation of the CIL and $\bar{Q}_t^s$ and $Q_t^s(1 \pm 1\%)$ liquidity measures explained by the first three factors resembles the well established intradaily trading activity patterns found in previous research. For example, mean returns (see e.g. Wood et al. (1985), Andersen and Bollerslev (1997)), return volatility (see Wood et al. (1985)), quoted spreads and volume (Lee et al., 1993) have been found on the NYSE to be the highest at the opening and closing and lower during the day.

6 Commonality in market activity

A necessary, but not sufficient condition for comovement of liquidity in the different stocks on the market is that market activity is also subject to common factors. We therefore turn to the analysis of market activity where we use as a proxy for market activity the following measures (see also the overview in Panel B of Table 8):

- LORDERSN: The number of buy, sell and total limit orders submitted for a given stock during the previous 15 minutes.
- LORDERSQ: The total quantity of the buy, sell and total limit orders submitted for a given stock during the previous 15 minutes.
- MORDERSN: The number of buy, sell and total market orders submitted for a given stock during the previous 15 minutes.
- MORDERSQ: The total quantity of the buy, sell and total market orders submitted for a given stock during the previous 15 minutes.
- TRADESN: The number of trades executed for a given stock during the previous 15 minutes.
- TRADESQ: The total quantity of the trades submitted for a given stock during the previous 15 minutes.

These time series are also plagued by intraweekly seasonalities. We therefore apply the same detrending procedure as above, estimate ARMA processes and use the residuals.

Table 17 (Table 16) reports the results from the principal components analyses of the intradaily (daily) series. For all proxies, the first principal component explains a large fraction of the variance, and generally there are only two eigenvalues statistically significant different from one. Similar as in the case of the liquidity proxies, the explanatory power of the principal components for the market activity proxies is higher for daily averages than for the intraday data, suggesting the existence of stock specific factors on an intradaily level. The first principal component explains between 12% and 74% (24% to 32% on a daily basis) of the variance. Most interestingly, there is for both sampling frequencies consistently higher commonality in MORDERSN than in LORDERSN, the first principal component explaining more than 60% in the variance of the number of market orders submitted. This suggests that the demand for liquidity, given by the market orders, is more affected by common factors than the supply of liquidity by limit orders.

We, thus, find evidence for common factor in the market activity that has high explanatory power. This common factor affects liquidity demand stronger than liquidity supply. The impact of stock specific influences appears to be less on a daily basis.

7 Financial variables driving commonality in liquidity

The analysis presented in this paper found empirical evidence of the existence of three to four factors affecting the proxies of liquidity of all stocks jointly on a daily level. Yet, principal components analysis does not give a hint on the nature of these factors. In this section, we attempt to identify financial variables that can be identified as these factors.

Chordia et al. (2000a) have analyzed the existence of commonality in liquidity by regressing first differences of liquidity proxies ($DLIQ$) of a sample of stocks first on the market average liquidity (the first differences are denoted by $DMLIQ$) and then also on the industry averages of these proxies where the respective stock is excluded from the average. When they estimated the equation

$$DLIQ_{j,t} = \alpha_j + \beta_{M,j} DMLIQ_t + \epsilon_{j,t},$$

they found that, depending upon the liquidity proxy being used, between 70% and 85% of the coefficients were positive and between 15% and 35% were significantly positive. The explanatory power (measured by the adjusted R^2) of their regression was about 1%.

Using the daily data for which we have found a higher degree of commonality, we test the explanatory power of the market average of the liquidity proxies which is regarded by Chordia et al. (2000a) as a factor. To this end, we estimate the following time-series regressions for each stock j, $1, 2, \ldots, 19$:

$$LIQ_{j,t} = \alpha_j + \beta_{MLIQ,j} MLIQ_t + \epsilon_{j,t}. \tag{6}$$

LIQ_j denotes the liquidity proxy for stock j and $MLIQ_t$ denotes the average of the liquidity proxies, excluding stock j. As discussed above, there is evidence that taking first differences induces autocorrelation in our sample. We therefore use, instead of first differences, the residuals of the autoregressive processes that are also the input for our principal components analysis above. Table 14 reports the results. Estimated coefficients are averaged across stocks; 'Sign' reports the number of stocks that had an estimate for this coefficient statistically different from zero. 'Pos' reports the percentage of the stocks that had a positive estimate for this coefficient, 'SPos' the percentage of the stocks that had a significant positive estimate for this coefficient. Finally, R^2 and the adjusted R^2 are also averaged across stocks.

Virtually all estimates $\hat{\beta}_{MLIQ}$ reported in Panel A of Table 14 are positive. For the CIL liquidity proxies, all estimates are positive, 70% also significant positive. On average, for 85% of the depth related liquidity proxies, $\hat{\beta}_{MLIQ}$ is positive, for 40% significant positive and also the mean values $\hat{\beta}_{MLIQ}$ are all positive. The adjusted R^2 is low, and the explanatory power is higher for the CIL measures (explaining 16%) than for the depth measures (at 6%). These results confirm the findings of the principal components analysis in that there is commonality in liquidity for our sample and that it has higher explanatory power for the CIL measures compared to the depth related liquidity proxies. The explanatory power of the market averages of our liquidity measures based on the limit order book is three to six times higher than for the liquidity proxies studies by Chordia et al. (2000a). Thus, the first common factor explains a larger fraction of the variation in the liquidity proxies than comparable studies have found for the NYSE. This confirms the result from the principal components analysis.

The low average values of the adjusted R^2 suggest that 'there is either a large component of noise and/or other influences on daily changes individual stock liquidity constructs.' (Chordia et al., 2000a, p. 12). Given that we have found evidence for the existence of several factors, it is not surprising that this single factor has only a low explanatory power. We will try to determine other financial variables that affect liquidity across assets. Such variables can be viewed as candidates for further factors.[4]

Market volatility is likely to affect liquidity provision and demand across assets, given that it represents a measure of investors' sentiment capturing the general degree of uncertainty and dispersion of opinions about the future development of stock prices. Further, changes in the general level of volatility will have an impact on the risk that investors accept in their portfolios and might induce them to adjust their exposure in a synchronous way across assets.

Another variable which is well known to have a market wide impact is the interest rate. It is an important state variable in asset pricing models such as in the intertemporal CAPM by Merton (1973). Representing an important

[4]Given the short period for which we have data, macro economic variables cannot be considered due to their low reporting frequency.

component of the cost of capital investors face, it is to be expected that it affects their liquidity provision and demand for all assets simultaneously.

We further consider market returns as a possible source of commonality. As displayed in Figure 4, liquidity decreased significantly while prices decreased considerably.

We estimate for each liquidity proxy LIQ the following time-series regression for all stocks j, $1, 2, \ldots, 19$:

$$LIQ^s_{j,t} = \alpha_j + \beta_{DIR,j} DIR_t + \beta_{MRET,j} MRET_t + \beta_{MVOL,j} MVOL_t + \beta_{MLIQ,j} MLIQ_t + \varepsilon_{j,t}. \tag{7}$$

As interest rate, the 1 month CHF LIBOR rate from Datastream is used.[5] Instead of interest rate levels, we consider the first differences DIR since interest rates decreased throughout the sample period and cannot be regarded as being stationary. MRET denotes the return on the SMI index. As a measure of volatility, we use the realized volatility (see e.g. Andersen and Bollerslev (1997, 1998), Andersen et al. (2001, 2002). This measure reflects the price variability throughout a day: A stock may be subject to large variations in the price, but have the same closing price as on the previous day. Realized volatility reflects this price variation, but volatility calculated from closing prices would be zero. To calculate the realized volatility, we first construct the return on the equally weighted portfolio consisting of all stocks in our sample.[6] $MVOL$ then denotes the realized volatility of this portfolio, defined as cumulated squared five minutes returns throughout the given day.

Panels B to D of Table 14 show the results from running univariate regression of the liquidity proxies first on each of the additional explanatory variables. Market volatility has the highest explanatory power with an average of 7% for the CIL measures. 83% of the CIL liquidity proxies have a positive coefficient, 38% are significant. The results for the depth related liquidity proxies are mixed: Market volatility has clearly a positive effect on the depth DEPTH$_t$ on the ask side (79 % of the coefficients are positive, 16% significant positive), the depth $Q^B_t(1-1\%)$ at a 1% premium on the bid side (37% positive, 16% significant) and the depth $Q^s_{t,5}$ on the bid side (74% positive, 11% significant). But for the other three depth measures, market volatility clearly has a negative effect, between 16% and 26% of the estimated coefficients having significant negative signs. Overall, this is evidence for the market volatility having a negative effect on liquidity.

[5] When the overnight interest rate from the Swiss National Bank, as provided by Datastream, is used, the results are almost identical.

[6] Our sample consists of one very large stock, NOVN, making up about 60% of the market capitalization of the whole portfolio and the second largest making up another 10% (see Table 2). Therefore, value weighted returns would reflect to a large extent the behavior of the two largest stocks.

The results from the univariate regression of the liquidity proxies on the market return and the interest rate document little effect of these quantities on liquidity. Adjusted R^2 are below 2% and only a small number of coefficients are significant.

MLIQ and MVOL display a relatively high correlation: Table 15 displays for each liquidity proxy the correlation of the corresponding market average of the liquidity variable with the volatility of the return on the equally weighted market portfolio (for every stock, the market average liquidity MLIQ excludes the current stock and therefore MLIQ differs slightly across stocks; therefore, correlations shown in Table 15 are averaged across stocks). The CIL measures generally have a correlation of about 25% to 40% with market volatility. For the depth measures, correlation is much less significant. To assess the effects of market volatility and market liquidity on individual stocks' liquidity separately, we regress the liquidity proxies on market volatility MVOL and market liquidity MLIQ. As shown in Panel E of Table 14, the adjusted R^2 is for the CIL liquidity proxies, at 20%, higher than in the univariate regressions. Hence, market volatility and liquidity have distinct effects individual stocks' liquidity. This is underlined by the smaller number of significant estimates compared to the univariate regression. These results remain largely unchanged in a multivariate regression adding interest rate and market return as explanatory variables, as shown in Panel F of Table 14.

When we repeat the above estimation using intradaily data (excluding the interest rate, for which no intradaily data are available), we obtain very similar results in terms of number of positive coefficients and number of positive and significant coefficients. Yet, the adjusted R^2 coefficients are much lower, between 2% and 4%. This confirms the results from the principal components analysis that stock specific factors play an important role within the trading day.

