Commonality in Liquidity: What does the order book say?

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Abstract

Taking the cost of trading as a liquidity proxy, we provide evidence of commonality in liquidity and look for sources of it in an emerging market, Turkey. We show that the commonality in non-index stocks is higher than the commonality in index stocks. As the position size to trade increases, the strength of commonality is preserved for the former, however it decreases for the latter, which is argued to depend on the differences in the behaviors of individual and institutional investors. Regarding non-index stocks, we also reveal that buy side liquidity has a stronger commonality than sell side liquidity for small positions to trade, whereas it is the opposite case for large trading positions, a possible outcome of the individual investors’ positive bias towards recent market performance. Further analysis on ownership effect shows that for mid-to-large cap firms, institutional investors are the main source of commonality in liquidity as expected, whereas individual investors are the main influence on commonality for small cap firms. A time varying perspective reveals that among several domestic and global macro-economic variables, liquidity commonality is significantly affected only by the interest rate decisions and GDP announcements of U.S.; and it tends to increase when the market is falling and/or volatile.

Keywords: Liquidity commonality, cost of trading, index trading, ownership structure, macro-announcements

\textit{JEL:} D23, D82, G12, G14, G23

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Last two decades have presented us an extensive body of research that examines the co-
movement between individual stock liquidity and market-wide liquidity. Starting with the
works of Chordia et al. (2000); Huberman and Halka (2001) and Hasbrouck and Seppi (2001),
previous empirical research has shown that there exists a significant common component that
influences firm-level liquidity; i.e., liquidity is subject to a spillover effect that influences other
firms traded in the same stock exchange. Accordingly, liquidity is not just the trading cost of
an individual stock but also a potential systemic risk factor due to commonality (Pastor and
Stambaugh, 2003; Acharya and Pedersen, 2005; Sadka, 2006; Bekaert et al., 2007; Korajczyk
and Sadka, 2008; Kamara et al., 2008). Therefore, understanding the commonality and its
sources is important as it might provide a clue to solving the puzzles of market dry-ups and
crashes, and further contribute to financial stabilization policies, improved market design
and more accurate guidance for portfolio selections. However, although the literature is ex-
haustive for developed markets (in particular U.S.), little research has been conducted on
emerging ones. Indeed, to the best of our knowledge, the only studies belong to Brockman
et al. (2009) and Karolyi et al. (2012). However, these studies do not carry out a compre-
hensive analysis on a single exchange but perform overall commonality comparisons between
emerging and developed markets or look for sources of commonality across global exchanges.

As noted by Bekaert et al. (2007), liquidity is more critical for emerging markets than
developed markets; however, the limitation of the number of studies on the former and their
approach to the subject as a whole group of stock exchanges leave us with incomprehensive
answers to important questions regarding emerging markets. In particular, is commonality
in liquidity present in emerging markets, and if it is, at what level? Does industry affiliation,
index inclusion or firm size play a significant role in liquidity commonality? Is commonality
stronger for buy or sell side liquidity? What are the sources of commonality? How do the
ownership structure, macro-economic announcements and direction of market movements in-
fluence market-wide commonality? Although some of these questions were already answered
for emerging markets, the subject requires further analysis due to the common liquidity
measures (such as bid-ask spreads, quoted depth or Amihud (2002) measure) used in the
previous studies which may be lack of important information hidden in the order book.

In this study, we try to answer the abovementioned questions by analyzing the common-
ality in liquidity in a leading emerging market, Turkey. Being Europe’s 6th and world’s
16th largest economy, Turkey has been a destination of extensive capital flows in the last
few years and its stock market has attracted a lot of attention. With 237 USD bn. market
capitalization and 431 USD bn. traded value at the end of 2013, equity market of Borsa
Istanbul\(^1\) is ranked 6th in traded value among all emerging markets in the world. Moreover,
it is ranked 3rd in the whole world with a share turnover velocity of 192.3% in the same year.
These statistics show that there is a high level of trading activity at a global scale in Borsa
Istanbul, and the fact that foreign ownership accounts for more than 62% of the free-float
value in the last four years makes this study even more important, not only for domestic
investors but also for foreign market participants.

Being a pioneering comprehensive study on the commonality in liquidity in an emerging
market, our work differs from the others in many perspectives. In most of the studies in
the literature, the liquidity measures are based on the best bid and ask quotes, such as the
quoted or effective spread and the average depth of the best quotes. The main problem
with the best quotes is that when investors have large positions to trade, their orders will
extend beyond best prices (Holden et al., 2013). Therefore, commonality beyond the best
prices is a potential concern especially to any institutional investor such as a pension fund
or a hedge fund that rebalances large positions across many stocks as the execution risk may
be non-diversifiable. Moreover, the best prices are heavily exposed to idiosyncratic shocks
and attract a lot of noise.\(^2\) However, although it is extremely important, the evidence of
commonality beyond best bids and asks in the order book is highly limited. Kempf and
Mayston (2008) examine commonality in liquidity using limit order books of 30 stocks in
the blue-chip DAX30 index on the Frankfurt Stock Exchange. Authors find that the more
liquidity measures are extended beyond best prices, the stronger is commonality. More
recently, Corwin and Lipson (2011) examine the order flow data of 100 NYSE-listed stocks
and find that the strength of commonality increases as more information from the limit

\(^1\)Formerly known as the Istanbul Stock Exchange, Borsa Istanbul is the only official stock exchange of
Turkey.

\(^2\)A further crucial point is related to tick size. Jain (2003) shows that larger and more developed stock
markets tend to have lower relative tick sizes (absolute tick size divided by price) than smaller and less
developed markets. If the tick size in a stock market is larger than it should be, then a possible outcome is
that bid-ask spreads always stick to one tick. In that case, two stocks with different order book characteristics
may seem very similar in terms of liquidity when one considers the spreads only at the best price levels.
Indeed, in our case, size of the best bid-ask spread is one tick more than 98% of the time, however, cost of
trading significantly differs when we walk up the order book.
order book is incorporated. In our work, by using full order flow data of each stock, we construct a special weighted spread that measures the cost of roundtrip (buying and selling simultaneously) for a given amount of position. By using different positions to trade, we look for commonality in liquidity at the different levels of the order book. Moreover, we also consider the commonality of buy and sell side separately. The importance of the asymmetry between different sides of liquidity has been emphasized in the study of Brennan et al. (2012). By using proxies for trading costs in both sides, authors show that sell-order liquidity is priced more strongly than buy-order liquidity, and their results hold even after controlling for several known determinants. From this perspective, commonality in different sides will bring a fresh approach to the subject. In addition, when the order book (or more generally intraday data) is involved, most studies use only one year of data or less (e.g. Chordia et al. (2000); Hasbrouck and Seppi (2001); Huberman and Halka (2001); Fabre and Frino (2004); Domowitz et al. (2005); Kempf and Mayston (2008); Corwin and Lipson (2011)); whereas, we use four years of data (2010-2013) to provide a robust evidence regarding to commonality in liquidity.

Besides using a different liquidity measure, the market structure of Borsa Istanbul brings additional differences into our work. In their study, Chordia et al. (2000) find evidence of correlated specialist inventory costs being the greater influence on commonality at the market-wide level in NYSE. Similarly, Coughenour and Saad (2004) find that in falling markets, specialist behavior is more strongly correlated across their stock portfolio than in rising markets which could produce stronger commonality in falling markets. However, the absence of specialist system in Borsa Istanbul suggests that inventory holding costs are less relevant when compared to markets such as the NYSE, NASDAQ or London Stock Exchange, therefore, commonality in liquidity may be less pronounced in Borsa Istanbul

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3At this step, one of the main differences of Borsa Istanbul and the other stock exchanges is the allowance of hidden or iceberg orders (the orders with price and volume information is completely or partially invisible). Such a situation brings out difficulties in constructing the order book since many stock exchanges (including Euronext, NYSE, London Stock Exchange, Swiss Stock Exchange, Australian Stock Exchange) allow these types of orders and they may reach up to 55% of the total volume waiting at the best price level which would yield to misleading information if one tries to construct a liquidity measure using the order book. For example, de Jong et al. (1995) emphasize the challenges they face when they compare the cost of trading in Paris Bourse and SEAQ International due to the hidden orders in the former. Borsa Istanbul does not allow hidden or iceberg orders, therefore our liquidity measure reflects true information in this setup.
an order-driven market. Indeed, the inconsistent evidence of the commonality in liquidity in the NYSE, and the stock exchanges of Hong Kong and Australia (which are order driven markets) might be attributed to this fact, as argued by Brockman and Chung (2002) and Fabre and Frino (2004). Moreover, in Borsa Istanbul, market makers (in continuous auction) were introduced in July 2010, and are allowed to act on securities listed only on the Emerging Companies Market and Corporate Products Market since then. In our sample period, only 21 securities (excluding warrants) were traded via this method and none of them were included in our analysis as they could not satisfy our selection criterion. In that way, we also investigate how the absence of a market maker; i.e., an environment devoid of any affirmative obligation to provide liquidity, impacts the commonality. Although commonality may be less pronounced as the inventory holding costs are less relevant, absence of a market maker may create an increased commonality, in particular during liquidity shocks, due to the free-exit aspect of order-driven trading (Brockman and Chung, 2002). Moreover, absence of market makers increases the importance of a separate buy and sell side liquidity analysis since without their symmetric quotations, order flow may increase to one direction resulting with an asymmetric stronger commonality.

The difference in market structure is not limited to the abovementioned properties. Many stock exchanges include cross-listed stocks and such listings may provide a firm with potential benefits, including expansion of the firm’s shareholder base, improvement of the firm’s information environment and investor protection. However, these benefits were also found to be drivers of commonality in liquidity (Karolyi et al., 2012), therefore, a significant influence of cross-listing on a stock’s liquidity commonality naturally arises (Dang et al., 2015). None of the stocks in Borsa Istanbul is cross-listed, furthermore, only one of them has an American depositary receipt listed in NYSE. A similar difference comes into play when we consider market fragmentation. The exchanges in most of the commonality studies had gone through a fragmentation due to the multilateral trading facilities (MTF, competitor trading venues that provide services similar to those of stock exchange) such as Chi-X and Turquoise. A recent study by Foucault and Menkveld (2008) shows that the entrance of the London Stock

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4Emerging Companies Market was established as a distinct market within Borsa Istanbul to create a transparent and organized platform where stocks of micro-cap firms can be traded. Corporate Products Market includes exchange traded funds, warrants and equities of mutual funds with a publicly offered market capitalization value of less than TL 10 mn.
Exchange with its MTF EuroSETS in the Dutch stock market increased the consolidated order book depth for the stocks traded on both venues; i.e., overall liquidity has increased but more interestingly, the depth has increased for these stocks in the Dutch stock exchange too, possibly leading to an unnatural liquidity commonality. In contrast, Degyrse et al. (2014) show that for stocks traded on different venues, limit orders migrate from the local exchange to the competing trading platforms, such that an investor with only access to the traditional market is worse off; i.e, creating an artificial illiquidity commonality for a specific group of stocks traded in the host market. These are not the cases in Borsa Istanbul as none of the listed stocks are traded in an alternative trading platform.

Another difference lies in the trading engine. Many stock exchanges around the world, in particular the ones in developed markets, use trading engines that allow high frequency trading (HFT). In Borsa Istanbul, although algorithmic trading is possible, HFT is not. Considering the fact that HFT contributes a lot to order flow and trading volume, a priori is that stocks may be less subject to commonality in a market without HFT. This assumption may get stronger with the fact that orders given by algorithmic traders constitute less than 5% of the total order flow in terms of volume, and the trade volume by these mechanisms is less than 4% of the total trade.\(^5\)

Further differences arise when we consider the derivatives market. Cao and Wei (2010) argue that the commonality in liquidity may be affected by the relationship between the dynamics of the option and the underlying stock. In Borsa Istanbul, single stock options and futures were introduced for only ten stocks in late 2012, and the market for these derivatives were completely dry in our sample period, therefore no exogenous effect on commonality is expected.

All these facts show that a commonality analysis in Borsa Istanbul will reveal results about the true nature of the trading strategies of investors, isolated from several external factors.

Building upon the existing published literature, we divide our empirical investigation into two main parts. In the first part, we use the methodology of Chordia et al. (2000) to measure commonality in the order book at different levels. Our results verify that commonality exists

\(^5\)These numbers were obtained from a survey conducted on all brokerage firms trading on Borsa Istanbul in 2013. The actual numbers are impossible to estimate as the orders are transmitted to the exchange via FIX API protocol which does not carry the information on orders being algorithmic or not.
in Borsa Istanbul at different levels of the order book and for both buy and sell side. In addition, we investigate the industry effect on commonality, however in contrast to the previous studies, we found limited evidence for such effect, and in the cases it exists, it is very little in magnitude. Previous micro-structure literature argues that individual trading volume, volatility, and price are influential determinants of liquidity (Benston and Hagerman, 1974; Stoll, 1978). Therefore, we also investigate the liquidity commonality by taking these factors into account, and show that commonality is indeed an omnipresent characteristic.

Motivated by the initial findings, we pass to the looking for sources of commonality in the second main part. A common observation in the recent studies (Harford and Kaul, 2005; Kamara et al., 2008; Koch et al., 2010) is that stocks belonging to a benchmark index posses higher commonality due to the arbitrage trading strategies using index derivatives or the index tracking activity as performed by many institutional investors. Therefore, we look for such an effect in Borsa Istanbul, however, find strictly the opposite result where non-index stocks have a significantly higher commonality. Intrigued by this result, we implement the approach of Kamara et al. (2008) and reveal that for mid-to-large cap firms, institutional investors are the source of commonality whereas for small cap firms, individual investors are significantly influential. We also reveal that commonality decreases with the increasing number of investors (for both types) at any firm size level. Chordia et al. (2001) and Chordia et al. (2005) approach to the commonality subject from a different perspective and find evidence that macro-economic announcements and monetary policy give rise to liquidity commonality in the stock market. Similar conclusions come from Brockman et al. (2009) where authors show that U.S. and domestic macro-economic announcements increase commonality in both developed and emerging stock markets. Motivated by these results, we check for similar effects in Borsa Istanbul, and reveal that among several developed countries, only U.S. monetary policy and macro-economic announcements raise commonality in liquidity, but only beyond the best price levels. More interestingly, we do not observe a significant impact of the same variables of Turkey on commonality. Finally, Chordia et al. (2001); Kempf and Mayston (2008) and Hameed et al. (2010) show that commonality particularly increases in falling markets. Similarly, Karolyi et al. (2012) show that liquidity commonality is greater during times of high market volatility. With a similar effort, we try to relate market-wide liquidity to the direction of market movements and find that the aggregate market liquidity responds asymmetrically to market movements. In particular, it increases modestly in
up markets, whereas declines significantly in down markets and on high volatile (at market level) days; suggesting that a higher liquidity commonality could be expected when market is falling.

In the rest of this work, we introduce our liquidity measure and its advantages in Section 1. Next, we mention about the fundamental market structure of Borsa Istanbul and explain our selection criterion of stocks to be analyzed. Section 2 and 3 contains the first and second main empirical parts described above. Finally, Section 4 concludes the paper with a brief summary and suggestions for future research.

1 Liquidity measure and market structure

1.1 Exchange liquidity measure

It is no doubt that liquidity is one of the most important determinants of market quality in stock exchanges. However, although the importance of liquidity is universally recognized, it is not an easy task to define and measure it. For a fair measurement of liquidity in Borsa Istanbul, we adopt the Xetra Liquidity Measure (XLM) methodology introduced by Deutsche Borse in 2002.

The main perspective of this methodology is that a liquidity measure should be derived from its direct benefit for the market participants. The direct benefit of liquid markets for the investors derives from the minimization of performance loss resulting from opening and/or closing a position. Therefore, the idea is to construct a methodology which would measure the cost of trading for a given position size \( Q \) (money) at a specific time \( t \).

Consider the snapshot of the order book of a stock at time \( t \). Let \( a_i \) and \( b_i \) be the \( i^{th} \) best ask and bid prices respectively at that instant. Denote by \( P_{\text{mid}} \equiv (a_1 + b_1)/2 \) the mid price of \( a_1 \) and \( b_1 \) (so called fair price); \( LP \equiv (a_1 - b_1)/2P_{\text{mid}} \) the half of the bid-ask spread (so-called liquidity premium); \( b(n) = (\sum b_i n_i)/n \) where \( \sum n_i = n \), the weighted average of bid quantities.

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6The same measure was previously used by Domowitz et al. (2005) and Rosch and Kaserer (2014) in the context of liquidity commonality. The main difference in the work of Domowitz et al. (2005) is that \( Q \) stands for the position in number of shares, not money. We believe that money-based trading makes more sense compared to share-based trading from an investor’s point of view, in particular for large position sizes. Therefore, we stick to the original methodology.
bid-price at which the total of $n$ shares can be sold; $a(n) = \left(\sum a_in_i\right)/n$ where $\sum n_i = n$, the weighted average ask-price; $APM_{bid}(Q) \equiv (b(1) - b(n))/P_{mid}$, where $P_{mid} \times n = Q$ the size of the position in TL,\(^7\) called the adverse price movement for the bid side; similarly $APM_{ask}(Q) \equiv (a(1) - a(n))/P_{mid}$, called the adverse price movement for the ask side. Then, the liquidity measures are calculated as the following:

\[
XLM_A(Q) = 100 \times (LP + APM_{ask}(Q)) \\
XLM_B(Q) = 100 \times (LP + APM_{bid}(Q)) \\
XLM_{RT}(Q) = XLM_A(Q) + XLM_B(Q)
\]

where $XLM_A(Q)$ ($XLM_B(Q)$) is the execution cost for ask (bid) side; i.e., buy (sell) order for a given position $Q$, measured in points, and $XLM_{RT}(Q)$ denotes the cost of roundtrip. For example, $XLM_{RT}(25000) = 0.2$ means that implicit cost for buying and selling a specific stock using a position of 25000 TL would have amounted to 50 TL. As easily understood, $XLM$ covers all the static dimensions of liquidity (tightness, depth and breadth); however, unable to capture the dynamic dimensions (resiliency and immediacy) as the measure can only be defined for immediate transactions,\(^8\) therefore, order splitting can not be taken into account. A visual explanation of $XLM_{RT}(Q)$ can be seen in Figure 1.

\(^7\)TL stands for Turkish Lira. Turkey has a liberal foreign exchange regime with a fully convertible currency. In our study, it is almost impossible to construct the liquidity measure using U.S. dollar since the order flow is not kept in another currency, therefore, we perform our analysis using TL. As a reference to the readers, we give the weekly average USD/TL values which are 1.51, 1.68, 1.80 and 1.91 for the years 2010, 2011, 2012 and 2013 respectively.

\(^8\)Tightness refers to the low transaction costs, such as the difference between buy and sell prices, like the bid-ask spreads. Depth refers to the existence of abundant orders; i.e., a market is deep if there is a large volume of bids and asks above and below the market price. Breadth, as a wider definition of depth, means that orders are both numerous and large in volume with minimal impact on prices. Resiliency is a measure of how quickly prices converge to their correct equilibrium value after they have been moved by large transactions. Finally, immediacy is the opportunity for the immediate processing of transactions.
1.2 Market structure and data selection

Founded as an autonomous, professional organization in early 1986, Borsa Istanbul is the sole exchange entity of Turkey for securities trading. Within the last few years, it has undergone several transformations including session hours and trading rules. During our sample period which covers from January 4, 2010 to December 31, 2013, the trading hours were initially from 09:30 to 17:30 until March 2, 2012. The first 20 minutes were devoted to an opening session consisting of a call phase and price determination. Main trading took place between 09:50 and 12:30 in the first part of the day. After a 90 minutes of mid break, second opening session, which includes another call phase and price determination, took place between 14:00 and 14:20. After this phase, second main trading took place between 14:20 and 17:30. On March 5, 2012, a closing session was introduced, covering the time period between 17:17 and 17:30. Finally, starting with April 5, 2013, main trading sessions were extended as the first opening session started to took place between 09:15 and 09:35, first main trading session from 09:35 to 12:30, second opening session from 14:00 to 14:15, second main trading session from 14:15 to 17:30 and finally, the closing session from 17:30 to 17:40.

