SSE Riga Student Research Papers
2012: 3 (142)

WHAT TYPES OF INVESTORS DRIVE COMMONALITY IN LIQUIDITY? EVIDENCE FROM THE ESTONIAN STOCK MARKET

Authors: Madara Bogdāne
Anastasija Oļeiņika

ISSN 1691-4643
ISBN 978-9984-842-56-1

November 2012
Riga

WHAT TYPES OF INVESTORS DRIVE COMMONALITY IN LIQUIDITY? EVIDENCE FROM THE ESTONIAN STOCK MARKET

Madara Bogdāne

and

Anastasija Oļeiņika

Supervisor: Tālis Putniņš

May 2012
Riga

Abstract

In this thesis we analyse the tendency for changes in liquidity to correlate across financial securities, so called commonality in liquidity, in the Estonian stock market. First, we apply two separate methods used by Hameed, Kang and Viswanathan (2010) and Chordia, Roll and Subrahmanyam (2000) to identify liquidity co-movement across stocks. Next, we examine how trading by different types of investors affects commonality in liquidity. We find that institutional, large, and foreign investors drive commonality in liquidity; in contrast, nominee investors decrease it. In down markets large and institutional investors drive commonality in liquidity, but foreign and individual investors decrease it. The results of this thesis have the following implications: first, our paper contributes to the existing literature on commonality in liquidity enhancing comprehension of its determinants and patterns. Second, by shedding light on the causes of systemic liquidity fluctuations, this thesis contributes to the understanding required to improve the design of markets in order to increase their stability.

Keywords: commonality in liquidity, liquidity, investor types, institutional investors, foreign investors, behavioural bias

Acknowledgements

We want to express gratitude to our thesis supervisor Tālis Putniņš for his valuable input in the development of our research focus and methodology and continuous support throughout our thesis writing process. He also provided us with a unique dataset, which was critical for carrying out the study.

We are thankful to the participants of Georgetown University's 11th Annual Carroll Round conference for insightful suggestions and comments and students of the Stockholm School of Economics in Riga who provided us with helpful feedback at different stages of thesis formation.

Table of Contents

List of Tables

1. Introduction

The recent financial crisis has drawn considerable attention to the concept of liquidity. Many claim that the crisis was not caused by solvency issues in the first place (as it might initially seem), but rather by lack of liquidity resulting in painful liquidity spirals and significant decrease in market activity (e.g., Brunnermeier, 2009). Even though it has been long understood that liquidity is an essential element required for proper functioning of financial markets, before the crisis less than enough attention was paid to studying and understanding the concept of liquidity and different aspects of it.

Developments in asset pricing theories have shown that liquidity (particularly, its systemic aspects) plays a major role in price formation of individual assets, which has been supported by empirical findings (e.g., Amihud, 2002; Brennan & Subrahmanyam, 1996). High levels of liquidity imply lower transaction costs and therefore encourage more trading. Liquidity is also vital for markets being informationally efficient, since illiquid securities and markets prevent arbitrageurs from driving prices towards their fundamentals. Informational efficiency results in higher overall welfare through more efficient capital allocation across different investment opportunities (Wurgler, 2000). Higher individual stock liquidity means lower transaction costs for traders, and consequently lower required returns, resulting in a lower cost of capital for the company and higher market capitalization. This has also been documented in empirical studies (e.g., Amihud & Mendelson, 1986; Easley, Hvidkjaer, & O'Hara, 2002). All these properties make liquidity a highly desired feature of any market and define the importance of understanding liquidity determinants for companies, investors, regulators, and exchanges.

Recently researchers have discovered another pivotal dimension of liquidity – its tendency to co-move across different stocks, instead of being an individual feature of each security. Such commonality in liquidity forms a systemic component of individual securities risk (Chordia, Roll & Subrahmanyam, 2000; Pastor & Stambaugh, 2003; Acharya & Pedersen, 2005), which cannot be diversified away, and hence is particularly important to understand for effective risk management and securities pricing. Commonality drives liquidity spillovers both during good times, when overall market liquidity increases, and during sudden liquidity dry-ups in the times of crisis, when liquidity is the most crucial feature to ensure financial market stability and resistance to even more extensive market declines. Understanding such liquidity effects and their main determinants is of critical importance for regulators in designing robust securities markets.

Notwithstanding the extensive evidence supporting the existence of commonality in liquidity, the determinants of stock co-movements remain largely unexplored. Some evidence suggests that different investor types influence commonality in liquidity differently (e.g., Karolyi, Lee, van Dijk, 2011; Bai & Qin, 2010); however, such research is often limited by data availability and focuses only on some particular investor type, for instance, mutual funds, where data are readily accessible. This thesis studies the extent, nature, and determinants of liquidity co-movements, answering the following research question "*What types of investors drive commonality in liquidity?*" To answer this research question, we use trade-level data from NASDAQ OMX Tallinn during the period from 2004 to 2010, documenting the ID and characteristics of traders behind each trade. This allows to investigate comparative effects of different types of investors on commonality in liquidity, e.g., institutional/individual, foreign/local, large/small.

No studies have been carried out documenting either the commonality in liquidity, or the effect of different investor trading on commonality in liquidity in any of the Baltic stock markets. As opposed to the majority commonality studies done on the New York Stock Exchange (NYSE), we can examine commonality existence and nature in an emerging market. Moreover, most of the previous papers use proxies for determining how different investor types affect commonality in liquidity (for example, by approximating institutional investor impact only by mutual funds, as such data is more readily available). In contrast, our dataset, allows us to distinguish institutional investors as a separate investor group and determine their distinct effect on liquidity co-movement. More importantly, existing literature is mostly constrained to the effects of some investor types on commonality in liquidity in down markets. Apart from looking at the down markets, we also aim to find the contributors to commonality in liquidity during market growth.

Empirical evidence of the study contributes to the general understanding of how various investor types affect co-variation in liquidity. An insight into this aspect of stock liquidity co-movement determinants would result in a better comprehension of financial processes, being useful for both regulators and traders. It has significant implications for designing more stable financial systems and diminishing the effects of future financial instabilities.

We study commonality across several liquidity dimensions, namely, market tightness, market depth, and resiliency. First, we apply the methodology as in Hameed, Kang and Viswanathan (2010), estimating the strength of commonality through sensitivity of changes in individual stock liquidity to changes in market liquidity. Second, following methodology by Chordia et al. (2000) we measure commonality in liquidity through the level of explanatory power when regressing individual stock liquidity measures on market liquidity measures. We test how different investor groups and presence of market makers affect the strength of liquidity co-movement. In addition, we examine the strength of commonality in NASDAQ OMX Tallinn, both in different market activity stages and compared to developed markets.

According to our results, commonality effects appear to be stronger in NASDAQ OMX Tallinn than in NYSE, which might imply that, as already discovered for returns (Morck, Yeung & Yu, 1999), the ratio of systemic to the total risk component in emerging markets is larger than in developed markets for liquidity as well. We find that the nature of co-movements in market tightness differs from that in the price impact of trading. The results suggest that incentivizing more trading by small, individual and nominee traders would reduce the negative commonality effects during market downturns. We propose another step towards markets becoming more resistant to liquidity crises, namely, a higher degree of international integration via increases in activity of foreign traders.

We contribute to the existing body of literature in several aspects. First, using a highly detailed dataset of investor trades and characteristics we supplement the scarce evidence on how different investor types affect commonality in liquidity. Second, we establish that commonality in liquidity in emerging markets is stronger than in developed ones, building a bridge between existing literature on the differences in the ratio of systemic to idiosyncratic risk components of returns (Morck et al., 1999) and a possibly similar phenomenon for liquidity risk. Third, we identify that commonality across different liquidity dimensions has different patterns. Co-movements in volume-return relation are stronger during tranquil market periods, while commonality in spreads is more distinct during crises.

The remainder of the paper is organized as follows. Section 2 provides an overview of the existing literature on commonality in liquidity, its drivers, and consequently outlines the hypotheses we examine. The description of our data is presented in Section 3. Section 4 describes the liquidity measures we use and the methodology we apply for determining commonality effects. In Section 5 we describe our results. Section 6 presents a discussion of our findings and their implications. Section 7 concludes the paper. Appendix A contains figures with data descriptives. Appendices B, C and D present tables with descriptive statistics, general results, and results by investor type, respectively.

2. Literature review

In the following section we review the empirical findings documenting commonality in liquidity and briefly touch upon the methodology used in each of the papers discussed. We then proceed with the discussion of possible factors affecting commonality in liquidity, such as market design and development level of the market. Subsequently, we review seminal findings on simultaneous trading activity. We then make inferences from empirical studies about the potential trading correlations and discuss the effect of trading by different investor types on the commonality in liquidity.

2.1. Commonality in liquidity

Several studies have investigated positive co-variation in stock liquidity (Chordia et al., 2000; Coughenour & Saad, 2004; Karolyi et al., 2011). Co-variation in liquidity adds to the systemic risk component of a stock, having implications for investors in terms of asset pricing (Amihud & Mendelson, 1986; Brennan & Subrahmanyam, 1996; Plastor & Stambaugh, 2003). Chordia et al. (2000) propose that co-movements in liquidity (proxied by bid-ask spreads, quoted depth, effective spreads) are induced by variation in trader inventory levels; and the cross-sectional changes in inventory levels depend on the costs incurred due to buying, holding or selling the inventory. Chordia et al. (2000) argue that when these costs are decreasing trading activity can be expected to increase. Based on the reasoning that spreads are the best proxy for transaction costs incurred during the trading process, they calculate quoted (bid-ask) spreads, quoted depth and effective spreads for 1169 stocks traded on NYSE on a daily basis. Given the fact, that they are mainly concerned with determining the effect from market-wide and intra-industry commonality on individual stock liquidity, they also construct market and intra-industry averages. After regressing the first differences of individual stock liquidity proxies on the market and intra-industry averages, they find that market and intra-industry liquidity proxies affect individual stock liquidity proxies. (Chordia et al. (2000) imply the existence of commonality from statistically significant coefficients on the market and intra-industry liquidity sensitivities).

Another approach for documenting commonality in liquidity is undertaken by Hasbrouck and Seppi (2001), who employ liquidity measures in levels (not in changes as Chordia et al. (2000)). They take a sample of 24 Dow Jones Industrial average stocks traded during 1994. The authors use the spread, log spread, log size, quote slope, log quote slope and effective spread measures as proxies for quoted liquidity. They use simple principal component analysis[1] and find that the logarithmic quote slope measure (which combines price and quantity information, and thus can be referred to as a proxy for depth and spreads) has the highest eigenvalue (i.e., has the highest variance of the first principal component) and thus shows the strongest commonality. The log quote slope measure is followed by spread and quoted depth measures with respect to the strength of commonality in liquidity. They also find that effective spreads are not explaining any commonality in liquidity, arguing that it is due to market makers on NYSE, whose ability to set quotes is the main reason for low liquidity effects. Hasbrouck and Seppi (2001) conclude that weak commonality in liquidity can be observed in steady markets (they use term "normal"); and that only severe market crisis exhibit strong, empirically evident liquidity co-movement.

Huberman and Halka (2001) use four liquidity proxies: absolute bid-ask spreads, the spread/price ratio, and two additional proxies derived from depth, namely, quantity depth and dollar depth. They sort stocks traded on NYSE by their market capitalization and then randomly select 60 stocks from each size-quartile. This leaves them with 240 stocks traded on the NYSE in 1996. Although aiming to discover the same phenomena, they undertake a different approach than Chordia et al. (2000), and Hasbrouck and Seppi (2001). They run auto-regressions for each stock group and find a positive correlation in residuals, which they assign to common variation in liquidity across stock groups. They also document a negative and positive correlation of variation in liquidity proxies with volatility and return, respectively.

As Chordia et al. (2000) point out liquidity co-movements are induced by co-variation in trading activity that is associated with the costs of trading. Most widely used measure for commonality in liquidity is spreads, which is a good transaction cost proxy. However, there are also other ways to capture common variation in liquidity, for instance, a principal component analysis (as in Hasbrouck and Seppi (2001)), positive residual auto-correlation (Huberman & Halka, 2001). Interestingly enough, all aforementioned studies are based on NYSE stock-level data, but obtain varying results. This is evidence in support of the diverse nature of liquidity. Therefore, we pay special attention to the choice of liquidity measures and the methods used to document commonality in liquidity.

[1] Principal component analysis is a mathematical procedure that allows linear combination of variables such as returns, order flow and liquidity, in order to determine factors that induce common variation in these variables. These common factors are also known as principal components. The variance (often referred to as eigenvalues) of these principal components then is interpreted as the strength of commonality in respective variable. See also Corwin and Lipson (2011) for principal component analysis usage.

2.2. Factors influencing commonality in liquidity

2.2.1. Market design

Literature presents evidence on the existence of commonality in liquidity in quote driven (Chordia et al., 2000; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001) and in order driven markets (Brockman & Chung[2], 2003; Zheng & Zhang, 2006). Findings of several papers indicate that different market structures might exhibit a different degree of liquidity co-movements, and sometimes its absence. Bauer (2004) studies commonality in liquidity in order driven markets and finds a difference in the level of commonality from that documented in quote driven markets. He undertakes a principal component analysis of liquidity proxies similar to Hasbrouck and Seppi (2001), who use a principal component analysis for quote driven markets (which makes the comparison between the results of the two market structures more robust). Bauer (2004) concludes that the fraction of common factors influencing liquidity is stronger in order driven than in quote driven markets[3], mentioning more complete data availability as one of the possible explanations[4]. There are several documented factors that might influence the presence and strength of commonality in a market, e.g., market design, trading mechanisms (Comerton-Forde & Rydge, 2006), as well as the presence of market makers (Pukthuanthong-Le & Visaltanachoti, 2009), who often are the main liquidity providers.

Since we carry out our study using a sample of stocks traded on NASDAQ OMX Tallinn, which is an order driven market, we are particularly interested in the findings of Bauer (2004). In general, he concludes that the explanatory power of such factors as the absolute bid-ask spreads, the spread/price ratio, quantity depth and dollar depth (he uses the method of Huberman and Halka (2001)), is higher in order driven markets as opposed to quote driven and/or hybrid markets[5]. This implies that market structure is an important aspect that should be considered when documenting commonality in liquidity. Also they document intra-day effects of variation in liquidity, i.e., find that its proportion explained by common factors varies during the day. They also note that the liquidity proxies calculated using the data available at a certain point in time might therefore give misleading results.

[2] Brockman and Chung (2003) were first to document the commonality in liquidity in order driven markets.
[3] Chordia et al. (2000), Hasbrouck and Seppi (2001) document commonality in liquidity in quote driven markets.
[4] Bauer (2004) also finds that the explained percentage of common factors varies throughout the day.
[5] Huberman and Halka (2001) explore NYSE stock market, i.e., a hybrid market.

2.2.2. Developed versus emerging markets

Other interesting implications about commonality in liquidity may derive from the differences between developed and emerging markets. Majority of the previous studies documenting commonality in liquidity are focused on developed markets (mainly based on NYSE data, as in Chordia et al., 2000; Huberman and Halka, 2001; Hasbrouck and Seppi, 2001). Recently, academics have focused much of their attention on emerging markets since liquidity risk is found to be stronger there than in developed markets (Bekaert, Harvey & Lundblad, 2007). Alongside the documented common features of both market types with respect to commonality in liquidity, liquidity co-movements in down markets are stronger in emerging markets, supporting the evidence of the pervasiveness of this phenomenon in emerging markets. Bekaert et al. (2007) propose incomplete liberalization as a possible explanation of the pronounced differences. They state that even if the functioning of emerging markets is connected to the global market, a stronger liquidity co-movement is present due to local risk factors such as political instability, law and order imbalances.

Morck et al. (1999) compare the synchronicity of stock returns over a 26-week period (for the year 1995) in developed and emerging markets. They find that stock prices show more persistent co-movement in emerging markets than in developed markets[6]. They measure stock market synchronicity through the average R-squared of firm-level regressions of stock returns on each country's market indexes. The USA (0.021), Ireland (0.058) and Canada (0.062) have the lowest market synchronicity as compared to other 40 countries (full sample) that are included in the sample. In contrast, Poland, China and Malaysia (representatives of emerging markets) have the highest market synchronicity (0.569, 0.453 and 0.429, respectively). Their findings suggest that commonality in stock returns is stronger in emerging markets as a result of a larger ratio of the systemic risk component to idiosyncratic risk. Domowitz and Wang (2002) find that commonality in returns and commonality in liquidity are driven by different forces; however, both represent the systemic risk component. Thus by testing whether commonality in liquidity is stronger in emerging markets (represented by Estonia) as opposed to developed markets, we can identify whether the proportion of systemic to idiosyncratic risk is larger in emerging markets for liquidity as well.

---

[6] They use Chinese, Malaysian and Polish stock markets as representatives of emerging markets and the stock markets of the USA, Ireland and Denmark as representatives of developed markets. (The authors use GDP per capita as a measure of economic development.)

2.3. Simultaneous and large scale trading activity

Commonality in liquidity is argued to be a result of common variability in trading activity (Chordia et al., 2000) when trading is on a large scale and simultaneous. Literature suggests that this variability can be induced by factors influencing demand for liquidity, supply-side[7] factors, or both. Influencing factors from demand side might be mutual fund ownership of stocks as in Koch, Ruenzi and Starks (2009), where they find that stocks owned by mutual funds have two times higher sensitivity to liquidity risk as compared to stocks that are not. Moreover, they also prove that more intensive trading by mutual funds strengthens the relationship between mutual fund ownership and the extent of commonality in liquidity. A recent paper finds that the supply side factors influencing liquidity co-movement is also trading by institutions (particularly foreign)[8] (Bai & Qin, 2010), who show similarity in their trading activity and have a similar rationale for information acquisition (Karolyi et al., 2011). Successively, short-term capital constraints of market makers (Comerton-Forde, Hendershott, Jones, Moulton & Seasholes, 2008) and financial intermediaries have an effect on stock market liquidity (Brunnermeier & Pedersen, 2009; Hameed, Kang & Viswanathan, 2010). And, as argued by Comerton-Forde et al. (2008) trading losses of market makers reduce their willingness to provide liquidity, when holding leverage constant. Thus, market makers and specialists might show similar trading activity and this could translate into supply-side factors affecting commonality in liquidity.