We further estimate (7) using the market activity proxies instead of the liquidity proxies. The same filtered time series as in section 6 are used. Our results confirm the findings from the principal components analyses of these time series: The adjusted R^2 of the market average activity is between 13% and 75% for daily data, more than 84% of the coefficients of market activity are positive and significantly different from zero. Market volatility and market returns have only little explanatory power. For the intradaily series, the adjusted R^2 ranges between 3% and 20%. This underpins our finding that there is more noise in the intraday level. A notable exception is the number of submitted market orders MORDERSN for which the adjusted R^2 is between 65% and 75% for the bid, ask and total orders. However, this is not a simple result of the liquidity demand reacting to overall market volatility or return, since the explanatory power of these variables in the regressions is negligible.

Our empirical analysis has shown that market liquidity and market volatility both have an effect on stocks liquidity and can be considered as two of the common factors that we have found previously. Yet, these factors only explain on average 20% of the variation of the CIL liquidity measures and 6% of the depth related measures. It remains for future research to determine whether this is really due to large noise or whether there are other sources of commonality as mentioned by Chordia et al. (2000a).

8 Conclusion

This paper finds empirical support for the existence of common factors affecting liquidity. We find that commonality also exists on pure limit order markets and that the common factors have even higher explanatory power than for quote driven markets. This is an important finding for two reasons: Firstly, it is not obvious that results from quote driven markets would extend to limit order markets which are a highly relevant market form given the large number of exchanges organized as pure limit order markets and plans of the NYSE to make some adjustments to its market design towards this market form. Secondly, previous research, having focused on quote driven markets, has found mixed evidence on commonality. In this study, we have access to the complete supply schedules of liquidity. It might well be that it is due to this better data basis that we find stronger evidence of commonality. We find evidence that changes in the number of stocks offered or demanded are more subject to stock specific factors than the costs at which they are available. A hypothesis that would be interesting to test is whether stock specific factors common factors determine market participants' decision to buy or sell, while the competitiveness of their orders are more subject to market wide factors.

Another new result is that the common factors affect liquidity at all order sizes, beyond the best offers or the market makers' quoted quantities. Further, we find that the proportion of the variation of liquidity explained by the common factors varies throughout the day. This new finding adds to the intraday seasonalities found in previous research. It is also a hint that one might arrive at misleading results when using liquidity proxies sampled at a certain time of the day.

A very large fraction of the variation in market activity also stems from a common factor. A new finding is that the demand for liquidity is more affected by common factors than the supply of liquidity.

Further, we find that both market liquidity and market volatility have a strong impact on liquidity across assets. Yet, these factors only explain on average 20% of the variation of the CIL liquidity measures and 6% of the depth related measures. It remains for future research to determine whether this is due to large noise or whether there are other sources of commonality. The reason for the higher degree of commonality on the limit order market, compared to quote driven markets, also remains open. It could well be a structural feature of pure limit order markets and it would be interesting to study other limit order markets. It could also be due to the adverse market environment during our sample period and therefore more data would be needed to answer this question. The reason could also be that on both quote driven and order driven market, commonality is high, but that this cannot be properly measured on quote driven markets due to the partial information that is available on the supply of liquidity.

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Price range		Tick size
From	To	
0.01	9.99	0.01
10.00	99.95	0.05
100.00	249.75	0.25
250.00	499.50	0.50
500.00	4'999.00	1.00
5'000.00	and more	5.00

Source: Swiss Stock Exchange (2003b)

Table 1: Tick size rules for stocks at the SWX

A Tables

Symbol	Short Name	Industry	NO	May 3rd 2002				July 31st 2002			
				Price	Cap.	Weight	FFl	Price	Cap.	Weight	FFl
ADEN	Adecco	Capital goods	186.0	101.00	11.4	1.41	60.6	67.40	7.6	1.19	60.6
BAER	Julius Baer	Finance & Insurance	9.3	517.00	4.8	0.60	100.0	378.00	3.5	0.55	100
BALN	Baloise	Finance & Insurance	55.3	132.75	5.8	0.72	79.0	89.90	3.9	0.61	79.03
CFR	Richemont	Consumer goods & services	522.0	37.00	14.9	1.85	77.2	27.30	11.0	1.72	77.22
CIBN	Ciba	Basic Industries	66.0	125.50	7.6	0.94	91.6	102.50	6.2	0.97	91.6
CLN	Clariant	Basic Industries	153.4	38.90	5.5	0.69	92.7	28.30	4.0	0.63	92.71
GIVN	Givaudan	Capital goods	8.4	597.00	4.5	0.56	90.0	595.00	4.5	0.70	90
HOLN	Holcim	Basic Industries	29.0	372.00	10.1	1.25	93.4	285.00	7.7	1.21	93.43
KUD	Kudelski	Capital goods	46.7	70.50	2.2	0.27	65.5	38.50	1.2	0.18	65.48
LONN	Lonza	Basic Industries	55.3	116.50	5.3	0.66	82.7	95.50	4.3	0.67	88.24
NOVN	Novartis	Consumer goods & services	2885.2	67.50	184.8	22.91	94.9	60.35	165.2	25.85	94.9
RUKN	Swiss Re	Finance & Insurance	316.2	166.00	48.1	5.96	91.7	124.00	35.9	5.62	91.66
SCMN	Swisscom	Utilities	73.6	475.00	12.1	1.49	34.5	431.50	10.9	1.71	34.5
SEO	Serono	Consumer goods & services	11.7	1276.00	8.8	1.09	59.3	775.00	5.4	0.84	59.33
SGSN	SGS	Capital goods	7.8	448.00	3.1	0.38	87.6	418.00	2.5	0.39	76.47
SYNN	Syngenta	Basic Industries	112.6	100.25	10.6	1.31	93.9	75.60	8.0	1.25	93.94
UHRI	Swatch	Consumer goods & services	34.3	157.00	5.4	0.67	100.0	125.25	4.3	0.67	100
UHRN	Swatch	Consumer goods & services	140.8	33.55	2.4	0.30	51.3	26.00	1.9	0.29	51.33
UNAX	Unaxis	Capital goods	13.2	187.75	1.6	0.20	66.1	147.00	1.3	0.20	66.12
					349.0	43.27			289.4	45.27	

Number of outstanding securities (NO) is given in millions. Market capitalization (Cap.) is given in billion CHF. Weight gives the weight of the stock in the SMI in percent. Free float (FFl) is in percent of the outstanding securities; data on the free float is provided by the SWX in order to determine the stocks' weight in the Swiss Market Index (SMI).

Table 2: Stocks in sample

	Turnover in millionth					
	10%	25%	50%	75%	90%	99%
Limit orders	1.3	3.2	8.7	18.7	39.8	152.8
Market orders	0.2	0.5	1.7	5.6	15.8	88.0
Trades	0.4	1.2	3.1	8.0	16.1	52.2

The quantiles are averaged across the stocks in the sample.

Table 3: Quantiles

	Number of times without trading
ADEN	45
BAER	33
BALN	51
CFR	40
CIBN	1
CLN	27
GIVN	25
HOLN	3
KUD	81
LONN	57
NOVN	5
RUKN	43
SCMN	0
SEO	35
SGSN	35
SYNN	10
UHRI	36
UHRN	53
UNAX	36

Table 4: Times without trading

	$\bar{Q}_t^s$		$Q_t^s(1 \pm 1\%)$		$Q_{t,5}^s$		Spread_t
	Ask	Bid	Ask	Bid	Ask	Bid	
Mean	1’821	986	240	232	80	80	28
1%	924	347	23	23	13	13	
5%	1’095	482	49	52	22	22	
10%	1’215	567	70	75	28	28	13
25%	1’379	673	120	127	43	42	15
50%	1’531	755	202	203	65	65	23
75%	1’655	834	311	296	98	98	34
99%	1’784	916	942	800	318	379	89

Depth is in millionths of the total number of free floating shares; spreads are stated in basis points. Numbers reported are averaged across stocks.

Table 5: Descriptive statistics of the quantiles of the different liquidity measures

	Q_{Sm}	Q_{Md}	Q_{MinD}	Q_{Gmin}
ADEN	0.8	2.2	140.8	18.9
BAER	0.5	2.0	72.3	18.9
BALN	0.4	1.2	18.9	18.9
CFR	0.5	1.5	33.6	18.9
CIBN	0.4	1.7	241.0	18.9
CLN	0.6	1.7	87.5	18.9
GIVN	0.4	1.3	265.2	18.9
HOLN	0.7	1.8	374.7	18.9
KUD	1.3	3.3	766.0	18.9
LONN	0.4	1.5	103.9	18.9
NOVN	0.1	0.2	118.0	18.9
RUKN	0.3	0.7	81.1	18.9
SCMN	0.5	1.6	229.9	18.9
SEO	0.9	2.5	113.6	18.9
SGSN	0.7	2.5	201.5	18.9
SYNN	0.1	0.5	105.9	18.9
UHRI	0.8	2.4	198.2	18.9
UHRN	0.4	1.4	155.0	18.9
UNAX	0.5	2.1	199.2	18.9

All numbers in millionths.
Symbols:
Q_{Sm}: First quartile of the size of the market orders of the respective stock.
Q_{Md}: Median size of the market orders of the respective stock.
Q_{MinD}: Minimum depth for the respective stock.
Q_{Gmin}: Minimum depth of the book across time and all stocks.

Table 6: Order size Q used to calculate costs of illiquidity

		CIL		CIL$^{(2)}$	
		Ask	Bid	Ask	Bid
Minimum		4.7	4.7	0.0	0.0
Maximum	Q_{Sm}	119.6	121.5	81.8	76.4
	Q_{Md}	125.4	131.4	113.7	118.3
	Q_{MinD}	809.0	963.3	826.6	1039.8
	Q_{Gmin}	232.5	256.9	230.4	243.8
Mean	Q_{Sm}	14.1	14.1	0.3	0.3
	Q_{Md}	14.5	14.5	0.9	1.0
	Q_{MinD}	76.1	72.0	70.7	66.2
	Q_{Gmin}	20.3	20.3	11.1	10.9

All numbers in basis points.
Symbols:
Q_{Sm}: Cost for order size, corresponding to the first quartile of the size of the market orders of the respective stock.
Q_{Md}: Cost for order size corresponding to the median of the size of the market orders of the respective stock.
Q_{MinD}: Cost for order size corresponding to minimum depth for the respective stock.
Q_{Gmin}: Cost for order size corresponding to the minimum depth of the book across all stocks.