Different from many of the stock exchanges in the previous commonality literature, Borsa Istanbul implements a price-range based tick size mechanism. The tick sizes also have undergone a transformation during our sample period as they were reduced to half of their previous values on November 1, 2010, if they were not already 0.01 TL (see Table 1).

The number of listed stocks on Borsa Istanbul were 323, 347, 372, 415 and 429 at the end of the years 2009, 2010, 2011, 2012 and 2013 respectively. The main requirement of the XLM methodology is that a stock should be traded via continuous auction (as the ask price must always be higher than the bid price). Therefore, we remove the stocks traded via single price auction from our sample which leaves us with 369 stocks to consider.\footnote{Stocks in the Watchlist Companies Market (which are subject to monitoring and examination) and the ones classified as “C” by Capital Market Board of Turkey are traded via single price auction.} Among these, \footnote{During continuous auction, a computerized system matches buy and sell orders on a price and time priority basis. The system enables members to execute several types of orders such as limit, fill or kill,}
one of the requirements we look for is to be listed on the stock exchange during the whole sample period as we do not want to be affected by any initial public offering or delisting effect, and more importantly, including delisted or late listed stocks would introduce a bias in performing a market cap based quantile classification. This criterion reduces the sample size to 276 stocks.

We only use the continuous trading period on each trading day, and take six snapshots of the order book of each stock at 10:00, 11:00, 12:00, 15:00, 16:00 and 17:00, and calculate the XLM (ask, bid and roundtrip) for five different position sizes of $Q = 1000, 10000, 25000, 50000, 100000$ TL accordingly.\textsuperscript{11,12} The last criterion to be introduced is based on the position availability as it is not always possible to find a hypothetical order of size $Q$, in particular when $Q$ is large. Accordingly, we removed the stocks if the order book does not carry the required positions more than 2% of the whole sample period. This criterion leaves us 133 stocks to analyze. For these stocks, in times the order book does not carry the required position, a hypothetical order book is constructed as if there were infinite orders at the last price levels in the order book. Since at least one bid and ask were present all the time, such a construction was not a problem.\textsuperscript{13} Moreover, there is not a day without a trade for any of the sample stocks. Although the sample size is smaller compared to the related studies in the literature, the daily market cap representation of these stocks ranges from 76.4% to 84.9% of the whole market, with a time average of 80.9%. Plus, comparing with the relevant studies looking for commonality at different levels of order book, our study includes one of the largest samples since the works by Domowitz et al. (2005); Friederich and Payne (2007); Kempf and Mayston (2008) and Corwin and Lipson (2011) cover 19, 100, 30

\textsuperscript{11}Deutsche Borse calculates this measure for position sizes ranging from ten thousand euros to three million euros per minute. Since it does not make sense to compare the two exchanges in terms of liquidity, the position sizes were selected to be suitable for the Borsa Istanbul’s structure.

\textsuperscript{12}The position $Q = 1000$ TL acts like an ordinary proportional-spread since this amount can be found at best price levels more than 90% of the time.

\textsuperscript{13}For 71 stocks, there was no need for a hypothetical construction, and for 33 stocks, the hypothetical construction was performed less than 0.3% of time. Indeed, only 2 stocks required such a construction for exactly 2% of the whole sample period.
and 100 stocks respectively. Finally, the daily liquidity measure is constructed by taking the arithmetic mean of the six intraday values.

Through the rest of this study, we denote $XLM_A$, $XLM_B$ and $XLM_{RT}$ by $A$, $B$ and $RT$ to simplify notations, and we will use $Q1, Q2, Q3, Q4, Q5$ to denote the position sizes $Q = 1000, 10000, 25000, 50000, 100000$ TL respectively. For example, $Q1_A, Q3_{RT}$ and $Q4_B$ would mean $XLM_A(1000)$, $XLM_{RT}(25000)$ and $XLM_B(50000)$ respectively. Overall, we have fifteen different daily liquidity measures per stock.

2 Evidence of commonality

2.1 Preliminary data analysis

Table 2 shows summary statistics for our sample stocks. Panel A of Table 2 contains the mean, standard deviation and selected percentile values for each variable over the entire sample. For each variable, we first calculate the daily time-series average for each stock and report cross-sectional statistics for the time-series means. Borrowing from Chordia et al. (2000), we let $D$ denote daily percentage change whenever it is used.

The mean values of the liquidity measures (i.e., cost of trading) are increasing with the position size to trade which is consistent with the theory. For relatively small positions to

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14Keeping other restrictions the same, if we include the stocks listed after January 4, 2010 or delisted before December 31, 2013; the sample size increases to 160 stocks. However, additional stocks contribute very little in terms of market representation.

15The choice of the calculation frequency solely depends on the computational burden. For randomly selected five stocks, the measure was also calculated at fifteen minutes intervals. The daily averages were the same to the second decimal point. The following fact about order cancellation (including revision) also increases the robustness of hourly calculations: Up until October 8, 2010, order cancellation was not allowed. After this date, cancellation was allowed with a penalty fee where this fee increases significantly if the cancellation occurs later than one minute after the order is given. Within the sample period, total orders canceled is less than 10% of the total order flow (in terms of volume), and more than half of the cancellations occur within the minute the order is given. Given these and the fact that no HFT activity exists in Borsa Istanbul validate the use of hourly snapshots.
trade (such as Q1 and Q2), the mean value of trading cost is larger than the median, showing that they are skewed, which is a common finding in the literature. For all positions, bid side illiquidity is slightly higher than the ask side illiquidity on the average, telling that cost of buying is cheaper compared to cost of selling in general within our sample period. For both buy and sell sides, the mean cost of trading for positions of Q1, Q2 and Q3 display relatively close values (0.32, 0.34 and 0.38 respectively, same for both sides), however, we observe a significant increase passing from Q3 to Q4 (0.38 to 0.45 for ask side, 0.38 to 0.46 for bid side), and from Q4 to Q5 (0.45 to 0.58 for ask side, 0.46 to 0.60 for bid side). Besides from levels, absolute daily percentage changes in cost of trading also increase with the position size to trade (6% to 22% for ask side, 7% to 26% for bid side). Moreover, similar to the case in levels, absolute daily percentage change in cost of selling is higher than the absolute daily percentage change in cost of buying for all positions on the average. As the position size to trade increases, absolute daily change in cost of trading becomes more volatile across stocks, possibly due to the cross-sectional heterogeneity of the order book.

Panel B of Table 2 reports the average correlations among the daily changes in cost of trading for different sides of the order book and different position sizes to trade. As in the previous case, we first calculate correlations using time-series data for each stock and then average the correlations across stocks. As expected, the correlations between cost of trading decreases as the position size to trade increases from Q1 to Q5 (0.70 to 0.34 for the ask side, 0.71 to 0.32 for the bid side, and 0.76 to 0.39 for roundtrip). However, the correlations between cost of trading adjacent position sizes (e.g. Q1 and Q2, or Q4 and Q5) are significantly high ranging from 0.70 to 0.89 for ask side, 0.71 to 0.87 for bid side, and 0.76 to 0.90 for roundtrip. For our smallest position Q1, average correlation among daily changes in cost of buying and selling yields to a relatively strong value of 0.68; however, it drastically drops to 0.40 (then 0.36, 0.35 and 0.33) when we consider Q2 (and Q3, Q4 and Q5), possibly reflecting the symmetry breaking characteristic of the order book for large volume of shares. Finally, for any given position size, the average correlation between the daily changes in cost of selling and cost of roundtrip is larger than the correlation between cost of buying and cost of roundtrip, suggesting that bid side is potentially more influential on the weighted spread. Indeed, the highest correlation level among all liquidity measure

\[16\] The correlations in Table 2 are significantly different from zero, t-statistics are not reported.
pairs is observed between costs of selling and roundtripping the position $Q1$.

2.2 The model

We start with the market model of Chordia et al. (2000) to examine the commonality in liquidity in the order book,

$$DL_{i,t} = \beta_{i0} + \beta_{i1}DL_{M,t} + \beta_{i2}DL_{M,t-1} + \beta_{i3}DL_{M,t-1}$$
$$+ \beta_{i4}R_{M,t} + \beta_{i5}R_{M,t-1} + \beta_{i6}R_{M,t+1} + \beta_{i7}DV_{i,t} + \varepsilon_{i,t}$$

(1)

where $L_{i,t}$ is a general notation to denote the measure of an individual liquidity for stock $i$ on day $t$; $L_{M,t}$ is equally-weighted cross sectional average of the liquidity variable for all stocks on day $t$ excluding stock $i$; $R_{M,t}$ is equally-weighted cross sectional average of the returns (daily percentage changes) for all stocks on day $t$ excluding stock $i$; and $V_{i,t} \equiv \frac{(P_{H_{i,t}} - P_{L_{i,t}})}{(P_{H_{i,t}} + P_{L_{i,t}})/2}$ is a proxy for the individual volatility of stock $i$ on day $t$, with $P_{H_{i,t}}$ and $P_{L_{i,t}}$ denoting the highest and lowest prices respectively. As previously stated, the operator $D$ stands for the daily percentage change wherever it is used.\textsuperscript{17} Exclusion of the individual stock variables in constructing the aggregate variables is to remove the effect of stock $i$’s own variation on the market average and remove the constraint that the cross-sectional average of the betas has to be unity. The additional lead and lag of the changes in the market average liquidity are used to capture the effect of non-concurrent adjustments in the liquidity variation at stock and market level. The (concurrent, lagged and lead) market return is added to remove spurious dependence induced by an association between returns and spread measures. The change in individual volatility is included as it might be an important variable influencing liquidity (Chordia et al., 2000). Finally, unless otherwise stated, all linear estimations are performed by Newey-West regressions.

---INSERT TABLE 3---

\textsuperscript{17}Using value-weighted market variables yields to similar conclusions obtained by equally-weighted market variables.
In our analysis, we first estimate the time-series model in Eq.(1) for each stock, and then report the cross-sectional mean of the estimated beta coefficients in Panel A of Table 3. The results reveal a clear evidence of co-movement in the order book liquidity for both buy and sell side, and also roundtrip. Focusing on the cost of roundtrip as a general liquidity measure, we observe a strong contemporaneous commonality as average $\beta_1$ values range from 0.82 to 0.95 with all t-statistics greater than 35. $\beta_2$ (lagged beta) means are usually small and insignificant compared with the $\beta_1$ (contemporaneous beta) averages. However, $\beta_3$ (lead beta) averages produce significant negative, albeit, little values in magnitude. Although a direct comparison may not make sense as we do not use the same liquidity measures with the previous studies, our results on average $\beta_1 + \beta_2 + \beta_3$ for smallest trading position Q1 (which could serve as a proxy for commonality in percentage spread) reveal that the commonality degree in Borsa Istanbul (an order-driven market) is close to the commonality in hybrid markets like NYSE (Chordia et al., 2000) and London Stock Exchange (Galariotis and Giouvris, 2007), and larger than order-driven markets like Hong Kong (Brockman and Chung, 2002), Australia (Fabre and Frino, 2004) and Deutsche Borse (Kempf and Mayston, 2008). Such an outcome is surprising as the literature suggests (and empirically shows) that the order-driven property is expected to decrease the commonality; however, since our sample period covers some of the most turbulent years in financial markets world-wide, absence of a market maker in this case may have created an increased commonality during liquidity shocks. The explanatory powers of the typical individual regressions are impressive in our models. The reported average adjusted R2 is between 1% and 4% in the previous studies, whereas this value ranges from 12% to 17% (and 10% to 19% for median adjusted R2), increasing as the position size to trade increases. Considering concurrent betas ($\beta_1$), more

The t-statistics associated with the mean coefficients in Panel A of Table 3 (and the similar mean coefficients in the next sub-sections) have been adjusted for cross-equation correlations as suggested by Hameed et al. (2010). The variance of each estimated market liquidity $\beta_i$ is obtained from stock $i$'s market model liquidity commonality regression in Eq.(1). The empirical correlation between the regression residuals for stocks $i$ and $j$ is used to estimate the pairwise correlation between the coefficients $\beta_i$ and $\beta_j$. Hence, the standard error of the mean estimated coefficient is provided by:

$$StdDev(\bar{\beta}) = StdDev\left(\frac{1}{N} \sum_{i=1}^{N} \beta_i\right) = \frac{1}{N} \sqrt{\sum_{i=1}^{N} Var(\beta_i) + \sum_{i=1}^{N} \sum_{j=1, j\neq i}^{N} \rho_{ij} \sqrt{Var(\beta_i)}Var(\beta_j)}$$
than 99% of our sample stocks have positive individual beta estimates and at least 88% of them are positively significant at the 95% confidence level for any given position size to trade. These ratios are much higher than the previously reported results for other markets. Moreover, there is no negative significant individual $\beta_1$ value. Our findings on the percentage of firms with significant positive and negative concurrent betas ($\beta_1$) are consistent with the results reported on Istanbul Stock Exchange by Brockman et al. (2009). The percentage of stocks with positive and negative significant lagged (lead) betas are less than 6% and 11% (6% and 17%) respectively, which are close to the previous findings on other markets.

Although we adjust the $t$-statistics for the mean concurrent ($\beta_1$), lagged ($\beta_2$) and lead ($\beta_3$) betas; we can not perform a similar procedure for the sum of the mean beta coefficients ($\beta_1 + \beta_2 + \beta_3$) since the market model regression in Eq.(1) does not provide its variance estimate. Therefore, to check whether this sum is also significant, we follow the procedure suggested by Chordia et al. (2000). We sort the sample stocks alphabetically and run 132 time series regressions between adjacent residuals; i.e.,

$$\varepsilon_{j+1,t} = \gamma_{j,0} + \gamma_{j,1}\varepsilon_{j,t} + \zeta_{j,t} \quad (j = 1, \ldots, 132),$$

where $\gamma_{j,0}$ and $\gamma_{j,1}$ are coefficients to be estimated. The $t$-statistics for $\gamma_{j,1}$ is expected to provide evidence about cross-equation dependence. Panel C of Table 3 displays the sample characteristics for the $t$-statistics of $\gamma_{j,1}$ and also presents the average correlations between $\varepsilon_{j+1,t}$ and $\varepsilon_{j,t}$. Accordingly, there is little evidence of cross-equation dependence in our sample. For all position sizes to trade, the proportion of significant $t$-values are less than 10%, with mean and median $t$-statistics being confined to the interval [-0.16, 0.08]. Plus, near zero average correlations (positive and less than 0.01 in any case) imply that adjusting for cross-equation dependence would not have a significant impact on the qualitative conclusions.

Taking mean $\beta_1 + \beta_2 + \beta_3$ as the main measure of commonality, we notice that when we walk up through the order book, commonality in cost of trading displays a humped figure, first by increasing (from 0.86 to 0.89) when we pass from position size $Q_1$ to $Q_2$, then decreasing monotonically (from 0.89 to 0.78) with the increasing position sizes to trade (see Figure 2a). Looking from a wider perspective, this situation suggests that commonality decreases as we go deeper into the order book, however further analysis is required (which will be performed in the following sub-sections) to get robust inference. A very interesting pattern
arises in the same case when we consider buy and sell sides separately. Accordingly, for relatively small trading positions, commonality in sell side is stronger than the commonality in buy side (see Figure 2b). This picture can be thought to be consistent with the findings of Brennan et al. (2012), in which authors state that sell-order liquidity is priced more strongly than buy-order liquidity. However, as the position size to trade exceeds a certain amount, the commonality in buy side becomes stronger than the commonality in sell side. This kind of a striking pattern motivates us further in comparing the commonalities in different sides of the order book.

2.3 Industry effect

In many studies in the literature, a common variable checked for a potential influence on liquidity commonality is the industry affiliation as it can affect a firm’s information asymmetry. Although significant industry effect is found in many studies, the results are not so clear from several perspectives. For example, Chordia et al. (2000) report that, in addition to market-wide effect, stocks exhibit significant responses to industry-wide changes in liquidity for NYSE. In fact, authors show that industry affiliation actually has larger effect on commonality for most of their liquidity measures. On the contrary, Galariotis and Giouvris (2007) find no evidence of industry effect for FTSE250 shares traded on London Stock Exchange, a market with a similar structure to NYSE; and authors depend this situation on the possible firm-specific noise variation. The finding of Chordia et al. (2000) is supported by Brockman and Chung (2002) as authors find industry-wide commonality in Hong Kong, an order-driven market without market makers. However, in the case of Australia (another order-driven market), findings of Fabre and Frino (2004) do not support the existence of commonality in liquidity at the industry group level. Consistent with the results of Chordia et al. (2000), Chung and Chuwonganant (2014) find a significant and positive contemporaneous relationship between individual liquidity and industry-wide liquidity for stocks traded on NYSE and NASDAQ. On the other hand, in another study on NYSE, Kamara et al. (2008) find that the industry betas are low relative to the market betas, which suggests that
liquidity commonality is mostly a market-wide effect, not industry specific. Finally, Brockman et al. (2009) show that there is a significant industry component in firm-level liquidity in both developed and emerging markets. However, industry level commonality is not as influential as the market-level component in terms of both magnitude and significance.

Depending on the existing literature, we honestly could not form an assumption on whether there exists an industry-wide effect or not on commonality in Borsa Istanbul. The literature presents evidence for significant industry effect in general, however, any possible outcome has also been observed. To reveal the truth, we proceed as Chordia et al. (2000) by implementing the following extended two-factor model,

\[
DL_{i,t} = \beta_{i0} + \beta_{i1}DL_{M,t} + \beta_{i2}DL_{M,t-1} + \beta_{i3}DL_{M,t-1}
+ \beta_{i4}DL_{I,t} + \beta_{i5}DL_{I,t-1} + \beta_{i6}DL_{I,t+1}
+ \beta_{i7}R_{M,t} + \beta_{i8}R_{M,t-1} + \beta_{i9}R_{M,t+1}
+ \beta_{i10}DV_{i,t} + \varepsilon_{i,t}
\]

(2)

where the additional regressor \(DL_I\) is an industry-specific average liquidity measure. As with market liquidity, firm \(i\) was excluded when computing the industry average. The results in Panel A of Table 4 reveal very little evidence of industry commonality.\(^{19}\) Out of fifteen liquidity measures we consider, only three of them display significant contemporaneous industry-wide commonality with the corresponding average concurrent betas \((\beta_5)\) being around 0.03 and their \(t\)-statistics being less than 2.10. Also, the results for average lagged \((\beta_5)\) and lead \((\beta_6)\) industry betas are no different in qualitative terms. The overall industry commonality \((\beta_4 + \beta_5 + \beta_6)\) is significant for limited number of cases in which most of them are cost of roundtrip for different position sizes, and the impact does not exceed 0.13 in its strongest case. In terms of explanatory power, adding industry component has practically no effect as the mean and median of adjusted R2s are almost the same with the one-factor

\(^{19}\)We use the Global Industry Classification System which is available from Bloomberg. The industries are Consumer Discretionary (32), Consumer Staples (11), Energy (3), Financials (28), Health Care (2), Industrials (23), Information Technology (3), Materials (26), Telecommunication Services (2) and Utilities (3). As there are not enough stocks for the formation of large enough portfolios in some of the industries, we repeated the analysis skipping the industries having less than ten stocks. Coefficient are very similar in both magnitude and significance, therefore they are not reported.
model. According to Panel B of Table 4, the individual firm betas also confirm the weak evidence of industry commonality as the percentage of significant positive or negative individual industry betas are less than 10% in almost all cases.