<u>Institutional investors</u>

There are several reasons to believe that institutional investors might strongly contribute to commonality in liquidity. First of all, there is considerable evidence in support of similar trading patterns across institutional investors. For instance, Sias and Starks (1997) find that institutions induce serial-autocorrelation in stock returns, the reason for which can be strategic trading, similar private signals, herding and positive feedback trading (the last two should be viewed together rather than independently). One of the empirical results of Campbell, Ramadorai and Schwartz (2009) suggest that in the short run, institutions buy stocks that perform well and sell stocks that perform poorly; however, in the long run the reverse holds, i.e., institutions are buying-up stocks that have proven to be a disappointing

[7] In literature a trader's decision to supply liquidity is usually characterized by submitting limit orders, while demand for liquidity means submitting market orders in a limit order market (e.g., Hollifield, Miller, Sandas & Silve, 2001).

[8] There is vast amount of findings documenting the influence of institutional investors on commonality in liquidity (Brunnermeier & Pedersen, 2009; Hameed et al., 2010; Karolyi et al., 2011) often taking mutual funds as representatives of this large group of institutional investors and explaining it with the ease of data availability. However, it should be noted that there are also other institutional investors (e.g., companies) that compose the major part of institutional investors in countries where mutual funds are relatively inactive.

investment strategy for previous months. They argue that institutions have persistent trading strategies. Proceeding work of Heston, Korajczyk and Sadka (2010) empirically proves that benchmarked mutual funds and index funds might be inducing serial autocorrelation in stock returns at specific intervals through correlated fund redemption, which supports former speculations by Campbell et al. (2009).

Secondly, Heston et al. (2010) argue that institutions are usually holding widely differentiated portfolios and, as argued by Bai and Qin (2010), large-scale and simultaneous buying and selling by institutions induces co-variation in liquidity across the stocks in their portfolios. Combining these two aspects together, we can simplify the argument with an example. Some institutions receive a private signal containing negative information about a particular industry, requiring them to change their portfolio balances. Subsequently, they start selling the stocks that are likely to lose their value soon after the news become public and buying other stocks to balance their portfolios. As a result of herding other institutions react to the trading behaviour of their rivals and undertake similar strategies. Such trading pattern creates co-variation in liquidity. This reasoning leads us to our first hypothesis:

H1: *Institutional investor trading induces co-variation across individual stock liquidity.*

Individual investors

To this point we have presented literature that documents trading co-variation across institutional investors and shows how such simultaneous and correlated trading patterns lead to commonality in liquidity. However, very little is known about individual investors and how, if at all, their trading similarities might affect commonality in liquidity. Very interesting findings are presented by Barber, Odean and Zhu (2009). They document trading correlation across individual investors and find a simple explanation, namely, that individuals are reluctant to change their trading patterns, implying that commonality arises from noise trading. For example, if an individual buys a particular stock at one point in time, it is very likely that she will also buy the same stock in the following period.

Individual investor induced commonality in liquidity may also be explained via investor overconfidence and behavioural biases. When markets are performing well, individual investors tend to become overconfident and by putting up too much bet on their own ability start buying stocks whose price has risen (Barber & Odean, 2005).

Existing literature emphasizes that the result of individual trading is characterized by demand for liquidity in both, up markets and down markets. Anginer (2010) finds that households create systemic variation in demand of liquid securities in down markets. For instance, in times of market volatility individual investors fear the uncertainty about the prospects of future income and start re-balancing their portfolios from illiquid stocks to more liquid ones (so called, flight-to-liquidity phenomenon, when investors sell illiquid stocks, and invest in more liquid securities). Flight-to-liquidity can also characterize institutional investor trading during times of market volatility; however, based on findings by Anginer (2010) we expect this phenomenon to be stronger among individuals. Due to flight-to-liquidity effect during market downturns, as well as simultaneous trading (as discussed in Barber et al. (2009)) individuals might induce co-variation across stock liquidity.

An alternative explanation for individual investors influencing commonality in liquidity is their behavioural biases in terms of disposition effect discussed in the seminal paper by Shefrin and Statman (1985), who are the first to document the disposition effect in a real-life setting as opposed to laboratory experiments done beforehand. Disposition effect implies selling of rising-return stocks by individuals when markets go up and holding on to value losing stocks in down markets. This might result in increases in commonality during good times, but no such effect during market downturns due to lower trading activity by individuals.

Although both previous arguments suggest that individual investors might drive commonality in liquidity in up markets (explained via investor confidence and behavioural biases), the possible effects in down markets are ambiguous (demand for liquidity as opposed to disposition effect). To determine the effect of individuals on the systemic risk deriving from commonality in liquidity in both up and down markets we propose the second and third hypotheses:

H2: *In general individual investors drive commonality in liquidity.*

H3: *Individual investors drive commonality in liquidity in down markets.*

When comparing individual to institutional investors, the second hypothesis contradicts our first hypothesis. However, since literature provides reasoning for both hypotheses, it is of particular interest to examine whether both investor types drive commonality in liquidity (as opposed to nominee traders) and if yes, which investor type actually has a stronger impact on commonality in liquidity.

Barber and Odean (2001) study overconfidence (as an aspect of behavioural finance) and its relation to the trading patterns between genders. Based on the vast amount of literature in support of men being more overconfident than women, and their own judgment that persistence of such behavioural bias induces more trading, they propose the hypothesis that men are trading more frequently than women; and find empirical support for it. They document that trading by men exceeds trading by women by 45 percent. Their findings imply that women are less active traders; therefore their trading (even in the presence of highly volatile markets) might have less impact on the market than trading by men. Considering findings by Anginer (2010), namely, that individuals create systemic variation in liquidity in down markets, we propose the fourth hypothesis:

H4: *In down markets trading by men drives commonality in liquidity more than trading by women.*

Large investors

Comparatively little evidence is presented in the literature on the varying trading effects of wealthy/large investors compared to investors with smaller portfolio balances. Despite very few studies exploring different investor type characteristics, we find that Anginer (2010) studies the effect of wealthy investor trading on liquidity. He finds that "wealthy" households (he ranks them by the market value of their portfolios) are liquidity suppliers in down markets. Consistent with the similar reasoning that is used for institutional investors, it can be argued that large investors account for their transaction costs by forming large-cap portfolios. According to Anginer (2010) these investors might be willing to supply liquidity to the market when it is absent. By providing liquidity to the markets, large investors can take advantage of investment opportunities during market instabilities and benefit from the high premium resulting from selling liquid stocks (Anginer, 2010). If all wealthy investors follow similar strategy (i.e., see the benefits of supplying the liquidity to the market) it is highly likely that their common trading would induce co-variation in liquidity across stocks. Therefore, we propose the following hypothesis:

H5: *Large investor trading drives commonality in liquidity in down markets.*

In general, the third and the fifth hypotheses can be interpreted through demand and supply drivers of commonality in liquidity. In this case large investors supply liquidity in down markets, while individual investors demand liquidity, both contributing to commonality. Thus we also test which investor type is the driving force of commonality in liquidity in down markets.

3. Data

In this section we provide an overview of the data used for our analysis and outline the main features of NASDAQ OMX Tallinn. We use four datasets, combining three datasets for determining trading activity in the market by investor type, and using another dataset for calculating necessary variable proxies.

NASDAQ OMX Tallinn is one of NASDAQ OMX Baltic exchanges. It is relatively illiquid and small order driven market with only some formal market makers[9] during the examined period (Appendix B, Table 2). The total market capitalization of NASDAQ OMX Tallinn is EUR 1.25 billion (NASDAQ OMX Group, 2011).

We conduct the research on NASDAQ OMX Tallinn trade-level data for the time period from January 2004 until November 2010, obtained from NASDAQ OMX Baltic. The first unique trade-level dataset contains a complete trade record by all investors that have owned equities traded on NASDAQ OMX Tallinn during the period from 2004 to 2010. In addition to trader ID number, the data contain identification code (ISIN) of the security traded, trade direction (buy or sell), trade date and settlement date, the quantity and price at which the trade took place.

This allows us to infer investor ID from the trades and through another dataset identify investor characteristics in terms of investor type (fund, individual, or institution), account type (nominee, standard, client), gender and date of birth (for individual investors), and origin (local or foreign). The third dataset contains stock balances of each investor portfolio on the first date of each month during the period, which allows us to determine wealth of each investor and use it as another investor characteristic.

In addition, we collect a full record of stock bid and ask prices, company number of shares, trade volumes, and stock turnover for the sample period from NASDAQ OMX Tallinn web site. These data are necessary for creating liquidity proxies and control variables for regression analysis, discussed in detail in the next section.

We undertake several measures to make the best use of the available data and obtain robust results in our analysis. Initially there are 37 stocks represented in the dataset, however, for having sufficient amount of observations in regressions containing lead and lag terms, we drop all the stocks that traded for less than two years (500 trading days) during the sample period (January 2004 to October 2010). After applying this filter we are left with 22 stocks for the analysis (the majority of stocks dropped actually are preference shares and additional issues; as a result only common stocks are left). Appendix B, Table 2 provides more detailed information on stocks and their selection. The dataset also contains the same data assigned to two different stock names, namely Nordecon and Eesti Ehitus. The search results on NASDAQ OMX Tallinn web site indicate that Eesti Ehitus joined the main list on May 18,

[9] From 2005 to 2007 NASDAQ OMX Baltics regulation required newly listed companies to assign a market maker for a minimum of one year in order to ensures the liquidity for particular stock. No company extended agreements with their market makers after the initial year (Čekauskas, Gerasimovs, Liatukas & Putniņš, 2011).

2006 and then changed its name to Nordecon. Thus, we drop the stock data for Eesti Ehitus, as it is identical to Nordecon. This results in 21 stocks left for the analysis and the average trading days of all stocks included in the final sample is 1271.

We use midquotes for calculating stock returns, which allows us to overcome microstructure noise in terms of negative price (and thus return) auto-correlation. We adjust midquotes for stock splits and dividends during the period. We calculate market return based on the market index obtained from NASDAQ OMX Tallinn web site. Missing values for bid-ask spreads are dealt with by filling in the information from preceding observations, which does not affect robustness of our results, because as can be seen in Appendix A, Figure 1 (ASPR measure) changes in spreads are rather steady. In several observations bid price is higher than ask price, which arises from either mistakes in the data or spreads being captured during trading suspension phases. We are interested in data that represents market in a continuous trading phases, thus we drop observations where the best bid exceeds the best ask.

4. Methodology

In this section, we provide a detailed description of the methodology used in this paper. First, we describe the overall structure of our research; then we present the two methods we use and the corresponding measures and tools applied.

The available literature presents a wide variety of different approaches for analyzing commonality in liquidity. We have identified the main two and apply both of them in order to obtain more robust results. The first approach (used e.g., by Hameed et al. (2010) and Chordia et al. (2000)) measures commonality in liquidity through the sensitivity of changes in stock liquidity to changes in marker-wide liquidity, determined by beta coefficients (both significance and size) in regression analysis. The second approach determines the extent to which market liquidity explains individual stock liquidity, measured by R-squared of particular regressions (e.g., Bai & Qin, 2010; Hameed et al., 2010). In both of these approaches we use two liquidity measures, capturing different dimensions of liquidity – tightness (measured through bid-ask spreads and having an economic interpretation of transaction costs) and the price impact of trading (interpreted as the volume of trades that can be absorbed by the market without causing price movements).

Another possible method of testing commonality in liquidity is a principal components analysis. It relies on variance-covariance relationship in the underlying data, choosing the most optimal linear combinations of the original variables so to maximize their explanatory power. Empirical studies by Corwin and Lipson (2011), and Hasbrouck and

Seppi (2000) use this method, and document some evidence of commonality in trading activity, mainly in the first three principal components in NYSE stocks in 1994 and1997/1998, respectively. The authors are very selective in terms of the sample period and sample stocks, choosing very active trading periods with high-frequency trading data available for very liquid stocks. Both availability of data and low market activity on the NASDAQ OMX Tallinn are limiting factors in application of the principal component approach in the context of this study.

4.1. Liquidity measures

Empirical literature outlines four main dimensions of liquidity, namely, tightness, market depth, resiliency, and trading time. In our analysis we use two different liquidity proxies – bid-ask spreads and volume-return relationship, representing tightness, depth and resiliency. The following sections outline the most common liquidity proxies. We present the liquidity measures used for our study and motivation behind our choice of these particular liquidity measures.

Tightness

Tightness is associated with the costs of undertaking a round-trip transaction at a point in time. More specifically, it is the cost investor bears if she buys and then sells the same stock at the same point in time. Therefore, the most widely used proxy for the tightness dimension of liquidity is the bid-ask spread.

The empirical literature suggests many modifications to the spread proxy. Effective spreads[10] are calculated as the difference between the execution price and the mid-quote. Goyenko, Holden and Trzcinka (2009) use the effective spread as one of their benchmarks of high-frequency data when analyzing the performance of 12 liquidity proxies representing spread dimension. They conclude that low frequency (for monthly and annual frequencies) effective spread and absolute spread are the best measures of spread dimension.[11] The effective spread captures the cost of trading more accurately compared to the absolute spread.

[10] For more effective comparison with other spread measures, it is suggested to multiply the price-midquote difference with 2 (also used in Hameed et al. (2010), Chordia et al. (2000)). This implies that effective spreads measures the same effect differently and their comparison might gauge important information. For example, Chordia et al. (2000) suggest that when the effective spread (multiplied by two) is smaller than the absolute spread, the trade has taken place within quotes. This signals about the aggressiveness of the trades and, therefore, induces important consideration for liquidity concept. In order to allow for across-stock comparison, the effective spread also is subject to proportional modification. In this case, the proportional effective spread is calculated as the module of the difference between the last trade price and the mid-quote and divided by the mid-quote or the last trading price (as in Chordia et al. (2000) and Chordia et al. (2001)).

[11] For more information on tested liquidity measures see Goyenko et al. (2009).

However, in a pure limit order market with no price improvements from security dealers effective spreads are equal to quoted (also known as absolute) spreads.

For example, Chordia et al. (2001) use the absolute spread[12] measured as the difference between the lowest ask price and highest bid price at a point in time for a particular stock.

Very often the proportional spread measures[13] are calculated, because it allows for cross-sectional stock comparison. The motivation behind the proportional spread measure usage is that nominally higher-priced stocks usually have higher spreads as opposed to smaller stocks, and therefore a fair comparison is not possible. For example, Hameed et al. (2010) use the proportional quoted spread (QSPR) calculated as the difference between the best bid and ask price and divided by the mid-quote.

Thus, the first liquidity measure we use is the proportional quoted spread (QSPR). We compute QSPR for each stock on a daily basis, based on the methodology by Hameed et al. (2010).[14]

$$QSPR = \frac{ask - bid}{midquote}, \text{ where } midquote = \frac{ask + bid}{2} \quad \textbf{(1)}$$

Depth and Resiliency

Another important liquidity dimension described in several papers is the depth of the market for a security or securities, or simply the ability to trade a certain security in large amount without affecting its price. If market or individual stock depth is high, it is said to be liquid.

Widely used liquidity proxies related to the depth dimension can be constructed either from one value (similar to spread proxies) or may include spreads, stock returns, and prices alongside depth, reflecting different dimensions of liquidity. For instance, the CompositeLiq measure used in Chordia et al. (2001) measures the slope of the liquidity in percent per dollar of volume and representing two dimensions of liquidity, namely, spread and depth.

Resiliency[15] is the third dimension of liquidity representing correction of after-shock pricing errors. Dong, Kempf and Yadav (2007) find that the relationship between the

[12] For the application of absolute spread (also known as a dollar spread or a quoted spread) see also Hasbrouck and Seppi (2001), Brockman and Chung (2003).
[13] Other modifications to the absolute spread measures include taking logs or differences to normalize the distribution as the distribution in the raw form is usually highly skewed.
[14] Particular method is also applied by Coughenour and Saad (2004), and Chordia et al. (2001).
[15] Evidence shows that there is similar common variation in resiliency across stocks as it is in liquidity, therefore proposing resiliency as another dimension of liquidity. Similarly, the trading time dimension (defined as the time necessary for trade to take place) is also varying across stocks in similar way as liquidity.

resiliency and other dimensions of liquidity though statistically significant is very weak. This can be explained by the relatively underdeveloped proxies for resiliency dimensions that are, in addition, mainly of use for intra-day transaction data, for example Variance Ratio and returns.

Amihud's (2002) ILLIQ measures an average price movement per unit volume, capturing both market depth and resiliency. High price sensitivity to order flow (high ILLIQ coefficient) indicates illiquidity. Amihud (2002) states that there are better liquidity measures out there; however, he acknowledges that his proposed measure is better compared to other measures in cases when microstructure data are not available and/or the data are available for relatively short period of time, as it is in our case. As concluded by Goyenko et al. (2009) Amihud's ILLIQ measure is a good proxy for price impact dimension (closely following the specification of Kyle's lambda), further referred to as volume-return relation. According to Bai and Qin (2010), this measure closely represents transaction costs for investors with large trade sizes.

Thus the second liquidity measure (LIQ) that we use in our paper is, calculated applying approach by Amihud (2002) and estimating a weekly illiquidity measure ($ILLIQ_{i,w}$) and then transforming it into a liquidity measure (as in Chordia et al. (2001); Korolyi et al. (2011); Kamara, Lou and Sadka (2007)).

$$ILLIQ_{i,w} = \frac{1}{D_{i,w}} \sum_{D=1}^{D} \frac{|R_{i,w,d}|}{DVOL_{i,w,d}}, \qquad \textbf{(2)}$$

where $R_{i,w,d}$ is the return on stock i on day d of week w and $DVOL_{i,w,d}$ is the respective daily volume in euro. $D_{i,w}$ is the number of days for which data are available for stock i in week w. By averaging the volume-return relationship over a weekly period we reduce the effects of market microstructure noise, present at higher frequencies. It would be more beneficial to calculate this measure at even lower frequencies or for longer time periods, however, the availability of observations limits us in doing so. We calculate the weekly liquidity measure as follows:

$$LIQ_{i,t} = -\log\left(1 + ILLIQ_{i,w}\right). \qquad \textbf{(3)}$$

<u>Trading time</u>

Even though the number of transactions per unit of time is a good trading time proxy (von Wyss, 2004), the relatively infrequent market activity can undermine the usability of such measure. In general this dimension shows different side of liquidity than spreads, depth and resiliency. However, due to intra-day data unavailability (which is crucial for the application of the proxy), and narrow empirical application, we consider appropriate to disregard this dimension for the purposes of this paper.