The exact order size for these categories are given in Table 6.
Numbers are averaged across stocks.

Table 7: Average CIL and CIL$^{(2)}$

	Panel A: Liquidity proxies
$l_t^s(Q_{\mathrm{Sm}})$	CIL for small orders as given by the 25% quantile of the observed order size distribution
$l_t^s(Q_{\mathrm{Md}})$	CIL for medium sized orders as given by the median of the observed order size distribution
$l_t^s(Q_{\mathrm{MinD}})$	CIL for large orders as given by the observed minimum depth for the respective stock
$l_t^s(Q_{\mathrm{Gmin}})$	CIL for large orders as given by the observed minimum depth of the book across time and all stocks
$L_t^s(Q_{\mathrm{Sm}})$	CIL$^{(2)}$ for small orders as given by the 25% quantile of the observed order size distribution
$L_t^s(Q_{\mathrm{Md}})$	CIL$^{(2)}$ for medium sized orders as given by the median of the observed order size distribution
$L_t^s(Q_{\mathrm{MinD}})$	CIL$^{(2)}$ for large orders as given by the observed minimum depth for the respective stock
$L_t^s(Q_{\mathrm{Gmin}})$	CIL$^{(2)}$ for large orders as given by the observed minimum depth of the book across time and all stocks
$\bar{Q}_t^s$	Total depth of the book
$Q_t^s(1 \pm 1\%)$	Depth available at a premium of 1% relative to the mid-price
$Q_{t,5}^s$	Depth provided by the best five orders
Spread	Spread between best bid and ask offer
	Panel B: Market activity proxies
LORDERSN	Number of limit orders submitted during the previous 15 minutes
LORDERSQ	Turnover (=fraction of outstanding freefloat) of the limit orders submitted during the previous 15 minutes
MORDERSN	Number of market orders submitted during the previous 15 minutes
MORDERSQ	Turnover (=fraction of outstanding freefloat) of the market orders submitted during the previous 15 minutes
TRADESN	Number of the trades executed during the previous 15 minutes
TRADESQ	Turnover (=fraction of outstanding freefloat) of the trades executed during the previous 15 minutes

Table 8: Liquidity and market activity measures used

Liquidity measure	Daily		Intraday	
	Actual series	First differences	Actual series	First differences
$l_t^A(Q_{\mathrm{Sm}})$	100	84	100	100
$l_t^B(Q_{\mathrm{Sm}})$	100	79	100	95
$l_t(Q_{\mathrm{Sm}})$	100	84	100	100
$l_t^A(Q_{\mathrm{Md}})$	100	84	100	100
$l_t^B(Q_{\mathrm{Md}})$	100	84	100	95
$l_t(Q_{\mathrm{Md}})$	100	84	100	100
$l_t^A(Q_{\mathrm{MinD}})$	100	74	100	95
$l_t^B(Q_{\mathrm{MinD}})$	95	89	100	95
$l_t(Q_{\mathrm{MinD}})$	95	84	100	95
$l_t^A(Q_{\mathrm{Gmin}})$	100	95	100	100
$l_t^B(Q_{\mathrm{Gmin}})$	95	74	100	95
$l_t(Q_{\mathrm{Gmin}})$	95	89	100	100
$L_t^A(Q_{\mathrm{Sm}})$	11	95	26	100
$L_t^B(Q_{\mathrm{Sm}})$	26	95	42	100
$L_t(Q_{\mathrm{Sm}})$	37	100	32	100
$L_t^A(Q_{\mathrm{Md}})$	47	100	68	100
$L_t^B(Q_{\mathrm{Md}})$	47	100	68	100
$L_t(Q_{\mathrm{Md}})$	58	100	79	100
$L_t^A(Q_{\mathrm{MinD}})$	100	79	100	95
$L_t^B(Q_{\mathrm{MinD}})$	84	89	100	95
$L_t(Q_{\mathrm{MinD}})$	95	84	100	95
$L_t^A(Q_{\mathrm{Gmin}})$	84	95	100	100
$L_t^B(Q_{\mathrm{Gmin}})$	89	100	100	100
$L_t(Q_{\mathrm{Gmin}})$	95	89	100	100
$\bar{Q}_t^A$	89	68	100	32
$\bar{Q}_t^B$	89	79	100	53
$Q_t^A(1+1\%)$	89	89	100	89
$Q_t^B(1-1\%)$	89	89	100	84
$Q_{t,5}^A$	32	89	100	100
$Q_{t,5}^B$	37	95	100	100
Spread	100	84	100	100

In the column actual series is the percentage of stocks reported for which first order autocorrelation is significantly positive, that is $\rho > 2/\sqrt{T}$.
In the column first differences is the percentage of stocks reported for which first order autocorrelation of the first differences is significantly negative, that is $\rho < -2/\sqrt{T}$.

Table 9: Effect of taking differences on first order autocorrelation

	Daily			Intraday		
	Ask	Bid	Total	Ask	Bid	Total
$l^s(Q_{\text{Sm}})$	99.5	100.0	100.0	99.5	98.4	98.9
$l^s(Q_{\text{Md}})$	99.5	100.0	100.0	97.9	95.8	100.0
$l^s(Q_{\text{MinD}})$	97.4	99.5	97.9	88.4	77.9	82.6
$l^s(Q_{\text{Gmin}})$	99.5	98.4	100.0	97.9	94.2	94.7
$L^s(Q_{\text{Sm}})$	100.0	100.0	100.0	96.8	95.8	100.0
$L^s(Q_{\text{Md}})$	100.0	100.0	98.4	100.0	100.0	99.5
$L^s(Q_{\text{MinD}})$	99.5	100.0	96.8	85.8	77.9	78.4
$L^s(Q_{\text{Gmin}})$	100.0	98.9	100.0	98.9	95.3	98.4
$\bar{Q}_t^s$	100.0	100.0		100.0	100.0	
$Q_t^s(1 \pm 1\%)$	84.4	95.6		99.4	100.0	
$Q_{t,5}^s$	97.8	98.9		100.0	98.9	
Spread			100.0			100.0
Average	98.0	99.2	99.2	96.8	94.0	94.7

Percentage of all stocks for which the null of the Ljung-Box test for nonzero autocorrelation in the residuals of the fitted autoregressive processes could be rejected at a confidence level of 95%. Ljung-Box test statistic is calculated for 10 lags.

Table 10: Goodness of fit for daily averages

	Ask side								Bid side								Total							
	Eigen values				Variance explained				Eigen values				Variance explained				Eigen values				Variance explained			
	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4
$l^s(Q_{\mathrm{Sm}})$	5.34	2.13	1.75	1.41	28.10	39.33	48.53	55.93	4.66	2.21	1.61	1.49	24.53	36.17	44.64	52.50	5.41	2.00	1.68	1.43	28.47	38.97	47.80	55.30
	(3.8)	(1.5)	(1.3)	(1.0)	(20.2)	(27.6)	(36.3)	(43.3)	(3.3)	(1.6)	(1.2)	(1.1)	(17.6)	(25.5)	(33.5)	(40.9)	(3.9)	(1.4)	(1.2)	(1.0)	(20.5)	(27.1)	(35.4)	(42.6)
$l^s(Q_{\mathrm{Md}})$	5.50	2.08	1.87	1.40	28.97	39.93	49.76	57.12	4.83	2.20	1.58	1.51	25.42	36.98	45.28	53.24	5.66	2.06	1.61	1.45	29.80	40.62	49.07	56.69
	(4.0)	(1.5)	(1.3)	(1.0)	(20.9)	(27.9)	(37.1)	(44.2)	(3.5)	(1.6)	(1.1)	(1.1)	(18.3)	(26.0)	(33.9)	(41.4)	(4.1)	(1.5)	(1.2)	(1.0)	(21.4)	(28.2)	(36.2)	(43.5)
$l^s(Q_{\mathrm{MinD}})$	4.91	3.32	1.80	1.41	25.84	43.33	52.79	60.23	4.84	2.10	1.95	1.50	25.45	36.50	46.76	54.63	4.66	2.36	1.58	1.49	24.51	36.92	45.22	53.08
	(3.5)	(2.4)	(1.3)	(1.0)	(18.7)	(31.3)	(40.3)	(47.4)	(3.5)	(1.5)	(1.4)	(1.1)	(18.5)	(26.1)	(35.7)	(43.2)	(3.4)	(1.7)	(1.1)	(1.1)	(17.8)	(26.5)	(34.3)	(41.7)
$l^s(Q_{\mathrm{Gmin}})$	5.68	2.27	1.50	1.28	29.88	41.84	49.76	56.52	4.28	2.39	1.75	1.60	22.54	35.11	44.34	52.75	5.24	2.49	1.67	1.47	27.58	40.66	49.47	57.18
	(4.1)	(1.6)	(1.1)	(0.9)	(21.5)	(29.3)	(36.9)	(43.4)	(3.1)	(1.7)	(1.3)	(1.1)	(16.2)	(25.0)	(33.6)	(41.5)	(3.8)	(1.8)	(1.2)	(1.1)	(19.9)	(28.8)	(37.1)	(44.5)
$L^s(Q_{\mathrm{Sm}})$	2.56	2.04	1.87	1.71	13.48	24.23	34.08	43.08	2.81	2.21	1.66	1.56	14.80	26.42	35.13	43.35	2.88	2.38	1.94	1.60	15.14	27.67	37.87	46.27
	(1.9)	(1.5)	(1.4)	(1.2)	(9.8)	(17.7)	(26.5)	(34.8)	(2.0)	(1.6)	(1.2)	(1.1)	(10.7)	(19.2)	(27.2)	(34.8)	(2.1)	(1.7)	(1.4)	(1.2)	(11.0)	(20.2)	(29.4)	(37.3)
$L^s(Q_{\mathrm{Md}})$	3.38	2.27	1.94	1.70	17.80	29.73	39.96	48.90	2.64	2.17	1.86	1.78	13.87	25.29	35.10	44.49	3.76	1.96	1.67	1.56	19.77	30.06	38.84	47.05
	(2.5)	(1.6)	(1.4)	(1.2)	(12.9)	(21.6)	(31.0)	(39.3)	(1.9)	(1.6)	(1.4)	(1.3)	(10.0)	(18.4)	(27.3)	(35.9)	(2.7)	(1.4)	(1.2)	(1.1)	(14.3)	(21.6)	(29.7)	(37.4)
$L^s(Q_{\mathrm{MinD}})$	4.54	3.38	1.76	1.50	23.91	41.70	50.99	58.91	4.71	2.20	1.92	1.42	24.79	36.35	46.48	53.97	4.53	2.19	1.69	1.54	23.83	35.34	44.26	52.35
	(3.3)	(2.4)	(1.3)	(1.1)	(17.3)	(30.2)	(39.0)	(46.5)	(3.4)	(1.6)	(1.4)	(1.0)	(18.0)	(25.9)	(35.4)	(42.5)	(3.3)	(1.6)	(1.2)	(1.1)	(17.3)	(25.3)	(33.6)	(41.3)
$L^s(Q_{\mathrm{Gmin}})$	4.41	2.13	1.72	1.44	23.19	34.41	43.47	51.06	3.63	2.42	1.81	1.55	19.11	31.83	41.36	49.52	4.69	2.07	1.61	1.42	24.68	35.57	44.06	51.53
	(3.2)	(1.5)	(1.2)	(1.0)	(16.8)	(24.5)	(33.0)	(40.2)	(2.6)	(1.8)	(1.3)	(1.1)	(13.8)	(23.1)	(31.9)	(39.6)	(3.4)	(1.5)	(1.2)	(1.0)	(17.9)	(25.4)	(33.4)	(40.5)
$\bar{Q}_t^s$	4.87	1.80	1.72	1.49	25.62	35.12	44.18	52.01	3.19	2.00	1.85	1.63	16.80	27.35	37.08	45.66								
	(3.6)	(1.3)	(1.3)	(1.1)	(18.7)	(25.0)	(33.5)	(41.0)	(2.3)	(1.5)	(1.3)	(1.2)	(12.2)	(19.8)	(28.7)	(36.6)								
$Q_t^s(1 \pm 1\%)$	4.02	2.03	1.75	1.53	21.18	31.86	41.06	49.10	3.18	1.90	1.76	1.59	16.75	26.74	36.02	44.36								
	(2.9)	(1.5)	(1.3)	(1.1)	(15.3)	(22.7)	(31.2)	(38.7)	(2.3)	(1.4)	(1.3)	(1.2)	(12.2)	(19.4)	(27.9)	(35.6)								
$Q_{t,5}^s$	2.74	2.36	1.84	1.58	14.41	26.82	36.49	44.79	2.49	2.22	1.66	1.59	13.10	24.80	33.54	41.90								
	(2.0)	(1.7)	(1.3)	(1.1)	(10.4)	(19.4)	(28.1)	(35.8)	(1.8)	(1.6)	(1.2)	(1.1)	(9.5)	(18.1)	(26.0)	(33.7)								
Spread																	5.15	1.98	1.72	1.48	27.09	37.50	46.57	54.37
																	(3.7)	(1.4)	(1.2)	(1.1)	(19.5)	(26.1)	(34.6)	(42.1)
Average	4.4	2.3	1.8	1.5	22.9	35.3	44.6	52.5	3.8	2.2	1.8	1.6	19.7	31.2	40.5	48.8	4.7	2.2	1.7	1.5	24.5	35.9	44.8	52.6