The qualitative and quantitative results on market-wide commonality are very similar for the models in Eq.(1) and Eq.(2). In particular, we would like to point out that market commonality again decreases as we walk up the order book (e.g., average $\beta_1 + \beta_2 + \beta_3$ decreases from 0.89 to 0.72 for the cost of roundtrip as position size increases from $Q_1$ to $Q_5$). Overall, we find that the market commonality is much more stronger than the industry commonality, and is not even lower than in the previous baseline analysis even though the commonality is split up into the market and industry effects. Results suggest that liquidity does not carry a industry-specific risk or is not exposed to a industry-wide information asymmetry in Borsa Istanbul, which is in contrast to the cases of many hybrid or quote-driven markets with specialists. Therefore, liquidity provision strategies of day traders (so called natural market makers) do not necessarily take the industry-specific risk into account for this specific market, even if these traders are risk averse or concern about adverse selection. Finally, Panel C of Table 4 validates the robustness of our results by showing that cross-equation dependence in the estimations would not have a significant impact on the qualitative conclusions.

2.4 Commonality vs. individual determinants

Previous literature states that individual properties like volatility, trading volume and price have significant effects on a share’s own liquidity (Benston and Hagerman, 1974; Stoll, 1978, 2000). Therefore, we estimate the following regression model given in Eq.(3) for each stock using daily time series to examine the commonality while controlling for main individual
\[
\log(L_{i,t}) = \alpha_{i0} + \alpha_{i1} \log(L_{M,t}) + \alpha_{i2} \log(L_{M,t-1}) + \alpha_{i3} \log(L_{M,t-1}) \\
+ \alpha_{i4} \log(L_{I,t}) + \alpha_{i5} \log(L_{I,t-1}) + \alpha_{i6} \log(L_{I,t+1}) \\
+ \alpha_{i7} \log(V_{i,t}) + \alpha_{i8} \log(V_{i,t-1}) + \alpha_{i9} \log(V_{i,t+1}) \\
+ \alpha_{i10} \log(P^{\text{w}}_{i,t}) + \alpha_{i11} \log(V ol_{i,t}) \\
+ \alpha_{i12} R_{M,t} + \alpha_{i13} R_{M,t-1} + \alpha_{i14} R_{M,t+1} + \varepsilon_{i,t}
\]

The additional variables \(P^{\text{w}}_{i,t}\) and \(V ol_{i,t}\) respectively denote the time-weighted price and TL trading volume of stock \(i\) on day \(t\). This time, in the spirit of Chung and Chuwonganant (2014), we proceed with a level regression, thus each estimated coefficient represents percent change in the liquidity measures given a 1% change (i.e., elasticity) in each independent variable. Panel A of Table 5 displays the separate marginal influences of individual attributes on liquidity and compares their magnitude with commonality, measured by market- and industry-wide liquidity in this case.\(^2\) As expected, individual volatility has a positive and highly significant influence on cost of trading. In particular the mean impact of concurrent (\(\alpha_7\)), lagged (\(\alpha_8\)) and lead (\(\alpha_9\)) individual volatility are all significant with the concurrent effect taking the largest values. Moreover, as reported by Panel B of Table 5, percentage of the positive significant individual volatility terms are considerably high with more than 70% for the concurrent, and 30% for the lag and lead values (and reaching up to more than 90% as we go deep in the order book). Significant lag and lead volatility effects indicate that day traders take historical uncertainty into account in adjusting their liquidity positions and also make anticipatory adjustments. One of the interesting results is that the effect of individual uncertainty on cost of trading increases as the position size to trade increases. In fact, for sizes \(Q_4\) and \(Q_5\), individual volatility is a stronger influence on cost of trading than market-wide commonality (e.g., average \(\alpha_1 + \alpha_2 + \alpha_3\), an indicator of market-wide commonality, is 0.30 and 0.23 whereas average \(\alpha_7 + \alpha_8 + \alpha_9\), an indicator of individual volatility’s influence, is 0.35 and 0.46 for roundtripping the positions \(Q_4\) and \(Q_5\) respectively). Also as expected, trading volume (\(\alpha_{11}\)) has a negative and highly significant impact on cost of trading. Similar to the case of volatility; trading activity has a small effect on liquidity in magnitude for small positions, however it increases strikingly as the position size increases, even exceeding the

\(^2\)\(t\)-statistics are corrected for first-order auto-correlation.
market-wide commonality level at the largest position size $Q_5$ (e.g., averages of $\alpha_1 + \alpha_2 + \alpha_3$ and $\alpha_{11}$ are 0.23 and -0.28 respectively for the cost of roundtrip). Regarding market-wide commonality, we obtain similar findings with the previous sub-sections; i.e., the impact of market-wide commonality ($\alpha_1 + \alpha_2 + \alpha_3$) has a decreasing trend (from 0.56 to 0.23 as position size changes from $Q_1$ to $Q_5$) as position size to trade increases. For us, the decreasing market-wide commonality and the increasing effect of individual determinants on liquidity as we walk up the order book remains as a puzzle to be solved.

---INSERT TABLE 5---

The findings on industry-wide commonality strengthen our previous results. When many factors are taken into account, the significance of industry affiliation vanishes almost completely. Another interesting result is the negative marginal impact of share price on the cost of trading; however our findings are in parallel to those of Chordia et al. (2000) where authors depends this situation on prices being not continuous but discrete. Accordingly, all stocks liquid enough to trade at the minimum spread would display a substantial negative correlation between price and proportional spread. This spurious effect would disappear only when price reaches a level high enough to support occasional spreads larger than the minimum. This is more than a suitable explanation in our case since the size of the best bid-ask spreads stick to one price tick more than 98% of the time. The argument of authors is also supported by the fact that price effect ($\alpha_{10}$) on liquidity decreases as we walk up the order book. As a final notification, we report that after controlling for several factors, the striking switching pattern between commonality in buy and sell side liquidity is still present. According to Figure 3b, market-wide commonality ($\alpha_1 + \alpha_2 + \alpha_3$) for cost of selling is higher than for cost of buying when we consider the smallest position size $Q_1$. However, as we walk up the order book, although the overall commonality decreases (Figure 3a), the commonality on buy side gets stronger. Finally, the high and impressive explanatory powers of the individual regressions displayed in Panel A of Table 5 (e.g., mean and median adjusted R2s range from 0.62 to 0.77), and the results on cross-equation dependence given in Panel C of Table 5 validate the robustness of our inferences.

---INSERT FIGURE 3---
Overall, market-wide commonality retains a strong influence on individual stock liquidity even after accounting for individual determinants like volatility, volume and price; showing that liquidity commonality is an omnipresent characteristic.

3 Sources of commonality

3.1 Index trading

In searching for sources of commonality, one of the most popular arguments in the literature is to be included in a benchmark index and there are two main reasons for that, both depending on the simultaneous trading of multiple stocks. First one is the market behavior of stock index arbitrageurs. When an index arbitrageur thinks that the index futures/option contract is above fair market value, he sells (or shorts) this contract and buys the underlying spot index at the same time; and vice versa. Therefore, it is expected that the arbitrageur’s block trade of shares in a relatively short time period leads to an increase in the commonality in liquidity for stocks included in the index. The second reason is the concept of index trading as performed by many mutual funds, in particular exchange traded funds (ETFs), which yields to a correlated trading activity and, in turn, creates common buying or selling pressure, eventually leading to higher levels of commonality in liquidity.\textsuperscript{21} For example, in the model of Gorton and Pennacchi (1993), equity basket trading increases the commonality in liquidity for the constitute stocks in the basket, but reduces liquidity commonality for individually traded stocks. Empirical results also support this argument. Chordia et al. (2000) show that commonality is higher for large cap NYSE stocks and speculate that the reason is the greater prevalence of institutional herd trading in larger firms. Harford and Kaul (2005) examine order flows of U.S. stocks and find significant common effects for S&P500 stocks, but weak effects for others. Kamara et al. (2008) show that the increase in commonality in liquidity among U.S. large cap stocks in the past 25 years can be attributed to the increasing

\textsuperscript{21}ETFs are mutual funds which are based on an index and aim to reflect the performance of its base index to the investors. ETFs invest in the securities on its base index in proportion to their weight in the index. Thereby, for example, an investor willing to invest in an index can invest in an ETF rather than purchasing the equities of the index separately. ETFs, which were initiated first in 1993, represent one of the fastest growing recent financial innovation.
importance of institutional and index-related trading. As a supporting argument, Koch et al. (2010) reveal that stocks with higher mutual fund ownership and stocks owned by mutual funds with high turnover exhibit greater commonality in liquidity. Similarly, Corwin and Lipson (2011) argue that correlated index/basket trading (either as natural or algorithmic) is an explanation of liquidity commonality in NYSE stocks. Further evidence is provided by Karolyi et al. (2012) for several stock exchanges.

The flagship index tracked by ETFs in Turkey is the BIST30. Almost all brokerage firms introduced their BIST30 ETFs in the last few years. The main strategies of these ETFs are to hold at least 80% of the stocks included in the index with closest ratios to their original weights and to achieve a higher correlation level than 0.9 for a given time interval. In this part, to see whether being included in an index leads to a liquidity commonality, we split our stocks into two groups. First group consists of stocks included in BIST30 (which is a quarterly updated index) for at least a year throughout the sample period. This group, which we call “index stocks”, contains 35 stocks which most of them are indeed included in BIST30 for the whole sample period. The second group, called “non-index stocks”, includes 92 stocks which have never been listed in this main index. Cross-sectional statistics show that while a non-index stock has a daily average of 2.2 mn. shares traded and 5.38 mn. TL traded value, these numbers are 11.88 mn. shares and 47.93 mn. TL for an index stock, displaying the big gap between the trading activity in these groups. Considering the facts that the index companies are mostly held by institutional investors and the most popular derivative product in Borsa Istanbul is BIST30 index futures, an initial guess depending on the previous literature is a higher commonality level in index stocks compared to non-index stocks. To reveal the truth, we calculate averages of liquidity betas (obtained from Eq.(1)) for the firms in index and non-index stock groups, and present the results in Panel A of Table 6.

---INSERT TABLE 6---

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22 Therefore, the remaining 6 stocks that have been listed in BIST30 for less than a year are not considered.

23 Among all derivative products (including index options/futures, single stock options/futures, currency options/futures and several commodity futures), BIST30 futures contracts constitute approximately 90% of the total trading volume in TL.
At a first glance, the outcomes are totally surprising with being completely in contrast to the previous literature. The liquidity commonality in non-index stocks is not only stronger than index stocks at the best price levels (e.g., average $\beta_1 + \beta_2 + \beta_3$ is 0.89 and 0.80 for non-index and index stocks respectively in roundtripping the position $Q_1$), but also the level of commonality in non-index stocks preserves its large magnitudes as we walk up the order book. For example, regarding cost of roundtrip as a general measure, average $\beta_1 + \beta_2 + \beta_3$ varies between 0.89 and 1 at the different levels in the order book for non-index stocks, whereas this value decreases monotonically for index stocks from 0.80 to a relatively low value of 0.40 with the increasing position size to trade (see Figure 4a). Although these findings are different from those previously reported and may not make sense at first, the following statement provides a reasonable explanation: As large shareholders (therefore corporate insiders), institutional investors do not have to extract information from trading. If these investors adopt a “buy-and-hold strategy”, their lack of active trading, together with their perceived information advantage, may reduce liquidity (Rhee and Wang, 2009). In the case of Borsa Istanbul, although there is a high amount of trade in index stocks, with the low level of algorithmic trading and the absence of HFTs; the institutional investors (who are major shareholders in index stocks) may not trade as actively as the others that were previously studied for different markets. Probably, the ETFs also adjust their position with a lower frequency compared to their counterparts investing in other countries. Accordingly, it is harder to expect a correlated trading activity as in the previous studies unless there is

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24Further details include the followings: the explanatory powers of the individual regressions are slightly higher for non-index stocks on the average and increase with the position size for both kinds of stock groups. Panel A of Table 6 shows that significant mean lagged ($\beta_2$) and lead ($\beta_3$) betas are limited to only a small set of liquidity measures for index stocks, whereas mean lead ($\beta_3$) beta is consistently significant for non-index stocks suggesting that anticipatory liquidity adjustment is more common for the latter group. This is also validated by the high percentage of significant individual $\beta_3$ values for non-index stocks displayed by Panel B of Table 6.

25The data for mean holding period is not available for individuals and institutions separately. However, we have this data for domestic and foreign investors. Accordingly, the mean duration of holding BIST30 stocks by foreign investors are 251, 305 and 260 days for the years 2011, 2012 and 2013 respectively. On the other hand, the mean by domestic investors are 35, 33 and 27 for the same years. Bearing in mind that the majority of the foreign investors are institutions, and individuals constitute a significant part of
common information leading the institutions to the same direction consistently. On the other hand, for non-index stocks where individual investors are possibly the main source of trading, investor base might be mostly focusing on the performance of the benchmark index or the stocks included in it as a common source of information to detect a possible trend in the market. The main assumption is that the investors of non-index stocks think of the investors of index stocks as smart and informed, therefore look up to their decisions, hence, they do not focus on the firm specific news related to the stocks in their portfolio. Therefore, a higher degree of order flow commonality, thus a stronger commonality in cost of trading is expected. This statement partially explains the lack of industry commonality in our work since most of the investors would disregard industry specific news in this case. It also suggests that herding is present in Borsa Istanbul, not necessarily amongst institutional investors but amongst individuals in relatively small cap stocks who keep an eye on the performances of large cap stocks or the market index. Furthermore, building upon this argument, the difference between the commonality structures of index and non-index stocks through the order book can be explained as follows: The investors in the index stocks are smart traders who give market orders and/or orders with prices very close to the market price (not far beyond the fair value), thus drawing an informed and realistic profile. Indeed, the fact that institutions are the main shareholders in these stocks supports this profile. This kind of a trade behavior creates a commonality only at the best price level and the commonality would be expected to decline as we go deep in the order book. On the other hand, the herding habit of individual investors (as explained above) yields to an overall shift in the order flow, thus preserving the degree of commonality at the different levels of the order book. Remembering that market makers usually act on illiquid stocks of small cap firms (which are not included in benchmark indexes) and the fact that our sample does not include any market makers (who are capable of increasing the commonality only at the best price levels due to their quotation strategy) further contribute to the preservation of domestic investors, these statistics strengthen our argument. However, another important point is that these mean durations are calculated using the end of day positions. For example, an institutional investor may change its position in a stock earlier in a day and rebalance it at the end of the same day. In that case, such an operation would not be reflected on the mean durations. If this kind of an operation is performed asynchronously between institutional investors, it could help us explain both the lower order book commonality and the higher trading activity in index stocks.
commonality strength throughout the order book for non-index stocks.\textsuperscript{26}

Considering buy and sell side separately, we end up with two distinct patterns (see Figure 4b and 4c). For the non-index stocks, our previous finding is still valid; i.e., for small positions to trade, sell side has a stronger commonality than buy side, however, as the position size increases, buy side commonality gets stronger. Holding onto our previous argument, we think that a possible explanation for this situation is the non-index investors’ biased recognition of the trend created by index stocks (Lakonishok et al., 1994; La Porta, 1996; La Porta et al., 1997; Barberis et al., 1998; Benartzi, 2001). Accordingly, non-index investors overreact to a positive trend of index stocks; i.e., over-extrapolate positive past performance into the future by believing that persistence of positive index performance to be higher than it actually will, thus even they wish to sell their stocks, they are not willing to do it at a price that is close to the market level; so their sell orders possibly concentrate in deep down the order book, resulting with a higher commonality for large position sizes to trade.\textsuperscript{27} On the other hand, these investors underreact to a negative trend of index stocks (anticipate this trend to end in a short while), thus set off buy orders with prices closer to the market level (showing that they are willing to pay relatively high prices since they think they will still profit as the market price will change its direction) which may create a higher sell-side commonality for small positions to trade.\textsuperscript{28} Regarding index stocks, although

\textsuperscript{26}An alternative, but less likely explanation for the preservation of the liquidity commonality in non-index stocks throughout the order book is a possible scheme performed by the largest shareholders. Accordingly, largest shareholder fills close amounts of buy (sell) orders at several price levels in the order book to create an artificial demand (supply). The aim is to manipulate other investors to trade so that the price increases (decreases) and the scheme-holder can sell (buy) his/her shares at higher (lower) prices. The close amounts of order fills at different price levels synchronously in multiple stocks for few days in a row can lead to a preservation of commonality throughout the order book.

\textsuperscript{27}This kind of a behavior is highly related to the “endowment effect” (Thaler, 1980) which prompts an implicitly irrational decision maker to ask a higher price when selling an asset than he would be willing to pay when buying it. A recent study on Australian stock exchange by Fursche and Johnstone (2006) shows that sellers appear to value their own shares higher than buyers independent of current market price, by consistently placing sell orders on average “further from the market” (i.e., from the best quote) than buy orders. Authors report that this asymmetry is much more pronounced in individual investors trading than in orders made through institutional investors.

\textsuperscript{28}An evidence supporting this positive-negative trend argument will be provided in sub-section 3.4.
a switching pattern is also observed, the situation is just the opposite of non-index stocks (i.e., for small positions to trade, buy side has a stronger commonality and as the position size increases, sell side commonality gets stronger) and this pattern still remains as a puzzle to be solved.

The analysis carried out in this sub-section suggests that ownership structure and firm size are important determinants of liquidity commonality in Borsa Istanbul, and an extensive research on the subject will be performed in the next sub-section; however, whether these findings are stylized facts of liquidity in emerging markets? remains an open question to be answered.

3.2 Firm size and the ownership structure

The results in the previous sub-section definitely raise questions about the effect of ownership structure on commonality in liquidity. However, this line of study remains relatively narrow due to limited data on ownership. Kamara et al. (2008) examine the impact of changing aggregate levels of institutional ownership on commonality in NYSE stocks. Using annual ownership data, they find that commonality increases over time through correlated trading patterns by institutional owners. Using quarterly ownership data, Koch et al. (2010) complement their findings by showing that mutual funds are an important factor in explaining commonality in liquidity in NYSE and AMEX stocks. Recently, Cao and Petrasek (2014) show that there is a significant and positive relationship between hedge fund ownership in quarter \( q - 1 \) and the liquidity risk in quarter \( q \) for NYSE, AMEX and NASDAQ stocks.

Their findings support the model of Brunnermeier and Pedersen (2009), in which adverse liquidity shocks force levered institutions to reduce their leverage by selling off assets, leading to declining liquidity spirals. Overall, there is evidence to support the hypothesis that institutional ownership lead to an increase in the liquidity commonality. However, our results on the commonality structure suggest that the findings may differ in the case of Borsa Istanbul. In particular, with the fact that index stocks mostly belong to the group of mid-to-large cap firms, we expect a positive institutional ownership effect on commonality in the firms with these sizes. However, our findings and arguments on non-index stocks may imply a different outcome for small cap firms.