4.2. Models

Although there are no studies indicating strong seasonality trends on NASDAQ OMX Tallinn, we do adjust both liquidity measures to discard seasonality effects and obtain adjusted spreads ($ASPR_{i,t}$) and adjusted depth measures ($ALIQ_{i,t}$) for each stock on a daily and weekly basis, respectively. We do this adjustment according to methodology by Hameed et al. (2010), apart from including dummies for tick size changes, because there were no such changes in the period of January 2004 to the end of October 2010.

$$liquidity\_measure_{i,t} = \sum_{k=1}^{4} d_{i,k} DAY_{k,t} + \sum_{k=1}^{11} e_{i,k} MONTH_{k,t} + \alpha_1 YEAR_t + adjusted\_liquidity\_measure_{i,t} \quad \textbf{(4)}$$

Equation (4) contains: (i) 4 day of the week dummies ($DAY_{k,t}$) for Monday through Thursday; (ii) 11 month of the year dummies ($MONTH_{k,t}$) for February through December; (iii) a time trend variable $YEAR_t$ is equal to the difference between the calendar year when the trade takes place and 2004 or the first year when stock *i* started trading on NASDAQ OMX Tallinn, whichever is later.

The regression residuals, including the intercept, provide us the adjusted proportional quoted spread ($ASPR_{i,t}$) and adjusted volume-return liquidity measure ($ALIQ_{i,t}$). Some portion of the adjusted spreads are negative; however, we disregard it, because adjusted spreads do not have a direct economic meaning of bid-ask spreads, but rather represent an illiquidity measure in terms of market tightness.

4.2.1. Beta as the determinant of commonality

The first method for analyzing commonality in liquidity is adopted from the methodology by Hameed et al. (2010), but is applied employing two different liquidity measures described above.

To test commonality in liquidity we regress individual stock liquidity estimates on market liquidity proxies and control variables. Thus we need to calculate market liquidity estimates for both liquidity proxies ($ASPR_{m,t}$ and $ALIQ_{m,t}$), which we obtain by taking the average of the daily and weekly measures of stock-level adjusted liquidity measures, excluding stock *i* from the average for the corresponding market measure (this is necessary because otherwise due to the low number of stocks the weight of each stock in the average (market) value would be rather high and thus might result in biased commonality effects). We adjust the skewed ASPR measure by computing daily changes in spreads $\Delta ASPR_{i,t} = ASPR_{i,t} - ASPR_{i,t-1}$ (as in, e.g., Hameed et al. (2010)). We do the same for the market adjusted spread measure ($ASPR_m$)**.** Following Chordia et al. (2001) we use logarithmic changes in ALIQ ($ALIQ = \ln(\frac{ALIQ_t}{ALIQ_{t-1}})$), rather than levels, which is a more stationary robust measure.

The commonality regression specification is as follows:

$$\Delta liquidity\_measure_{i,t} = \alpha_i + \beta_{1i}\Delta liquidity\_measure_{m,t} + \sum_{k=1}^{n}\beta_{ki}\Delta liquidity\_measure_{i,t-k} + control\ variables \quad \textbf{(5)}$$

We regress changes in stock liquidity on changes in the market liquidity and lead and lag term of changes in adjusted stock liquidity measures. We use additional lead and lag terms for changes stock liquidity measures to determine the best regression specification and to account for possible autocorrelation effects, deriving the best regression specification according to AIC and p-value tests. Based on methodology by Hameed et al. (2010) we add to the regression the following control variables: (i) daily market returns data ($R_{m,t}$) and individual stock returns data ($R_{i,t}$), calculated as logarithm of price in period *t* divided by price in period *t-1* (OMX index for market returns) and their lagged values; (ii) changes in stock and market volatility ($\Delta STD_{m,t}$ and $\Delta STD_{i,t}$) and their lagged values to account for the increase in required liquidity premium in volatile times (as suggested by Vayanos (2004)) and overall changes in volatility; (iii) lagged change in market turnover ($\Delta TURN_{i,t-1}$), calculated as trade volume divided by the number of shares.

The time series regression equation is estimated for each stock in our sample, allowing the intercept and the coefficients for market liquidity measures and lead/lag terms of stock liquidity measures to vary on stock-by-stock basis, following Hameed et al. (2010) and acquiring mean coefficient values, standard errors and t-values. From β_{1i} (denoting sensitivity of the changes in individual stock illiquidity to changes in overall market illiquidity in case of ASPR regression and sensitivity of changes in individual stock liquidity to changes in overall market liquidity for ALIQ regression) in equation (5) we can see, whether there are commonality effects in the market (whether β_{1i} is statistically and economically significant).

We run additional tests to determine, whether commonality was present in NASDAQ OMX Tallinn both prior and after the crisis started, taking July 1, 2007 as the threshold.[16] We also look for possible impact of market makers on liquidity co-movements by creating a dummy variable MM equal to 1 when there was a market maker for a particular stock and equal to 0 otherwise. By interacting this dummy variable with changes in market liquidity measure, we can see whether there is any significant impact of market maker activity on commonality in liquidity.

At this point we can test for investor characteristics driving commonality in liquidity. We create variables denoting different investor types:

a) Institutional as opposed to individual investor impact is measured by a variable $Instit_{i,t}$, calculated as a ratio of volume of trades in a particular day made by institutional traders and funds to the total volume of trades. We calculate volume of trades made by multiplying quantity of the shares bought/sold by the price in a particular transaction. We separate nominee[17] trades and classify them as a separate, third type of investors ($Nom_{i,t}$), while funds are included in institutional investor category.

b) Local as opposed to foreign investor impact is measured by a variable $For_{i,t}$, calculated as a ratio of volume of trades in a particular day made by local traders to the total volume of trades.

c) Impact of investor gender is measured by a variable $Male_{i,t}$, calculated as a ratio of volume of trades in a particular day made by males traders to the total volume of trades made by local individuals (foreign individuals in the majority of cases do not have their gender specified in the dataset).

d) Large as opposed to small investor impact is measured by a variable $Large_{i,t}$, calculated as a ratio in volume of trades in a particular day made by large traders to the total volume of trades. We regard a trader as large if the size of his portfolio in the beginning of a particular month is in the top 20% of all portfolio values (sort investors in the beginning of each month by EUR value of their portfolios and create a dummy variable denoting that an investor is large for the top 20%).

[16] This date has been chosen, because shortly after the beginning of July 2007 the market experienced its first decline after a long period of growth, followed by more massive declines starting from August 2007 (see Appendix A, Figure 6).

[17] A nominee is an entity that trades on behalf of another entity.

At this point we look at volume of each trade, consisting of the volume sold and the volume bought, i.e., one transaction volume is counted in twice (for each trade party).[18] We include fractions of volumes for each stock on each particular trade date made by each trader type. To avoid perfect multicollinearity, we include only one of the two of each comparative investor types (e.g., only local for comparing local/foreign impact). We interact investor type trade proportion variables with changes in market liquidity proxies to determine the effect of particular investor types increasing liquidity co-movements.

$$\begin{aligned}\Delta liq\_measure_{i,t} &= \alpha_i + \beta_{1t}\Delta liq\_measure_{m,t} \\ &+ \sum_{n=-2}^{2} x_{ni}\Delta liq\_measure_{i,t-n} + \gamma_{1i}\left(Instit_{i,t} \times \Delta liq\_measure_{m,t}\right) \\ &+ \gamma_{2i}\left(Ind_{i,t} \times \Delta liq\_measure_{m,t}\right) + \gamma_{3i}\left(For_{i,t} \times \Delta liq\_measure_{m,t}\right) \\ &+ \gamma_{4i}\left(Large_{i,t} \times \Delta liq\_measure_{m,t}\right) + \gamma_{5i}\left(Male_{i,t} \times \Delta liq\_measure_{m,t}\right) \\ &+ \sum_{k=0}^{2} \delta_{ki}R_{m,t-k} + \sum_{p=0}^{2} \theta_{pi}R_{s,t-p} + \mu_{1i}\Delta STD_{i,t} + \mu_{2i}\Delta STD_{i,t-1} + \mu_{3i}\Delta STD_{m,t} \\ &+ \mu_{4i}\Delta STD_{m,t-1} + \mu_{5i}\Delta TURN_{i,t-1} + \varepsilon_{i,t}\end{aligned} \quad \textbf{(6)}$$

The coefficients in front of the interaction terms (γ) show whether and how changes in trade volume proportions by particular investor groups affect commonality in liquidity, i.e., whether the coefficient is positive/negative and significant. While β coefficients show general effect of changes in market liquidity on changes in individual stock liquidity, the γ coefficients show the additional effect of changes in market liquidity interacted with changes in trading volume proportions by particular investor types.

Including all investor types in the regression simultaneously allows us to account for cross-group membership of some investors and see just the net effect of each investor type on commonality in liquidity. We also add interaction terms (e.g., large institutions) to determine more detailed profiles of different investors affecting commonality in liquidity.

Afterwards, we check for the differences in results for down and up markets, by interacting the terms with a dummy variable for down market, defined as return being 1.5

[18] Such approach has some limitations in terms of continuity of variables (they can be only in boundaries from 0 to 1); however, it is more robust than dummy variables approach. We did test whether including log-transformed investor type variables into regressions would give us more robust results than using 0 to 1 bounded proportions. However, regression R^2 and AIC test showed that simple proportion regressions are better.

standard deviations smaller than the mean value of the observation period (as in Hameed et al., 2010).

Further, we also look at the effects of particular types of investors being on the sell/buy side. For this we create the following variables for investor type:

$$InstSell_{i,t} = \frac{Volume\_sold\_by\_institutional\_investors}{Total\_volume\_sold} \quad \textbf{(7)}$$

$$InstBuy_{i,t} = \frac{Volume\_bought\_by\_institutional\_investors}{Total\_volume\_bought} \quad \textbf{(8)}$$

This helps us see which types of investors drive commonality as sellers and which as buyers, and whether some particular group of investors drives commonality in liquidity both as a seller and a buyer, or just from one side, distinguishing between demand and supply-side drivers of commonality.

4.2.2. R-squared as the determinant of commonality

Our alternative method is derived from Amihud (2002) (see also, Bai and Qin, 2010; Chordia et al., 2000). R-squared of the regression is used as an alternative measurement of the effect of market liquidity on individual stock liquidity.

$$\Delta liquidity\_measure_{i,t} = \alpha_i + \beta_{liq,i}\Delta liquidity\_measure_{m,t} + \varepsilon_{i,t} \quad \textbf{(9)}$$

Liquidity measures used in this regression are calculated on a daily basis, which introduces more noise into the estimates, however, it allows us to have sufficient number of observations. As in Chordia et al. (2000) we add (i) one lead and lag of the market liquidity, (ii) contemporaneous, lead and lag market return, and (iii) stock return volatility measure (Chordia et al. (2001) use stock squared return for this purpose) of the same period to the regression specification. These variables are particularly important in the spread regression. Market liquidity leads and lags are necessary to capture any lagged adjustment in commonality. Market return is included to remove the co-variation between liquidity measures and market return (particularly relevant to the spread measure, which is a function of the prices). Volatility control variable captures the increase in required liquidity premium in volatile times.

We run this regression for each stock on a two-month basis, save R-squared of this regression, and create a new variable

$$ComLiq_{i,t} = \log\left(\frac{R_{i,t}^2}{1-R_{i,t}^2}\right), \quad \textbf{(10)}$$

as in Bai and Qin (2010), where they perform logit transformation of the R^2 (bounded within the interval from 0 to 1) in order to make it a continuous unbounded variable. This is done for each stock, which has at least 30 observations on a two-month basis.

For each two-month period and each stock we regress commonality in liquidity on proportions of trade volume by investor types in the period for a particular stock, adding control variables (supplemented by the overall level of liquidity ($LevLIQ_t$), captured through $ALIQ_m$ and $ASPR_m$ variables).

$$ComLiq_{i,t} = \alpha_i + \gamma_{1i}Inst_{i,t} + \gamma_{2i}Ind_{i,t} + \gamma_{3i}For_{i,t} + \gamma_{4i}Large_{i,t} + \gamma_{5i}Male_{i,t} + \mu_{1i}R_{m,t} + \mu_{2i}STD_{m,t} + \mu_{3i}TURN_{i,t} + \mu_{4i}LevLiq_t + \varepsilon_{i,t} \quad \textbf{(11)}$$

From the γ coefficients on the investor characteristic variables we can see how the different investor groups affect commonality in liquidity (whether the effect is statistically significant and positive or negative).

Afterwards, we perform similar tests as in the first method to distinguish the effects of particular investors being on the sell/buy side of the transaction, and check for the differences between liquidity determinants in down and up markets.

5. Results

5.1. Descriptive statistics

We start our analysis by exploring the relationship between the four dependent variables on which basic regressions were based. ALIQ and ASPR show negative relationship as ALIQ measures liquidity and ASPR measures illiquidity.[19] Their correlation coefficient is -0.2488 (see Appendix B, Table 3). The negative correlation is reasonable, since ALIQ is a liquidity measure, while ASPR measures illiquidity (transaction costs). The extreme volatility is present on NASDAQ OMX Tallinn from 2008 to 2010, where the liquidity measured by ALIQ fluctuates in the range of more than 6 standard deviations below its mean value compared to negligible fluctuations from 2005 to 2008 in the range up to 3 standard deviations. It can be observed that during the two periods when ALIQ coefficients

[19] We explain the differences in ALIQ and ASPR measures in methodology section of this paper.

are extremely volatile the spreads (ASPR) are the highest, clearly outlining the negative relationship between the two measures (see Appendix A, Figure 1).

As opposed to ASPR and ALIQ relationship, both measures of commonality in liquidity (ComLiqALIQ and ComLiqASPR, based on ALIQ and ASPR measures, respectively) have large positive co-movement with correlation coefficient between the two being 0.7670 (Appendix B, Table 4). The high correlation between the two coefficients means that although they capture different dimensions of commonality, they tend to fluctuate across all three dimensions in a similar manner.

We are also interested in the trading patterns of various investor types, determined using the trade-level data of NASDAQ OMX Tallinn. As specified in the methodology we distinguish investor types according to their portfolio size, gender, account type (individual, institution, nominee), and whether investor is local or foreign. Figures 7 to 10 (see Appendix A) show daily average trading volume proportions that each investor type contributes to the total trading volume on a daily basis. It can be observed that large investors[20] trading volume contributions have a cyclical trend (see Appendix A, Figure 7). Large investors contributed on average around 40% of the trading volume during periods of 2004 to mid-2005 and 2007 to mid-2008. During the rest of the observation period their trading activity contribution decreased significantly to negligible proportion of around 5-10%. Such variation in the trading proportions is good for identifying the effects of investor types on commonality. Small investor trading volumes contribute on average around 75% of the total market trading volume throughout the whole sample period. The vast majority of individuals are male investors contributing 85% of individual trading volume (see Appendix A, Figure 10).

Figure 8 (see Appendix A) portrays that institutional investors have the highest trading volume proportion as opposed to individuals and nominees with a tendency to decrease since mid-2007. It is also important to note that the trading volume proportion of nominee investors has increased since mid-2007 to approximately 25%. However, nominees (2256 unique trading accounts) mainly consist of foreign institutions (2246 unique trading accounts in the sample). This implies that institutional investors (both foreign and local) contribute around 70% of the total trading volume.

NASDAQ OMX Tallinn has persistent domestic investor activity in the market during the whole sample period. Their average trading volume contributes more than 60% of the whole trading volume. However, trading proportion by foreign investors has increased

---

[20] Large investor defined as one whose portfolio size in the beginning of each month is in top 20 percentile of all investors' portfolio holdings.

significantly in recent years capturing 30% of all trading volume generated on NASDAQ OMX Tallinn (see Appendix A, Figure 9).

5.2. Commonality in liquidity

We measure commonality in liquidity in two ways. First, when regressing individual stock liquidity measures by market liquidity measures, we see presence of commonality if the beta coefficient for market liquidity measure (denoting sensitivity of individual stock liquidity changes to changes in market liquidity) is positive and significant. As can be seen in Appendix C, Table 7, these coefficients are significant and positive both for liquidity measured through bid-ask spreads and volume-return relation. The coefficient denoting sensitivity of changes in individual stock tightness (spreads) to changes in market tightness (ASPR) is 0.105 and significant at 5% significance level. Such effect has a high economic significance equal to more than 10 standard deviations of the mean changes in adjusted spread for individual stocks (dASPR). The commonality coefficient for the price impact of trading (ALIQ) is 0.071 (significant at 1% significance level), but it has a lower economic strength, equal to 0.3 of a standard deviation of the changes in volume-return liquidity measure on individual stock level (dALIQ). Due to the level of complexity and seasonality adjustments made to the liquidity measures no straightforward economic interpretation of the results can be made. Therefore, we analyze our results in terms of significance, direction, and comparative magnificence (whenever possible).

Another way of measuring commonality in liquidity is through R-squared of regression, where changes in individual stock liquidity are regressed on changes in overall market liquidity and control variables. Variation in R-squared represents variation in commonality in liquidity and can be used for determining factors influencing it. The R-squared for volume-return liquidity measure (ALIQ) ranges from 0.0004 to 1 (mean of 0.3281), while that for the spreads (ASPR) is higher, ranging from 0.0408 to 1 (mean of 0.6173). Both are approximately normally distributed. Correlation coefficient between R-squared measures is 0.7504, showing that co-movement in spreads and co-movement in volume-return relation are highly correlated (Appendix A, Figures 4 and 5).

We test whether the commonality depends on the presence of market makers in the market by interacting a dummy denoting presence of market makers for a particular stock at a particular time with changes in market liquidity measures (see Appendix C, Table 8). We do not find any significant evidence for market makers having an impact on commonality in liquidity.

