ANALYSIS OF TRADING ACTIVITY AND LIQUIDITY IN ISTANBUL STOCK EXCHANGE

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Dissertation Abstract

Mehmet Oğuz Karahan, " Analysis of Trading Activity and Liquidity in Istanbul Stock Exchange"

In this dissertation, I examine trading activity and liquidity in Istanbul Stock Exchange (ISE) for a sample of 254 stocks. I observe that trading volume follows an L-shaped pattern in the morning session and a J-shaped pattern in the afternoon session. Duration of high trading activity during open and close of the day diminishes from one-hour period for most active stocks to 5-minute period for least active stocks. For active stocks, I observe concentration in trading immediately after 3:30 pm. Also, I find a significant increase in trading volume during opening periods of both sessions after introduction of order cancellation mechanism. Additionally, intraday behavior of price impact ratios indicate higher illiquidity during the close of morning session. Analysis of different zeros measures suggests that active intraday trading occurs mostly on stocks with high Turkish Lira turnover. Finally, I provide evidence for commonality in trading activity and liquidity in Istanbul Stock Exchange.

Tez Özeti

Mehmet Oğuz Karahan, " İstanbul Menkul Kıymetler Borsası'ndaki İşlem Hareketliliği ve Likiditenin Analizi "

Bu tezde İstanbul Menkul Kıymetler Borsası'ndaki (İMKB) işlem hareketliliği ve likidite 254 hisse senedi için incelenmiştir. İşlem hacminin birinci seansta L-şeklinde ve ikinci seansta J-şeklinde bir seyir izlediği gözlemlenmiştir. Günün açılış ile kapanış periyotlarındaki yüksek işlem hareketliliğinin süresi en aktif hisse senetleri için bir saatten en az aktif hisse senetleri için beş dakikaya düşmektedir. Aktif hisse senetleri için işlem hacminin 15:30'dan hemen sonra arttığı gözlemlenmiştir. Ayrıca emir iptali uygulamasına geçildikten sonraki dönemde her iki seansin açılış periyotlarındaki işlem hacminin arttığı bulunmuştur. Buna ek olarak fiyat etki oranlarının gün içi seyri birinci seansın kapanışında likidite azlığına işaret etmektedir. Farklı sıfır ölçütlerinin analizi gün içerisinde aktif ticaretin çoğunlukla yüksek hacimli senetlerde var olduğunu belirtmektedir. Son olarak, İstanbul Menkul Kıymetler Borsası'nda işlem hacmi ve likiditede ortaklık olduğu gösterilmiştir.

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CHAPTER 1

INTRODUCTION

Liquidity provision is one of the main functions of stock exchanges.[1] One can buy (sell) a stock as long as there exists a counterparty to sell (buy) it from her. As essential as liquidity is for a financial market, it is not easy to establish conditions to identify a market as "liquid". As O'Hara (2007) puts it: "Liquidity is easy to identify when seen, but hard to define." For example, institutional traders take price impacts of their trades into account before entering or exiting a position, however there may be times they would be content to find a counter-party to trade with. On the other hand, a day trader would like to face a smaller bid-ask spread, to minimize her transaction cost. It can be said that liquidity has various dimensions and different types of traders may not necessarily care about all of them.

A compact definition of liquidity is "the ability to buy or sell significant quantities of security quickly, anonymously, and with relatively little price impact" (Campbell et al. (1997), pp.99-100). A general characterization is given by Black (1971) and Kyle (1985), who define a liquid market as (i) tight, (ii) deep and (iii) resilient. Tightness is related to bid-ask spread, which is the transaction cost incurred by a trader when she buys a unit stock and immediately sells it. Depth refers to the total amount of stocks which traders (or market maker, when exists) are willing to buy or sell at a given time. Depth is generally measured by quoted depth which is the total

[1] O'Hara (1999), Madhavan (2000), Biais et al. (2005) and Ekinci and Kayacan (2005) provide detailed surveys of market microstructure concepts. Subrahmanyam (2009) reviews how market liquidity is pertinent to several areas of finance. For a general theoretical survey, see O'Hara (2007).

liquidity supply at the best bid and ask prices. Resiliency requires the price impacts caused by trades to be temporary.