To reveal the truth, we follow the methodology of Kamara et al. (2008). In their study,
authors run the following time-series regression in Eq. (4) (a simplified version of Eq. (1)) for each stock $i$ in each year from 1981 to 2005,

$$DL_{i,t} = \alpha + \beta_i DL_{M,t} + \varepsilon_{i,t}$$  \hspace{1cm} (4)

then, they calculate equally-weighted averages of liquidity betas for all the firms in each size quintile which gives the authors a time-varying beta per quantile. Within these quantiles, to examine the cross-sectional relation between liquidity beta and institutional ownership, they estimate the cross-sectional regression given in Eq. (5) for each year $t$, where $INST\_RATIO_{i,t-1}$ measures firm $i$’s market cap owned by institutions as the percentage of total market cap at the end of year $t-1$.

$$\beta_{i,t} = a + \lambda INST\_RATIO_{i,t-1} + \theta \log(MCAP_{i,t-1}) + v_{i,t}$$ \hspace{1cm} (5)

Because a firm’s institutional ownership and size are highly positively correlated, firm size, denoted by $MCAP$, is also included in the regression to alleviate any concerns that the institutional ownership coefficients may be capturing a pure size effect. Ownership data is limited to annual frequency in authors’ sample, but the length of their sample size is long enough to produce satisfactory number of betas in time for a robust cross-sectional analysis.

Our unique dataset provides us the weekly ownership structure of each firm in our study. In particular, it contains market cap owned by institutions as the percentage of total market cap at the end of each Wednesday. However, beta estimations from the time-series regression in Eq. (4) in each week would produce unreliable results as we would have at most five daily liquidity data available per stock.\(^{29}\) To overcome this problem, we implement the recently introduced methodology of Dynamic Conditional Beta (DCB) by Bali et al. (2014), which allows us to estimate a time-varying liquidity beta for each firm without consuming any initial data (The implementation of the methodology is explained in detail in the Appendix A). Therefore, we end up with a liquidity beta value for each Thursday associated with an ownership data for each preceding Wednesday.\(^{30}\)

\(^{29}\)For example, Koch et al. (2010) mention that 30 to 50 daily observations are required at this stage for robustness.

\(^{30}\)The raw ownership data is stamped as Friday. Since settlement day is $T+2$ in Borsa Istanbul, i.e., the
Figure 5 shows some of the time-varying weekly liquidity betas belonging to different size quantiles and Table 7 presents their time averages. For the rest of this section, $M_5$ ($n = 27$), $M_4$ ($n = 26$), $M_3$ ($n = 27$), $M_2$ ($n = 26$) and $M_1$ ($n = 27$) will refer to the quantiles constructed by daily average (of four years) market cap, with $M_5$ and $M_1$ denoting the largest and smallest firms respectively.\footnote{A common concern in such a classification is that the cross-sectional distribution of firm size may have changed over the sample period; i.e., a small firm in the beginning may fall into large firm quantile in the end of the sample period. This does not pose a big threat in our situation as we consider four years of data, a relatively short sample period for such a sharp change. For example, 23 out of the 27 $M_5$ firms in our study are also $M_5$ firms in each of the four sample years, and the remaining 4 firms are considered as $M_5$ in at least 2 years based on their daily average market cap values. Similar results are also valid for different size quantiles.} Although estimation methods are different, the time averages of dynamic betas show consistent characteristics with our previous mean beta estimates across index and non-index stocks. According to Table 7, we observe higher commonality for small firms compared to large firms. For example, time average beta for $M_1$ and $M_2$ firms is 0.98 and 1.05 respectively for roundtripping the position $Q_1$, whereas this value is 0.79 and 0.75 for $M_5$ and $M_4$ firms respectively.\footnote{Regarding the relationship between firm size and liquidity (spread) commonality, literature usually leads to two main findings. In particular, first group of studies states that commonality increases with the firm size (Chordia et al., 2000; Fabre and Frino, 2004; Kamara et al., 2008), whereas the second group claims the opposite (Brockman and Chung, 2002; Brockman et al., 2009). Table 7 suggests that commonality in Borsa Istanbul increases as the firm size decreases, putting our work into the second group.} Further, the strength of second business day following the transaction, we obtain the real ownership data by shifting the time stamp two days back. However, we have to mention about a caveat with our dataset in this case. As in many stock exchanges around the world, there is a transaction method called “wire transfer” in Borsa Istanbul used for trading stocks between market participants. There are nine versions of this method in which four of them, the settlement of the transaction occurs on the same day. Although the exact numbers are not known, informal discussions with the settlement & custody authorities state that the majority of the volume traded via this method is in-between foreign institutions, or in-between domestic institutions. Therefore, error in the overall ownership structure implied by our dataset is assumed to be negligible.
the commonality preserves its levels throughout the order book for small firms whereas commonality tends to decline for large firms with the increasing position size to trade (e.g., time average liquidity beta for small firms varies between 0.98 and 1.11, whereas for large firms, it decreases from 0.78 to 0.70 monotonically as position size to roundtrip increases from Q1 to Q5).

First, we start by checking whether there exist a stochastic or deterministic time trend in the commonality in liquidity by estimating the models in Eq.(6) and Eq.(7) respectively, and the corresponding results are displayed in Table 8.

\[
\beta_t = a + \delta t + \gamma \beta_{t-1} + u_t \quad (6)
\]

\[
\beta_t = a + \delta t + u_t \quad (7)
\]

In the work of Kamara et al. (2008), authors find two different time trends in U.S. markets when they separate the firms in the small and large size quintiles. In particular, the betas have significantly decreased for small firms and increased for large firms, suggesting that large (small)-cap firms have become more (less) sensitive to market-wide liquidity variations. However, we do not observe such a divergence in our case nor we expected to do so. The significant stochastic trends are limited to only a few buy side commonalities in different quantiles. We also observe some significant deterministic trends, however, we could not come up with a meaningful interpretation on the significance patterns. May be the most relevant information is that all significant trends are positive, thus, there is a partial increase in the liquidity commonality in Borsa Istanbul in the last few years.

Turning back to the ownership effect, we estimate the following cross-sectional regression:

\[
\beta_{i,t} = a + \lambda_1 INST\_RATIO_{i,t-1} + \lambda_2 INST\_NUMBER_{i,t-1} + \theta \log(MCAP_{i,t-1}) + v_{i,t} \quad (8)
\]

where \(\beta_{i,t}\) is the liquidity beta for firm \(i\) on the \(t^{th}\) Thursday, and \(INST\_RATIO_{i,t-1}\) is the ratio of the market cap of firm \(i\) owned by institutional investors on the preceding
Wednesday. As an additional variable to the model in Eq.(5), we include the number of institutional investors denoted by \( \text{INST\_NUMBER} \) since we think that it is a potential determinant of commonality. In particular, as the number of investors in a stock increases, we expect an increase in the heterogeneity of market views, thus, a decrease in liquidity commonality.

---INSERT TABLE 9---

Table 9 reports the results of the time-series averages of the coefficients in the regressions and their \( t \)-statistics using the Fama and MacBeth (1973) methodology, with a Newey and West (1987) correction. Accordingly, except the small firms, the ownership effect on commonality is consistent with the previous findings. That is, an increase in the fraction of institutional ownership at the end of each Wednesday is associated with a significantly greater sensitivity to market-wide liquidity in the following Thursday. Thus, institutional investing appears to be a reason for commonality in liquidity for the firms except in \( M1 \) category. Moreover, the coefficient on the firm’s market value is significantly positive at conventional levels in the regressions of all quantiles. However, although the value of the coefficient on the fraction of institutional ownership is highest for the largest firms (\( M5 \)), we do not observe a monotonic decrease in this coefficient as we go from large to small firm quantile, unlike the case of Kamara et al. (2008). Also, there is not an obvious pattern in this coefficient throughout the order book, except that it takes its maximum value not at the smallest nor the largest positions to trade, but somewhere in the middle.

As expected, an interesting situation appears for the small (\( M1 \)) firms. Accordingly, an increase in the fraction of institutional ownership leads to a lesser sensitivity to market-wide liquidity, which is in sharp contrast to the previous findings. Analogously, we estimate the cross-sectional regression in Eq.(9) for \( M1 \) firms where \( \text{INDV\_RATIO} \) and \( \text{INDV\_NUMBER} \) refer to the fraction of individual ownership and the number of individual investors respectively.

\[
\beta_{i,t} = a + \lambda_1 \text{INDV\_RATIO}_{i,t-1} + \lambda_2 \text{INDV\_NUMBER}_{i,t-1} \\
+ \theta \log(\text{MCAP}_{i,t-1}) + \nu_{i,t}
\]

(9)

Below of the Table 9 reports that an increase in the fraction of individual ownership
is associated with a significantly greater sensitivity to market-wide liquidity for small firms. This result supports our argument on the commonality differences between index and non-index stocks provided in the previous sub-section, and also partially agrees with the theory of Baker and Stein (2004) that market liquidity is driven by individual investor sentiment in special cases. As an additional contribution to the literature, we find that the sensitivity of firm liquidity to market liquidity decreases significantly as the number of the firm’s investors (both individual and institutional) increases, possibly due to the increased variability in the views of market participants.

Other than being weekly, the main advantage of our dataset is that we can categorize the individual and institutional investors further as foreign and domestic (in the sense that investors residing abroad or in the host country). The origins of investors and the differences in their trading patterns have always been hot topics in the literature. Some argue that foreign investors are at an information disadvantage about a local firm compared with domestic investors (Choe et al., 2005), whereas others show that foreign institutional investors with a short investment horizon carry high information asymmetry and are superior in processing public information and producing private information than domestic individual investors (Grinblatt and Keloharju, 2000). To the best of our knowledge, effect of the ownership’s origin on a firm’s liquidity commonality has not been studied previously. Moreover, the ability to split the origin of investors is especially important in our case considering the fact that more than 62% of the free float of Borsa Istanbul was held by foreign investors through the sample period. For further investigation, we estimate the following cross-sectional regression in Eq.(10):

$$\beta_{i,t} = a + \lambda_1 FOR_{INST\_RATIO}_{i,t-1} + \lambda_2 DOM_{INST\_RATIO}_{i,t-1}$$
$$+ \lambda_3 FOR_{INST\_NUMBER}_{i,t-1} + \lambda_4 DOM_{INST\_NUMBER}_{i,t-1}$$
$$+ \theta \log(MCAP_{i,t-1}) + v_{i,t} \tag{10}$$

Table 10 reports the estimated coefficients, and it shows that stock ownership by institutional investors with different origins has a different impact on liquidity commonality. Very
interestingly, for the large firms (M5), only the fraction of foreign institutional ownership has a significant positive impact on liquidity beta, whereas for the firms in M4, M3 and M2 quantiles, the fraction of both foreign and domestic institutional ownership have a significant positive impact. As in the previous case, an increase in the fraction of institutional ownership (both types) leads to a lesser sensitivity to market-wide liquidity for small firms. Thus, we also estimate the analogous model given in Eq.(11) for the M1 quantile using the individual investor data.

\[
\beta_{i,t} = a + \lambda_1 FOR_{INDV\_RATIO}\left(t\right) + \lambda_2 DOM_{INDV\_RATIO}\left(t\right) + \lambda_3 FOR_{INDV\_NUMBER}\left(t\right) + \lambda_4 DOM_{INDV\_NUMBER}\left(t\right) + \theta \log(MCAP_{i,t}) + v_{i,t}
\]

As expected and reported at the bottom of Table 10, we observe that ownership by both types of individual investors leads to a higher commonality for small firms. However, we reveal an interesting fact by showing that domestic individuals are a significant source of commonality only for relatively small positions to trade (Q1, Q2 and Q3), whereas foreign individuals have significant positive impact on commonality only for relatively large positions to trade (Q3, Q4 and Q5). This may be due to the fact that foreign individual investors in Borsa Istanbul are mostly originated from countries with GDP per capita significantly higher than Turkey, which allows them to give orders of large sizes. Regarding the effect of the number of investors on commonality, an unexpected outcome arises in the case of foreign individuals as Table 10 reports a positive significant relationship. That is, as the number of foreign individual owners increases in a small firm, this firm shows greater sensitivity to market-wide liquidity, which contradicts with our heterogeneity argument and we can only speculate on the reason why: If a foreigner wants to trade in Borsa Istanbul, s/he first has to open an account at a brokerage firm in her/his home country, which also has an entity or a bilaterally agreed brokerage firm in Turkey. Then, a unique ID is assigned for this account. However, if this investor opens multiple accounts from different brokerage firms in her/his home country, then each one of these accounts are considered to belong to different investors; i.e., accounts can not be consolidated, which is a unique case for foreign individual investors in our sample. If a group of foreign individuals open multiple accounts in their home country, the number of investors would seem to increase artificially whereas the
homogeneity of the investor base is increasing in real terms. Considering the fact that foreign individual ownership is less than 1% in Borsa Istanbul, opening multiple accounts would have a significant positive impact on commonality even with a limited number of investors. Indeed, our informal discussions with brokerage firms confirm that this is a common operation done for speculative trading.

Overall, in parallel to the previous studies, we find that institutional investors are the main source of liquidity commonality, but only for mid-to-large cap firms. In the case of small cap firms, only individual investors have a significant impact on commonality. Moreover, the level of commonality decreases with the increasing number of investors in general.

### 3.3 Monetary policy and macro-economic announcements

A limited line of research points at the monetary policy and the macroeconomic announcements as reasonable sources of liquidity commonality. For example, Chordia et al. (2001, 2005) find evidence for U.S. macro-economic announcements and monetary policy giving rise to liquidity commonality in the U.S. stock market. Similarly, Brockman et al. (2009) show that domestic and also U.S. macro-economic announcements increase commonality in both developed and emerging stock markets. These studies were performed prior to the global financial crisis, and special attention is required to the subject now more than ever. In particular, the quantitative easing policies that have been launched by the Federal Reserve (Fed), and the expansionary monetary policies implemented in other major currency areas like eurozone and Japan affected all the markets around the world. Combined with the low yields in developed countries’ bond markets, excess liquidity environment has generated high capital inflows to emerging markets, leading to new financial structures. In the present case, few financial issues receive more attention in the press than central banks’ actions or what their governors say or might say about the economy, interest rates or the markets. Motivated by these facts, we investigate the impact of specific monetary policy decisions and macroeconomic announcements on the liquidity commonality in Borsa Istanbul.

We begin with analyzing the effects of (scheduled and unscheduled) monetary policy committee meetings, therefore interest rate announcements by selected central banks. The list naturally includes the Central Bank of the Republic of Turkey (CBRT), the Fed and the European Central Bank (ECB). In addition, the Bank of Japan (BOJ) and the Swiss National
Bank (SNB) are included since their currencies are always considered as safe haven, thus, their decisions may have significant impact on the global capital flight structure. Finally, we consider the Bank of England (BOE) since U.K. based investors are ranked first in aggregate foreign trades, and ranked second in aggregate foreign ownership in Borsa Istanbul.

In our sample period, there were 32, 48, 48, 57, 17 and 49 number of monetary policy committee meetings by the Fed, ECB, BOE, BOJ, SNB and CBRT respectively. As in the cases of Chordia et al. (2001) and Brockman et al. (2009), we use a three-day event window (2,-1,0) to measure the liquidity impact of the announcement in order to capture pre-announcement portfolio rebalancing. Similar to Brockman et al. (2009), we employ the “simple and direct measure of synchronicity” of Morck et al. (2000). In particular, we measure the co-movement of liquidity for each trading day by first counting the number of stocks with positive and negative changes in their daily liquidity measure and then dividing the larger of these two numbers by their total. Then, we average daily co-movement percentages first across all trading days (first column, Panel A of Table 11), then across only those trading days in event window (columns 2-7, Panel A of Table 11). The mean comparison of the whole sample and the event window is based on a one-tail, two-sample t-test for differences in means. Further, the t-statistics are corrected for unequal variances whenever appropriate using the Satterthwaite (1941) approximation. Panel A of Table 11 reports the summary results for the responses of liquidity co-movements to interest rate announcements.

Interestingly, the results in Panel A of Table 11 show that the interest rate announcements do not significantly increase liquidity co-movements at the best price levels. In fact when $Q_1$ is the position size to trade, liquidity co-movements in event window are not even higher than the sample average except on the announcement dates by Fed and the ECB. As we have mentioned before, the main possible reason for this situation is that bid-ask spreads stick to one tick in Borsa Istanbul for most of the time. However, the difference comes up

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**Table 11**

Interestingly, the results in Panel A of Table 11 show that the interest rate announcements do not significantly increase liquidity co-movements at the best price levels. In fact when $Q_1$ is the position size to trade, liquidity co-movements in event window are not even higher than the sample average except on the announcement dates by Fed and the ECB. As we have mentioned before, the main possible reason for this situation is that bid-ask spreads stick to one tick in Borsa Istanbul for most of the time. However, the difference comes up

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33 Fed meetings occur between 19:30 and 21:30 in Turkey’s local timezone. Therefore, the event day for a Fed meeting is taken as the next day of the original meeting day. The event window was alternatively selected as (-3,-2-1,0); (-1,0); (0); (-1,0,1) and (0,1). The most clear picture was observed in the original window.

34
as we walk up the order book; i.e., interest rate announcements by Fed significantly increase co-movements between cost of trading the positions $Q_2$, $Q_3$, $Q_4$ and $Q_5$. This picture shows that a liquidity analysis based on best prices can be misleading, and also suggests that tick sizes in Borsa Istanbul are larger than they should be since they do not allow the information to be reflected at best price quotes. In addition, even we use a different commonality measure, Table 11 shows that commonality is highest for smallest position ($Q_1$) to trade, and significantly lower deep down the order book, supporting our previous findings. A curious case is that the interest rate announcements by the Turkey’s own central bank do not have a significant impact on liquidity commonality at any level in the order book. Brockman et al. (2009) state that they find some emerging markets where country’s own interest rate announcements do not have a significant impact on bid-ask spread or depth commonality. Although they do not give specific names, our results suggest that one of those countries could be Turkey. Moreover, the difference between the impact powers of Fed and the other central banks shows the increased importance of the Fed decisions on investor sentiment after the global financial crisis, and stresses on the potential challenges faced with other central banks when one clearly dominates the others.

The results on Fed’s and ECB’s interest rate announcements motivate us further to analyze the impact of macro-economic news on commonality in liquidity. This time we focus on unemployment (UN), gross domestic product (GDP) and inflation (INF) announcements of Turkey, U.S. and eurozone. During the sample period, there were 48 unemployment, 16 GDP and 48 inflation announcements for each of these countries/region, and Panel B of Table 11 shows that the qualitative results are very similar to the interest rate announcements. For example, although the liquidity co-movement on these announcement dates are larger than whole sample average at best price levels, none of these differences are significant. This further strengthens our claim on tick sizes being larger than they should be. As we walk up the order book, only U.S. GDP announcements create a consistent positive significant impact on liquidity commonality (for position sizes $Q_2$, $Q_3$ and $Q_4$ to trade). So we see that not only Turkey’s own interest rate announcements, but also disclosure of its other major macro-economic variables do not make a significant impact on the commonality in liquidity.

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34 U.S. announces 3 different GDP values in each of the 3 months following the past quarter, where the second and third month announcements are the revisions of the announced value in the first month. A similar situation also exists in the eurozone. In this case, we only consider the first announcements.
Overall, the results show that among several domestic and global macro-economic variables, liquidity commonality in Borsa Istanbul is significantly affected only by the interest rate decisions and GDP announcements of U.S.; suggesting that investors in this market are highly sensitive, not to the Turkish economy or other developed economies, but only to the U.S. economy.