In addition, we examine existence and strength of commonality in NASDAQ OMX Tallinn during different time periods, namely, before and after July 2007. As can be seen in Appendix C, Tables 9 and 10, we find significant commonality effects for both liquidity measures after July 2007. Before July 2007, only commonality in volume-return measure is significant and even stronger than after mid-2007. Commonality coefficient for spreads before July 2007 is not statistically significant, but after July 2007 it is 0.151 (17 standard deviations). The coefficient for the price impact of trading before July 2007 equals 0.095 (0.4 standard deviations), while after July 2007 it equals 0.060 (0.27 standard deviations).

5.3. Drivers of commonality in liquidity

Regressions determining effect of investor trading activity on commonality in liquidity have considerably high explanatory power with R-squared of 0.3 to 0.5, depending on the liquidity measure and regression type.[21]

Institutions/individuals

First, we compare individual, institutional investors, and nominees. Results suggest that increases in individual investor trading lead to increases in commonality in liquidity (see Appendix D) across all liquidity dimensions. For example, an increase in individual trading proportion from 0 to 1 has a significant and positive impact on commonality in spreads of 1.335 times (Appendix D, Table 11, Regression 1). When liquidity is measured in terms of the price impact of trading, particularly, selling proportion increase by individuals contributes to increases in commonality (Appendix D, Table 15). However, as suggested by results in Appendix D, Table 12 increase in sales proportion by individuals from 0 to 1 (as opposed to selling by institutions and nominees, and purchases by all three investor groups) reduces commonality in spreads by 1.4. Results also suggest that the positive impact on commonality in spreads by individual investors is reduced when proportion of male buying increases (Appendix D, Table 12). Interaction terms regressions suggest that increase in trading proportion, and particularly buying, by large individuals considerably decreases commonality in spreads (Tables 11 and 12), but has a positive impact on commonality in volume-return relation (Tables 14 and 20).

The effect of institutional investor trading proportions increases on commonality in liquidity is positive. Both spread and market-depth regressions suggest that increases in

[21] Regression R^2 are not reported in the results section due to regressions being run on stock-by-stock basis and high variability of their explanatory power. However, when running pooled panel regressions (to ensure robustness of results and standard errors, but not reported here) the R^2 values for dASPR, dALIQ, ComLiqASPR, ComLiqALIQ regressions were as follows: 0.45, 0.32, 0.33, and 0.37, respectively.

institution trading increases commonality in liquidity. For example, increase in institutional trading proportion from 0 to 1 leads to volume-return commonality beta increase by 0.171 (Table 14). Institutional selling increases commonality in the price impact of trading (0.480), but decreases commonality in spreads (-2.376).

When comparing coefficients of individual as opposed to institutional investor impact on commonality, individuals seem to be stronger commonality drivers across all three liquidity dimensions (Tables 11 and 14). Even though the results for individual/institutional investors are not highly conclusive in terms of comparative magnificence of the effects of their trades, a clear trend emerges showing that individual and institutional trades increase commonality in liquidity as opposed to trades by nominees, who reduce commonality in all liquidity dimensions. However, as discussed in the descriptive statistics section, the majority of nominees are foreign institutions. Subsequently, the results that derive from the investor group classified as nominees should be interpreted with caution.

When interacting investor type trade proportion variables with market downturn dummy, we discover that the trend in spread commonality determinants reverses for spreads (Appendix D, Table 13). In the down markets increases in individual investor trades reduce commonality in spreads as opposed to trades by institutions and nominees. Institutions still increase commonality in market-depth (particularly, foreign) and spreads during downturns (Tables 13, 16, 19).

Local/foreign

Comparing impact on commonality of trading by foreign and local investors, we find that increases in foreign investor trading decreases liquidity for volume-return relation (-0.160, Table 14), but increases commonality in spreads (0.349, Table 11). This trend seems to be driven by foreign investor selling for commonality in spreads (1.499, Table 12). For both dimensions these results are not robust to adding controls for whether an investor is institutional or individual, large or small.

In down markets, however, the trend reverses completely. Increases in proportion of trading by foreign institutions increase commonality in market depth and resiliency (3.491, Table 16), but strongly decrease commonality in spreads (-7.128, Table 13). During downturns large foreign investor trading increases commonality in bid-ask spreads.

Large/small

The results with regard to investor size are similar to those for institutions. In general large investors increase commonality in volume-return relation both during stable times and in market downturns. The impact of investor size on commonality in liquidity is different for co-movements in spreads and in volume-return relation. Increase in trading proportion by large investors reduces commonality in bid-ask spreads (-0.571, Table 11), particularly, buying by large investors. However, this is likely to be because institutional investors are often large and the result can be attributed to the institutional investors, because size effect becomes insignificant or even reversed when we control for institutional trades (Table 11, regression 5; Table 17, regression 5). Results suggest that large investors increase commonality in price impact of trading (0.342, Table 14), with a significant impact coming from sales by large investors. This result is robust to including proportions of institutional and individual regressions, which preserve their initial impact (Table 14, regression 5). When we include in the regression all interaction terms and determine a pure effect of large investor trading activity increases on commonality in liquidity, we find that large investors decrease commonality across both dimensions (Tables 11 and 14, regression 10). However, in the real life majority of large investors are actually institutions or nominees with the respective impact on commonality.

During market downturns increase in proportion of trading by large investors leads to higher commonality in liquidity across the three liquidity dimensions studied.

Table 1. Results summary

The table summarizes conformity of the results with the proposed hypotheses. “Yes” means a statistically significant impact in the expected direction. “No” means a statistically significant impact in the opposite direction from what was expected. “-” denotes no statistically significant effect.

Hypotheses		ASPR	ALIQ
H1	Institutional (foreign and domestic) investor trading induces co-variation across individual stock liquidity	yes	yes
H2	In general individual investors drive commonality in liquidity	yes	yes
H3	Individual investors drive commonality in liquidity in down markets	no	-
H4	In down markets trading by men drive commonality in liquidity more than trading by women	-	-
H5	Large investor trading drives commonality in liquidity in down markets	yes	yes

Source: created by the authors.

6. Discussion

We find strong evidence of existing commonality in liquidity both in terms of bid-ask spreads and price impact of trading in the Estonian stock market in the period of 2004-2010. As opposed to findings by Hasbrouck and Seppi (2001), the effects are strong and significant both during market downturns and market growth. Commonality in price-volume relation is actually even stronger during steady market phases. Moreover, the effects of commonality in spreads are stronger than documented in previous research. For instance, Hameed et al. (2010) document the sensitivity of changes in individual stock ASPR to changes in market

ASPR to be around 0.56 (around 0.6 standard deviations of ASPR mean measure) in NYSE (see Appendix B, Table 6 for more details), while our results suggest it is 0.105 (3 standard deviations of ASPR mean). Even though the measures cannot be perfectly compared due to the little amount of descriptive statistics Hameed et al. (2010) provide in their paper, this indicates that commonality effects might be significantly stronger in emerging as compared to developed markets. This could be caused, first, by a different market design (order driven instead of a hybrid market) and, second, by the level of development of NASDAQ OMX Tallinn, which as discussed earlier are factors contributing to stronger liquidity co-movement (Zheng & Zhang, 2006; Bekaert et al., 2007). Such finding has important implications for future research. Morck et al. (1999) find that the systemic component and commonality in returns in emerging markets is larger than in developed markets, leading to higher commonality in returns. Our finding suggests that a similar phenomenon might also exist for commonality in liquidity, which is higher in emerging markets due to a larger ratio of systemic to idiosyncratic liquidity risk of a security.

The results of both methods applied in this thesis also suggest that commonality in market tightness is in general stronger than commonality in market depth and resiliency. This might imply that to some extent commonality in spreads can be controlled through incentivizing market maker activity, both formal and informal, since market makers have to keep bid-ask spreads in some specific range. However, the results of market makers having a negative impact on commonality in spreads are not statistically significant. This might be the case due to the small number of observations in which formal market maker is present, especially during the period when commonality in spreads was the strongest (after mid-2007).

Our results support findings by Bai and Qin (2010) and our first hypothesis that institutional investor trading induces liquidity co-movements. The authors measure liquidity in terms of the price impact of trading, using the same specification of dollar volume-return relation. In addition we find that institutional investor sales are a stronger driver of commonality in liquidity than institutional stock purchases, which is in line with findings of Heston et al. (2010) regarding autocorrelation in fund redemptions. Moreover, this effect cannot be attributed only to extreme market conditions during crises. Institutional investors drive commonality in all liquidity dimensions studied at all times, which can be explained by similarities in trading patterns among institutions, arising from similar private signals and positive feedback trading (Sias & Starks, 1997). During stable times the effect on commonality in liquidity arising from institutional trades in general is weaker for institutions compared to individuals. However, in down markets institutions become the main commonality drivers. One possible explanation for this is that institutions perform functions of informal market makers (i.e., providing liquidity (depth) and stabilizing spreads during tranquil times), but withdrawing and undertaking flight-to-liquidity behaviour due to rising inventory risk when returns become negative (as discussed in Chordia et al., 2000). During downturns institutions (often characterized as more informed traders) are likely to actively strive to exit their portfolio positions, as a result reducing market depth and resiliency by large trades (Bai & Qin, 2010) and widening bid-ask spreads across a wide range of securities.

Individual investors, in general, drive commonality in liquidity (both tightness and depth), which supports our second hypothesis. The positive effect of increases in individual trade proportions on volume-return relation and on spread co-movements is even higher than that of institutional investor trades. This might suggest that commonality during stable times arises from noise trading and reluctance of individuals to change their trading patterns (as in Barber et al. (2009)). The results, however, contradict our third hypothesis, namely, that individual investors' trading drives commonality in liquidity in down markets. This might not imply that the reasoning with regard to individuals demanding liquidity during crises is wrong; rather that institutional portfolio rebalancing impact is much more vigorous due to the larger shareholdings of institutions. As a result, increases in the proportion of trading by individuals lead to lower commonality in liquidity, because it means a relative decrease in trading by institutions. Moreover, such result supports the theory of disposition effect (Shefrin & Statman, 1985), namely that individuals tend to hold on to stocks during their price decreases.

Our data support findings of previous research (e.g., Barber & Odean, 2001) documenting more active trading by men as opposed to women (Appendix A, Figure 10). The regression results, however, do not provide strong evidence in favour of our fourth hypothesis that males drive commonality in liquidity in down markets. Even though increases in the proportion of trading by males, relative to females, leads to higher commonality in the volume-return relation during market downturns, the effect is not significant when controlling for trading by individuals in general. This suggests that there is no significant difference in how males and females affect the commonality of liquidity.

The results for investor size are similar to those for institutions. Large investors increase commonality in liquidity, particularly, during market downturns. For bid-ask spreads this result remains robust after adding controls for cross-group investor belonging (e.g., investor being both large and institution, identifying the pure effect of the portfolio size), implying that the effect of large investors increasing commonality in spreads is independent of the fact that most large investors are institutions. Moreover, the effect of large investors on co-movements in all liquidity dimensions studied is at least three-times as strong during market downturns (Tables 13 and 16), which supports our fifth hypothesis that large investor trading drives liquidity in down markets. This is in line with suggestion by Anginer (2010) that in down markets large investors supply liquidity to benefit from high return premium from sales of liquid stocks.

When examining the results jointly from the perspective of our third and fifth hypotheses, we find that both stock sales by individuals and purchases by large investors drive commonality in the volume-return relation, with a marginally stronger effect from the latter. This suggests that in general co-movements in volume-return relations are driven by the supply side. In down markets, this effect for the volume-return relation is not significant, while bid-ask spread results clearly suggest that large investors drive commonality in spreads during market downturns by supplying liquidity to the market.

The detailed investor information in the dataset allows us to analyze how local compared to foreign investors affect commonality in liquidity. Due to the lack of literature directly related to this issue we did not propose any particular hypotheses. The results suggest that in general increases in the proportion of foreign investor trading increases commonality in spreads. This can be explained by foreign investors being highly subject to positive feedback trading (as argued by Choe, Kho & Stulz (1999)) and therefore exhibiting more similar trading patterns than local investors. As a result, foreign investor sales drive spread co-movement. In down markets, however, foreign investors reduce commonality in spreads as opposed to local investors. Foreign investors are likely to hold more internationally diversified portfolios, which might lead to more rational behaviour when deciding upon entering/exiting a position with a larger consideration given to liquidity effects (i.e., due to international diversification foreign investors are more likely to have more capacity to avoid fire-sales and wait for better conditions in a particular market in terms of prices and liquidity). Such change in trading behaviour of foreign investors has been identified earlier. Choe et al. (1999) studied Korean stock market and found evidence in favour of strong positive feedback trading by foreign investors before the Korean crisis and its significant diminution during the crisis. As a result, we can conclude that in down markets local investors drive liquidity co-movements. We disregard the effect of foreign investors on volume-return co-movements since its significance is highly subject to controlling for other investor characteristics.

The results on how different investor types affect commonality in liquidity allow us to make inferences for possible ways of general welfare maximization. If we consider an investor's contribution to commonality in liquidity as a negative externality imposed on other investors, according to the principles of welfare economics taxation and/or subsidies can be used as tools to reduce the negative effects of such externality. Since it is the most important to limit liquidity commonality in down markets, we discuss the possible solutions exactly from this perspective. Institutional and large traders are strong commonality drivers during market downturns. On one hand, increasing fees for these investor groups or lowering trading fees for individual and small investors would reduce commonality in liquidity during market downturns. However, in general this is likely to result in less informationally efficient[22] and less liquid markets, since institutional investor activity in terms of informal market making would decrease and, as a result, so would their positive effect on spread stability. The resulting trade-off should be evaluated for each stock market individually to identify the benefits and costs of the proposed solution. Nominees clearly reduce commonality in liquidity, which implies that encouraging more trading activity by brokers and other nominees would reduce liquidity co-movements. Exchanges could offer nominee traders more beneficial terms and conditions. This would allow them to lower commission fees and shift market activity towards more trades by nominees as opposed to individual and institutional investors. Moreover, nominees are also likely to be involved in informal market making, thus their trading increase would lead to higher liquidity and more stability in spreads.

Even though foreign investors in general are stronger commonality drivers than local investors, to limit commonality effects in down markets foreign investor trading should be incentivized. Higher cross-market integration would also result in a higher trading proportion by foreign investors. The finding with regard to foreign investor trading reducing commonality during downturns might imply that higher level of market integration and more interconnected market networks would reduce the systemic component of liquidity risk. Several recent studies of network structure effects on systemic risk (e.g., Acemoglu (2012)) arrive at similar conclusions, showing that large and interconnected networks are more robust to systemic shocks occurring in separate network entities.

[22] According to findings by Krustiņš and Siliņa (2011) institutional investors have a disproportionately positive contribution to price discovery and informational efficiency.

7. Conclusions

The purpose of this thesis is to study commonality in liquidity in NASDAQ OMX Tallinn and determine what investor types drive it. By applying two different methodological approaches we examine liquidity co-movements across three liquidity dimensions (namely, bid-ask spreads, market depth and resiliency) represented by two liquidity measures. We find strong commonality for both and establish that trading activity by different investor groups affects commonality differently.

Our results suggest that liquidity co-movement in NASDAQ OMX Tallinn in general is strong during the whole sample period. Commonality in the volume-return relation is stronger before mid-2007 than in the following period (2004-2010), while commonality in spreads becomes significant only after the beginning of the crisis in 2007. Overall, commonality in spreads appears to be larger than commonality in the price impact of trading. Our data provide no significant evidence with regard to the impact of market maker presence on commonality in either liquidity dimension, despite the theoretically logical reasoning of market makers reducing commonality in spreads. Further studies in markets with more permanent activity of market makers might benefit the body of knowledge by determining whether encouraging market maker presence helps to limit commonality in spreads.

We find that in general increases in the proportion of trading by individual, large, and foreign investors lead to higher commonality in liquidity, but trading by nominees, small, and local investors decreases commonality. Due to particularly high importance of commonality leading to liquidity dry-ups during market downturns, we distinguish the effects of different investor types during phases of market declines and increases separately. The results suggest that in down markets trading by small individual investors and by foreign investors reduces commonality in liquidity.

On the theoretical level our results imply that to enhance market stability by reducing commonality in liquidity policy-makers, exchanges, and regulators could consider measures that provide incentives for individual and nominee trading as opposed to institutional trading, e.g., by discriminating in terms of trading costs. Practically, however, less institutional and large investor trading might result in adverse effects on market quality and this downside would have to be weighed against the benefits. Our findings provide evidence that a higher level of international market integration (resulting in more active trading by foreign investors) would make the liquidity of markets more robust to systemic shocks.

As the systemic component of liquidity risk, the strength of commonality in liquidity has implications for asset pricing. Market participants should expect stocks actively traded by commonality-increasing investor groups (e.g., large investors) to be more risky and have higher required returns, all else equal.

Our paper outlines several directions for future research. First, stronger liquidity commonality in NASDAQ OMX Tallinn than in NYSE might mean that the ratio of systemic to idiosyncratic components of liquidity is significantly higher in emerging than developed markets (as already identified for commonality in returns by Morck et al., 1999). Second, in-depth investigation of the effects of formal and informal market makers on commonality in liquidity would have important practical implications for ensuring market stability. Third, since we study only the impact of investor trade proportions on commonality, investigating additional effects of investor stock holdings and trade initiation would contribute to the existing body of literature on commonality in liquidity.

8. References

Acemoglu, D. (2012, January 6). Systemic risk: Insights from networks [Video webcast] [AFA Lecture]. In *The American Finance Association* website. Retrieved from http://www.afajof.org/

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets, 5*(1), 31-56.

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics, 17*(2), 223-249.

Anginer, D. (2010). Liquidity clienteles. Transaction costs and investment decisions of individual investors. Policy Research Working Paper, 5318, The World Bank.

Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics, 77*(2), 375-410.

Bai, M., & Qin, Y. (2010). Who Are Driving Commonality in Liquidity? *Global Economy and Finance Journal, 3*(1), 61-77.

Barber, B. M., & Odean, T. (2001). *Boys will be boys: gender, overconfidence, and common stock investment. Quarterly Journal of Economics, 116*(1), 261-292.

Barber, B. M., & Odean, T. (2005). Individual investors, in R. Thaler *Advances in behavioural finance* Volume II, Princeton Univesity Press, Princeton.

Barber, B. M., Odean, T., & Zhu, N. (2009). Systemic noise. *Journal of Financial Markets, 12*(4), 547-569.