Cumulated variance explained is in percent.
The first row for each liquidity proxy gives the estimate, the second row in brackets the corresponding lower bound of the 95% confidence interval.
Number of stocks used for the analysis: 19

Table 11: Principal components of daily averages of liquidity proxies

	Ask side								Bid side								Total							
	Eigen values				Variance explained				Eigen values				Variance explained				Eigen values				Variance explained			
	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4
$l^s(Q_{\text{Sm}})$	2.4	1.4	1.2	1.1	12.8	20.0	26.3	32.2	2.3	1.4	1.2	1.2	11.9	19.1	25.4	31.6	2.4	1.4	1.2	1.1	12.8	20.0	26.3	32.3
	(2.2)	(1.3)	(1.1)	(1.0)	(11.7)	(18.7)	(24.9)	(30.7)	(2.1)	(1.3)	(1.1)	(1.1)	(10.9)	(17.9)	(24.1)	(30.1)	(2.2)	(1.3)	(1.1)	(1.1)	(11.8)	(18.7)	(24.9)	(30.8)
$l^s(Q_{\text{Md}})$	2.5	1.4	1.2	1.1	13.1	20.3	26.5	32.3	2.2	1.4	1.2	1.2	11.6	18.9	25.1	31.2	2.5	1.4	1.2	1.1	13.2	20.4	26.7	32.6
	(2.3)	(1.3)	(1.1)	(1.0)	(12.0)	(18.9)	(25.1)	(30.8)	(2.0)	(1.3)	(1.1)	(1.1)	(10.7)	(17.7)	(23.8)	(29.8)	(2.3)	(1.3)	(1.1)	(1.0)	(12.1)	(19.1)	(25.2)	(31.1)
$l^s(Q_{\text{MinD}})$	2.5	1.6	1.3	1.2	13.2	21.8	28.7	35.0	2.2	1.6	1.3	1.2	11.6	19.9	26.8	33.0	2.6	1.5	1.4	1.2	13.7	21.4	28.8	35.1
	(2.3)	(1.5)	(1.2)	(1.1)	(12.1)	(20.4)	(27.1)	(33.3)	(2.0)	(1.4)	(1.2)	(1.1)	(10.6)	(18.6)	(25.4)	(31.5)	(2.4)	(1.3)	(1.3)	(1.1)	(12.5)	(20.0)	(27.2)	(33.5)
$l^s(Q_{\text{Gmin}})$	2.7	1.3	1.2	1.1	14.0	20.6	26.9	32.8	2.0	1.4	1.3	1.2	10.7	18.1	24.7	31.1	2.6	1.4	1.2	1.1	13.8	21.2	27.4	33.3
	(2.4)	(1.2)	(1.1)	(1.0)	(12.8)	(19.3)	(25.5)	(31.3)	(1.9)	(1.3)	(1.2)	(1.1)	(9.9)	(16.9)	(23.4)	(29.6)	(2.4)	(1.3)	(1.1)	(1.0)	(12.7)	(19.8)	(25.9)	(31.7)
$L^s(Q_{\text{Sm}})$	1.3	1.2	1.2	1.1	6.6	13.1	19.4	25.4	1.3	1.3	1.2	1.2	7.0	13.9	20.4	26.6	1.3	1.3	1.2	1.2	7.1	13.8	20.3	26.5
	(1.2)	(1.1)	(1.1)	(1.0)	(6.1)	(12.3)	(18.4)	(24.3)	(1.2)	(1.2)	(1.1)	(1.1)	(6.5)	(13.0)	(19.3)	(25.4)	(1.2)	(1.2)	(1.1)	(1.1)	(6.5)	(12.9)	(19.3)	(25.3)
$L^s(Q_{\text{Md}})$	1.5	1.3	1.2	1.2	7.8	14.4	20.7	26.8	1.4	1.3	1.2	1.2	7.5	14.5	21.0	27.2	1.5	1.3	1.3	1.2	7.8	14.7	21.5	27.7
	(1.4)	(1.2)	(1.1)	(1.1)	(7.1)	(13.5)	(19.7)	(25.6)	(1.3)	(1.2)	(1.1)	(1.1)	(6.9)	(13.6)	(19.9)	(26.0)	(1.4)	(1.2)	(1.2)	(1.1)	(7.2)	(13.8)	(20.4)	(26.5)
$L^s(Q_{\text{MinD}})$	2.5	1.6	1.4	1.2	13.0	21.5	28.7	34.9	2.1	1.4	1.4	1.2	10.9	18.6	25.7	32.0	2.5	1.4	1.3	1.2	13.2	20.7	27.5	33.6
	(2.3)	(1.5)	(1.3)	(1.1)	(11.9)	(20.2)	(27.2)	(33.2)	(1.9)	(1.3)	(1.3)	(1.1)	(10.1)	(17.4)	(24.4)	(30.5)	(2.3)	(1.3)	(1.2)	(1.1)	(12.1)	(19.4)	(26.0)	(32.0)
$L^s(Q_{\text{Gmin}})$	2.1	1.3	1.3	1.2	10.8	17.8	24.5	30.7	1.7	1.3	1.2	1.2	9.0	15.9	22.3	28.4	2.0	1.3	1.2	1.1	10.3	16.9	23.2	29.1
	(1.9)	(1.2)	(1.2)	(1.1)	(9.9)	(16.7)	(23.3)	(29.3)	(1.6)	(1.2)	(1.1)	(1.1)	(8.3)	(14.9)	(21.1)	(27.1)	(1.8)	(1.2)	(1.1)	(1.0)	(9.5)	(15.8)	(21.9)	(27.8)
$\bar{Q}_t^s$	2.7	1.5	1.3	1.2	14.3	22.2	29.1	35.7	2.4	1.4	1.2	1.2	12.7	20.1	26.4	32.6								
	(2.5)	(1.4)	(1.2)	(1.1)	(13.1)	(20.8)	(27.6)	(34.0)	(2.2)	(1.3)	(1.1)	(1.1)	(11.7)	(18.8)	(25.0)	(31.1)								
$Q_t^s(1 \pm 1\%)$	2.1	1.7	1.2	1.2	11.3	20.1	26.6	32.8	1.7	1.2	1.2	1.1	9.0	15.5	21.7	27.6								
	(2.0)	(1.5)	(1.1)	(1.1)	(10.4)	(18.8)	(25.2)	(31.3)	(1.6)	(1.1)	(1.1)	(1.0)	(8.3)	(14.5)	(20.6)	(26.4)								
$Q_{t,5}^s$	2.4	1.4	1.2	1.1	12.7	20.3	26.5	32.5	1.6	1.2	1.2	1.2	8.3	14.9	21.2	27.3								
	(2.2)	(1.3)	(1.1)	(1.1)	(11.7)	(18.9)	(25.0)	(31.0)	(1.5)	(1.1)	(1.1)	(1.1)	(7.7)	(14.0)	(20.2)	(26.1)								
Spread																	2.4	1.4	1.2	1.1	12.7	19.8	26.0	32.0
																	(2.2)	(1.2)	(1.1)	(1.0)	(11.7)	(18.5)	(24.6)	(30.5)
Average	2.2	1.4	1.2	1.2	11.8	19.3	25.8	31.9	1.9	1.4	1.2	1.2	10.0	17.2	23.7	29.9	2.2	1.4	1.2	1.2	11.6	18.8	25.3	31.4

Cumulated variance explained is in percent.
The first row for each liquidity proxy gives the estimate, the second row in brackets the corresponding lower bound of the 95% confidence interval.
Number of stocks used for the analysis: 19

Table 12: Principal components of intradaily time series of liquidity proxies

	Number of factors			Goodness of fit		
	Ask	Bid	Total	Ask	Bid	Total
$l^s(Q_{\mathrm{Sm}})$	4.4	4.6	4.6	99.4	99.2	99.2
$l^s(Q_{\mathrm{Md}})$	4.7	4.8	4.4	99.4	99.1	99.5
$l^s(Q_{\mathrm{MinD}})$	4.8	5.1	4.6	98.6	99.6	99.5
$l^s(Q_{\mathrm{Gmin}})$	4.4	4.6	4.7	99.8	99.2	99.4
$\bar{Q}_t^s$	4.1	5.6		99.8	99.6	
$Q_t^s(1 \pm 1\%)$	5.2	5.0		93.5	95.7	
$Q_{t,5}^s$	5.0	5.2		98.9	97.6	
Spread			4.6			99.5
Average	4.6	4.9	4.6	98.4	98.8	99.4

All number are averages across all times of the day. Time intervals of 1 hour length have been used. Number of factors is equal to the number of eigen values that are statistically significant larger than 1.
Goodness of fit reports the percentage of all stocks for which the null of the Ljung-Box test for nonzero autocorrelation in the residuals of the fitted autoregressive processes could be rejected at a confidence level of 95%. Ljung-Box test statistic is calculated for 10 lags.