3.4 Market movements

As a final analysis, we focus on the impact of market movements on market-wide liquidity. Starting with the study of Chordia et al. (2001), several studies related market-wide liquidity to the direction and magnitude of market movements. In particular, Chordia et al. (2001) find that the aggregate market spread responds asymmetrically to market movements; i.e., it narrows modestly in up markets and widens significantly in down markets. Kempf and Mayston (2008) and Hameed et al. (2010) show that commonality particularly increases in falling markets. Karolyi et al. (2012) show that liquidity commonality is greater during times of high market volatility. Motivated by these findings, we would like to see the response of market-wide liquidity to market variables. Our main model in this part is adopted from the study of Chordia et al. (2001); however, authors also include some macroeconomic variables to capture the impact of economy-wide information on liquidity. Since we have covered that topic in the previous sub-section, we run a simplified version of their regression as given in the following:

\[
DL_{M,t} = \beta_0 + \beta_1 R^+_{M,t} + \beta_2 R^-_{M,t} + \beta_3 R^+_{M(5),t} + \beta_4 R^-_{M(5),t} + \beta_5 V_{M,t} + \beta_6 \sigma_{M(5),t} + \varepsilon_t \quad (12)
\]

where \(DL_{M,t}\) is the daily percentage change of the market liquidity (different from the previous sections, the market liquidity variable in this part is constructed without excluding any of the sample individual stocks), \(R^+_{M,t}\) \((R^-_{M,t})\) is the daily return of the all share index of Borsa Istanbul when the return is positive (negative) and zero otherwise. \(R^+_{M(5),t}\) \((R^-_{M(5),t})\) is the past five trading-day all share index return if it is positive (negative) and zero otherwise. Market volatility, denoted by \(V\), is defined as \(V \equiv \frac{(P^H_t - P^L_t)}{(P^H_t + P^L_t)/2}\) where \(P^H_t\) and \(P^L_t\) are the highest and lowest values of all share index on day \(t\), and \(\sigma_{M(5),t}\) is the market standard deviation in the past five trading days. As explained by Chordia et al. (2001), the daily all share index moves could trigger changes in investor expectations while also prompting
changes in optimal portfolio compositions. In addition, the direction of the movements could trigger asymmetric effects. Recent market history is also included since many investors, in particular individuals, use technical analysis strategies in their trading activity. Finally, concurrent and historic volatility is included due to their potential influence on short-term speculative trading. Since OLS runs indicate significant negative serial correlations as displayed in Panel A of Table 12, we apply the Cochrane and Orcutt (1949) iterative correction procedure in the time-series regressions. Panel B of Table 12 reports the estimation results.

| INSERT TABLE 12 |

The adjusted R²s in Panel B range from 0.33 to 0.45; showing that the explanatory variables capture a satisfactory variation in market-wide liquidity. The negative signs of \( \beta_1 \) and \( \beta_2 \) is consistent with the findings of Chordia et al. (2001) and Hameed et al. (2010). Accordingly, aggregate cost of trading decreases in up markets and increases in down markets. Further, there is a distinct asymmetric response to market movements; i.e., aggregate cost of trading modestly declines in up markets and strongly increases in down markets. For example, considering cost of roundtrip as a general measure, the pair of concurrent positive and negative market return coefficients \((\beta_1, \beta_2)\) are \((-0.69,-1.09), (-1.40,-2.14), (-2.38,-3.24), (-3.61,-4.40)\) and \((-4.73,-5.54)\) for the positions \(Q_1, Q_2, Q_3, Q_4,\) and \(Q_5\) respectively; which satisfies the inequality \(\beta_1 < \beta_2\) all the time. Interestingly, the effect of the concurrent market movements increases as we walk up the order book, suggesting that aggregate cost of trading is more sensitive to daily market movements for larger positions to trade. Another interesting point is that for the days with positive market movement, average of the sell side \(\beta_1\) across different positions to trade is -2.68 whereas same average for buy side is -2.44. Similarly, for the days with negative market movement, average of the sell side \(\beta_2\) across different positions to trade is -3.09 whereas same average for buy side is -3.50. Therefore, not only is there an asymmetric response of aggregate liquidity to market movements, there is also an asymmetric response of buy and sell sides within themselves depending on the sign of the concurrent market return. Although the model in Eq.(12) does not focus on commonality directly, the asymmetric response of market-wide liquidity to market movements could indicate that commonality is stronger in falling markets.

\(^{35}\) Using BIST30 index instead of the all share index produces almost the same quantitative results.
Similar to the case of individual volatility (Benston and Hagerman, 1974); concurrent market volatility ($V_M$) tends to push the aggregate cost of trading up as expected. However, high levels of recent market-wide volatility ($\sigma_{M(5)}$) is associated with a decrease in cost of trading. Although, this result is surprising, it was also the same case in the work of Chordia et al. (2001). According to authors, the sluggish trading following recent volatility allows dealers to reduce inventory imbalances, which then prompts them to reduce spreads. However, the absence of market makers in our sample suggests that this may not be the exact case in Borsa Istanbul, or such kind of a behavior is performed by day traders.

Finally, we would like to combine the results in this sub-section with our argument on investors’ biased behavior explained in sub-section 3.1. According to this argument, we stated that non-index investors overreact to a positive trend of index stocks; i.e., over-extrapolate positive past performance into the future by believing that persistence of positive index performance to be higher than it actually will, thus even they wish to sell their stocks, they are not willing to do it at a price that is close to the market price; possibly leading to an accumulation of sell orders deep down the order book, hence a higher commonality for larger position sizes to trade. On the other hand, these investors underreact to a negative trend of index stocks (anticipate this trend to end in a short while), thus set off buy orders with prices closer to the market level (i.e. they are willing to pay relatively high prices since they think they will still profit as the price will change its direction) which creates a higher sell-side commonality for small positions to trade. Now, the results reported in Panel B of Table 12 reveal that a recently falling market ($R_{M(5),t}^-$) tends to be associated with decreased aggregate cost of trading. For example, potential buyers become willing to buy a stock at a significantly higher price (closer to the market value) on the average, possibly thinking that they will profit anyway as the stock price will go up. On the other hand, a recently rising market ($R_{M(5),t}^+$) has no effect on aggregate liquidity. Therefore, when a positive trend occurs in the market, potential sellers are not willing the sell their stocks at a significantly lower price; possibly thinking that they will still profit since the stock price will not change its direction soon.

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4 Conclusion

This study contains one of the most comprehensive researches on commonality in liquidity. Different from most of the studies in the literature, we investigate the liquidity commonality in an emerging market, an understated topic in single exchange studies. By using a special weighted spread that measures the cost of trading for a given amount of position, we look for commonality in liquidity at different levels of the order book. Moreover, for the first time, we consider the commonality in buy and sell sides separately.

We find that market-wide commonality in liquidity exists in Borsa Istanbul at different levels of the order book and for both buy and sell sides, even after controlling for several individual determinants of liquidity. However, industry-wide commonality is little to none.

Looking for sources of commonality, we show that commonality in non-index stocks is higher than the commonality in index stocks, a result in contrast to the previous literature. We argue that these results are due to the (i) absence of HFTs and low level of algorithmic trading; (ii) buy-and-hold strategies and/or asynchronous trading activities of institutional investors in index stocks; and (iii) herding habit of individual investors in non-index stocks leading to synchronous order flow in consecutive days.

Interestingly, the strength of commonality is preserved throughout the order book for non-index stocks, whereas commonality decreases as we walk up the order book for index stocks. These results are argued to depend on the (i) smart trading strategies of institutional investors, giving market orders (which do not wait in the order book) or orders that are close to the best price levels, thus creating commonality only at small positions to trade in index stocks; and (ii) herding habit of individual investors in non-index stocks. In particular, we claim that these individual investors follow the market trend created by institutional investors, thus creating an overall shift in the order book status.

We reveal that for non-index stocks, buy side liquidity has a stronger commonality than sell side liquidity for small positions to trade, whereas it is the opposite case for large trading positions. We argue (and empirically support) that this is due to the individual investors’ biased recognition of the market trend. In particular, investors overreact to a positive market trend; i.e., over-extrapolate successful past performance into the future by believing that persistence of positive market performance to be higher than it actually will, thus even they wish to sell their stocks, they are not willing to do it at a price that is close to the market
level; possibly leading to an accumulation of sell orders deep down the order book, hence a higher commonality for larger position sizes to trade. On the other hand, they underreact to a negative trend of the market (anticipate this trend to end in a short while), thus set off buy orders with prices closer to the market level, showing that they are willing to pay relatively high prices since they think they will still profit as the price will change its direction, which creates a higher sell-side commonality for small positions to trade.

Motivated by the results on index inclusion, we analyze the impact of ownership structure on commonality. Accordingly, we show that for mid-to-large cap firms, institutional investors are the main source of commonality in liquidity as expected, whereas individual investors are the main influence on commonality for small cap firms, a result supporting our previous arguments, but also in contrast to the commonality literature. A deeper analysis shows that foreign institutions are the only source of commonality for the largest firms. Very interestingly, domestic individuals are found to be the only source of commonality for small positions to trade in small firms, whereas foreign individuals are the only source of commonality for large positions to trade in small firms; a possible reflection of the noticeable difference between the corresponding GDP per capita values on order sizes. We also reveal that commonality decreases with the increasing number of investors (for both types) at any firm size level, suggesting that as the number of investors in a firm increases, their views become more heterogeneous overall, thus lowering the liquidity commonality.

Looking for sources of commonality at the intersection of the macro-economy and the financial markets, we reveal that among several domestic and global macro-economic variables, liquidity commonality in Borsa Istanbul is significantly affected (increased) only by the interest rate decisions and GDP announcements of U.S.; suggesting that investors in this market are highly sensitive, not to the domestic economy or other developed economies, but only to the U.S. economy. Furthermore, the significant increase in commonality due to these announcements is found only beyond the best price levels.

A byproduct of our analysis is that the size of the best bid-ask spread is one price tick for almost all the time, however, cost of trading significantly differs as we walk up the order book. This shows that a liquidity analysis based on best bid-ask quotes can be misleading. Moreover, we have found that the individual percentage spread tends to decrease with the increasing price of a share, which has no logical explanation except the arithmetic of the percentage spread calculation. Combining these results with the fact that U.S. macro-
announcements increase commonality only beyond the best price levels suggests that tick sizes in sample period are larger than they should be since (i) they are not small enough to remove the spurious price effect which would disappear only when there are occasional spreads larger than the minimum; and (ii) they do not allow the information to be reflected at the best price quotes.

Finally, we find that the aggregate market liquidity responds asymmetrically to market movements. In particular, it increases modestly in up markets, whereas declines significantly in down markets and on high volatile (at market level) days; suggesting that commonality in liquidity tends to increase when the market is falling and/or volatile.

In this study, we report several genuine and interesting results on commonality in liquidity. Moreover, some of our findings contradict with the previous literature on developed markets. Therefore, further research should aim to find out whether our findings are specific to this market, or are they stylized facts of liquidity commonality in emerging markets?

**References**


URL http://dx.doi.org/10.2139/ssrn.2089636


A Dynamic conditional beta

To get the dynamic conditional liquidity beta, we start with the following (to prevent misunderstandings, the reader is asked to consider the mathematical notations in Section A mostly independent from the other parts of the manuscript):

\[ DL_t = \mu + \epsilon_t \]  

(A.1)

where \( DL_t = [DL_{i,t} \ DL_{M,t}]' \) is the vector of weekly liquidity changes (from Thursday to Thursday) in the individual asset \( i \) and the corresponding market \( M \), \( \mu \) is a vector of constants, and \( \epsilon_t = [\epsilon_{i,t} \ \epsilon_{M,t}]' \) is the vector of residuals.

In the next step, we obtain the conditional volatilities \( h_t \) from the univariate GJR-GARCH(1,1) process.

\[ h_{i,t}^2 = \omega_i + (\alpha_i + \gamma_i I_{\epsilon_{i,t-1} < 0})\epsilon_{i,t-1}^2 + \beta_i h_{i,t-1}^2 \]
\[ h_{M,t}^2 = \omega_M + (\alpha_M + \gamma_M I_{\epsilon_{M,t-1} < 0})\epsilon_{M,t-1}^2 + \beta_M h_{M,t-1}^2 \]  

(A.2)

In this setup, \( E_{t-1}[\epsilon_t] = 0 \) and \( E_{t-1}[\epsilon_t \epsilon_t'] = H_t \), where \( E[\cdot] \) is the conditional expectation on \( \epsilon_t, \epsilon_{t-1}, ... \). The conditional covariance matrix \( H_t \) can be written as

\[ H_t = D_t^{1/2} R_t D_t^{1/2} \]  

(A.3)

where \( R_t \) is the conditional correlation matrix and the diagonal matrix of the conditional variances is given by \( D_t = diag(h_{i,t}, h_{M,t}) \). Engle (2002) models the right hand side of Eq.(A.3) rather than \( H_t \) directly and proposes the dynamic correlation structure

\[ R_t = \{Q_t^\ast\}^{-1/2}Q_t\{Q_t^\ast\}^{-1/2}, \]
\[ Q_t = (1 - a - b)S + au_{t-1}u_{t-1}' + bQ_{t-1}, \]  

(A.4)

where \( Q_t \) is the dynamic covariance driving process, \( u_t = [u_{i,t} \ u_{M,t}]' \) with \( u_{i,t} \) and \( u_{M,t} \) are the transformed residuals; i.e., \( u_{i,t} = \epsilon_{i,t}/h_{i,t} \) and \( u_{M,t} = \epsilon_{M,t}/h_{M,t} \); \( S \equiv E[u_t u_t'] \) is the \( n \times n \) unconditional covariance matrix of \( u_t \); \( Q_t^\ast = diag(Q_t) \) and \( a,b \) are non-negative scalars satisfying \( a + b < 1 \). The final estimation is performed by maximizing the joint log-likelihood.
of the model given by

\[
\mathbb{L} = -\frac{1}{2} \sum_{t=1}^{T} (n \ln(2\pi) + \ln |D_t| + \epsilon_t' D_t^{-1} \epsilon_t) \\
- \frac{1}{2} \sum_{t=1}^{T} (\ln |R_t| + \epsilon_t' R_t^{-1} \epsilon_t - \epsilon_t' \epsilon_t)
\]  

(A.5)

and the resulting model is called DCC. We estimate the time-varying conditional covariance matrix, giving us the dynamic covariance between stock liquidity \( L_i \) and the market liquidity \( L_M \), and also the dynamic variance of the market liquidity \( L_M \). Finally, simple division yields to the time-varying liquidity betas based on the mean-reverting DCC model of Engle (2002). For recent applications of dynamic conditional beta on stock markets, see Bali and Engle (2010); Engle et al. (2014).
Table 1: Tick sizes in Borsa Istanbul

<table>
<thead>
<tr>
<th>Price range (TL)</th>
<th>Tick size (TL)</th>
<th>Price range (TL)</th>
<th>Tick size (TL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01-2.50</td>
<td>0.01</td>
<td>0.01-5.00</td>
<td>0.01</td>
</tr>
<tr>
<td>2.52-5.00</td>
<td>0.02</td>
<td>5.02-10.00</td>
<td>0.02</td>
</tr>
<tr>
<td>5.05-10.00</td>
<td>0.05</td>
<td>10.05-25.00</td>
<td>0.05</td>
</tr>
<tr>
<td>10.10-25.00</td>
<td>0.10</td>
<td>25.10-50.00</td>
<td>0.10</td>
</tr>
<tr>
<td>25.25-50.00</td>
<td>0.25</td>
<td>50.25-100.00</td>
<td>0.25</td>
</tr>
<tr>
<td>50.50-100.00</td>
<td>0.50</td>
<td>100.50-250.00</td>
<td>0.50</td>
</tr>
<tr>
<td>101.00-250.00</td>
<td>1.00</td>
<td>251.00-500.00</td>
<td>1.00</td>
</tr>
<tr>
<td>252.50-500.00</td>
<td>2.50</td>
<td>502.50-1000.00</td>
<td>2.50</td>
</tr>
<tr>
<td>500.00 ≤</td>
<td>5.00</td>
<td>1000.00 ≤</td>
<td>5.00</td>
</tr>
</tbody>
</table>
Table 2

PANEL A: Cross-sectional statistics for time-series means

<table>
<thead>
<tr>
<th>Traded value (million TL)</th>
<th>20%</th>
<th>40%</th>
<th>60%</th>
<th>80%</th>
<th>Mean</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.76</td>
<td>4.65</td>
<td>8.36</td>
<td>16.79</td>
<td>16.98</td>
<td>38.91</td>
</tr>
<tr>
<td>Number of shares traded (million)</td>
<td>0.59</td>
<td>1.46</td>
<td>2.86</td>
<td>5.18</td>
<td>4.74</td>
<td>7.84</td>
</tr>
<tr>
<td>Market capitalization (billion TL)</td>
<td>0.15</td>
<td>0.43</td>
<td>0.85</td>
<td>2.36</td>
<td>2.83</td>
<td>5.95</td>
</tr>
<tr>
<td>Price (TL)</td>
<td>1.18</td>
<td>2.15</td>
<td>4.10</td>
<td>12.11</td>
<td>13.47</td>
<td>34.58</td>
</tr>
<tr>
<td>Institutional Ownership</td>
<td>21.4%</td>
<td>40.6%</td>
<td>60.7%</td>
<td>79.9%</td>
<td>50.3%</td>
<td>29.1%</td>
</tr>
</tbody>
</table>

\[
Q_{1,A} = 0.1991 
Q_{1,B} = 0.2001 
Q_{1,RT} = 0.3984 
Q_{2,A} = 0.2124 
Q_{2,B} = 0.2147 
Q_{2,RT} = 0.4258 
Q_{3,A} = 0.2259 
Q_{3,B} = 0.2296 
Q_{3,RT} = 0.4538 
Q_{4,A} = 0.2539 
Q_{4,B} = 0.2637 
Q_{4,RT} = 0.5234 
Q_{5,A} = 0.3062 
Q_{5,B} = 0.3113 
Q_{5,RT} = 0.6158
\]

DQ\_1\_A = 0.0238 
DQ\_1\_B = 0.0274 
DQ\_1\_RT = 0.0248 
DQ\_2\_A = 0.0416 
DQ\_2\_B = 0.0484 
DQ\_2\_RT = 0.0423 
DQ\_3\_A = 0.0616 
DQ\_3\_B = 0.0727 
DQ\_3\_RT = 0.0622 
DQ\_4\_A = 0.0899 
DQ\_4\_B = 0.0985 
DQ\_4\_RT = 0.0827 
DQ\_5\_A = 0.1336 
DQ\_5\_B = 0.1440 
DQ\_5\_RT = 0.1163

PANEL B: Cross-sectional means of time series correlations between daily changes in liquidity measure pairs for an individual stock

<table>
<thead>
<tr>
<th>DQ_1_A</th>
<th>DQ_1_RT</th>
<th>DQ_2_A</th>
<th>DQ_2_B</th>
<th>DQ_3_A</th>
<th>DQ_3_B</th>
<th>DQ_3_RT</th>
<th>DQ_4_A</th>
<th>DQ_4_B</th>
<th>DQ_4_RT</th>
<th>DQ_5_A</th>
<th>DQ_5_B</th>
<th>DQ_5_RT</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.683</td>
<td>0.929</td>
<td>0.493</td>
<td>0.708</td>
<td>0.714</td>
<td>0.403</td>
<td>0.569</td>
<td>0.342</td>
<td>0.472</td>
<td>0.463</td>
<td>0.282</td>
<td>0.318</td>
<td>0.362</td>
</tr>
<tr>
<td>0.684</td>
<td>0.635</td>
<td>0.403</td>
<td>0.803</td>
<td>0.859</td>
<td>0.560</td>
<td>0.569</td>
<td>0.342</td>
<td>0.472</td>
<td>0.463</td>
<td>0.282</td>
<td>0.318</td>
<td>0.362</td>
</tr>
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<td>0.560</td>
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<td>0.342</td>
<td>0.472</td>
<td>0.463</td>
<td>0.282</td>
<td>0.318</td>
<td>0.362</td>
</tr>
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<td>0.463</td>
<td>0.282</td>
<td>0.318</td>
<td>0.362</td>
</tr>
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<td>0.569</td>
<td>0.342</td>
<td>0.472</td>
<td>0.463</td>
<td>0.282</td>
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<td>0.362</td>
</tr>
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<td>0.803</td>
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<td>0.569</td>
<td>0.342</td>
<td>0.472</td>
<td>0.463</td>
<td>0.282</td>
<td>0.318</td>
<td>0.362</td>
</tr>
<tr>
<td>0.684</td>
<td>0.635</td>
<td>0.403</td>
<td>0.803</td>
<td>0.859</td>
<td>0.560</td>
<td>0.569</td>
<td>0.342</td>
<td>0.472</td>
<td>0.463</td>
<td>0.282</td>
<td>0.318</td>
<td>0.362</td>
</tr>
</tbody>
</table>

Q1, Q2, Q3, Q4 and Q5 refer to the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures A, B and RT stand for the cost of buying (ask side), selling (bid side) and roundtripping (buying and selling simultaneously) a given amount of position respectively. D preceding the acronym denotes a proportional change in the variable across successive trading days, and |…| denotes the absolute value.
After estimating 133 time series regressions of individual liquidity measures on equal weighted market liquidity, residuals for stock \( j \) + 1 are compared with residuals for stock \( j \), where \( j \) is ordered alphabetically. From these 132 pairs, the table reports the average correlation coefficient. Also reported from pair-wise regressions above are the sample mean and median of the regression slope coefficient and the frequency of absolute t-statistics (for the slope) exceeding typical critical levels, 5% and 2.5%. Because there are two tails, these double critical percentages (i.e. 10% and 5% respectively) should be found just by chance if, in fact, there is no dependence.