Bauer, W. (2004). Commonality in liquidity in pure order driven markets. Working paper. The National Centre of Competence in Research.

Bekaert, G., Harvey, C. R., & Lundblad, C. (2007). Liquidity and expected returns: lessons from emerging markets. *Review of Financial Studies, 20*(5), 1783-1831.

Brennan, M., & Subrahmanyam, A. (1996). Market microstructure and asset pricing: on the compensation for illiquidity in stock returns. *Journal of Financial Economics, 41*(3), 441-464.

Brockman, P., & Chung, D. Y. (2003). Investor protection and firm liquidity. *Journal of Finance, 58*(2), 921-937.

Brunnermeier, M. K. (2009). Deciphering the Liquidity and Credit Crunch 2007-2008. *Journal of Economic Perspectives, 23*(1), 77-100.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies, 22*(6), 2201-2238.

Campbell, J.Y., Ramadorai, T., & Schwartz, A. (2009). Caught on tape: Institutional trading, stock returns, and earnings announcements. *Journal of Financial Economics, 92*(1), 66-91.

Čekauskas, K., Gerasimovs, R., Liatukas, V., & Putniņš, T.J. (2011). The effects of market makers and stock analysts in emerging markets. *International Review of Finance (forthcoming).*

Choe, H., Kho, B. K., & Stulz, R. M. (1999). Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics, 54*(2), 227-264.

Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics, 56*(1), 3-28.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. *Journal of Finance, 56*(2), 501–530.

Comerton-Forde, C., & Rydge, J. (2006). Director holdings, shareholder concentration and illiquidity. Working paper. University of Sydney.

Comerton-Forde, C., Hendershott, T., Jones, C. M., Moulton, P. C., & Seasholes, M. S. (2008). Time variation in liquidity: the role of market maker inventories and revenues. *Journal of Finance (forthcoming).*

Corwin, S. A., & Lipson, M. L. (2011). Order characteristics and the sources of commonality in prices and liquidity, *Journal of Financial Markets (forthcoming).*

Coughenour, J. F. & Saad, M. M. (2004). Common market makers and commonality in liquidity. *Journal of Financial Economics, 73*(1), 37-69.

Dong, J., Kempf, A., & Yadav, P. K. (2007). Resiliency, the neglected dimension of market liquidity: Empirical evidence from the New York Stock Exchange. Working paper. Lancaster University Management School, University of Cologne, Oklahoma University.

Domowitz, I., & Wang, X. (2002). Liquidity, liquidity commonality and its impact on portfolio theory. SSRN Working Paper. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=296870&

Easley, D., Hvidkjaer, S. & O’Hara, M. (2002). Is information risk a determinant of asset returns? *Journal of Finance, 57*(5), 2185-2221.

Goyenko, Y., Holden, C.W. & Trzcinka, C.A. (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics, 92*(5), 153-181.

Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock market declines and liquidity, *Journal of Finance, 65*(1), 257-293.

Hasbrouck, J., & Seppi, D. J. (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics, 58*(3), 383-411.

Heston, S.L., Korajczyk, R.A., Sadka, R. (2010) Intraday patterns in the cross-section of stock returns. *Journal of Finance, 65*(4), 1369-1407.

Hollifield, B., Miller, R. A., Sandas, P., & Slive J. (2001). Liquidity supply and demand: Empirical evidence from the Vancouver Stock Exchange. Working paper. Rodney L. White Center for Financial Research.

Huberman, G., & Halka, D. (2001). Systemic liquidity. *Journal of Financial Research, 24*(2), 161-178.

Kamara, A., Lou, X., & Sadka, R. (2007). The divergence of liquidity commonality in the cross-section of stocks. Working paper. University of Washington.

Karolyi, G. A., Lee, K., & van Dijk, M. A. (2011). Understanding commonality in liquidity around the world. *Journal of Financial Economics (forthcoming).*

Koch, A., Ruenzi, S., & Starks, L. (2009). Commonality in liquidity: a demand-side explanation. Working paper. University of Pittsburgh.

Krustiņš, K., & Siliņa, Z. (2011). Cross-market and micro-level price discovery in the Baltic stock market. SSE Riga Student Research Papers.

Morck, R., Yeung, B., & Yu, W. (1999). The information content of stock markets: Why do emerging markets have synchronous stock price movements? Working paper. University of Michigan.

NASDAQ OMX Group. (2011). *The NASDAQ OMX Group.* Retrieved November 12, 2011, from www.nasdaqomxbaltic.com

Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*(3), 642-685.

Pukthuanthong-Le, K., & Visaltanachoti, N. (2009). Commonality in liquidity: evidence from the stock exchange of Thailand. *Pacific-Basin Finance Journal, 17*(1), 80-99.

Shefrin, H., & Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. *Journal of Finance, 40*(3), 777-790.

Sias, R.W., & Starks, L.T. (1997). Return autocorrelation and institutional investors. *Journal of Financial Economics, 46*(1), 103-131.

Vayanos, D. (2004). Flight to quality, flight to liquidity and the pricing of risk. Working paper. London School of Economics.

von Wyss, R. (2004). *Measuring and predicting liquidity in the stock market.* (Unpublished doctoral dissertation). University of St.Gallen. Riazzino: Novidea di Luigi Hofmann.

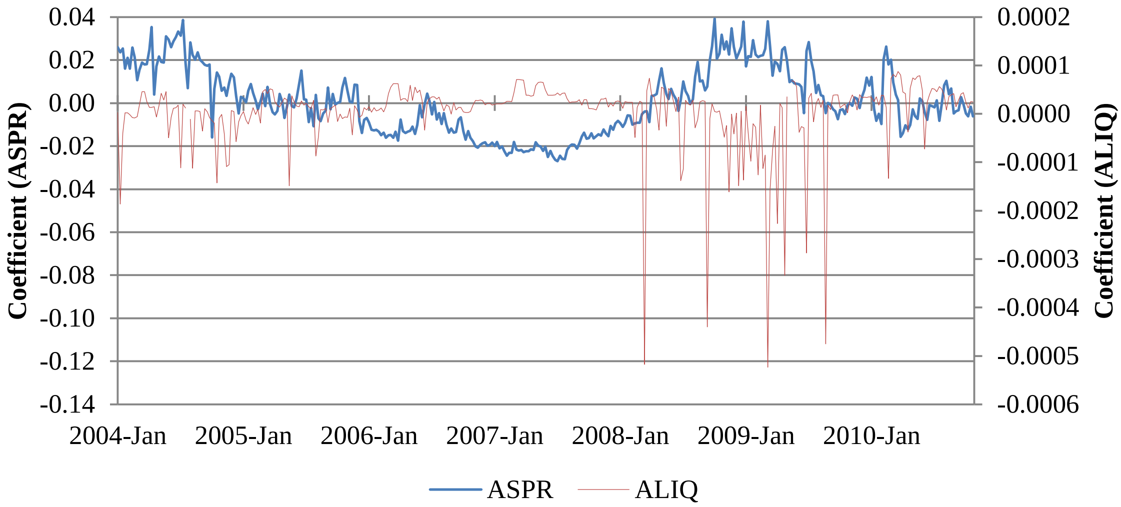
Wurgler, J. (2000). Financial markets and the allocation of capital. *Journal of Financial Economics, 58*(1), 187-214.

Zheng, X., & Zhang, Z. (2006). Commonality in liquidity in emerging markets: Evidence from the Chinese stock market. Working paper. University of Durham.

Appendix A: Figures

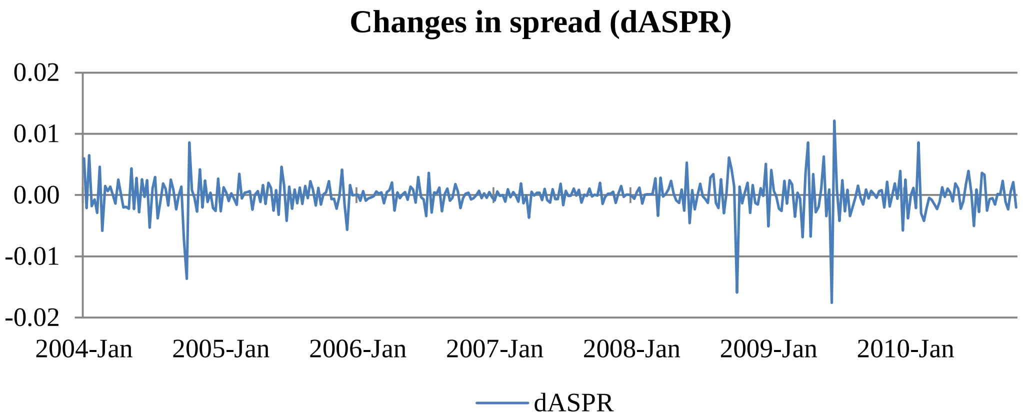
Figure 1. Interconnection of spread (ASPR) and liquidity (ALIQ)

The figure plots weekly evolvement of ASPR and ALIQ coefficients through for period from January 2004 to October 2010. ASPR and ALIQ are average liquidity measures of all stocks on a weekly basis, computed from adjusted liquidity measures ($ASPR_{i,t}$ and $ALIQ_{i,t}$) for each stock on a daily basis using the following specification: $liquidity\_measure_{i,t} = \sum_{k=1}^{4} d_{i,k} DAY_{k,t} + \sum_{k=1}^{11} e_{i,k} MONTH_{k,t} + \alpha_1 YEAR_t + \ asjusted\_liquidity\_measure_{i,t}$



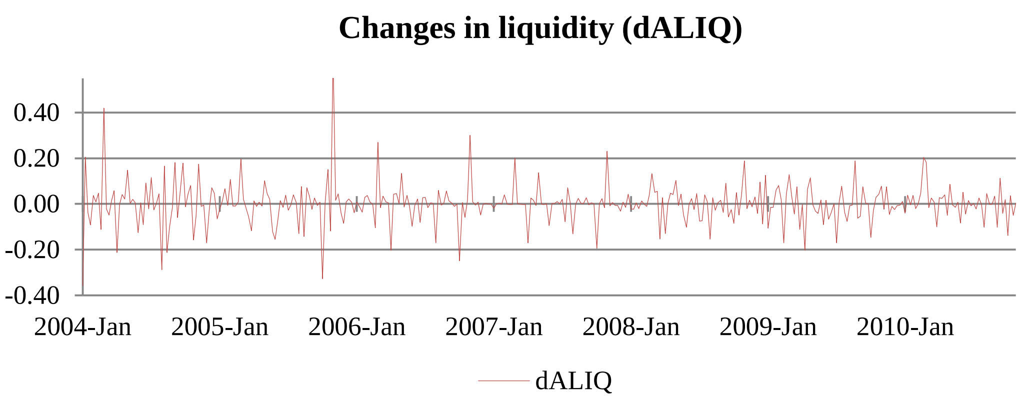
Source: created by the authors using regression outputs from NASDAQ OMX Tallinn trade-level data.

Figure 2. Interconnection of spread changes (dASPR) and liquidity changes (dALIQ).



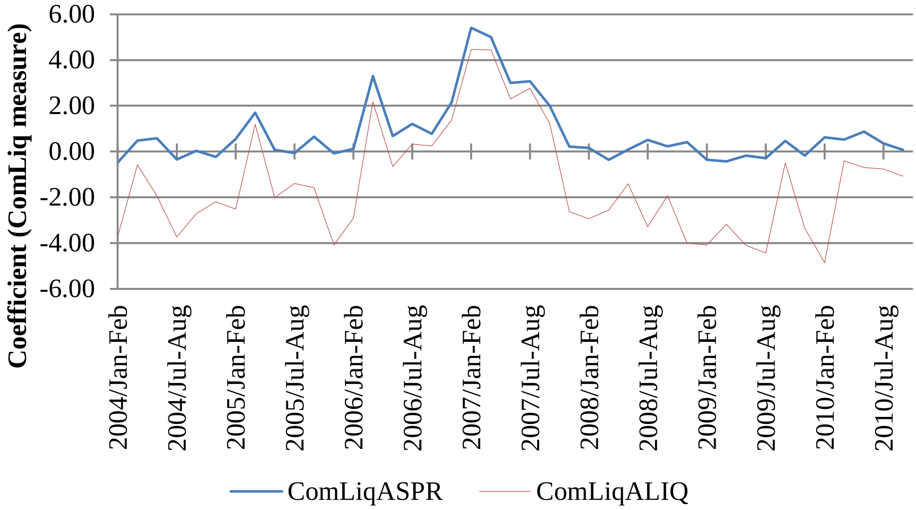
Source: created by the authors using regression outputs from NASDAQ OMX Tallinn trade-level data.

Figure 3.



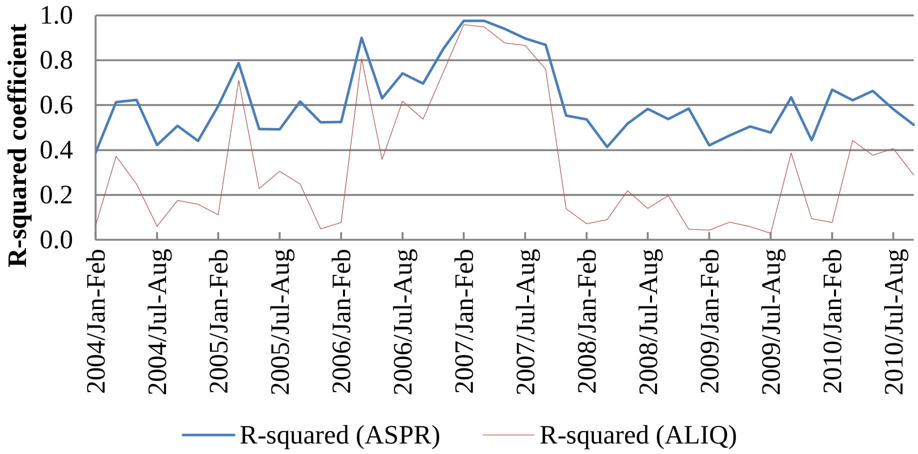
Source: created by the authors using regression outputs from NASDAQ OMX Tallinn trade-level data.

Figure 4. Commonality in liquidity measured by ALIQ and ASPR
This graph plots commonality in liquidity on NASDAQ OMX Tallinn using two separate measures ComLiqASPR (mean -0.12) and ComLiqALIQ (mean 2.27) on a 2-month basis from January 2004 to October 2010.



Source: created by the authors using regression outputs from NASDAQ OMX Tallinn trade-level data.

Figure 5. R-squared of ALIQ and ASPR type regressions

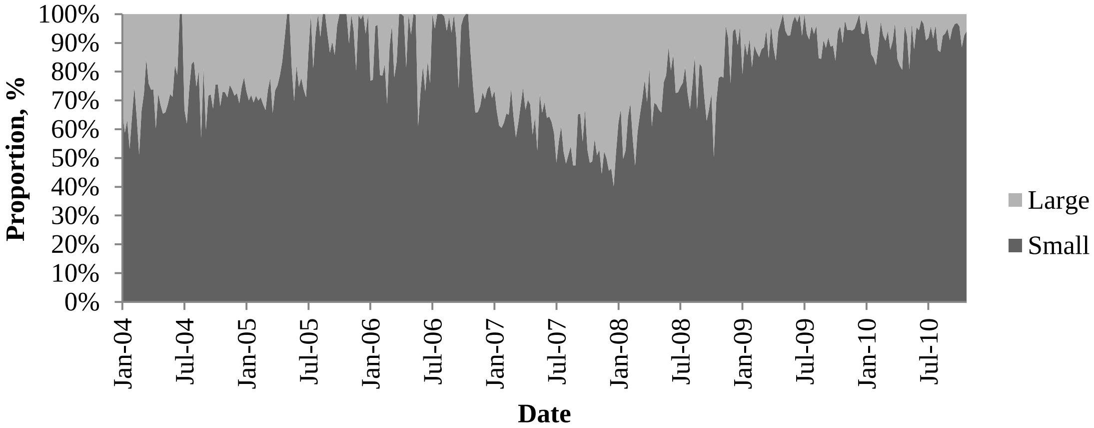


Source: created by the authors using regression outputs from NASDAQ OMX Tallinn trade-level data.

Figure 6. NASDAQ OMX Tallinn Market Index

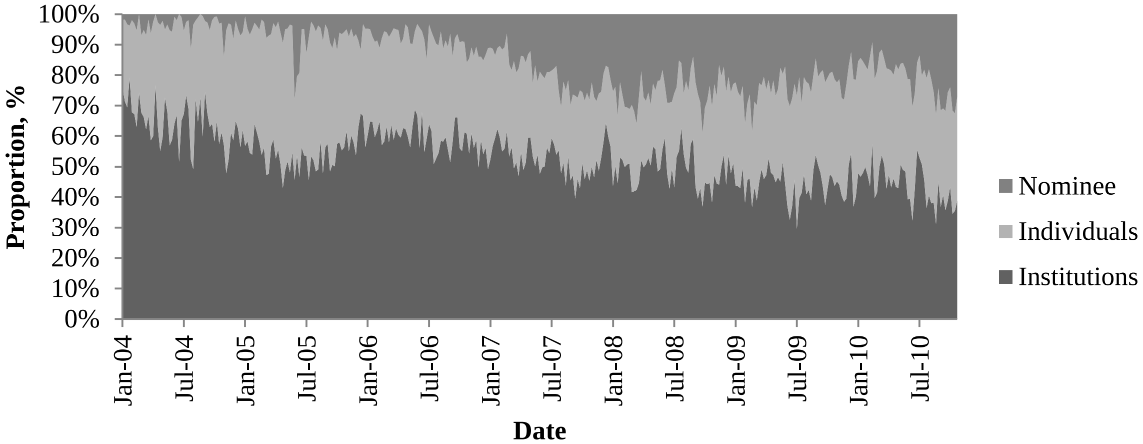
Source: created by the authors using data from NASDAQ OMX web site.

Figure 7. Weekly average trading volume proportions of small and large investors
This figure plots the proportion of average trading volume contributed by large and small investors on a weekly basis. Large refers to the investor whose portfolio size in the beginning of each month is in top 20 percentile of all other investors and then sort them by the EUR value of their portfolio size. Small refers to the remaining portion of investors. Proportions of large and small groups sum up to 1.