Table 13: Results on commonality of time of day series

Table 14: Sensitivity of liquidity proxies with respect to financial variables

Panel A: $LIQ^s_{j,t} = \alpha_j + \beta_{MLIQ,j} MLIQ_t + \varepsilon_{j,t}$																		
	β_{DIR}				β_{MRET}				$\beta_{MVOL,j}$				$\beta_{MLIQ,j}$				R^2	Adj. R^2
	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos		
$l^A_t(Q_{\mathrm{Sm}})$													0.75	(79)	[100]	[79]	19	17
$l^B_t(Q_{\mathrm{Sm}})$													0.73	(74)	[100]	[74]	19	17
$l_t(Q_{\mathrm{Sm}})$													0.74	(79)	[100]	[79]	19	17
$l^A_t(Q_{\mathrm{Md}})$													0.76	(74)	[100]	[74]	20	18
$l^B_t(Q_{\mathrm{Md}})$													0.74	(74)	[100]	[74]	20	18
$l_t(Q_{\mathrm{Md}})$													0.76	(79)	[100]	[79]	21	19
$l^A_t(Q_{\mathrm{MinD}})$													0.80	(68)	[100]	[68]	16	14
$l^B_t(Q_{\mathrm{MinD}})$													0.63	(68)	[95]	[68]	13	11
$l_t(Q_{\mathrm{MinD}})$													0.72	(74)	[100]	[74]	14	12
$l^A_t(Q_{\mathrm{Gmin}})$													0.84	(89)	[100]	[89]	21	20
$l^B_t(Q_{\mathrm{Gmin}})$													0.68	(58)	[100]	[58]	15	13
$l_t(Q_{\mathrm{Gmin}})$													0.78	(68)	[100]	[68]	19	17
CIL average														**(74)**	**[100]**	**[74]**	**18**	**16**
$\bar{Q}^A_t$													0.72	(68)	[89]	[68]	16	14
$\bar{Q}^B_t$													0.21	(32)	[79]	[26]	7	5
$Q^A_t(1+1\%)$													0.45	(53)	[84]	[47]	8	6
$Q^B_t(1-1\%)$													0.63	(37)	[95]	[37]	8	6
$Q^A_{t,5}$													0.44	(26)	[79]	[26]	4	2
$Q^B_{t,5}$													0.42	(21)	[84]	[21]	4	2
Depth average														**(39)**	**[85]**	**[38]**	**8**	**6**

Continued on next page

Table 14: (continued)

Panel B: $LIQ^s_{j,t} = \alpha_j \beta_{MVOL,j} MVOL_t + \varepsilon_{j,t}$																		
	β_{DIR}				β_{MRET}				$\beta_{MVOL,j}$				$\beta_{MLIQ,j}$				R^2	Adj. R^2
	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos		
$l^A_t(Q_{\text{Sm}})$									0.02	(42)	[84]	[37]					9	7
$l^B_t(Q_{\text{Sm}})$									0.03	(47)	[84]	[42]					10	8
$l_t(Q_{\text{Sm}})$									0.04	(42)	[84]	[37]					9	7
$l^A_t(Q_{\text{Md}})$									0.02	(42)	[84]	[37]					9	7
$l^B_t(Q_{\text{Md}})$									0.02	(58)	[84]	[53]					9	7
$l_t(Q_{\text{Md}})$									0.05	(53)	[84]	[47]					9	8
$l^A_t(Q_{\text{MinD}})$									0.03	(47)	[79]	[47]					11	9
$l^B_t(Q_{\text{MinD}})$									0.03	(16)	[74]	[5]					5	3
$l_t(Q_{\text{MinD}})$									0.05	(42)	[74]	[37]					7	5
$l^A_t(Q_{\text{Gmin}})$									0.02	(42)	[89]	[42]					9	7
$l^B_t(Q_{\text{Gmin}})$									0.02	(32)	[74]	[26]					7	6
$l_t(Q_{\text{Gmin}})$									0.04	(47)	[79]	[47]					8	6
CIL average										**(43)**	**[82]**	**[38]**					**9**	**7**
$\bar{Q}^A_t$									0.02	(16)	[79]	[16]					3	1
$\bar{Q}^B_t$									-0.01	(26)	[26]						3	1
$Q^A_t(1+1\%)$									0.00	(16)	[32]						2	0
$Q^B_t(1-1\%)$									0.00	(21)	[37]	[16]					1	-1
$Q^A_{t,5}$									0.00	(16)	[47]						2	0
$Q^B_{t,5}$									0.00	(11)	[74]	[11]					2	0
Depth average										**(18)**	**[49]**	**[7]**					**2**	**0**

Continued on next page

Table 14: (continued)

Panel C: $LIQ^s_{j,t} = \alpha_j \beta_{MRET,j} MRET_t + \varepsilon_{j,t}$																		
	β_{DIR}				β_{MRET}				$\beta_{MVOL,j}$				$\beta_{MLIQ,j}$				R^2	Adj. R^2
	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos		
$l^A_t(Q_{\mathrm{Sm}})$					0.00	(0)	[63]	[5]									3	1
$l^B_t(Q_{\mathrm{Sm}})$					0.00		[58]										2	0
$l_t(Q_{\mathrm{Sm}})$					0.00		[63]										3	1
$l^A_t(Q_{\mathrm{Md}})$					0.00		[63]										3	1
$l^B_t(Q_{\mathrm{Md}})$					0.00		[63]										2	0
$l_t(Q_{\mathrm{Md}})$					0.00		[63]										3	1
$l^A_t(Q_{\mathrm{MinD}})$					0.00	(0)	[42]										5	3
$l^B_t(Q_{\mathrm{MinD}})$					0.02	(0)	[79]	[21]									6	4
$l_t(Q_{\mathrm{MinD}})$					0.01	(0)	[63]	[16]									4	3
$l^A_t(Q_{\mathrm{Gmin}})$					0.00	(0)	[53]	[5]									3	1
$l^B_t(Q_{\mathrm{Gmin}})$					0.00	(0)	[74]	[11]									3	1
$l_t(Q_{\mathrm{Gmin}})$					0.00	(0)	[74]	[5]									3	1
CIL average						**(6)**	**[63]**	**[5]**									**3**	**1**
$\bar{Q}^A_t$					0.00	(11)	[53]	[11]									3	1
$\bar{Q}^B_t$					0.00	(11)	[47]	[11]									1	0
$Q^A_t(1+1\%)$					0.00	(11)	[68]	[11]									3	1
$Q^B_t(1-1\%)$					0.00	(11)	[32]										2	0
$Q^A_{t,5}$					0.00	(11)	[84]	[11]									4	2
$Q^B_{t,5}$					0.00	(5)	[16]										2	0
Depth average						**(10)**	**[50]**	**[7]**									**2**	**1**

Continued on next page

Table 14: (continued)

Panel D: $LIQ^{s}_{j,t} = \alpha_j + \beta_{DIR,j} DIR_t \varepsilon_{j,t}$																		
	β_{DIR}				β_{MRET}				$\beta_{MVOL,j}$				$\beta_{MLIQ,j}$				R^2	Adj. R^2
	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos		
$l^A_t(Q_{\mathrm{Sm}})$	0.000		[16]														0	-2
$l^B_t(Q_{\mathrm{Sm}})$	0.00		[21]														0	-2
$l_t(Q_{\mathrm{Sm}})$	0.00		[26]														0	-2
$l^A_t(Q_{\mathrm{Md}})$	0.00		[21]														0	-2
$l^B_t(Q_{\mathrm{Md}})$	0.00		[26]														0	-2
$l_t(Q_{\mathrm{Md}})$	0.00		[26]														0	-2
$l^A_t(Q_{\mathrm{MinD}})$	0.00		[26]														1	-1
$l^B_t(Q_{\mathrm{MinD}})$	0.00		[42]														0	-2
$l_t(Q_{\mathrm{MinD}})$	0.00		[37]														0	-2
$l^A_t(Q_{\mathrm{Gmin}})$	0.00		[21]														0	-2
$l^B_t(Q_{\mathrm{Gmin}})$	0.00		[21]														0	-2
$l_t(Q_{\mathrm{Gmin}})$	0.00		[26]														0	-2
CIL average			**[26]**														**0**	**-2**
$\bar{Q}^A_t$	0.00		[32]														0	-1
$\bar{Q}^B_t$	0.00		[79]														0	-2
$Q^A_t(1+1\%)$	0.00		[63]														1	-1
$Q^B_t(1-1\%)$	0.00		[58]														0	-2
$Q^A_{t,5}$	0.00		[53]														0	-2
$Q^B_{t,5}$	0.00		[47]														0	-2
Depth average	**(0)**		**[55]**														**0**	**-2**

Continued on next page

Table 14: (continued)