This table presents the market-wide commonality in liquidity using the following multiple regressions:

\[
DL_{i,t} = \beta_0 + \beta_1 DL_{M,t} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t-1} + \beta_4 R_{M,t} + \beta_5 R_{M,t-1} + \beta_6 D_{V,t} + \epsilon_{i,t}
\]

\( Q1, Q2, Q3, Q4 \) and \( Q5 \) refer to the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures \( A, B \) and \( RT \) stand for the cost of buying (ask side), selling (bid side) and roundtripping (buying and selling simultaneously) a given amount of position respectively.

Panel A reports the cross-sectional mean of time series slope coefficients with the corresponding t-statistics (Only the coefficients of the market liquidity are reported).

In Panel B, \( (+) \) reports the proportion of positive coefficients, while \( \text{sig.}(+) \) and \( \text{sig.}(-) \) present the percentage which the adjusted t-statistics is significantly positive and negative at the 5% critical level respectively.

Panel C checks for cross-equation dependence:

\[
\varepsilon_{j+1,t} = \gamma_{j,0} + \gamma_{j,1} \varepsilon_{j,t} + \gamma_{j,0} \varepsilon_{j,t-1}
\]

\( j = 1, \ldots, 132 \), after estimating 133 time series regressions of individual liquidity measures on equal weighted market liquidity, residuals for stock \( j + 1 \) are compared with residuals for stock \( j \), where \( j \) is ordered alphabetically. From these 132 pairs, the table reports the average correlation coefficient. Also reported from pair-wise regressions above are the sample mean and median t-statistic of the regression slope coefficient and the frequency of absolute t-statistics (for the slope) exceeding typical critical levels, 5% and 2.5%.
For each stock, daily percentage changes in liquidity variables for the individual stock $i$ span the time period $t$. For $i$, the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures $Q_i$ refer to the amounts of $10^3$, $10^4$, $10^5$, $10^6$ and $10^7$ respectively. 

PANEL A: Cross-sectional averages of time series slope coefficients are reported with $t$-statistics below.

<table>
<thead>
<tr>
<th>$Q_{1,t}$</th>
<th>$Q_{2,t}$</th>
<th>$Q_{3,t}$</th>
<th>$Q_{4,t}$</th>
<th>$Q_{5,t}$</th>
<th>$Q_{6,t}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$</td>
<td>$\beta_2$</td>
<td>$\beta_3$</td>
<td>$\beta_4$</td>
<td>$\beta_5$</td>
<td>$\beta_6$</td>
</tr>
<tr>
<td>$t$-statistics</td>
<td>$t$-statistics</td>
<td>$t$-statistics</td>
<td>$t$-statistics</td>
<td>$t$-statistics</td>
<td>$t$-statistics</td>
</tr>
<tr>
<td>(27.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>(20.27)</td>
<td>(1.73)</td>
<td>(2.63)</td>
<td>(15.09)</td>
<td>(0.77)</td>
<td>(-1.06)</td>
</tr>
<tr>
<td>(24.71)</td>
<td>(10.40)</td>
<td>(2.43)</td>
<td>(16.10)</td>
<td>(1.34)</td>
<td>(-1.21)</td>
</tr>
<tr>
<td>(26.84)</td>
<td>(0.57)</td>
<td>(-2.36)</td>
<td>(15.49)</td>
<td>(2.36)</td>
<td>(-0.96)</td>
</tr>
<tr>
<td>(21.25)</td>
<td>(0.57)</td>
<td>(-4.83)</td>
<td>(13.58)</td>
<td>(-36.36)</td>
<td>(1.65)</td>
</tr>
<tr>
<td>(25.90)</td>
<td>(0.19)</td>
<td>(-3.12)</td>
<td>(16.97)</td>
<td>(0.65)</td>
<td>(0.79)</td>
</tr>
<tr>
<td>(34.84)</td>
<td>(0.25)</td>
<td>(-3.61)</td>
<td>(20.61)</td>
<td>(2.48)</td>
<td>(-0.33)</td>
</tr>
<tr>
<td>(30.61)</td>
<td>(0.13)</td>
<td>(-2.75)</td>
<td>(18.05)</td>
<td>(3.47)</td>
<td>(-0.51)</td>
</tr>
<tr>
<td>(38.82)</td>
<td>(0.05)</td>
<td>(-0.09)</td>
<td>(15.72)</td>
<td>(0.53)</td>
<td>(-0.03)</td>
</tr>
<tr>
<td>(39.51)</td>
<td>(0.05)</td>
<td>(-0.09)</td>
<td>(19.15)</td>
<td>(2.88)</td>
<td>(-0.46)</td>
</tr>
<tr>
<td>(45.10)</td>
<td>(1.12)</td>
<td>(-3.03)</td>
<td>(15.88)</td>
<td>(1.41)</td>
<td>(-1.17)</td>
</tr>
</tbody>
</table>

PANEL B: Percentage of positive and negative slope coefficients.

<table>
<thead>
<tr>
<th>$\beta_1$</th>
<th>$\beta_2$</th>
<th>$\beta_3$</th>
<th>$\beta_4$</th>
<th>$\beta_5$</th>
<th>$\beta_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$+$</td>
<td>$\sigma_+$</td>
<td>$\sigma_-$</td>
<td>$\sigma_+$</td>
<td>$\sigma_-$</td>
<td>$\sigma_+$</td>
</tr>
<tr>
<td>$-$</td>
<td>$\sigma_+$</td>
<td>$\sigma_-$</td>
<td>$\sigma_+$</td>
<td>$\sigma_-$</td>
<td>$\sigma_+$</td>
</tr>
</tbody>
</table>

Table 4

This table presents the market-wide and industry-wide comovement in liquidity by using the following multiple regressions:

$$DL_{i,t} = \beta_{0,t} + \beta_{1,t}DL_{M,t} + \beta_{2,t}DL_{M,t-1} + \beta_{3,t}DL_{M,t-2} + \beta_{4,t}DL_{t-1,t} + \beta_{5,t}DL_{t-1, t-1} + \beta_{6,t}R_{M,t} + \beta_{7,t}R_{M,t-1} + \beta_{8,t}R_{M,t-1} + \beta_{9,t}DV_{t, i} + \epsilon_{i,t}$$

Q1, Q3, Q4 and Q5 refer to the amounts of 1000, 10000, 50000 and 100000 TL respectively, whereas the liquidity measures $A$, $B$ and $RT$ stand for the cost of buying (ask side), selling (bid side) and roundingtrip (buying and selling simultaneously) given a amount of position respectively. $D$ preceding the acronym denotes a proportional change in the variable across trading days.

For each stock, daily percentage changes in liquidity variables for the individual stock $i$, $DL_{i,t}$, are regressed in time series on the percentage change of an equally weighted cross-sectional average of the liquidity variable for all stocks excluding stock $i$, $DL_{-i,t}$, and the sample in the same industry excluding stock $i$, $DL_{-I,t}$. Other explanatory variables are the percentage change of the equally weighted cross-sectional average of the return variable for all stocks excluding stock $i$, $R_{M,t}$, and in the sample; and daily percentage change in the individual volatility $V_{i,t}$.

Panel A reports the cross-sectional mean of time series slope coefficients with the corresponding t-statistics (Only the coefficients of the market liquidity are reported).

In Panel B, $\pm$ reports the proportion of positive coefficients, while $\sigma_+$ and $\sigma_-$ present the percentage which the adjusted t-statistics is significantly positive and negative at the 5% critical level respectively.

Panel C checks for cross-equation dependence in estimation error

Table 4 presents the market-wide and industry-wide comovement in liquidity by using the following multiple regressions:

$$DL_{i,t} = \beta_{0,t} + \beta_{1,t}DL_{M,t} + \beta_{2,t}DL_{M,t-1} + \beta_{3,t}DL_{M,t-2} + \beta_{4,t}DL_{t-1,t} + \beta_{5,t}DL_{t-1, t-1} + \beta_{6,t}R_{M,t} + \beta_{7,t}R_{M,t-1} + \beta_{8,t}R_{M,t-1} + \beta_{9,t}DV_{t, i} + \epsilon_{i,t}$$

Q1, Q3, Q4 and Q5 refer to the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures $A$, $B$ and $RT$ stand for the cost of buying (ask side), selling (bid side) and roundingtrip (buying and selling simultaneously) given a amount of position respectively. $D$ preceding the acronym denotes a proportional change in the variable across trading days.

For each stock, daily percentage changes in liquidity variables for the individual stock $i$, $DL_{i,t}$, are regressed in time series on the percentage change of an equally weighted cross-sectional average of the liquidity variable for all stocks excluding stock $i$, $DL_{-i,t}$, and the sample in the same industry excluding stock $i$, $DL_{-I,t}$. Other explanatory variables are the percentage change of the equally weighted cross-sectional average of the return variable for all stocks excluding stock $i$, $R_{M,t}$, and in the sample; and daily percentage change in the individual volatility $V_{i,t}$.

Panel A reports the cross-sectional mean of time series slope coefficients with the corresponding t-statistics (Only the coefficients of the market liquidity are reported).

In Panel B, $\pm$ reports the proportion of positive coefficients, while $\sigma_+$ and $\sigma_-$ present the percentage which the adjusted t-statistics is significantly positive and negative at the 5% critical level respectively.

Panel C checks for cross-equation dependence:

$$\epsilon_{i,t} = \gamma_{i,0} + \gamma_{i,1,t} + \gamma_{i,t} + \epsilon_{i,t}$$

(j = 1, ..., 132).

After estimating 133 time series regressions of individual market liquidity measures on equal weighted market liquidity, residuals for stock $j$ + 1 are compared with residuals for stock $j$, where $j$ is ordered alphabetically. From these 132 pairs, the table reports the average correlation coefficient. Also reported from pair-wise regressions above are the sample mean and median t-statistic of the regression slope coefficient and the frequency of absolute t-statistics (for the slope) exceeding typical critical levels, 5% and 2.5%. Because there are two tails, double these critical percentages (i.e. 10% and 5% respectively) should be found just by chance if, in fact, there is no dependence.

This table presents the market-wide and industry-wide comovement in liquidity by using the following multiple regressions:

$$DL_{i,t} = \beta_{0,t} + \beta_{1,t}DL_{M,t} + \beta_{2,t}DL_{M,t-1} + \beta_{3,t}DL_{M,t-2} + \beta_{4,t}DL_{t-1,t} + \beta_{5,t}DL_{t-1, t-1} + \beta_{6,t}R_{M,t} + \beta_{7,t}R_{M,t-1} + \beta_{8,t}R_{M,t-1} + \beta_{9,t}DV_{t, i} + \epsilon_{i,t}$$

Q1, Q3, Q4 and Q5 refer to the amounts of 1000, 10000, 50000 and 100000 TL respectively, whereas the liquidity measures $A$, $B$ and $RT$ stand for the cost of buying (ask side), selling (bid side) and roundingtrip (buying and selling simultaneously) given a amount of position respectively. $D$ preceding the acronym denotes a proportional change in the variable across trading days.

For each stock, daily percentage changes in liquidity variables for the individual stock $i$, $DL_{i,t}$, are regressed in time series on the percentage change of an equally weighted cross-sectional average of the liquidity variable for all stocks excluding stock $i$, $DL_{-i,t}$, and the sample in the same industry excluding stock $i$, $DL_{-I,t}$. Other explanatory variables are the percentage change of the equally weighted cross-sectional average of the return variable for all stocks excluding stock $i$, $R_{M,t}$, and in the sample; and daily percentage change in the individual volatility $V_{i,t}$.

Panel A reports the cross-sectional mean of time series slope coefficients with the corresponding t-statistics (Only the coefficients of the market liquidity are reported).

In Panel B, $\pm$ reports the proportion of positive coefficients, while $\sigma_+$ and $\sigma_-$ present the percentage which the adjusted t-statistics is significantly positive and negative at the 5% critical level respectively.

Panel C checks for cross-equation dependence:

$$\epsilon_{i,t} = \gamma_{i,0} + \gamma_{i,1,t} + \gamma_{i,t} + \epsilon_{i,t}$$

(j = 1, ..., 132).

After estimating 133 time series regressions of individual market liquidity measures on equal weighted market liquidity, residuals for stock $j$ + 1 are compared with residuals for stock $j$, where $j$ is ordered alphabetically. From these 132 pairs, the table reports the average correlation coefficient. Also reported from pair-wise regressions above are the sample mean and median t-statistic of the regression slope coefficient and the frequency of absolute t-statistics (for the slope) exceeding typical critical levels, 5% and 2.5%. Because there are two tails, double these critical percentages (i.e. 10% and 5% respectively) should be found just by chance if, in fact, there is no dependence.
<table>
<thead>
<tr>
<th>Q1, Q2</th>
<th>α_1</th>
<th>α_2</th>
<th>α_3</th>
<th>Q2, Q3</th>
<th>α_4</th>
<th>α_5</th>
<th>α_6</th>
<th>α_7</th>
<th>α_8</th>
<th>Q4, Q5</th>
<th>α_9</th>
<th>α_10</th>
<th>α_11</th>
<th>α_12</th>
<th>α_13</th>
<th>α_14</th>
<th>α_15</th>
<th>α_16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1, Q2</td>
<td>0.758</td>
<td>-0.163</td>
<td>-0.025</td>
<td>0.571</td>
<td>0.058</td>
<td>0.026</td>
<td>0.308</td>
<td>0.121</td>
<td>0.051</td>
<td>0.014</td>
<td>0.011</td>
<td>0.076</td>
<td>-0.391</td>
<td>-0.039</td>
<td>0.738</td>
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<tr>
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<td>0.795</td>
<td>-0.188</td>
<td>-0.061</td>
<td>0.561</td>
<td>0.062</td>
<td>0.027</td>
<td>0.041</td>
<td>0.129</td>
<td>0.05</td>
<td>0.014</td>
<td>0.011</td>
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<td>-0.064</td>
<td>0.562</td>
<td>0.033</td>
<td>0.006</td>
<td>0.018</td>
<td>0.046</td>
<td>0.096</td>
<td>0.026</td>
<td>0.014</td>
<td>0.136</td>
<td>-0.385</td>
<td>-0.077</td>
<td>0.848</td>
<td>0.668</td>
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</tr>
<tr>
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<td>0.711</td>
<td>-0.158</td>
<td>-0.012</td>
<td>0.541</td>
<td>0.024</td>
<td>0.011</td>
<td>0.056</td>
<td>0.063</td>
<td>0.013</td>
<td>0.028</td>
<td>0.018</td>
<td>0.145</td>
<td>-0.374</td>
<td>-0.085</td>
<td>0.865</td>
<td>0.650</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q1, Q2</td>
<td>0.641</td>
<td>-0.066</td>
<td>-0.031</td>
<td>0.541</td>
<td>0.024</td>
<td>0.011</td>
<td>0.056</td>
<td>0.063</td>
<td>0.013</td>
<td>0.028</td>
<td>0.018</td>
<td>0.145</td>
<td>-0.374</td>
<td>-0.085</td>
<td>0.865</td>
<td>0.650</td>
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<tr>
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<td>0.641</td>
<td>-0.066</td>
<td>-0.031</td>
<td>0.541</td>
<td>0.024</td>
<td>0.011</td>
<td>0.056</td>
<td>0.063</td>
<td>0.013</td>
<td>0.028</td>
<td>0.018</td>
<td>0.145</td>
<td>-0.374</td>
<td>-0.085</td>
<td>0.865</td>
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<td></td>
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</tr>
<tr>
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<td>0.641</td>
<td>-0.066</td>
<td>-0.031</td>
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<td>0.024</td>
<td>0.011</td>
<td>0.056</td>
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<td>0.028</td>
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<td>0.145</td>
<td>-0.374</td>
<td>-0.085</td>
<td>0.865</td>
<td>0.650</td>
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</tr>
<tr>
<td>Q1, Q2</td>
<td>0.641</td>
<td>-0.066</td>
<td>-0.031</td>
<td>0.541</td>
<td>0.024</td>
<td>0.011</td>
<td>0.056</td>
<td>0.063</td>
<td>0.013</td>
<td>0.028</td>
<td>0.018</td>
<td>0.145</td>
<td>-0.374</td>
<td>-0.085</td>
<td>0.865</td>
<td>0.650</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q1, Q2</td>
<td>0.641</td>
<td>-0.066</td>
<td>-0.031</td>
<td>0.541</td>
<td>0.024</td>
<td>0.011</td>
<td>0.056</td>
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<td>0.018</td>
<td>0.145</td>
<td>-0.374</td>
<td>-0.085</td>
<td>0.865</td>
<td>0.650</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Q1, Q2</td>
<td>0.641</td>
<td>-0.066</td>
<td>-0.031</td>
<td>0.541</td>
<td>0.024</td>
<td>0.011</td>
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<td>0.028</td>
<td>0.018</td>
<td>0.145</td>
<td>-0.374</td>
<td>-0.085</td>
<td>0.865</td>
<td>0.650</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 5