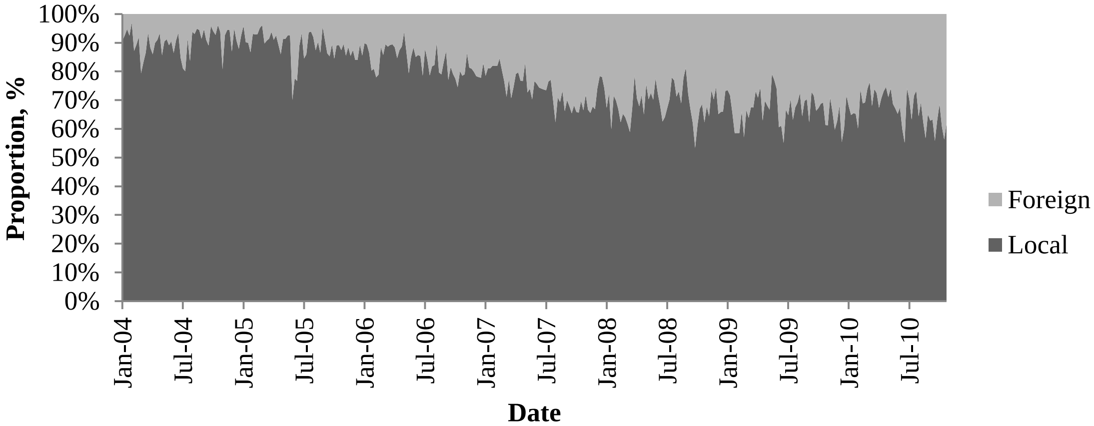
Source: created by the authors based on NASDAQ OMX Tallinn trade-level data.

Figure 8. Weekly average trading volume proportions of investors classified as individual, institutional and nominee
This figure plots the proportion of average trading volume contributed by individual, institution, and nominee investors on a weekly basis. Institution refers to the proportion in volume of trades made by institutional traders and funds. Individual refers to the proportion in volume of trades made by individual traders. Nominee refers to the proportion in volume of trades made by traders trading on behalf of other entity. Volume of trades is calculated by multiplying quantity of the shares bought/sold by the price in a particular transaction. Proportions of individual, institution and nominee groups sum up to 1.



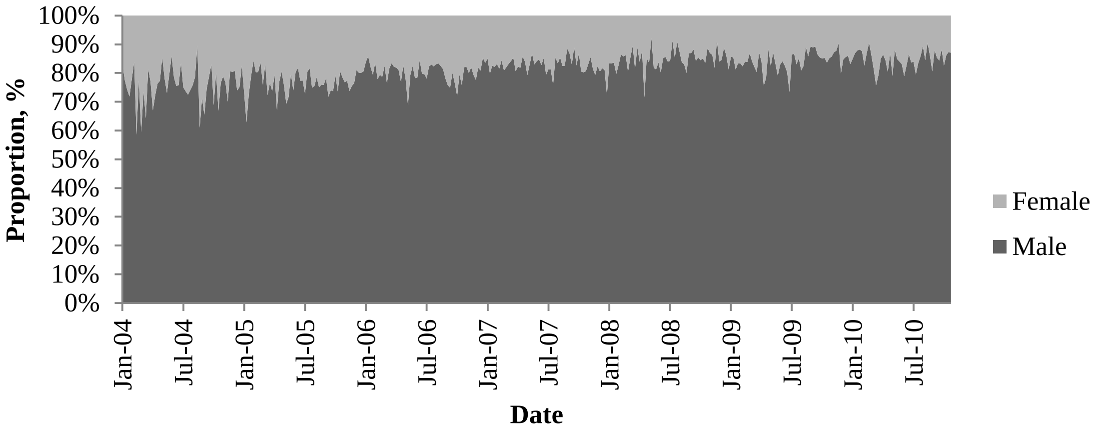
Source: created by the authors based on NASDAQ OMX Tallinn trade-level data.

Figure 9. Weekly average trading volume proportions of foreign and local investors
This figure plots the proportion of average trading volume contributed by foreign and local investors on a weekly basis. Foreign refers to the proportion in volume of trades made by foreign investors. Local refers to the proportion in volume of trades made by local traders. Volume of trades is calculated by multiplying quantity of the shares bought/sold by the price in a particular transaction. Proportions of foreign and local groups sum up to 1.



Source: created by the authors based on NASDAQ OMX Tallinn trade-level data.

Figure 10. Weekly average trading volume proportions of male and female investors
This figure plots the proportion of average trading volume contributed by male and female investors on a weekly basis. Male refers to the proportion in volume of trades made by male investors to the total volume of trades made by local individuals (foreign individual investors do not have their gender specified in most cases). Female refers to the proportion in volume of trades made by local female traders to the total volume of trades made by local individuals. Volume of trades is calculated by multiplying quantity of the shares bought/sold by the price in a particular transaction. Proportions of male and female groups sum up to 1.



Source: created by the authors based on NASDAQ OMX Tallinn trade-level data.

Appendix B: Descriptive statistics tables

Table 2. Sample stocks

ISIN	Stock name	Number of days traded	Dates for which spreads are available	Dates when formal market makers present	Stock included in the sample
EE3100007220	Eesti Telekomi	1533	02.01.2004 - 12.01.2010		+
EE0000001063	Hansapanga[1]	192	04.10.2004 - 30.06.2005		
EE3100004250	Harju Elektri	1737	02.01.2004 - 29.10.2010		+
EE0000001105	Tallinna Kaubamaja	1737	02.01.2004 - 29.10.2010		+
EE3100001850	Norma	1650	02.01.2004 - 30.06.2004		+
EE3100003609	Baltika	1737	02.01.2004 - 29.10.2010		+
EE3100002460	Kalevi	1552	02.01.2004 - 09.09.2009		+
EE3100002486	Rakvere Lihakombinaadi	705	02.01.2004 - 29.09.2006		+
EE3100003559	Merko Ehituse[2]	-	-		
EE3100003443	Trigon Property Development	1737	02.01.2004 - 29.10.2010		+
EE3100026436	Tallinna Vesi A	1375	01.06.2005 - 29.10.2010	01.06.2005 - 01.06.2007	+
EE3100008830	Starman	957	28.06.2005 - 31.03.2009	28.06.2005 - 28.06.2006	+
EE0000001287	Saku Xlletehase	1205	02.01.2004 - 19.09.2008		+
EE3100004466	Tallink Grupp	1239	09.12.2005 - 29.10.2010	09.12.2005 - 09.12.2006	+
EE3100039496	EESTI EHITUS[3]	1129	18.05.2006 - 29.10.2010	09.12.2005 - 09.12.2006	
EE3100001751	Silvano Fashion Group	1737	02.01.2004 - 29.10.2010		+
EE3100001744	Tallinna Farmaatsiatehase	803	02.01.2004 - 19.02.2007		+
EE3100084021	Olympic Entertainment Group	1017	23.10.2006 - 29.10.2010	23.10.2006 - 23.10.2007	+
EE3808004461	Tallink Grupp additional issue[4]	99	31.08.2006 - 19.01.2007		
EE3809004460	Tallink Grupp additional issue[4]	11	01.02.2007 - 15.02.2007		
EE3100034653	Arco Vara	849	21.06.2007 - 29.10.2010	21.06.2007 - 21.06.2008	+
EE3100016965	Ekspress Grupp	902	05.04.2007 - 29.10.2010	23.10.2006 - 23.10.2007	+
EE3100092503	Viisnurk	781	25.09.2007 - 29.10.2010		+
EE3100098328	MERKO EHITUS	562	11.08.2008 - 29.10.2010		+
EE3100039496	Nordecon International	1129	18.05.2006 - 29.10.2010		+
EE3100003559	Järvevana	1737	02.01.2004 - 29.10.2010		+
EE3100101031	Premia Foods[1]	126	05.05.2010 - 29.10.2010		
EE3802002461	Kalevi[4]	37	13.12.2004 - 01.02.2005		
EE3803004250	Harju Elekter[4]	10	09.05.2005 - 20.05.2005		
EE3701016968	Ekspress Grupp[5]	8	16.04.2010 - 27.04.2010		
EE3100002460	Luterma[1]	104	14.04.2009 - 09.09.2009		
EE3804039495	EESTI EHITUS[1]	6	31.05.2007 - 07.06.2007		
EE3804001065	Hansapanga [1]	33	06.05.2004 - 21.06.2004		
EE3100001702	Estiko [1]	125	02.01.2004 - 30.06.2004		
EE3802007221	Eesti Telekom[1]	47	22.06.2004 - 30.08.2004		
EE3804084020	Olympic Entertainment Group[4]	4	15.05.2007 - 18.05.2007		
EE3804003558	Merko Ehitus[1]	8	11.05.2005 - 20.05.2005		

Reasons for stock exclusion:
1) We restrict our sample to the stocks that have sufficient number of observations, that is 500 trading days.
2) Only ISIN and stock name reported in the raw dataset.
3) The stock was re-named in 2006 to Nordecon International.
4) Additional issue. We restrict our sample to the stocks that have sufficient number of observations, that is 200 trading days.
5) Pre-emtion shares. We restrict our sample to the stocks that have sufficient number of observations, that is 200 trading days.

Source: created by the authors, using data from NASDAQ OMX.

Table 3. Correlation coefficient matrix of dALIQ and dASPR
ALIQ and ASPR measures are constructed on daily frequencies.

	Correlation coefficient			
	ALIQ	**ASPR**	**dALIQ**	**dASPR**
ALIQ	1.0000			
ASPR	-0.2488	1.0000		
dALIQ	0.0614	0.1010	1.0000	
dASPR	-0.1141	-0.0179	-0.0694	1.0000

Source: created by the authors using output from STATA regressions.

Table 4. Correlation coefficient matrix of ComLiqALIQ and ComLiqASPR
ComLiqALIQ refers to the commonality in liquidity measure capturing the depth of the market. ComLiqASPR refers to the commonality in liquidity measure capturing the spread of the market. ComLiqALIQ and ComLiqASPR are constructed with a frequency of 2-months.

	Correlation coefficient	
	ComLiqALIQ	**ComLiqASPR**
ComLiqALIQ	1.0000	0. 7670
ComLiqASPR	0.7670	1.0000

Source: created by the authors using output from STATA regressions.

Table 5. Descriptive statistics of dependent and key control variables
The descriptive statistics for ComLiqALIQ and ComLiqASPR measures are reported for 2-month frequencies. The descriptive statistics of dASPR and dALIQ measures, and control variables are reported on weekly basis.

	N	Mean	SD	Min	Max
Dependent variables					
dASPR	5430	-0.0000875	0.0090848	-0.1978468	0.1322425
dALIQ	5270	0.0011989	0.2210082	-3.4959940	4.1562230
ComLiqALIQ	633	-1.3664050	2.873419	-11.69851	5.955513
ComLiqASPR	621	0.7994697	1.749179	-3.311286	6.905993
Control variables					
ASPR	5430	0.0005180	0.0378480	-0.0370356	0.2783908
ASPRm	5430	0.0000891	0.0151426	-0.0278610	0.0451086
dASPRm	5430	-0.0000129	0.0024054	-0.0338511	0.0296218
ALIQ	5271	-0.0000028	0.0004505	-0.0235521	0.0000885
ALIQm	5430	0.0000001	0.0001025	-0.0011215	0.0000877
dALIQm	5423	-0.0046049	0.2330972	-4.0011300	1.5753640
SDm	5416	0.0017067	0.0013949	0.0001382	0.0107596
SDs	5359	0.0037110	0.0041081	0.0000000	0.0698603
dSD	5359	-0.0000085	0.0008594	-0.0077412	0.0093515
dSDm	5398	-0.0000081	0.0003161	-0.0021667	0.0062363
Rs	5412	-0.0002892	0.0157028	-0.1765674	0.1177831
Rm	5416	0.0003719	0.0072200	-0.0456995	0.0641747
turnover	5430	160205	591814	0.0000000	18600000
dTURN	5412	4535	352416	-7123979	11600000

Source: created by the authors using output from STATA regressions.

Table 6. Statistics comparison with Hameed et al. (2010)

	Number of securities	Mean ASPR	Standard deviation	beta dASPRm	beta/SD
Hameed et al. (2010)	1400	1.372	0.933	0.560	0.600
Our results	21	-0.064	0.036	0.105	2.917

Source: created by the authors using output from STATA regressions and statistics from Hameed et al. (2010)

Appendix C: Commonality regression output tables

Table 7. Basic commonality regression output

This table presents commonality regressions for the dependent variables dALIQ, dASPR with control variables. The derivations and meanings of these measures can be found in the methodology section of this paper. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates.

ASPR variable denotes deseasoned proportional spread. ALIQ denotes deseasoned and log-transformed volume-return measure. dALIQ and dASPR are constructed on a weekly frequency. "L" before the control variable implies its lag value, "L2" is a two-period lag, "F" denotes lead term, and "d" implies that the variable is constructed calculating difference between its value in period t and period t-1. "m" denotes relation to market. SD and SD_m refers to the return standard deviation of a particular stock or market, respectively. TURN denotes stock turnover. R_s refers to the individual stock returns. R_m refers to the market returns calculated using market indices. Coefficients and t-values are reported for each of the control variables in respective regression. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	dASPR				**dALIQ**		
	N 4906				N 4475		
	coefficient	*SE*	*p-value*		*coefficient*	*SE*	*p-value*
L.dASPR	-0.542***	0.012	0.000	L.dALIQ	-0.434***	0.013	0.000
L2.dASPR	-0.227***	0.011	0.000	L2.dALIQ	-0.169***	0.013	0.000
F.dASPR	-0.437***	0.010	0.000	F.dALIQ	-0.417***	0.013	0.000
F2.dASPR	-0.197***	0.010	0.000	F2.dALIQ	-0.146***	0.013	0.000
dSD	0.539***	0.090	0.000	dSD	1.419	3.143	-0.650
L.dSD	0.330***	0.091	0.000	L.dSD	-1.114	3.137	-0.720
dSDm	0.049	0.249	-0.850	dSDm	5.657	8.458	-0.500
L.dSDm	0.055	0.251	-0.830	L.dSDm	0.339	8.502	-0.970
L.dTURN	0.000	0.000	-0.710	L.dTURN	0.000	0.000	-0.730
Rm	-0.008	0.011	-0.500	Rm	-0.474	0.389	-0.220
L.Rm	-0.001	0.012	-0.960	L.Rm	-0.012	0.395	-0.980
L2.Rm	0.009	0.011	-0.410	L2.Rm	-0.313	0.377	-0.410
Rs	-0.026***	0.005	0.000	Rs	-0.296*	0.174	-0.090
L.Rs	0.006	0.005	-0.230	L.Rs	0.062	0.175	-0.720
L2.Rs	0.007	0.005	-0.170	L2.Rs	-0.208	0.175	-0.240
dASPRm	0.105**	0.044	-0.020	dALIQm	0.071***	0.011	0.000
constant	0.000	0.000	-0.850	*constant*	0.001	0.002	-0.770

Source: created by the authors using output from STATA regressions.

Table 8. Basic commonality regression output with market makers

This table presents commonality regressions for the dependent variables dALIQ, dASPR with control variables. The derivations and meanings of these measures can be found in the methodology section of this paper. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates.

ASPR variable denotes deseasoned proportional spread. ALIQ denotes deseasoned and log-transformed volume-return measure. dALIQ and dASPR are constructed on a weekly frequency. $dALIQ_m MM$ and $dASPR_m MM$ variables represent changes in liquidity measures interacted with a dummy variable MM equal to 1 if market makers are present for a particular stock *i* at a particular time *t* and 0 otherwise. "L" before the control variable implies its lag value, "L2" is a two-period lag, "F" denotes lead term, and "d" implies that the variable is constructed calculating difference between its value in period t and period t-1. "m" denotes relation to market. SD and SD_m refers to the return standard deviations of a particular stock or market, respectively. TURN denotes stock turnover. R_s refers to the individual stock returns. Rm refers to the market returns calculated using market indices. Coefficients and t-values are reported for each of the control variables in respective regression. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	dASPR				**dALIQ**		
	N 4906				N 4475		
	coefficient	*SE*	*p-value*		*coefficient*	*SE*	*p-value*
L.dASPR	-0.542***	0.012	0.000	L.dALIQ	-0.434***	0.013	0.000
L2.dASPR	-0.227***	0.011	0.000	L2.dALIQ	-0.169***	0.013	0.000
F.dASPR	-0.437***	0.010	0.000	F.dALIQ	-0.417***	0.013	0.000
F2.dASPR	-0.197***	0.010	0.000	F2.dALIQ	-0.146***	0.013	0.000
dSD	0.539***	0.090	0.000	dSD	1.389	3.142	-0.660
L.dSD	0.330***	0.091	0.000	L.dSD	-1.130	3.136	-0.720
dSDm	0.048	0.249	-0.850	dSDm	5.674	8.455	-0.500
L.dSDm	0.055	0.251	-0.820	L.dSDm	0.461	8.501	-0.960
L.dTURN	0.000	0.000	-0.700	L.dTURN	0.000	0.000	-0.730
Rm	-0.008	0.011	-0.500	Rm	-0.464	0.389	-0.230
L.Rm	-0.001	0.012	-0.960	L.Rm	-0.020	0.395	-0.960
L2.Rm	0.009	0.011	-0.410	L2.Rm	-0.312	0.376	-0.410
Rs	-0.026***	0.005	0.000	Rs	-0.293*	0.174	-0.090
L.Rs	0.006	0.005	-0.230	L.Rs	0.059	0.175	-0.740
L2.Rs	0.007	0.005	-0.170	L2.Rs	-0.212	0.175	-0.230
dASPRm	0.107**	0.044	-0.020	dALIQm	0.070***	0.011	0.000
dASPRmMM	-0.037	0.199	-0.850	dALIQmMM	0.053	0.072	-0.460
constant	0.000	0.000	-0.850	*constant*	0.001	0.002	-0.770

Source: created by the authors using output from STATA regressions.