Panel E: $LIQ^s_{j,t} = \alpha_j + \beta_{MVOL,j} MVOL_t + \beta_{MLIQ,j} MLIQ_t + \varepsilon_{j,t}$																		
	β_{DIR}				β_{MRET}				$\beta_{MVOL,j}$				$\beta_{MLIQ,j}$				R^2	Adj. R^2
	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos		
$l^A_t(Q_{\text{Sm}})$									0.01	(21)	[74]	[16]	0.722	(63)	[100]	[63]	23	20
$l^B_t(Q_{\text{Sm}})$									0.01	(21)	[74]	[16]	0.70	(63)	[95]	[63]	24	20
$l_t(Q_{\text{Sm}})$									0.02	(16)	[74]	[11]	0.71	(63)	[95]	[63]	23	20
$l^A_t(Q_{\text{Md}})$									0.01	(21)	[68]	[16]	0.73	(74)	[100]	[74]	24	21
$l^B_t(Q_{\text{Md}})$									0.01	(16)	[79]	[11]	0.71	(63)	[100]	[63]	24	21
$l_t(Q_{\text{Md}})$									0.02	(16)	[74]	[11]	0.73	(74)	[100]	[74]	25	22
$l^A_t(Q_{\text{MinD}})$									-0.02	(47)	[63]	[42]	0.81	(74)	[95]	[74]	26	23
$l^B_t(Q_{\text{MinD}})$									0.04	(21)	[79]	[11]	0.65	(63)	[95]	[63]	18	15
$l_t(Q_{\text{MinD}})$									-0.01	(37)	[68]	[21]	0.73	(68)	[100]	[68]	20	17
$l^A_t(Q_{\text{Gmin}})$									-0.01	(26)	[63]	[21]	0.82	(79)	[100]	[79]	26	23
$l^B_t(Q_{\text{Gmin}})$									0.00	(21)	[68]	[11]	0.66	(58)	[100]	[58]	19	16
$l_t(Q_{\text{Gmin}})$									-0.01	(21)	[63]	[11]	0.76	(74)	[100]	[74]	23	20
CIL average										**(24)**	**[71]**	**[16]**		**(68)**	**[98]**	**[68]**	**23**	**20**
$\bar{Q}^A_t$									0.02	(21)	[74]	[21]	0.73	(74)	[89]	[74]	18	15
$\bar{Q}^B_t$									0.00	(21)	[32]		0.31	(32)	[84]	[26]	10	6
$Q^A_t(1+1\%)$									0.00	(11)	[42]		0.45	(53)	[84]	[47]	10	6
$Q^B_t(1-1\%)$									0.00	(21)	[42]	[16]	0.64	(37)	[95]	[37]	9	5
$Q^A_{t,5}$									0.00	(16)	[53]		0.44	(26)	[79]	[26]	6	2
$Q^B_{t,5}$									0.00		[63]		0.41	(21)	[84]	[21]	5	2
Depth average										**(15)**	**[51]**	**[6]**		**(40)**	**[86]**	**[39]**	**10**	**6**

Continued on next page

Table 14: (continued)

Panel F: $LIQ^s_{j,t} = \alpha_j + \beta_{DIR,j} DIR_t + \beta_{MRET,j} MRET_t + \beta_{MVOL,j} MVOL_t + \beta_{MLIQ,j} MLIQ_t + \varepsilon_{j,t}$																		
	β_{DIR}				β_{MRET}				$\beta_{MVOL,j}$				$\beta_{MLIQ,j}$				R^2	Adj. R^2
	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos	Estim	Sign	Pos	SPos		
$l^A_t(Q_{\mathrm{Sm}})$	0.00	(5)	[47]		0.00	(5)	[53]	[5]	0.03	(21)	[74]	[16]	0.66	(58)	[95]	[58]	26	20
$l^B_t(Q_{\mathrm{Sm}})$	0.00		[47]		0.00	(11)	[58]	[11]	0.05	(21)	[74]	[16]	0.67	(68)	[95]	[68]	26	19
$l_t(Q_{\mathrm{Sm}})$	0.00		[53]		0.00	(11)	[63]	[11]	0.02	(32)	[68]	[26]	0.69	(68)	[100]	[68]	26	20
$l^A_t(Q_{\mathrm{Md}})$	0.00		[37]		0.00	(5)	[58]	[5]	0.03	(16)	[74]	[11]	0.67	(53)	[100]	[53]	27	20
$l^B_t(Q_{\mathrm{Md}})$	0.00		[47]		0.00	(11)	[53]	[11]	0.05	(21)	[74]	[16]	0.69	(68)	[100]	[68]	27	21
$l_t(Q_{\mathrm{Md}})$	0.00	(26)	[42]	[16]	0.00	(21)	[37]	[16]	-0.03	(42)	[58]	[37]	0.81	(79)	[95]	[79]	30	24
$l^A_t(Q_{\mathrm{MinD}})$	0.00	(5)	[42]	[5]	0.01	(21)	[58]	[11]	0.08	(32)	[68]	[26]	0.58	(58)	[95]	[58]	23	17
$l^B_t(Q_{\mathrm{MinD}})$	0.00	(16)	[47]	[5]	0.01	(11)	[58]	[5]	0.04	(37)	[68]	[26]	0.71	(63)	[100]	[63]	24	18
$l_t(Q_{\mathrm{MinD}})$	0.00	(5)	[53]	[5]	0.00	(11)	[58]	[5]	-0.01	(16)	[68]	[16]	0.80	(74)	[100]	[74]	28	21
$l^A_t(Q_{\mathrm{Gmin}})$	0.00		[53]		0.00	(21)	[68]	[16]	0.01	(26)	[58]	[16]	0.57	(47)	[95]	[47]	23	16
$l^B_t(Q_{\mathrm{Gmin}})$	0.00		[53]		0.00	(5)	[63]		0.01	(21)	[68]	[16]	0.71	(68)	[100]	[68]	25	19
$l_t(Q_{\mathrm{Gmin}})$			[48]			(12)	[57]	[9]		(26)	[68]	[20]		(64)	[98]	[64]	26	19
CIL average	0.00	**(16)**	**[47]**	**[11]**	**0.00**	**(11)**	**[47]**	**[11]**	**0.03**	**(11)**	**[79]**	**[11]**	**0.73**	**(74)**	**[89]**	**[74]**	**21**	**15**
$\bar{Q}^A_t$	0.00		[58]		0.00	(16)	[42]	[11]	-0.01	(16)	[42]		0.30	(32)	[84]	[26]	11	4
$\bar{Q}^B_t$	0.00	(5)	[74]	[5]	0.00		[63]		0.00	(5)	[37]		0.46	(53)	[84]	[42]	13	5
$Q^A_t(1+1\%)$	0.00		[47]		0.00		[37]		0.00	(16)	[32]	[16]	0.63	(32)	[89]	[32]	11	4
$Q^B_t(1-1\%)$	0.00	(5)	[58]	[5]	0.00	(16)	[63]	[16]	0.00	(11)	[63]		0.41	(16)	[68]	[16]	10	2
$Q^A_{t,5}$	0.00		[37]		0.00	(5)	[32]		0.00		[58]		0.41	(21)	[84]	[21]	8	0
$Q^B_{t,5}$			[54]	[4]		(8)	[47]	[6]		(10)	[52]	[4]		(38)	[83]	[35]	12	5
Depth average			**[54]**	**[4]**		**(8)**	**[47]**	**[6]**		**(10)**	**[52]**	**[4]**		**(38)**	**[83]**	**[35]**	**12**	**5**

Daily data is used. Estimated coefficients are averaged across stocks; 'Sign': number of stocks that had an estimate for this coefficient statistically different from zero;

'Pos': percentage of the stocks that had a positive estimate for this coefficient; 'SPos': percentage of the stocks that had a significant positive estimate for this coefficient; R^2 and adjusted R^2 are averages across stocks.

Liquidity measure	Correlation
$l_t^A(Q_{\mathrm{Sm}})$	0.37
$l_t^B(Q_{\mathrm{Sm}})$	0.42
$l_t(Q_{\mathrm{Sm}})$	0.37
$l_t^A(Q_{\mathrm{Md}})$	0.37
$l_t^B(Q_{\mathrm{Md}})$	0.39
$l_t(Q_{\mathrm{Md}})$	0.41
$l_t^A(Q_{\mathrm{MinD}})$	0.23
$l_t^B(Q_{\mathrm{MinD}})$	-0.06
$l_t(Q_{\mathrm{MinD}})$	0.16
$l_t^A(Q_{\mathrm{Gmin}})$	0.38
$l_t^B(Q_{\mathrm{Gmin}})$	0.36
$l_t(Q_{\mathrm{Gmin}})$	0.38
$\bar{Q}_t^A$	0.13
$\bar{Q}_t^B$	-0.09
$Q_t^A(1+1\%)$	-0.13
$Q_t^B(1-1\%)$	-0.03
$Q_{t,5}^A$	-0.07
$Q_{t,5}^B$	0.18

Correlations are averaged across all stocks.

Table 15: Correlation of MLIQ with MVOL

	Ask side								Bid side								Total							
	Eigen values				Variance explained				Eigen values				Variance explained				Eigen values				Variance explained			
	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4
LORDERSN	8.65	1.46	1.27	1.05	45.52	53.19	59.85	65.37	9.74	1.26	1.24	1.15	51.29	57.90	64.42	70.46	5.89	1.76	1.55	1.49	31.00	40.25	48.41	56.26
	(6.2)	(1.0)	(0.9)	(0.8)	(32.8)	(35.3)	(41.7)	(47.1)	(6.9)	(0.9)	(0.9)	(0.8)	(36.3)	(36.5)	(42.9)	(48.8)	(4.2)	(1.3)	(1.1)	(1.1)	(22.3)	(27.7)	(35.5)	(43.0)
LORDERSQ	6.15	1.74	1.54	1.28	32.36	41.53	49.65	56.38	6.15	1.88	1.58	1.30	32.37	42.27	50.56	57.42	5.18	1.81	1.59	1.47	27.24	36.74	45.13	52.86
	(4.4)	(1.2)	(1.1)	(0.9)	(23.0)	(27.8)	(35.5)	(42.0)	(4.4)	(1.4)	(1.1)	(0.9)	(23.4)	(29.3)	(37.2)	(43.8)	(3.7)	(1.3)	(1.2)	(1.1)	(19.7)	(25.7)	(33.6)	(40.9)
MORDERSN	13.78	1.52	0.77	0.48	72.54	80.52	84.55	87.08	14.96	1.11	0.61	0.39	78.75	84.60	87.80	89.85	11.77	1.80	0.96	0.84	61.92	71.40	76.47	80.88
	(10.0)	(1.1)	(0.6)	(0.3)	(52.5)	(52.7)	(56.7)	(59.2)	(10.8)	(0.8)	(0.4)	(0.3)	(56.9)	(54.2)	(57.4)	(59.5)	(8.5)	(1.3)	(0.7)	(0.6)	(44.8)	(47.6)	(52.5)	(56.9)
MORDERSQ	6.09	1.81	1.59	1.44	32.03	41.57	49.94	57.50	6.05	2.13	1.66	1.48	31.85	43.06	51.82	59.59	4.57	1.95	1.56	1.46	24.07	34.33	42.56	50.24
	(4.4)	(1.3)	(1.1)	(1.0)	(22.9)	(28.3)	(36.3)	(43.5)	(4.3)	(1.5)	(1.2)	(1.1)	(22.8)	(29.7)	(38.0)	(45.4)	(3.3)	(1.4)	(1.1)	(1.1)	(17.4)	(24.4)	(32.1)	(39.4)
TRADESN																	9.27	1.49	1.10	0.92	48.76	56.60	62.40	67.23
																	(6.7)	(1.1)	(0.8)	(0.7)	(35.1)	(37.4)	(43.1)	(47.8)
TRADESQ																	6.51	1.70	1.56	1.36	34.25	43.19	51.43	58.58
																	(4.7)	(1.2)	(1.1)	(1.0)	(24.7)	(29.6)	(37.5)	(44.3)
Average	8.7	1.7	1.3	1.1	45.6	54.5	61.4	67.0	9.1	1.7	1.3	1.1	47.7	56.6	63.4	69.0	6.2	1.5	1.1	1.0	32.7	40.4	46.3	51.6