**Panel A:** Cross-sectional averages of time series slope coefficients are reported with t-statistics below.

**Panel B:** Percentage of positive and negative slope coefficients.

**Panel C:** Check for cross-equation dependence.

This table presents the market-wide and industry-wide commonality in liquidity for the individual determinants of liquidity using the following multiple regressions:

\[
\log(\frac{1}{t} \left( \frac{V_{j,t}}{P_{j,t} - D_{j,t}} \right) \right) = \alpha_0 + \alpha_1 \log(V_{j,t-1}) + \alpha_2 \log(L_{j,t}) + \alpha_3 \log(L_{j,t-1}) + \alpha_4 \log(V_{j,t-1}) + \alpha_5 \log(V_{j,t-1}) + \alpha_6 \log(V_{j,t-1}) + \alpha_7 \log(V_{j,t-1}) + \alpha_8 \log(V_{j,t-1}) + \alpha_9 \log(V_{j,t-1}) + \alpha_{10} \log(V_{j,t-1}) + \alpha_{11} \log(V_{j,t-1}) + \alpha_{12} \log(V_{j,t-1}) + \alpha_{13} \log(V_{j,t-1}) + \alpha_{14} \log(V_{j,t-1}) + \alpha_{15} \log(V_{j,t-1}) + \alpha_{16} \log(V_{j,t-1})
\]

Q1, Q2, Q3, and Q4 refer to the beta of 1000, 10000, 25600, 50000 and 10000000, respectively, whereas the liquidity measures A, B, and C refer to the cost of buying (ask side), selling (bid side) and rounding (buying and selling liquidity), respectively. **Q5** and **Q6** report the betas for the cost of buying (ask side), selling (bid side), and rounding (buying and selling liquidity), respectively, in industry segments for each stock, including the returns for all stocks excluding stock i. **RM,t** and **i,t** are the return for all stocks excluding stock i. **RM,t** and **i,t** are the median t-statistics for evaluating the average correlation.
**Table 6**

**PANEL A: Cross-sectional averages of time series slope coefficients are reported with t-statistics below**

<table>
<thead>
<tr>
<th>β₁ (index)</th>
<th>β₂ (index)</th>
<th>β₃</th>
<th>β₁ + β₂ + β₃</th>
<th>(mean) (index)</th>
<th>(median) (index)</th>
<th>(mean) (non-index)</th>
<th>(median) (non-index)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1_A</td>
<td>0.836</td>
<td>0.022</td>
<td>0.005</td>
<td>0.006</td>
<td>0.115</td>
<td>0.080</td>
<td>0.097</td>
</tr>
<tr>
<td>(0.01)</td>
<td>(-0.66)</td>
<td>(0.16)</td>
<td>(13.03)</td>
<td>(29.2)</td>
<td>(0.72)</td>
<td>(-2.46)</td>
<td>(16.79)</td>
</tr>
<tr>
<td>Q1_B</td>
<td>0.781</td>
<td>0.001</td>
<td>0.022</td>
<td>0.005</td>
<td>0.116</td>
<td>0.084</td>
<td>0.097</td>
</tr>
<tr>
<td>(0.01)</td>
<td>(-0.65)</td>
<td>(0.17)</td>
<td>(10.14)</td>
<td>(23.34)</td>
<td>(1.28)</td>
<td>(-3.58)</td>
<td>(15.18)</td>
</tr>
<tr>
<td>Q1_RT</td>
<td>0.828</td>
<td>0.003</td>
<td>0.015</td>
<td>0.093</td>
<td>0.124</td>
<td>0.093</td>
<td>0.084</td>
</tr>
<tr>
<td>(0.01)</td>
<td>(-0.40)</td>
<td>(0.10)</td>
<td>(15.17)</td>
<td>(28.15)</td>
<td>(0.90)</td>
<td>(-4.10)</td>
<td>(17.74)</td>
</tr>
<tr>
<td>Q2_A</td>
<td>0.655</td>
<td>0.008</td>
<td>0.004</td>
<td>0.087</td>
<td>0.068</td>
<td>0.094</td>
<td>0.095</td>
</tr>
<tr>
<td>(12.83)</td>
<td>(-1.36)</td>
<td>(0.10)</td>
<td>(8.75)</td>
<td>(30.19)</td>
<td>(0.04)</td>
<td>(-3.22)</td>
<td>(18.64)</td>
</tr>
<tr>
<td>Q2_B</td>
<td>0.559</td>
<td>0.022</td>
<td>0.002</td>
<td>0.084</td>
<td>0.066</td>
<td>0.096</td>
<td>0.090</td>
</tr>
<tr>
<td>(10.34)</td>
<td>(0.43)</td>
<td>(-0.90)</td>
<td>(8.24)</td>
<td>(24.53)</td>
<td>(2.11)</td>
<td>(-2.76)</td>
<td>(18.10)</td>
</tr>
<tr>
<td>Q2_RT</td>
<td>0.579</td>
<td>0.021</td>
<td>0.016</td>
<td>0.099</td>
<td>0.117</td>
<td>0.099</td>
<td>0.099</td>
</tr>
<tr>
<td>(13.34)</td>
<td>(-0.83)</td>
<td>(-0.63)</td>
<td>(6.97)</td>
<td>(35.71)</td>
<td>(1.27)</td>
<td>(-3.29)</td>
<td>(23.91)</td>
</tr>
<tr>
<td>Q3_A</td>
<td>0.456</td>
<td>0.004</td>
<td>0.006</td>
<td>0.049</td>
<td>0.087</td>
<td>0.072</td>
<td>0.093</td>
</tr>
<tr>
<td>(16.35)</td>
<td>(-0.99)</td>
<td>(-1.46)</td>
<td>(10.73)</td>
<td>(51.88)</td>
<td>(0.34)</td>
<td>(-3.03)</td>
<td>(33.60)</td>
</tr>
<tr>
<td>Q3_B</td>
<td>0.407</td>
<td>0.030</td>
<td>0.046</td>
<td>0.096</td>
<td>0.063</td>
<td>0.022</td>
<td>0.076</td>
</tr>
<tr>
<td>(11.81)</td>
<td>(0.38)</td>
<td>(-1.97)</td>
<td>(6.45)</td>
<td>(38.72)</td>
<td>(1.03)</td>
<td>(-3.38)</td>
<td>(24.62)</td>
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<tr>
<td>Q4_A</td>
<td>0.511</td>
<td>0.020</td>
<td>0.030</td>
<td>0.122</td>
<td>0.107</td>
<td>1.002</td>
<td>0.005</td>
</tr>
<tr>
<td>(13.54)</td>
<td>(-1.82)</td>
<td>(-0.27)</td>
<td>(9.35)</td>
<td>(43.01)</td>
<td>(0.11)</td>
<td>(-2.29)</td>
<td>(26.82)</td>
</tr>
<tr>
<td>Q5_A</td>
<td>0.459</td>
<td>0.004</td>
<td>0.035</td>
<td>0.074</td>
<td>0.060</td>
<td>0.097</td>
<td>0.097</td>
</tr>
<tr>
<td>(14.47)</td>
<td>(0.16)</td>
<td>(-1.83)</td>
<td>(9.29)</td>
<td>(44.35)</td>
<td>(0.14)</td>
<td>(-3.19)</td>
<td>(26.99)</td>
</tr>
<tr>
<td>Q5_B</td>
<td>0.484</td>
<td>0.031</td>
<td>0.037</td>
<td>0.129</td>
<td>0.127</td>
<td>0.961</td>
<td>0.009</td>
</tr>
<tr>
<td>(20.08)</td>
<td>(-1.68)</td>
<td>(-1.89)</td>
<td>(11.48)</td>
<td>(64.46)</td>
<td>(-0.81)</td>
<td>(-2.49)</td>
<td>(40.52)</td>
</tr>
<tr>
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<td>0.030</td>
<td>0.107</td>
<td>0.093</td>
<td>0.905</td>
<td>0.005</td>
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<td>(17.72)</td>
<td>(-0.48)</td>
<td>(-1.91)</td>
<td>(9.08)</td>
<td>(42.49)</td>
<td>(0.85)</td>
<td>(-1.91)</td>
<td>(26.56)</td>
</tr>
<tr>
<td>Q5_RT</td>
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<td>0.043</td>
<td>0.173</td>
<td>0.119</td>
<td>0.200</td>
<td>0.003</td>
</tr>
<tr>
<td>(22.53)</td>
<td>(-2.60)</td>
<td>(-2.34)</td>
<td>(11.48)</td>
<td>(67.45)</td>
<td>(-0.54)</td>
<td>(-2.60)</td>
<td>(44.14)</td>
</tr>
</tbody>
</table>

This table presents the market-wide comonality in liquidity for index and non-index stocks separately using the following multiple regressions:

\[ DL_{i,t} = \beta_0 + \beta_1 DL_{i,t-1} + \beta_2 DL_{M,t-1} + \beta_3 DL_{M,t-1} + \beta_4 RM_{i,t} + \beta_5 RM_{i,t-1} + \beta_6 RM_{i,t-1} + \beta_7 DV_{i,t} + \epsilon_{i,t} \]

Q1, Q2, Q3, Q4 and Q5 refer to the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures A, B and RT stand for the cost of buying (ask side), selling (bid side) and roundtripping (buying and selling simultaneously) a given amount of position respectively. D preceding the acronym denotes a proportional change in the variable across successive trading days.

For each stock, daily percentage changes in liquidity variables for the individual stock \( i \), \( DL_{i,t} \), are regressed in time series on the percentage change of an equally weighted cross-sectional average of the liquidity variable for all stocks excluding stock \( i \), \( DL_{M,t} \), in the sample. Other explanatory variables are the percentage change of the equally weighted cross-sectional average of the return variable for all stocks excluding stock \( i \), \( RM_{i,t} \), in the sample; and daily percentage change in the individual volatility \( V_{i,t} \). **Panel A** reports the cross-sectional mean of time series slope coefficients with the corresponding t-statistics for index and non-index stocks separately (Only the coefficients of the market liquidity are reported).

In **Panel B**, \( (+) \) reports the proportion of positive coefficients for index and non-index stocks, while \( \text{sig.}(+) \) and \( \text{sig.}(-) \) present the percentage which the adjusted t-statistics is significantly positive and negative at the 5% critical level respectively.

![Table 6](image-url)
Table 7: Time average of the dynamic betas

<table>
<thead>
<tr>
<th></th>
<th>$Q_{1A}$</th>
<th>$Q_{1B}$</th>
<th>$Q_{1RT}$</th>
<th>$Q_{2A}$</th>
<th>$Q_{2B}$</th>
<th>$Q_{2RT}$</th>
<th>$Q_{3A}$</th>
<th>$Q_{3B}$</th>
<th>$Q_{3RT}$</th>
<th>$Q_{4A}$</th>
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<th>$Q_{4RT}$</th>
<th>$Q_{5A}$</th>
<th>$Q_{5B}$</th>
<th>$Q_{5RT}$</th>
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</thead>
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<td>$M_5$</td>
<td>0.786</td>
<td>0.745</td>
<td>0.791</td>
<td>0.764</td>
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<td>0.726</td>
<td>0.762</td>
<td>0.684</td>
<td>0.754</td>
<td>0.679</td>
<td>0.594</td>
<td>0.700</td>
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</tr>
<tr>
<td>$M_4$</td>
<td>0.733</td>
<td>0.732</td>
<td>0.747</td>
<td>0.876</td>
<td>0.853</td>
<td>0.829</td>
<td>0.902</td>
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<td>0.903</td>
<td>0.923</td>
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<td></td>
</tr>
<tr>
<td>$M_3$</td>
<td>0.887</td>
<td>0.922</td>
<td>0.919</td>
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<td>0.968</td>
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<td>0.875</td>
<td>0.912</td>
<td></td>
</tr>
<tr>
<td>$M_2$</td>
<td>1.035</td>
<td>1.021</td>
<td>1.046</td>
<td>1.206</td>
<td>1.106</td>
<td>1.166</td>
<td>1.099</td>
<td>1.044</td>
<td>1.092</td>
<td>1.024</td>
<td>1.093</td>
<td>1.012</td>
<td>0.959</td>
<td>0.963</td>
<td>0.990</td>
</tr>
<tr>
<td>$M_1$</td>
<td>1.104</td>
<td>0.976</td>
<td>0.979</td>
<td>1.086</td>
<td>1.082</td>
<td>1.108</td>
<td>1.036</td>
<td>0.980</td>
<td>1.025</td>
<td>0.982</td>
<td>0.944</td>
<td>0.983</td>
<td>0.980</td>
<td>0.980</td>
<td>0.998</td>
</tr>
</tbody>
</table>

We implement the methodology of Dynamic Conditional Beta (Bali et al., 2014) to estimate a time-varying liquidity beta for each firm using the following multiple regressions:

$$DL_{i,t} = \alpha + \beta_i DL_{M,t} + \varepsilon_{i,t}$$

where liquidity variables for the individual stock $i$ on $t^{th}$ Thursday is represented by $L_{i,t}$; and the equally weighted cross-sectional average of the liquidity variable for all stocks excluding stock $i$ on the same Thursday is denoted by $L_{M,t}$. Here, $D$ preceding the acronym denotes a proportional change in the variable across successive Thursdays. $M_5$ (n=27), $M_4$ (n=26), $M_3$ (n=27), $M_2$ (n=26) and $M_1$ (n=27) refer to the quantiles constructed by daily average (of four years) market cap, with $M_5$ and $M_1$ denoting the largest and smallest firms respectively. We calculate equally-weighted averages of liquidity betas for all the firms in each size quintile which produces a time-varying beta per quantile. This table reports the time averages of these dynamic liquidity betas.

In the manuscript, $Q_1$, $Q_2$, $Q_3$, $Q_4$ and $Q_5$ refer to the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures $A$, $B$ and $RT$ stand for the cost of buying (ask side), selling (bid side) and roundtripping (buying and selling simultaneously) a given amount of position respectively. In this table, they refer to the time average betas of these liquidity measures.
Table 8: Time trend tests

<table>
<thead>
<tr>
<th>PANEL A: Deterministic time trend test</th>
</tr>
</thead>
<tbody>
<tr>
<td>( (M1) \delta \times 10^6 )</td>
</tr>
<tr>
<td>(1.81)</td>
</tr>
<tr>
<td>115.73</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>PANEL B: Stochastic time trend test</th>
</tr>
</thead>
<tbody>
<tr>
<td>( (M1) \gamma \times 10^6 )</td>
</tr>
<tr>
<td>(1.34)</td>
</tr>
<tr>
<td>102.86</td>
</tr>
</tbody>
</table>

This table presents the time trend tests for average liquidity betas of firms in each of the five size quintiles (\( M5 \): largest, \( M1 \): smallest firm size quintile). First, we regress the beta series on a constant and a time trend; i.e., \( \beta_t = a + \delta t + \delta \), to see if there is any deterministic trend. Panel A reports the coefficient estimate of the time-trend and its \( t \)-statistic. Panel B presents the estimate of the first lag, time trend and their \( t \)-statistics. The \( t \)-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) standard errors.

In the manuscript, \( Q1, Q2, Q3, Q4 \) and \( Q5 \) refer to the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures A, B and RT stand for the cost of buying (ask side), selling (bid side) and roundtripping (buying and selling simultaneously) a given amount of position respectively. In this table, they refer to the betas of these liquidity measures.
### PANEL A: Systematic liquidity and institutional ownership in the cross-section

<table>
<thead>
<tr>
<th>(M5)</th>
<th>λ₁</th>
<th>Q1A</th>
<th>Q1B</th>
<th>Q1RT</th>
<th>Q2A</th>
<th>Q2B</th>
<th>Q2RT</th>
<th>Q3A</th>
<th>Q3B</th>
<th>Q3RT</th>
<th>Q4A</th>
<th>Q4B</th>
<th>Q4RT</th>
<th>Q5A</th>
<th>Q5B</th>
<th>Q5RT</th>
</tr>
</thead>
<tbody>
<tr>
<td>(M5)</td>
<td>λ₂ × 10³</td>
<td>-1.090</td>
<td>-1.050</td>
<td>-1.100</td>
<td>-1.170</td>
<td>-1.340</td>
<td>-1.020</td>
<td>-1.000</td>
<td>-1.190</td>
<td>-1.000</td>
<td>-0.700</td>
<td>-0.970</td>
<td>-1.210</td>
<td>-1.170</td>
<td>-1.240</td>
<td>-1.000</td>
</tr>
<tr>
<td>(M5)</td>
<td>θ</td>
<td>0.163</td>
<td>0.135</td>
<td>0.156</td>
<td>0.114</td>
<td>0.123</td>
<td>0.153</td>
<td>0.061</td>
<td>0.132</td>
<td>0.074</td>
<td>0.063</td>
<td>0.101</td>
<td>0.070</td>
<td>0.026</td>
<td>0.110</td>
<td>0.078</td>
</tr>
<tr>
<td>(M4)</td>
<td>λ₁</td>
<td>0.565</td>
<td>0.333</td>
<td>0.413</td>
<td>0.129</td>
<td>0.998</td>
<td>1.028</td>
<td>1.359</td>
<td>1.205</td>
<td>1.323</td>
<td>1.241</td>
<td>1.291</td>
<td>1.339</td>
<td>1.204</td>
<td>1.137</td>
<td>1.153</td>
</tr>
<tr>
<td>(M4)</td>
<td>λ₂ × 10³</td>
<td>0.070</td>
<td>-0.160</td>
<td>-0.150</td>
<td>0.010</td>
<td>0.210</td>
<td>0.030</td>
<td>-0.290</td>
<td>0.200</td>
<td>0.080</td>
<td>-0.450</td>
<td>-0.090</td>
<td>-0.260</td>
<td>-0.060</td>
<td>-0.420</td>
<td>-0.430</td>
</tr>
<tr>
<td>(M4)</td>
<td>θ</td>
<td>0.527</td>
<td>0.636</td>
<td>0.525</td>
<td>0.519</td>
<td>0.934</td>
<td>0.721</td>
<td>0.469</td>
<td>0.830</td>
<td>0.607</td>
<td>0.508</td>
<td>0.676</td>
<td>0.598</td>
<td>0.447</td>
<td>0.595</td>
<td>0.584</td>
</tr>
<tr>
<td>(M3)</td>
<td>λ₁</td>
<td>0.858</td>
<td>1.000</td>
<td>0.901</td>
<td>1.147</td>
<td>0.986</td>
<td>1.078</td>
<td>1.240</td>
<td>0.796</td>
<td>1.127</td>
<td>1.127</td>
<td>0.801</td>
<td>1.013</td>
<td>0.953</td>
<td>0.715</td>
<td>0.844</td>
</tr>
<tr>
<td>(M3)</td>
<td>θ</td>
<td>0.374</td>
<td>0.132</td>
<td>0.327</td>
<td>0.439</td>
<td>0.416</td>
<td>0.420</td>
<td>0.264</td>
<td>0.207</td>
<td>0.249</td>
<td>0.124</td>
<td>0.239</td>
<td>0.212</td>
<td>0.025</td>
<td>0.195</td>
<td>0.131</td>
</tr>
<tr>
<td>(M2)</td>
<td>λ₁</td>
<td>1.092</td>
<td>1.040</td>
<td>1.115</td>
<td>1.275</td>
<td>1.053</td>
<td>1.173</td>
<td>0.637</td>
<td>1.022</td>
<td>0.855</td>
<td>0.221</td>
<td>0.526</td>
<td>0.299</td>
<td>0.332</td>
<td>0.170</td>
<td>0.297</td>
</tr>
<tr>
<td>(M2)</td>
<td>θ</td>
<td>0.038</td>
<td>0.220</td>
<td>0.153</td>
<td>0.397</td>
<td>0.495</td>
<td>0.435</td>
<td>0.369</td>
<td>0.461</td>
<td>0.453</td>
<td>0.398</td>
<td>0.520</td>
<td>0.520</td>
<td>0.383</td>
<td>0.515</td>
<td>0.450</td>
</tr>
<tr>
<td>(M1)</td>
<td>λ₁</td>
<td>-0.530</td>
<td>-0.393</td>
<td>-0.172</td>
<td>-0.604</td>
<td>-0.497</td>
<td>-0.354</td>
<td>-0.096</td>
<td>-0.045</td>
<td>-0.018</td>
<td>-0.123</td>
<td>-0.031</td>
<td>-0.265</td>
<td>-0.159</td>
<td>0.041</td>
<td>0.036</td>
</tr>
<tr>
<td>(M1)</td>
<td>θ</td>
<td>0.581</td>
<td>0.534</td>
<td>0.478</td>
<td>0.666</td>
<td>0.599</td>
<td>0.701</td>
<td>0.442</td>
<td>0.351</td>
<td>0.408</td>
<td>0.225</td>
<td>0.225</td>
<td>0.203</td>
<td>0.147</td>
<td>0.138</td>
<td>0.102</td>
</tr>
</tbody>
</table>

Panel A presents the results of Fama and MacBeth (1973) regressions of weekly liquidity beta on institutional ownership, number of institutional investors and firm size; i.e.,

$$\beta_{it} = a + \lambda_1 \text{INST\_RATIO}_{it-1} + \lambda_2 \text{INST\_NUMBER}_{it-1} + \theta \log(MCAP_{it-1}) + \epsilon_{it}$$

Institutional ownership is a firm’s market value owned by institutions as the percentage of capitalization of the entire market. Size is the logarithm of firm’s market capitalization (in million TL). All variables are measured at the end of each Wednesday. Panel B presents the results of the similar Fama and MacBeth (1973) regressions for institutional ownership in only small firms; i.e.,

$$\beta_{it} = a + \lambda_1 \text{INDV\_RATIO}_{it-1} + \lambda_2 \text{INDV\_NUMBER}_{it-1} + \theta \log(MCAP_{it-1}) + \epsilon_{it}$$

The table presents the averages and t-statistics of the coefficients estimates in each quintile (M5: largest, M1: smallest size quintile). The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) standard errors.