It has been shown that liquidity and liquidity risk of assets are reflected in prices.[2] Since it is more costly to buy or sell illiquid assets, investors demand premium to invest in such assets and therefore this premium is reflected in the asset prices. A similar argument can be made for liquidity risk, i.e. uncertainty in liquidity. For example, consider a hypothetical illiquid market where *only* buyers exist in one period and they all vanish in the following period and sellers arrive. In this scenario, no trade occurs in both periods and therefore price does not exist.[3] Additionally, markets with higher liquidity have a tendency to be more efficient and are more likely to be arbitrage-free. (Subrahmanyam, 2009)

Limit order markets are the markets where designated liquidity suppliers (such as specialists or market-makers) do not exist. In limit order markets, traditionally, traders who submit limit orders are identified as liquidity suppliers and those who submit market orders are called liquidity demanders. Limit order traders are also referred as patient traders, who seek better execution prices while facing a positive non-execution probability, where as market order traders are referred as impatient traders who obtain execution with certainty albeit incurring trading costs.[4]

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[2]Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Datar et al. (1998), Amihud (2002) and Pastor and Stambaugh (2003) analyze the effect of liquidity and liquidity related variables on asset prices. Acharya and Pedersen (2005) develop a liquidity-adjusted capital asset pricing model.

[3]While existence of market makers eliminate this possibility, such cases may exist in pure limit order markets.

[4]See Hasbrouck and Saar (2009) for a discussion on changing role and definition of limit orders in modern trading environment. They find that 36.69 percent of limit orders are canceled within two seconds of their submission and discuss the possible reasons of this increase in "impatient" limit orders.

In this study, I investigate two main research questions using a large sample of 254 ISE stocks over 106 trading days: (i) Are there intra-day patterns in trading activity and liquidity in Istanbul Stock Exchange (ISE)? If so, how do they behave? (ii) Is there commonality in trading activity and liquidity across stocks in ISE?

Previous literature show that liquidity measures in different markets follow different intraday patterns. Therefore, trading costs are not constant throughout the trading session. Ceteris paribus, traders would like to minimize (implicit) costs of trading. Therefore, it is important to identify the behavior of trading activity and liquidity in a given market during the day.

As mentioned above, it is shown that liquidity and liquidity risks of assets are reflected in asset prices. This leads to the question of whether liquidity risks of assets can be incorporated to general asset pricing models. Establishing the co-movement of individual asset liquidity measures is necessary to argue the existence of a common market factor for liquidity, which can therefore be considered as an additional factor in market models.

To the best of my knowledge, this study is the first to analyze market-wide behavior of trading activity and liquidity for ISE.

This dissertation is organized as follows: Chapter 2 provides a review of market microstructure literature, with special focus on liquidity, limit order markets, intraday trading behaviors and commonality in liquidity. In Chapter 3, I analyze intraday trading behavior of trading activity and liquidity in ISE. In Chapter 4, I explore the existence of commonality in trading activity and liquidity in ISE. Chapter 5 concludes this dissertation.

CHAPTER 2

LITERATURE REVIEW

In this chapter, I briefly revisit microstructure literature with specific focus on trading activity and liquidity in equity markets. Then I discuss previous work on intraday patterns of trading activity and liquidity and commonality in liquidity. Last section describes institutional structure of ISE.

Theoretical Background

Early work in market microstructure and liquidity generally focus on U.S. markets, more specifically New York Stock Exchange (NYSE), which in its early days was a pure dealer market. Therefore specialist's role in suppling liquidity is the main focus of these work. Demsetz (1968) is first to formally provide economic explanations for the existence of double equilibria in securities markets, definitions and effects of transaction costs, costs of immediacy and the role of specialists in the NYSE. He also compares the behavior of these variables in active (liquid) and inactive (illiquid) stocks. He relates differences between the spreads of different stocks to the waiting costs which arise from different transaction rates.

Bagehot (1971) argues that specialists' trades against privately informed traders result in losses, however they make profit from trades initiated by liquidity traders. Therefore existence of informed traders increase illiquidity (bid-ask spreads) due to adverse selection.[5] Models based on this asymmetric information between different types of traders in dealer markets and its impact on bid-ask spreads were the focus of

[5]Papers analyzing specialists' decision making and strategies include Tinic (1972), Benston and Hagerman (1974), Stoll (1978) and Amihud and Mendelson (1980).

early equilibrium models. The adverse selection effect created by insiders is modeled for auction markets by the seminal papers Kyle (1985) and Glosten and Milgrom (1985).

In Kyle (1985) model, market makers observe the order imbalance and compete to supply liquidity for this imbalance. This competition results in a market-clearing price. In equilibrium, the informed trader hides his orders within those of noise traders and trades in such a way that his private information is reflected in prices gradually.[6] From the liquidity standpoint, this model shows that market depth increases in the number noise traders and decreases in the amount of private information which are yet to be incorporated in prices. Glosten and Milgrom (1985) model a similiar microstructure, however in their model, traders' orders arrive sequentially to the market and market makers set bid and ask prices by using the probability of whether any given order is initiated by an uninformed or informed investor.[7] Kyle model yields a λ parameter, where $1/\lambda$ is the amount of order flow that is necessary to change equilibrium price by one unit. Kyle's lambda is the main intuition behind the price impact measures (Amihud (2002)) which are also used in this study.