Cumulated variance explained is in percent.
The first row for each market activity proxy gives the estimate, the second row in brackets the corresponding lower bound of the 95% confidence interval.
Number of stocks used for the analysis: 19

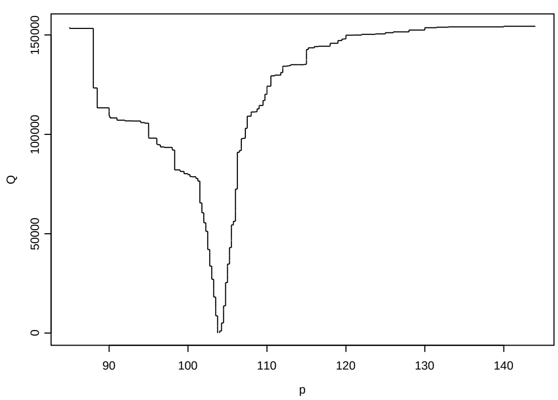
Table 16: Principal components of daily averages of proxies of market activity

	Ask side								Bid side								Total							
	Eigen values				Variance explained				Eigen values				Variance explained				Eigen values				Variance explained			
	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{\lambda}_3$	$\hat{\lambda}_4$	V_1	V_2	V_3	V_4
LORDERSN	5.0	1.3	1.1	1.0	26.6	33.6	39.2	44.6	5.4	1.2	1.0	1.0	28.3	34.4	39.9	45.0	4.7	1.2	1.1	1.0	24.6	31.1	37.0	42.3
	(4.6)	(1.2)	(1.0)	(0.9)	(24.4)	(31.1)	(36.7)	(42.1)	(4.9)	(1.1)	(1.0)	(0.9)	(26.0)	(31.9)	(37.3)	(42.4)	(4.3)	(1.1)	(1.0)	(0.9)	(22.6)	(28.9)	(34.7)	(39.9)
LORDERSQ	3.1	1.3	1.2	1.1	16.2	23.1	29.7	35.7	3.0	1.4	1.2	1.1	16.0	23.4	29.7	35.7	2.7	1.4	1.2	1.1	14.1	21.3	27.4	33.3
	(2.8)	(1.2)	(1.1)	(1.0)	(14.9)	(21.6)	(28.0)	(33.9)	(2.8)	(1.3)	(1.1)	(1.0)	(14.7)	(21.9)	(28.1)	(33.9)	(2.5)	(1.3)	(1.1)	(1.0)	(12.9)	(19.9)	(25.9)	(31.7)
MORDERSN	14.0	0.8	0.5	0.4	73.7	78.1	80.9	83.2	14.9	0.7	0.4	0.3	78.3	81.9	84.1	85.9	13.3	0.9	0.7	0.5	70.1	75.1	78.5	81.1
	(12.9)	(0.8)	(0.5)	(0.4)	(67.7)	(71.6)	(74.4)	(76.6)	(13.7)	(0.6)	(0.4)	(0.3)	(72.0)	(75.0)	(77.2)	(78.9)	(12.2)	(0.9)	(0.6)	(0.4)	(64.4)	(68.8)	(72.3)	(74.8)
MORDERSQ	2.3	1.2	1.2	1.1	12.3	18.5	24.6	30.6	2.7	1.3	1.2	1.1	14.3	20.9	27.1	33.0	2.4	1.3	1.2	1.1	12.5	19.1	25.5	31.5
	(2.1)	(1.1)	(1.1)	(1.0)	(11.3)	(17.3)	(23.3)	(29.1)	(2.5)	(1.2)	(1.1)	(1.0)	(13.2)	(19.5)	(25.6)	(31.4)	(2.2)	(1.2)	(1.1)	(1.0)	(11.5)	(17.9)	(24.1)	(30.0)
TRADESN																	7.6	1.0	0.9	0.8	39.9	45.0	49.8	54.1
																	(7.0)	(0.9)	(0.8)	(0.8)	(36.7)	(41.4)	(46.2)	(50.5)
TRADESQ																	4.7	1.2	1.1	1.0	24.6	31.2	36.9	42.3
																	(4.3)	(1.1)	(1.0)	(1.0)	(22.6)	(28.9)	(34.6)	(40.0)
Average	6.5	1.1	1.0	0.9	34.1	39.9	45.1	49.8	6.9	1.1	0.9	0.9	36.2	42.1	47.0	51.5	5.1	1.0	0.8	0.8	26.9	31.9	36.3	40.4

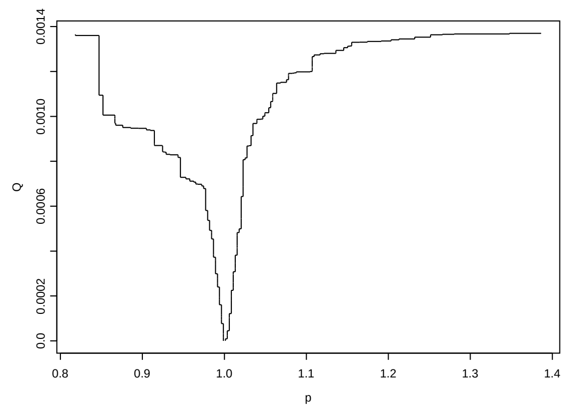
Cumulated variance explained is in percent.
The first row for each market activity proxy gives the estimate, the second row in brackets the corresponding lower bound of the 95% confidence interval.
Number of stocks used for the analysis: 19

Table 17: Principal components of intradaily proxies of market activity

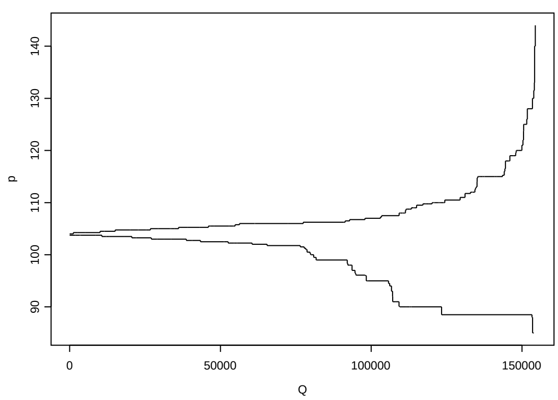
B Figures



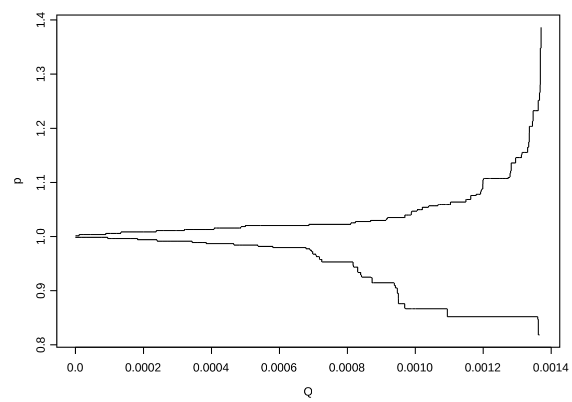
(a) Actual



(b) Standardized



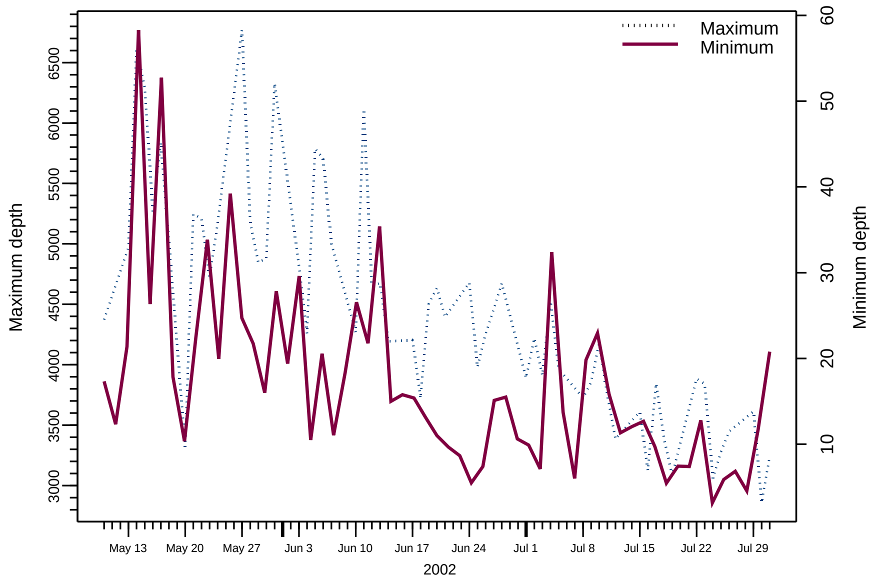
(c) Actual (Inverse)



(d) Standardized (Inverse)