Table 9. Basic commonality regression output before and after the end of July 2007 with dASPR as a dependent variable

The table represents the same regression as in Table 7 split in two periods – before and after the beginning of July 2007, respectively.

dASPR	**Before the beginning of July 2007**			**After the beginning of July 2007**		
	coefficient	*SE*	*p-value*	*coefficient*	*SE*	*p-value*
L.dASPR	-0.543***	0.017	0.000	-0.538***	0.016	0.000
L2.dASPR	-0.236***	0.017	0.000	-0.218***	0.016	0.000
F.dASPR	-0.514***	0.018	0.000	-0.399***	0.013	0.000
F2.dASPR	-0.235***	0.018	0.000	-0.181***	0.012	0.000
dSD	1.555***	0.242	0.000	0.386***	0.099	0.000
L.dSD	1.335***	0.240	0.000	0.176*	0.100	-0.080
dSDm	1.717**	0.851	-0.040	0.008	0.271	-0.980
L.dSDm	1.096	0.868	-0.210	0.025	0.273	-0.930
L.dTURN	0.000	0.000	-0.570	0.000	0.000	-0.800
Rm	0.006	0.024	-0.800	-0.016	0.014	-0.240
L.Rm	-0.021	0.024	-0.390	0.001	0.014	-0.940
L2.Rm	0.013	0.024	-0.570	0.008	0.013	-0.520
Rs	-0.036***	0.008	0.000	-0.018***	0.007	-0.010
L.Rs	0.006	0.008	-0.410	0.005	0.007	-0.440
L2.Rs	0.010	0.008	-0.220	0.006	0.007	-0.360
dASPRm	0.054	0.061	-0.380	0.151***	0.050	0.000
constant	0.000	0.000	-0.660	0.000	0.000	-0.530
N	**2236**			**2605**		

Table 10. Basic commonality regression output before and after the end of July 2007 with dALIQ as a dependent variable

The table represents the same regression as in Table 7 split in two periods – before and after the beginning of July 2007, respectively.

dALIQ	**Before the end of July 2007**			**After the end of July 2007**		
	coefficient	*SE*	*p-value*	*coefficient*	*SE*	*p-value*
L.dALIQ	-0.372***	0.021	0.000	-0.486***	0.017	0.000
L2.dALIQ	-0.094***	0.021	0.000	-0.228***	0.017	0.000
F.dALIQ	-0.352***	0.021	0.000	-0.477***	0.017	0.000
F2.dALIQ	-0.089***	0.022	0.000	-0.182***	0.015	0.000
dSD	19.329*	10.589	-0.070	-0.475	3.214	-0.880
L.dSD	1.882	9.934	-0.850	-2.289	3.227	-0.480
dSDm	-14.127	36.186	-0.700	8.957	8.555	-0.300
L.dSDm	-126.853***	36.513	0.000	9.458	8.596	-0.270
L.dTURN	0.000	0.000	-0.430	0.000	0.000	-0.880
Rm	-1.863**	0.912	-0.040	-0.203	0.429	-0.630
L.Rm	-1.290	0.927	-0.160	0.571	0.437	-0.190
L2.Rm	-2.702***	0.888	0.000	0.428	0.415	-0.300
Rs	-0.147	0.291	-0.610	-0.493**	0.217	-0.020
L.Rs	0.549*	0.288	-0.060	-0.347	0.219	-0.110
L2.Rs	0.273	0.292	-0.350	-0.694***	0.218	0.000
dALIQm	0.095***	0.021	0.000	0.060***	0.014	0.000
constant	0.013***	0.004	0.000	-0.007*	0.004	-0.070
N	**1950**			**2460**		

Source: created by the authors using output from STATA regressions.

Appendix D: Investor type regression output tables

Table 11. dASPR simple

Simple investor type regression output. This table presents the summary of regression outputs for the dependent variable dASPR. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in Table 7. ASPR variable denotes deseasoned proportional spread. dASPR is constructed on a weekly frequency.

$$\Delta liq\_measure_{i,t} = \alpha_i + \beta_{1t}\Delta liq\_measure_{m,t} + \sum_{n=-2}^{2} x_{ni}\Delta liq\_measure_{i,t-n} + \sum_{k=0}^{2}\delta_{ki}R_{m,t-k} + \sum_{p=0}^{2}\theta_{pi}R_{s,t-p} + \mu_{1i}\Delta STD_{i,t} + \mu_{2i}\Delta STD_{i,t-1} + \mu_{3i}\Delta STD_{m,t} + \mu_{4i}\Delta STD_{m,t-1} + \mu_{5i}\Delta TURN_{i,t-1} + investor\_type\_variables \times \Delta liq\_measure_{m,t} + \varepsilon_{i,t}$$

Investor type trade proportion variables are interacted with $dASPR_m$ measures for regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. "Large x Individual", "Large x Institution", "Large x Foreign", "Foreign x Individual", and "Foreign x Institution" are interaction terms constructed using the respective variables. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
dASPRm	0.995***	1.426***	1.604***	1.443***	0.975***	1.040***	0.825***	0.953***	1.621***	0.916***
Individual	1.335***				1.236***	1.180***	1.752***	0.878***		1.091***
Institution	0.095				0.135	0.095	0.329	0.300		0.540*
Foreign		0.349*			0.457**	0.528**		-0.383	-0.084	-1.035
Large			-0.571**		-0.230	-0.212	1.934***		-1.071***	1.296*
Male				0.075		-0.052				
Large x Individual							-5.363***			-5.601***
Large x Institution							-1.584			-0.998
Foreign x Individual								3.818***		5.056***
Foreign x Institution								-0.555		-0.759
Large x Foreign									2.196*	2.013*
constant	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
N	**4634**	**4634**	**4634**	**4615**	**4634**	**4615**	**4634**	**4634**	**4634**	**4634**

Source: created by the authors using output from STATA regressions.

Table 12. dASPR sell buy

This table presents the summary of regression outputs for the dependent variable dASPR. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in Table 7. ASPR variable denotes deseasoned proportional spread. dASPR is constructed on a weekly frequency.

$$\Delta liq\_measure_{i,t} = \alpha_i + \beta_{1t}\Delta liq\_measure_{m,t} + \sum_{n=-2}^{2} x_{ni}\Delta liq\_measure_{i,t-n} + \sum_{k=0}^{2} \delta_{ki} R_{m,t-k} + \sum_{p=0}^{2} \theta_{pi} R_{s,t-p} + \mu_{1i}\Delta STD_{i,t} + \mu_{2i}\Delta STD_{i,t-1} + \mu_{3i}\Delta STD_{m,t} + \mu_{4i}\Delta STD_{m,t-1} + \mu_{5i}\Delta TURN_{i,t-1} + investor\_type\_variables \times \Delta liq\_measure_{m,t} + \varepsilon_{i,t}$$

Investor type trade proportion variables are interacted with dASPRm measures for regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. For example, “Individual Sell” is a proportion of sales and “Individual Buy” is a proportion of purchases made by individuals. “Large Individual Sell” is a proportion of trades that classifies as sales, and is made by wealthy (i.e., large) individuals. Particular variable is an interaction term constructed using “Large Sell” and “Individual Sell” variables. Similarly, “Large Individual Buy” is a proportion of trades that classifies as stock purchases and is made by wealthy (i.e., large) individuals. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
dASPRm	1.780***	1.391***	1.619***	1.224***	1.709***	1.729***	1.334***	2.410***	1.631***	2.078**	2.025***	1.309***
Individual Sell	-1.351***				-1.039	-0.952	-0.942	-2.682**		-2.674*	-0.704	
Individual Buy	1.940***				1.612*	1.592*	2.414***	1.534		2.104		1.181
Institution Sell	-2.376***				-1.929**	-1.977**	-1.859***	-3.483**		-3.305**	-1.857**	
Institution Buy	0.614				0.613	0.677	1.454**	0.601		1.699		0.063
Foreign Sell		1.499***			0.371	0.324		-2.683	0.841*	-3.076	0.526	
Foreign Buy		-0.651			-0.053	0.020		-0.389	-1.173**	-0.694		-0.177
Large Sell			-0.370		-0.263	-0.267	1.438		-1.048**	-2.192	-0.249	
Large Buy			-1.323***		-0.692**	-0.666*	2.093		-1.497***	14.152**		-0.807**
Male Sell				0.115		-0.110						
Male Buy				0.535***		0.006						
Large Individual Sell							-5.081			0.043		
Large Individual Buy							-5.225			-29.166**		
Large Institution Sell							-3.757			4.260		
Large Institution Buy							-6.149*			-30.386**		
Foreign Individual Sell								10.448**		11.351***		
Foreign Individual Buy								3.836		6.075		
Foreign Institution Sell								5.459		4.392		
Foreign Institution Buy								-2.887		-2.070		
Large Foreign Sell									5.961	7.635		
Large Foreign Buy									4.105	-21.777*		
constant	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
N	**3470**	**3470**	**3470**	**3470**	**3470**	**3470**	**3470**	**3470**	**3470**	**3470**	**3470**	**3470**

Source: created by the authors using output from STATA regressions.

Table 13. dASPR Ddown

This table presents the summary of regression outputs for the dependent variable dASPR. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in Table 7. ASPR variable denotes deseasoned proportional spread. dASPR is constructed on a weekly frequency. Ddown is a dummy variable equal to 1 if market return for a particular week was lower than 1.5 standard deviations than its mean value and equal to 0 otherwise.

$$\Delta liq\_measure_{i,t} = \alpha_i + \beta_{1t}\Delta liq\_measure_{m,t} + \sum_{n=-2}^{2} x_{ni}\Delta liq\_measure_{i,t-n} + \sum_{k=0}^{2}\delta_{ki}R_{m,t-k} + \sum_{p=0}^{2}\theta_{pi}R_{s,t-p} + \mu_{1i}\Delta STD_{i,t} + \mu_{2i}\Delta STD_{i,t-1} + \mu_{3i}\Delta STD_{m,t} + \mu_{4i}\Delta STD_{m,t-1} + \mu_{5i}\Delta TURN_{i,t-1} + investor\_type\_variables \times \Delta liq\_measure_{m,t} + investor\_type\_variables \times \Delta liq\_measure_{m,t} \times Ddown_{m,t} + \varepsilon_{i,t}$$

Investor type trade proportion variables are interacted with dASPRm measures for regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. For example, "Individual DDown" is an interaction term constructed using individual investor trade proportion and a dummy variable "Ddown". T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
dASPRm	2.066***	1.831***	2.306***	1.695***	2.348***	2.343***	2.135***	2.114***	2.180***	2.100***	2.039***
Individual	0.780**				0.121	0.089	0.863**	0.029		0.117	
Individual DDown	-4.074***				-2.903**	-1.087	-4.778***	-2.515		-2.394	-2.649*
Institution	-0.876***				-0.581**	-0.618**	-0.236	-0.857**		0.146	
Institution DDown	-0.834				-1.837	-0.080	-2.258	-0.354		-3.058	-2.259
Foreign		0.970***			0.788**	0.786**		-1.384	0.741*	-0.891	
Foreign DDown		-7.128***			-3.892**	-2.610		-1.175	-7.622***	1.201	-2.933
Large			-2.563***		-2.461***	-2.434***	1.335		-2.911***	1.271	
Large DDown			-1.942		5.100**	4.905**	-20.228		0.196	-30.148	2.833
Male				0.416		0.038					
Male DDown				-2.713***		-2.139					
Large Individual DDown							41.555**			50.466*	
Large Institution DDown							23.085			31.359	
Large x Individual							-9.043***			-9.560***	
Large x Institution							-2.982*			-2.725	
Foreign x Individual								5.521***		5.620***	
Foreign x Institution								1.501		-0.771	
Foreign Individual DDown								-6.116		-15.121	
Foreign Institution DDown								-2.371		3.354	
Large x Foreign									1.527	0.434	
Large Foreign DDown									7.737	14.557	
constant	-0.000**	-0.000**	-0.000**	-0.000**	-0.000*	-0.000*	-0.000*	-0.000**	-0.000*	-0.000*	-0.000**
N	**2126**	**2126**	**2126**	**2124**	**2126**	**2124**	**2126**	**2126**	**2126**	**2126**	**2126**

Source: created by the authors using output from STATA regressions.

Table 14. dALIQ simple.

This table presents the summary of regression outputs for the dependent variable dALIQ. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in Table 7. ALIQ variable denotes deseasoned log-transformed volume-return measure. dALIQ is constructed on a weekly frequency.

$$\Delta liq\_measure_{i,t} = \alpha_i + \beta_{1t}\Delta liq\_measure_{m,t} + \sum_{n=-2}^{2} x_{ni}\Delta liq\_measure_{i,t-n} + \sum_{k=0}^{2} \delta_{ki}R_{m,t-k} + \sum_{p=0}^{2} \theta_{pi}R_{s,t-p} + \mu_{1i}\Delta STD_{i,t} + \mu_{2i}\Delta STD_{i,t-1} + \mu_{3i}\Delta STD_{m,t} + \mu_{4i}\Delta STD_{m,t-1} + \mu_{5i}\Delta TURN_{i,t-1} + investor\_type\_variables \times \Delta liq\_measure_{m,t} + \varepsilon_{i,t}$$

Investor type trade proportion variables are interacted with dALIQm measures for regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. “Large x Individual”, “Large x Institution”, “Large x Foreign”, “Foreign x Individual”, and “Foreign x Institution” are interaction terms constructed using the respective variables. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
dALIQm	0.020	0.217***	0.142***	0.176***	-0.029	-0.033	-0.091	0.108	0.182***	-0.009
Individual	0.240***				0.348***	0.344***	0.329***	0.237*		0.276*
Institution	0.171**				0.122	0.119	0.223***	0.017		0.122
Foreign		-0.160**			-0.100	-0.101		-0.260	-0.169*	-0.217
Large			0.342***		0.442***	0.445***	0.349		0.363**	0.321
Male				0.006		0.009				
Large x Individual							0.868			0.973*
Large x Institution							-0.215			-0.246
Foreign x Individual								-0.307		0.012
Foreign x Institution								0.790*		0.380
Large x Foreign									-0.091	-0.036
constant	0.006	0.007	0.005	0.007	0.005	0.005	0.005	0.007	0.005	0.005
N	**2752**	**2752**	**2752**	**2746**	**2752**	**2746**	**2752**	**2752**	**2752**	**2752**

Source: created by the authors using output from STATA regressions.

Table 15. dALIQ sell buy

This table presents the summary of regression outputs for the dependent variable dALIQ. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in Table 7. ALIQ variable denotes deseasoned log-transformed volume-return measure. dALIQ is constructed on a weekly frequency.

$$\Delta liq\_measure_{i,t} = \alpha_i + \beta_{1t}\Delta liq\_measure_{m,t} + \sum_{n=-2}^{2} x_{ni}\Delta liq\_measure_{i,t-n} + \sum_{k=0}^{2} \delta_{ki}R_{m,t-k} + \sum_{p=0}^{2} \theta_{pi}R_{s,t-p} + \mu_{1i}\Delta STD_{i,t} + \mu_{2i}\Delta STD_{i,t-1} + \mu_{3i}\Delta STD_{m,t} + \mu_{4i}\Delta STD_{m,t-1} + \mu_{5i}\Delta TURN_{i,t-1} + investor\_type\_variables \times \Delta liq\_measure_{m,t} + \varepsilon_{i,t}$$

Investor type trade proportion variables are interacted with dALIQm measures for regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. For example, “Individual Sell” is a proportion of sales and “Individual Buy” is a proportion of purchases made by individuals. “Large Individual Sell” is a proportion of trades that classifies as sales, and is made by wealthy (i.e., large) individuals. Particular variable is an interaction term constructed using “Large Sell” and “Individual Sell” variables. Similarly, “Large Individual Buy” is a proportion of trades that classifies as stock purchases and are made by wealthy (i.e., large) individuals. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
dALIQm	0.025	0.188***	0.126***	0.197***	0.034	-0.010	-0.008	0.348	0.133***	0.156	-0.034	0.178
Individual Sell	0.264*				0.430*	0.301	0.146	0.252		0.455	0.405*	
Individual Buy	0.085				0.015	0.170	0.218	-0.417		-0.286		0.106
Institution Sell	0.480**				0.416*	0.498**	0.214	0.265		0.330	0.351	
Institution Buy	-0.084				-0.373	-0.396	-0.010	-0.699*		-0.721*		-0.148
Foreign Sell		-0.137			0.237	0.290		-0.292	0.103	0.229	0.105	
Foreign Buy		0.003			-0.280	-0.345		-0.640	-0.134	-0.865		-0.260
Large Sell			0.488*		0.547*	0.504*	-1.173*		0.962***	3.036*	0.617**	
Large Buy			0.254		0.439**	0.418**	0.421		0.132	1.938		0.481***
Male Sell				-0.022		0.129						
Male Buy				-0.028		-0.034						
Large Individual Sell							7.153***			-0.154		
Large Individual Buy							2.363			0.685		
Large Institution Sell							2.634			-5.954*		
Large Institution Buy							-0.767			-3.881		
Foreign Individual Sell								-0.032		-1.019		
Foreign Individual Buy								-0.107		0.120		
Foreign Institution Sell								2.556*		2.396		
Foreign Institution Buy								1.476		2.959**		
Large Foreign Sell									-4.052***	-8.104***		
Large Foreign Buy									0.952	-2.712		
constant	0.004	0.004	0.002	0.005	0.003	0.003	0.003	0.004	0.001	0.003	0.002	0.004
N	**2109**	**2109**	**2109**	**2109**	**2109**	**2109**	**2109**	**2109**	**2109**	**2109**	**2109**	**2109**

Source: created by the authors using output from STATA regressions.