In the manuscript, Q1, Q2, Q3, Q4 and Q5 refer to the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures A, B and RT stand for the cost of buying (ask side), selling (bid side) and roundtripping (buying and selling simultaneously) a given amount of position respectively. In this table, they refer to the betas of these liquidity measures.
### Table 10

#### PANEL A: Systematic liquidity and foreign-domestic institutional ownership in the cross-section

<table>
<thead>
<tr>
<th>(M5) λ2</th>
<th>Q1,t</th>
<th>Q2,t</th>
<th>Q3,t</th>
<th>Q4,t</th>
<th>Q5,t</th>
<th>Q1,t</th>
<th>Q2,t</th>
<th>Q3,t</th>
<th>Q4,t</th>
<th>Q5,t</th>
</tr>
</thead>
<tbody>
<tr>
<td>λ1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.20</td>
<td>0.34</td>
<td>0.30</td>
<td>0.24</td>
<td>0.20</td>
<td>0.18</td>
<td>0.18</td>
<td>0.16</td>
<td>0.14</td>
<td>0.12</td>
<td>0.10</td>
</tr>
<tr>
<td>-0.008</td>
<td>-0.004</td>
<td>-0.003</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td>0.157</td>
<td>0.150</td>
<td>0.149</td>
<td>0.148</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
</tr>
<tr>
<td>-0.641</td>
<td>-0.606</td>
<td>-0.572</td>
<td>-0.540</td>
<td>-0.507</td>
<td>-0.474</td>
<td>-0.441</td>
<td>-0.408</td>
<td>-0.375</td>
<td>-0.342</td>
<td>-0.309</td>
</tr>
<tr>
<td>-0.587</td>
<td>-0.553</td>
<td>-0.519</td>
<td>-0.486</td>
<td>-0.452</td>
<td>-0.419</td>
<td>-0.386</td>
<td>-0.353</td>
<td>-0.320</td>
<td>-0.287</td>
<td>-0.254</td>
</tr>
</tbody>
</table>

#### PANEL B: Systematic liquidity and foreign-domestic individual ownership in the cross-section

<table>
<thead>
<tr>
<th>(M5) λ2</th>
<th>Q1,t</th>
<th>Q2,t</th>
<th>Q3,t</th>
<th>Q4,t</th>
<th>Q5,t</th>
<th>Q1,t</th>
<th>Q2,t</th>
<th>Q3,t</th>
<th>Q4,t</th>
<th>Q5,t</th>
</tr>
</thead>
<tbody>
<tr>
<td>λ1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.20</td>
<td>0.34</td>
<td>0.30</td>
<td>0.24</td>
<td>0.20</td>
<td>0.18</td>
<td>0.18</td>
<td>0.16</td>
<td>0.14</td>
<td>0.12</td>
<td>0.10</td>
</tr>
<tr>
<td>-0.008</td>
<td>-0.004</td>
<td>-0.003</td>
<td>-0.002</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
<td>-0.001</td>
</tr>
<tr>
<td>0.157</td>
<td>0.150</td>
<td>0.149</td>
<td>0.148</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
<td>0.147</td>
</tr>
<tr>
<td>-0.641</td>
<td>-0.606</td>
<td>-0.572</td>
<td>-0.540</td>
<td>-0.507</td>
<td>-0.474</td>
<td>-0.441</td>
<td>-0.408</td>
<td>-0.375</td>
<td>-0.342</td>
<td>-0.309</td>
</tr>
<tr>
<td>-0.587</td>
<td>-0.553</td>
<td>-0.519</td>
<td>-0.486</td>
<td>-0.452</td>
<td>-0.419</td>
<td>-0.386</td>
<td>-0.353</td>
<td>-0.320</td>
<td>-0.287</td>
<td>-0.254</td>
</tr>
</tbody>
</table>

**Panel A** presents the results of Fama and MacBeth (1973) regressions of weekly liquidity beta on foreign and domestic institutional investors, number of foreign and domestic institutional investors and firm size; i.e.,

\[ \beta_{f,t} = \alpha + \lambda_1 \text{FORINST}_{i,t-1} + \lambda_2 \text{DOMINST}_{i,t-1} + \lambda_3 \text{FORINST}_{t-1} + \lambda_4 \text{DOMINST}_{t-1} + \theta \text{MCAP}_{i,t-1} + \epsilon_{f,t} \]

(For foreign or domestic institutional ownership is a firm’s market value owned by (foreign or domestic) institutions as the percentage of capitalization of the entire market. Size is the logarithm of firm’s market capitalization (in million TL). All variables are measured at the end of each Wednesday. Panel B presents the results of the similar Fama and MacBeth (1973) regressions for foreign and domestic institutional ownership in only small firms; i.e.,

\[ \beta_{f,t} = \alpha + \lambda_1 \text{FORINDV}_{i,t-1} + \lambda_2 \text{DOMINDV}_{i,t-1} + \lambda_3 \text{FORINDV}_{t-1} + \lambda_4 \text{DOMINDV}_{t-1} + \theta \text{MCAP}_{i,t-1} + \epsilon_{f,t} \]

(The table presents the averages of the coefficient estimates in each quintile (M5: largest, M1: smallest firm size quintile). The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) standard errors.)
respectively.

stand for the cost of buying (ask side), selling (bid side) and roundtripping (buying and selling simultaneously) a given amount of position
using the Satterthwaite approximation.

The columns show the liquidity co-movement measure averaged across all trading days over the whole sample period and across event days on
which four separate types of macroeconomic news are released: Panel A reports the results for interest rate settings of U.S. Federal Reserve (Fed), European Central Bank (ECB), Bank of England (BOE), Bank of Japan (BOJ), Swiss National Bank (SNB) and the Central Bank of the Republic of Turkey (CBRT).

Panel B reports the results for the release of unemployment, GDP and inflation data of U.S., Turkey and eurozone. To capture the effects of the
announcements, a three-day event window is used covering Day 2 to Day 0, where Day 0 is the day on which the macroeconomic release is made.
Macroeconomic news releases are obtained from Bloomberg. The co-movement measure is computed for each trading day by first counting the
number of firms with positive change in the daily liquidity measure and the number of firms with negative change in the daily liquidity measure,
then dividing the larger of these two numbers by their total. Then, for each liquidity measure, the co-movement measure is averaged across all
trading days over the whole sample period and across event days on the abovementioned macro-announcements. Here, *, and ** cells indicate that the test statistic is significant at the 10% and 5% confidence levels, respectively, in a one-tail, two sample t-test for difference in means between the average of the co-movement measure on macro event days and the unconditional sample average. The t-statistics are corrected for unequal variances whenever appropriate using the Satterthwaite approximation.

Q1, Q2, Q3, Q4 and Q5 refer to the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures A, B and
RT stand for the cost of buying (ask side), selling (bid side) and roundtripping (buying and selling simultaneously) a given amount of position
respectively.
Table 12

PANEL A: Autocorrelations of liquidity variables

<table>
<thead>
<tr>
<th></th>
<th>1&lt;sup&gt;st&lt;/sup&gt; order</th>
<th>2&lt;sup&gt;nd&lt;/sup&gt; order</th>
<th>3&lt;sup&gt;rd&lt;/sup&gt; order</th>
<th>4&lt;sup&gt;th&lt;/sup&gt; order</th>
<th>5&lt;sup&gt;th&lt;/sup&gt; order</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-0.289</td>
<td>-0.011</td>
<td>0.001</td>
<td>-0.020</td>
<td>0.019</td>
</tr>
<tr>
<td>Q1&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-0.316</td>
<td>0.000</td>
<td>-0.007</td>
<td>-0.034</td>
<td>0.039</td>
</tr>
<tr>
<td>Q1&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-0.300</td>
<td>-0.005</td>
<td>-0.002</td>
<td>-0.030</td>
<td>0.032</td>
</tr>
<tr>
<td>Q2&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-0.249</td>
<td>-0.013</td>
<td>-0.039</td>
<td>-0.015</td>
<td>0.011</td>
</tr>
<tr>
<td>Q2&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-0.281</td>
<td>-0.025</td>
<td>-0.017</td>
<td>-0.052</td>
<td>0.081</td>
</tr>
<tr>
<td>Q3&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-0.256</td>
<td>-0.023</td>
<td>-0.026</td>
<td>-0.040</td>
<td>0.054</td>
</tr>
<tr>
<td>Q3&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-0.204</td>
<td>-0.039</td>
<td>-0.027</td>
<td>-0.039</td>
<td>0.026</td>
</tr>
<tr>
<td>Q3&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-0.215</td>
<td>-0.079</td>
<td>-0.011</td>
<td>-0.049</td>
<td>0.079</td>
</tr>
<tr>
<td>Q4&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-0.196</td>
<td>-0.065</td>
<td>-0.019</td>
<td>-0.047</td>
<td>0.057</td>
</tr>
<tr>
<td>Q4&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-0.162</td>
<td>-0.061</td>
<td>-0.022</td>
<td>-0.045</td>
<td>0.017</td>
</tr>
<tr>
<td>Q4&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-0.178</td>
<td>-0.107</td>
<td>0.003</td>
<td>-0.036</td>
<td>0.045</td>
</tr>
<tr>
<td>Q4&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-0.154</td>
<td>-0.091</td>
<td>-0.010</td>
<td>-0.043</td>
<td>0.036</td>
</tr>
<tr>
<td>Q5&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-0.133</td>
<td>-0.098</td>
<td>-0.004</td>
<td>-0.044</td>
<td>0.004</td>
</tr>
<tr>
<td>Q5&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-0.146</td>
<td>-0.118</td>
<td>-0.030</td>
<td>-0.017</td>
<td>0.034</td>
</tr>
<tr>
<td>Q5&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-0.121</td>
<td>-0.117</td>
<td>-0.016</td>
<td>-0.036</td>
<td>0.024</td>
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</tbody>
</table>

PANEL B: Impact of market movements on market-wide liquidity

<table>
<thead>
<tr>
<th></th>
<th>(\beta_1)</th>
<th>(\beta_2)</th>
<th>(\beta_3)</th>
<th>(\beta_4)</th>
<th>(\beta_5)</th>
<th>(\beta_6)</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-0.662</td>
<td>-1.025</td>
<td>0.029</td>
<td>0.046</td>
<td>0.361</td>
<td>-0.435</td>
<td>0.33</td>
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<tr>
<td>Q1&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-0.723</td>
<td>-1.149</td>
<td>0.064</td>
<td>0.018</td>
<td>0.368</td>
<td>-0.446</td>
<td>0.34</td>
</tr>
<tr>
<td>Q1&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-0.692</td>
<td>-1.088</td>
<td>0.048</td>
<td>0.031</td>
<td>0.363</td>
<td>-0.442</td>
<td>0.34</td>
</tr>
<tr>
<td>Q2&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-1.363</td>
<td>-2.089</td>
<td>0.2</td>
<td>0.526</td>
<td>0.826</td>
<td>-0.886</td>
<td>0.40</td>
</tr>
<tr>
<td>Q2&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-1.442</td>
<td>-2.186</td>
<td>0.028</td>
<td>0.431</td>
<td>0.793</td>
<td>-0.650</td>
<td>0.34</td>
</tr>
<tr>
<td>Q2&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-1.399</td>
<td>-2.14</td>
<td>0.123</td>
<td>0.474</td>
<td>0.803</td>
<td>-0.777</td>
<td>0.37</td>
</tr>
<tr>
<td>Q3&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-2.34</td>
<td>-3.354</td>
<td>0.336</td>
<td>1.232</td>
<td>1.478</td>
<td>-1.350</td>
<td>0.43</td>
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<tr>
<td>Q3&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-2.424</td>
<td>-3.139</td>
<td>-0.151</td>
<td>1.153</td>
<td>1.522</td>
<td>-1.078</td>
<td>0.36</td>
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<tr>
<td>Q3&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-2.382</td>
<td>-3.243</td>
<td>0.098</td>
<td>1.195</td>
<td>1.497</td>
<td>-1.222</td>
<td>0.40</td>
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<tr>
<td>Q4&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-3.424</td>
<td>-4.74</td>
<td>0.503</td>
<td>1.951</td>
<td>2.167</td>
<td>-1.824</td>
<td>0.45</td>
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<tr>
<td>Q4&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-3.777</td>
<td>-4.105</td>
<td>-0.163</td>
<td>1.79</td>
<td>2.203</td>
<td>-1.458</td>
<td>0.38</td>
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<tr>
<td>Q4&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-3.609</td>
<td>-4.405</td>
<td>0.17</td>
<td>1.892</td>
<td>2.191</td>
<td>-1.649</td>
<td>0.42</td>
</tr>
<tr>
<td>Q5&lt;sub&gt;A&lt;/sub&gt;</td>
<td>-4.404</td>
<td>-6.294</td>
<td>0.529</td>
<td>2.946</td>
<td>2.818</td>
<td>-2.275</td>
<td>0.45</td>
</tr>
<tr>
<td>Q5&lt;sub&gt;B&lt;/sub&gt;</td>
<td>-5.015</td>
<td>-4.853</td>
<td>-0.134</td>
<td>2.76</td>
<td>2.725</td>
<td>-1.642</td>
<td>0.40</td>
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<tr>
<td>Q5&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-4.73</td>
<td>-5.538</td>
<td>0.198</td>
<td>2.898</td>
<td>2.780</td>
<td>-1.963</td>
<td>0.44</td>
</tr>
<tr>
<td>Q5&lt;sub&gt;RT&lt;/sub&gt;</td>
<td>-10.21</td>
<td>-11.05</td>
<td>0.25</td>
<td>3.79</td>
<td>5.81</td>
<td>-5.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Panel A reports the autocorrelation coefficients for the market-wide equally weighted averages of individual liquidity variables. Q1, Q2, Q3, Q4 and Q5 refer to the amounts of 1000, 10000, 25000, 50000 and 100000 TL respectively, whereas the liquidity measures A, B and RT stand for the cost of buying (ask side), selling (bid side) and roundtripping (buying and selling simultaneously) a given amount of position respectively. Numbers in bold font indicate a p-value less than 0.0001 for an asymptotic test that the autocorrelation coefficient is zero.

Panel B reports the results of the following time-series regressions:

\[
DL_{M,t} = \beta_0 + \beta_1 R_{M,t} + \beta_2 R_{M(t)} + \beta_3 R_{M(5),t} + \beta_4 V_{M,t} + \beta_5 \sigma_{M(5),t} + \varepsilon_t
\]

where the dependent variable \(DL_{M,t}\) is the daily percentage change of an equally weighted cross-sectional average of the liquidity variable for all stocks in the sample. \(R_{M,t}^L\) (\(R_{M,t}^L\)) is the daily return of the all share index of Borsa Istanbul when the return is positive (negative) and zero otherwise. \(R_{M(5),t}^L\) (\(R_{M(5),t}^L\)) is the past five trading-day all share index return if it is positive (negative) and zero otherwise. Market volatility, denoted by \(V\), is defined as \(V = \left(\frac{R_{M(t)}^L - P_{M(t)}^L}{(R_{M(t)}^H - P_{M(t)}^L)^2}\right)^{0.5}\). where \(P_{M(t)}^H\) and \(P_{M(t)}^L\) are the highest and lowest values of all share index on day \(t\), and \(\sigma_{M(5),t}\) is the market standard deviation in the past five trading days.
Figure 1: Visual representation of the $XLM_{RT}$.

$$XLM_{RT}(Q) = \frac{\int_0^{n(Q)} \text{ask curve}(x)dx - \int_0^{n(Q)} \text{bid curve}(x)dx}{Q}$$
Figure 2: Sum of the cross-sectional means of concurrent, lagged and lead market liquidity coefficients: (a) for different position sizes to roundtrip; (b) for different position sizes and for buy and sell side separately. Position sizes $Q_1$, $Q_2$, $Q_3$, $Q_4$ and $Q_5$ refer to 1000, 10000, 25000, 50000 and 100000 TL respectively.
Figure 3: Sum of the cross-sectional means of concurrent, lagged and lead market liquidity coefficients when the industry affiliation and individual liquidity determinants taken into account: (a) for different position sizes to roundtrip; (b) for different position sizes and for buy and sell side separately. Position sizes \( Q_1, Q_2, Q_3, Q_4 \) and \( Q_5 \) refer to 1000, 10000, 25000, 50000 and 100000 TL respectively.
Figure 4: Sum of the cross-sectional means of concurrent, lagged and lead market liquidity coefficients: (a) for different position sizes to roundtrip for index and non-index stocks; (b) for different position sizes and for buy and sell side separately for index stocks; (c) for different position sizes and for buy and sell side separately for non-index stocks. Position sizes $Q_1, Q_2, Q_3, Q_4$ and $Q_5$ refer to 1000, 10000, 25000, 50000 and 100000 TL respectively.
Figure 5: Selected time varying liquidity betas for different firm size quintiles (M5: largest firms, M1: smallest firms) estimated by Dynamic Conditional Beta methodology: (a) for smallest position (Q1) to roundtrip; (b) for largest position (Q5) to roundtrip.