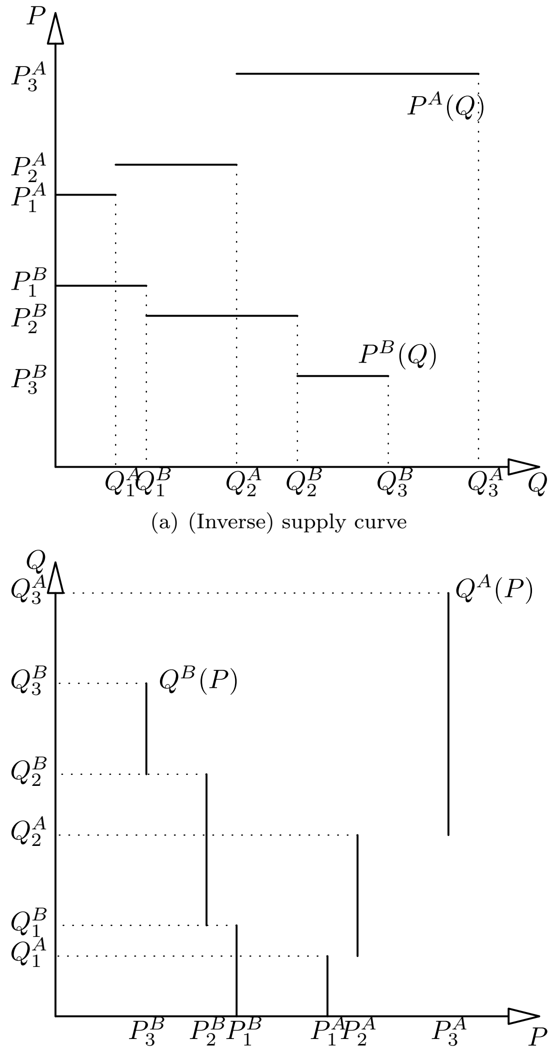
Supply curves of liquidity for ADEN on 22 May 2002, 10:00.

Figure 1: Example of order book



The upper (lower) panel shows the maximum (minimum) of the number of shares available at the best bid and ask offer on a single day, averaged across all stocks.

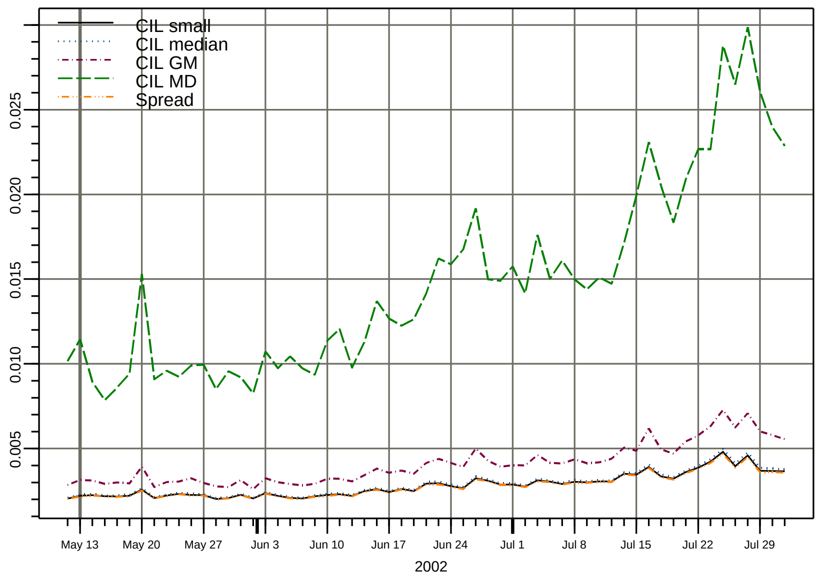
Figure 2: Daily dispersion of depth of best bid and ask offers



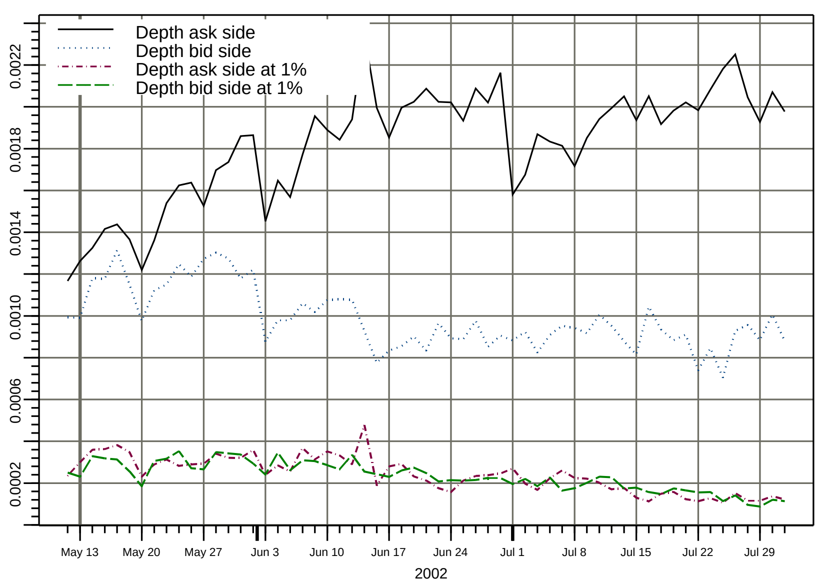
(a) (Inverse) supply curve

(b) Supply curve

Figure 3: Supply curves of liquidity

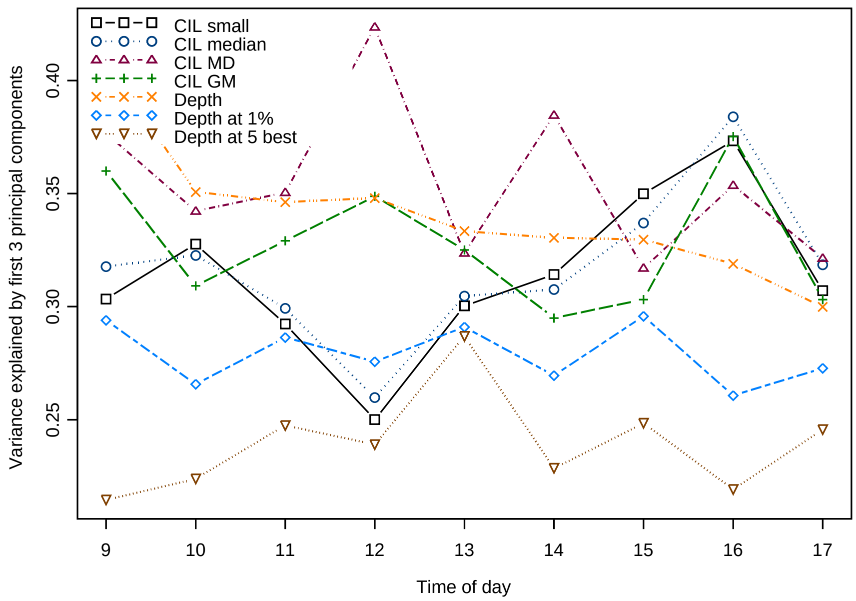


(a) CIL

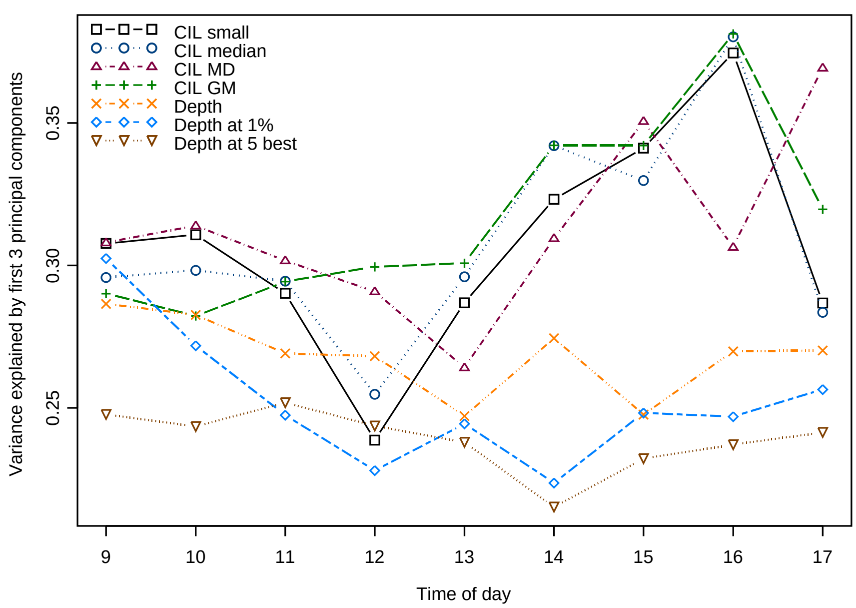


(b) Depth

Figure 4: Daily averages of liquidity proxies



(a) Ask side



(b) Bid side

Figure 5: Commonality at time of day on ask and bid side

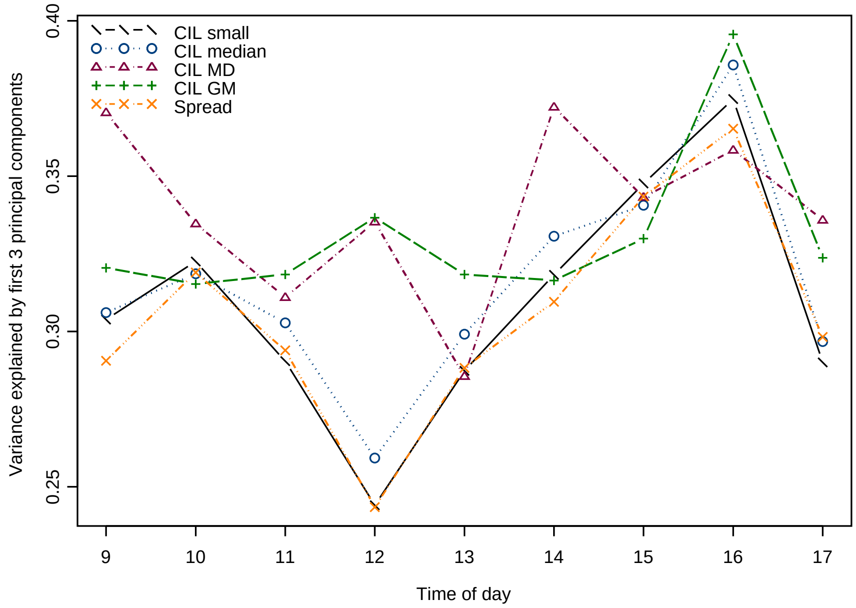


Figure 6: Commonality at time of day for total quantities