Table 16. dALIQ Ddown
This table presents the summary of regression outputs for the dependent variable dALIQ. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in Table 7. ALIQ variable denotes deseasoned log-transformed volume-return measure. dALIQ is constructed on a weekly frequency. Ddown is a dummy variable equal to 1 if market return for a particular week was lower than 1.5 standard deviations than its mean value and equal to 0 otherwise.

$$\Delta liq\_measure_{i,t} = \alpha_i + \beta_{1t}\Delta liq\_measure_{m,t} + \sum_{n=-2}^{2} x_{ni}\Delta liq\_measure_{i,t-n} + \sum_{k=0}^{2} \delta_{ki}R_{m,t-k} + \sum_{p=0}^{2} \theta_{pi}R_{s,t-p} + \mu_{1i}\Delta STD_{i,t} + \mu_{2i}\Delta STD_{i,t-1} + \mu_{3i}\Delta STD_{m,t} + \mu_{4i}\Delta STD_{m,t-1} + \mu_{5i}\Delta TURN_{i,t-1} + investor\_type\_variables \times \Delta liq\_measure_{m,t} + investor\_type\_variables \times \Delta liq\_measure_{m,t} \times Ddown_{m,t} + \varepsilon_{i,t}$$

Investor type trade proportion variables are interacted with dALIQm measures for regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. For example, “Individual DDown” is an interaction term constructed using individual investor trade proportion and a dummy variable “Ddown”. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
dALIQm	-0.110	0.303***	0.194***	0.404***	-0.203**	-0.169	-0.222***	-0.087	0.254***	-0.086	0.256***
Individual	0.414***				0.508***	0.508***	0.556***	0.408**		0.384*	
Individual DDown	0.481				0.389	0.832	0.287	1.461		1.865	0.322
Institution	0.502***				0.470***	0.480***	0.500***	0.373**		0.308*	
Institution DDown	1.113**				-0.209	0.142	0.494	0.063		-2.100	0.047
Foreign		-0.068			0.217	0.249		-0.238	-0.113	-0.646	
Foreign DDown		3.491***			1.125	1.276		1.723	1.439	-20.536*	0.440
Large			0.753***		0.691***	0.686***	1.309***		0.587***	0.751	
Large DDown			2.102***		1.346	1.575	6.440		1.758	30.950**	1.912
Male				-0.168		-0.045					
Male DDown				0.988***		-0.553					
Large Individual DDown							-5.697			-30.443*	
Large Institution DDown							-6.247			-29.391*	
Large x Individual							-0.175			0.639	
Large x Institution							-0.987			-0.820	
Foreign x Individual								0.405		0.890	
Foreign x Institution								1.247**		1.409**	
Foreign Individual DDown								-6.809		14.844	
Foreign Institution DDown								2.506		37.572*	
Large x Foreign									0.675	0.888	
Large Foreign DDown									-2.387	-19.292	
constant	0.005	0.007	0.006	0.007	0.004	0.005	0.005	0.007	0.007	0.007	0.007
N	**1788**	**1788**	**1788**	**1788**	**1788**	**1788**	**1788**	**1788**	**1788**	**1788**	**1788**

Source: created by the authors using output from STATA regressions.

Table 17. ComLiqASPR simple

This table presents the summary of regression outputs for the dependent variable ComLiqASPR. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in the regression specification below. ComLiqASPR denotes log-transformed R^2 of the regressions for each stock where $dASPR_{i,t}$ is regressed on $dASPR_{m,t}$ on a two-month basis. LevLiq variable include $ASPR_m$ (deseasoned proportional spreads) and $ALIQ_m$ (deseasoned and log-transformed volume-return measure). STD_m refers to the return standard deviations of the market. TURN denotes stock turnover. R_m refers to the market returns calculated using market indices.

$$ComLiq_{i,t} = \alpha_i + \mu_{1i}R_{m,t} + \mu_{2i}STD_{m,t} + \mu_{3i}TURN_{i,t} + \mu_{4i}LevLiq_t + investor\_type\_variables + \varepsilon_{i,t}$$

Investor type trade proportion variables are added to the regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. "Large x Individual", "Large x Institution", "Large x Foreign", "Foreign x Individual", and "Foreign x Institution" are interaction terms constructed using the respective variables. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
Individual	1.142**				1.219	1.223	0.348	2.661**		1.058
Institution	1.470***				1.313*	1.313*	1.022	2.543**		1.187
Foreign		-1.010***			-0.107	-0.107		2.621	-0.689	1.497
Large			0.757**		0.748*	0.748*	-1.759		1.026*	-10.719**
Male				0.000		0.054				
Large x Individual							6.365**			14.626***
Large x Institution							1.833			10.136**
Foreign x Individual								-5.341**		-5.573**
Foreign x Institution								-2.588		-2.023
Large x Foreign									-1.509	9.169**
constant	-1.188***	0.175	-0.068	0.06	-1.239	-1.282	-0.864	-2.294**	-0.008	-1.031
N	**621**	**621**	**621**	**621**	**621**	**621**	**621**	**621**	**621**	**621**

Source: created by the authors using output from STATA regressions.

Table 18. ComLiqASPR sell buy

This table presents the summary of regression outputs for the dependent variable ComLiqASPR. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in the regression specification below. ComLiqASPR denotes log-transformed R^2 of the regressions for each stock where $dASPR_{i,t}$ is regressed on $dASPR_{m,t}$ on a two-month basis. LevLiq variable include $ASPR_m$ (deseasoned proportional spreads) and $ALIQ_m$ (deseasoned and log-transformed volume-return measure). STD_m refers to the return standard deviations of the market. TURN denotes stock turnover. R_m refers to the market returns calculated using market indices.

$$ComLiq_{i,t} = \alpha_i + \mu_{1i}R_{m,t} + \mu_{2i}STD_{m,t} + \mu_{3i}TURN_{i,t} + \mu_{4i}LevLiq_t + investor\_type\_variables + \varepsilon_{i,t}$$

Investor type trade proportion variables are added to the regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. For example, “Individual Sell” is a proportion of sales and “Individual Buy” is a proportion of purchases made by individuals. “Large Individual Sell” is a proportion of trades that classifies as sales, and is made by wealthy (i.e., large) individuals. Particular variable is an interaction term constructed using “Large Sell” and “Individual Sell” variables. Similarly, “Large Individual Buy” is a proportion of trades that classifies as stock purchases and is made by wealthy (i.e., large) individuals. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
Individual Sell	1.091				1.273	-0.339	-0.693	4.719**		2.335	2.186*	
Individual Buy	0.896				0.821	2.636	1.083	1.050		1.705		1.207
Institution Sell	0.358				0.230	0.092	-0.574	1.693		0.070	1.264	
Institution Buy	2.082**				1.993	2.096	2.553**	1.889		2.545		2.013
Foreign Sell		-0.196			0.042	0.250		4.283	0.350	3.382	0.313	
Foreign Buy		-1.477**			-0.312	-0.404		0.202	-2.004**	0.207		-0.520
Large Sell			0.797		1.138	1.353*	-5.007		1.289	-11.691	1.282*	
Large Buy			0.502		0.115	-0.014	1.328		0.068	-2.919		0.561
Male Sell				0.417		0.826						
Male Buy				-0.577		-0.723						
Large Individual Sell							31.717***			44.980***		
Large Individual Buy							-3.094			5.385		
Large Institution Sell							9.123			22.333		
Large Institution Buy							(dropped)			(dropped)		
Foreign Individual Sell								-26.849***		-25.328***		
Foreign Individual Buy								-5.032		-6.585		
Foreign Institution Sell								-4.520		-2.743		
Foreign Institution Buy								0.060		-2.453		
Large Foreign Sell									-5.827	11.857		
Large Foreign Buy									4.538	14.688		
constant	-1.102**	0.088	-0.122	-0.002	-1.138	-1.244	-0.897	-1.984	-0.019	-1.519	-0.884	-0.845
N	**591**	**591**	**591**	**591**	**591**	**591**	**591**	**591**	**591**	**591**	**591**	**591**

Source: created by the authors using output from STATA regressions.

Table 19. ComLiqASPR Ddown

This table presents the summary of regression outputs for the dependent variable ComLiqASPR. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in the regression specification below. ComLiqASPR denotes log-transformed R^2 of the regressions for each stock where $dASPR_{i,t}$ is regressed on $dASPR_{m,t}$ on a two-month basis. LevLiq variable include $ASPR_m$ (deseasoned proportional spreads) and $ALIQ_m$ (deseasoned and log-transformed volume-return measure). STD_m refers to the return standard deviations of the market. TURN denotes stock turnover. R_m refers to the market returns calculated using market indices.

$$ComLiq_{i,t} = \alpha_i + \mu_{1i}R_{m,t} + \mu_{2i}STD_{m,t} + \mu_{3i}TURN_{i,t} + \mu_{4i}LevLiq_t + investor\_type\_variables + investor\_type\_variables \times Ddown + \varepsilon_{i,t}$$

Investor type trade proportion variables and their interactions with Ddown are added to the regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. Ddown is a dummy variable equal to 1 if market return for a particular week was lower than 1.5 standard deviations than its mean value and equal to 0 otherwise. "Large x Individual", "Large x Institution", "Large x Foreign", "Foreign x Individual", and "Foreign x Institution" are interaction terms constructed using the respective variables. For example, "Individual DDown" is an interaction term constructed using individual investor trade proportion and a dummy variable "Ddown". T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
Individual	-0.095				-1.574	-1.494	-0.595	-2.492		-4.736**	
Individual Ddown	2.169				2.835	-1.755	0.053	6.268		3.189	2.336
Institution	1.050				-0.455	-0.397	0.888	-1.353		-3.040	
Institution Ddown	3.750**				4.777**	-2.127	6.522	4.676		8.265	5.177**
Foreign		-1.127*			-1.561	-1.504		-3.163	-1.187	-4.879*	
Foreign Ddown		3.031			-2.802	-5.940		7.545	4.780	12.517	-4.010
Large			0.801		0.504	0.523	-0.516		0.490	-15.995**	
Large Ddown			3.420		-0.338	-1.367	0.158		9.858*	19.044	0.786
Male				0.342		0.204					
Male Ddown				0.940		6.855					
Large Individual Ddown							6.318			-9.688	
Large Institution Ddown							-11.046			-32.948	
Large x Individual							4.744			19.421**	
Large x Institution							0.378			14.540*	
Foreign x Individual								1.020		0.845	
Foreign x Institution								2.007		2.284	
Foreign Individual Ddown								-24.974		-28.319	
Foreign Institution Ddown								-14.593		-20.289	
Large x Foreign									1.677	14.885**	
Large Foreign Ddown									-27.669**	-19.157	
constant	-1.967***	-1.353***	-1.624***	-0.870	-0.503	-0.723	-1.908**	0.476	-1.439***	2.274	-1.400***
N	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**

Source: created by the authors using output from STATA regressions.

Table 20. ComLiqALIQ simple

This table presents the summary of regression outputs for the dependent variable ComLiqALIQ. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in the regression specification below. ComLiqALIQ denotes log-transformed R^2 of the regressions for each stock where $dALIQ_{i,t}$ is regressed on $dALIQ_{m,t}$ on a two-month basis. LevLiq variable include $ASPR_m$ (deseasoned proportional spreads) and $ALIQ_m$ (deseasoned and log-transformed volume-return measure). STD_m refers to the return standard deviations of the market. TURN denotes stock turnover. R_m refers to the market returns calculated using market indices.

$$ComLiq_{i,t} = \alpha_i + \mu_{1i} R_{m,t} + \mu_{2i} STD_{m,t} + \mu_{3i} TURN_{i,t} + \mu_{4i} LevLiq_t + investor\_type\_variables + \varepsilon_{i,t}$$

Investor type trade proportion variables are added to the regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. "Large x Individual", "Large x Institution", "Large x Foreign", "Foreign x Individual", and "Foreign x Institution" are interaction terms constructed using the respective variables. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
Individual	0.289				-1.337	-1.325	-0.245	-2.411		-4.825**
Institution	1.323*				-0.264	-0.267	1.261	-1.357		-2.988
Foreign		-1.108*			-1.781*	-1.787*		-3.558	-1.339*	-5.338*
Large			0.892		0.400	0.401	-0.567		0.506	-16.614**
Male				0.269		0.190				
Large x Individual							5.179			20.285**
Large x Institution							0.171			14.751*
Foreign x Individual								1.004		1.006
Foreign x Institution								2.060		2.220
Large x Foreign									1.473	15.445**
constant	-2.413***	-1.408***	-1.703***	-1.748**	-0.793	-0.942	-2.371***	0.321	-1.508***	2.205
N	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**

Source: created by the authors using output from STATA regressions.

Table 21. ComLiqALIQ sell buy

This table presents the summary of regression outputs for the dependent variable ComLiqALIQ. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in the regression specification below. ComLiqALIQ denotes log-transformed R^2 of the regressions for each stock where $dALIQ_{i,t}$ is regressed on $dALIQ_{m,t}$ on a two-month basis. LevLiq variable include $ASPR_m$ (deseasoned proportional spreads) and $ALIQ_m$ (deseasoned and log-transformed volume-return measure). STD_m refers to the return standard deviations of the market. TURN denotes stock turnover. R_m refers to the market returns calculated using market indices.

$$ComLiq_{i,t} = \alpha_i + \mu_{1i} R_{m,t} + \mu_{2i} STD_{m,t} + \mu_{3i} TURN_{i,t} + \mu_{4i} LevLiq_t + investor\_type\_variables + \varepsilon_{i,t}$$

Investor type trade proportion variables are added to the regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. For example, “Individual Sell” is a proportion of sales and “Individual Buy” is a proportion of purchases made by individuals. “Large Individual Sell” is a proportion of trades that classifies as sales, and is made by wealthy (i.e., large) individuals. Particular variable is an interaction term constructed using “Large Sell” and “Individual Sell” variables. Similarly, “Large Individual Buy” is a proportion of trades that classifies as stock purchases and is made by wealthy (i.e., large) individuals. T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
Individual Sell	-0.886				-3.355	-5.320**	-2.076	-2.059		-3.879	-2.700	
Individual Buy	0.884				-0.318	1.822	1.612	-4.929		-4.160		-0.926
Institution Sell	0.250				-2.381	-2.639	-0.172	-2.338		-2.909	-1.608	
Institution Buy	1.620				1.051	1.211	3.615**	-4.511		-2.490		0.241
Foreign Sell		-1.277			-2.776*	-2.685*		-0.990	-0.787	-1.049	-2.698*	
Foreign Buy		-0.551			-1.119	-1.106		-9.984**	-2.711*	-10.415**		-1.563
Large Sell			1.770		0.956	1.211	-3.028		1.645	-11.672	0.862	
Large Buy			-0.299		-0.534	-0.681	4.553		-2.076*	-2.493		-0.194
Male Sell				0.669		0.909						
Male Buy				0.128		-0.860						
Large Individual Sell							26.342			44.583*		
Large Individual Buy							-14.204*			-0.469		
Large Institution Sell							4.869			20.811		
Large Institution Buy							(dropped)			(dropped)		
Foreign Individual Sell								-15.707		-14.949		
Foreign Individual Buy								12.719		13.909		
Foreign Institution Sell								-1.104		-1.856		
Foreign Institution Buy								22.379**		17.742		
Large Foreign Sell									-2.678	12.871		
Large Foreign Buy									19.576**	23.208		
constant	-2.175***	-1.537***	-1.758***	-1.978***	-0.425	-0.495	-2.684***	1.921	-1.469***	1.720	-0.613	-1.443
N	**602**	**602**	**602**	**602**	**602**	**602**	**602**	**602**	**602**	**602**	**602**	**602**

Source: created by the authors using output from STATA regressions.

Table 22. ComLiqALIQ Ddown

This table presents the summary of regression outputs for the dependent variable ComLiqALIQ. The regression intercepts and coefficients of independent variables are allowed to vary on stock-by-stock basis. The reported coefficients and standard errors are mean values of the resulting estimates. Detailed information on control variables used in the regression can be seen in the regression specification below. ComLiqALIQ denotes log-transformed R^2 of the regressions for each stock where $dALIQ_{i,t}$ is regressed on $dALIQ_{m,t}$ on a two-month basis. LevLiq variable include $ASPR_m$ (deseasoned proportional spreads) and $ALIQ_m$ (deseasoned and log-transformed volume-return measure). STD_m refers to the return standard deviations of the market. TURN denotes stock turnover. R_m refers to the market returns calculated using market indices.

$$ComLiq_{i,t} = \alpha_i + \mu_{1i}R_{m,t} + \mu_{2i}STD_{m,t} + \mu_{3i}TURN_{i,t} + \mu_{4i}LevLiq_t + investor\_type\_variables + investor\_type\_variables \times Ddown + \varepsilon_{i,t}$$

Investor type trade proportion variables and their interactions with Ddown are added to the regressions. The respective trading volume contributions of each investor type can be seen in Figures 7 to 10, Appendix A. Ddown is a dummy variable equal to 1 if market return for a particular week was lower than 1.5 standard deviations than its mean value and equal to 0 otherwise. "Large x Individual", "Large x Institution", "Large x Foreign", "Foreign x Individual", and "Foreign x Institution" are interaction terms constructed using the respective variables. For example, "Individual DDown" is an interaction term constructed using individual investor trade proportion and a dummy variable "Ddown". T-statistics is reported to the right of the estimated coefficient. *** represents significance at 1% level. ** and * represents significance at 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	coefficient	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*	*coefficient*
Individual	-0.095				-1.574	-1.494	-0.595	-2.492		-4.736**	
Individual Ddown	2.169				2.835	-1.755	0.053	6.268		3.189	2.336
Institution	1.050				-0.455	-0.397	0.888	-1.353		-3.040	
Institution Ddown	3.750**				4.777**	-2.127	6.522	4.676		8.265	5.177**
Foreign		-1.127*			-1.561	-1.504		-3.163	-1.187	-4.879*	
Foreign Ddown		3.031			-2.802	-5.940		7.545	4.780	12.517	-4.010
Large			0.801		0.504	0.523	-0.516		0.490	-15.995**	
Large Ddown			3.420		-0.338	-1.367	0.158		9.858*	19.044	0.786
Male				0.342		0.204					
Male Ddown				0.940		6.855					
Large Individual Ddown							6.318			-9.688	
Large Institution Ddown							-11.046			-32.948	
Large x Individual							4.744			19.421**	
Large x Institution							0.378			14.540*	
Foreign x Individual								1.020		0.845	
Foreign x Institution								2.007		2.284	
Foreign Individual Ddown								-24.974		-28.319	
Foreign Institution Ddown								-14.593		-20.289	
Large x Foreign									1.677	14.885**	
Large Foreign Ddown									-27.669**	-19.157	
constant	-1.967***	-1.353***	-1.624***	-0.870	-0.503	-0.723	-1.908**	0.476	-1.439***	2.274	-1.400***
N	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**	**633**

Source: created by the authors using output from STATA regressions.