Although more than half of world's stock exchanges are order-driven (limit order) markets (Jain (2003)), literature on this type of market structure is relatively recent. Models of limit order markets focus on order choice of investors between a market order or a limit order at a certain price. Since there is no designed liquidity

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[6]Holden and Subrahmanyam (1992) show that if there are multiple informed traders, these traders compete aggresively and therefore the speed of price adjustment increases in number of such traders.

[7]Back and Baruch (2004) show that under certain assumptions Glosten-Milgrom model converges to Kyle model.

supplier in these markets, limit orders are the only source of market liquidity.[8] Limit order behavior in the presence of adverse selection is modeled by Glosten (1994) , Chakravarty and Holden (1995) , Handa and Schwartz (1996) and Seppi (1997) in a static framework. Glosten (1994) models a electronic limit order market where a risk-averse trader submits a market order in a setting where a large number of risk-neutral traders submit limit orders. He assumes that informed traders and liquidity traders submit market orders, whereas uninformed traders submit limit orders. This is because, for informed traders, patience is costly for two reasons: (i) public announcements depreciate value of the information and (ii) they compete with other informed traders. For liquidity traders, he argues that gains from optimally balancing portfolios are greater than small losses incurred by submitting limit orders in general. Handa and Schwartz (1996) allow traders to choose between market and limit orders. Seppi (1997) models a hybrid market where limit order trading co-exist with a specialist. She concludes that a hybrid market offers better liquidity to large (institutional) and small (retail) trades while a pure limit order market provide better liquidity to mid-sized trades.

Dynamic models of limit order book focus more on waiting and non-execution (rather than adverse selection) costs of limit orders. In these models traders generally face the trade-off betwen submitting a market order and getting immediate execution at a higher price or submitting a limit order and facing waiting costs (including those conditioned on non-execution probabilities) according to the price priority rules.

[8]Here I discuss pure limit order markets. There are many hybrid exchanges (NYSE, NASDAQ, London) where liquidity supply is a result of competition between limit orders and market maker. It has been reported that majority of trades in hybrid exchanges involve limit orders. For example, Hasbrouck and Sofianos (1993) find that specialists participate in only 13 percent of total trades in NYSE and this rate lower in more active stocks.

Parlour (1998) develops a two-tick dynamic model of limit order book where traders choose their order type by taking its effect on future traders' strategies into account. However, in this model asset values have no volatility and hence lacks explanation of various risks involved in limit order trading.

Limit orders can be regarded as zero-price options written by limit order traders. Consider a limit sell order: While its active, every market participant has a right to buy these stocks at the order price and these "options" are freely available. Foucault (1999) examines this aspect of limit order trading and computes a subgame perfect equilibrium based on volatility of the asset value and the order flow. In this model, traders arrive sequantially and submit a market order or a limit order which lasts one period, traders' beliefs on execution probabilities are endogenous and all traders act rationally (there are no noise traders). Limit order investors face two distinct risks to obtain a better execution price: (i) non-execution risk and (ii) risk of being "picked-off" (*winner's curse*). In the case of a negative (with respect to the trader's limit order position) information shock which changes the asset value, outstanding limit orders at the inferior price can be picked-off by market orders. Such cases are identified as winner's curse, because buy (sell) limit orders execute with probability one, only if the asset value decreases (increases) to a level lower (higher) than the order price. In equilibrium, limit orders traders demand more premium as execution risk increases. This is because as execution risk increases, probability of the next order being a market order increases and therefore limit order traders capture larger rents, which increases the spread. He concludes that the volatility of the asset value (which also determines the execution risk) is the main determinant of the order choice.

Foucault et al. (2005) model a limit order market where all traders are risk neutral liquidity traders and they differ in waiting costs, such that patient (impatient) traders have low (high) waiting costs. Arrival times of traders follow a Poisson distribution. Model assumes that (i) each trader arrives only once, can not delay order submission and can not cancel or modify submitted orders, (ii) limit orders must reduce the spread and (iii) a buyer follows a seller who follows another buyer and so-on. In equilibrium, patient traders are more likely to submit limit orders than impatient traders and due improved resiliency, spread gets smaller as the ratio of impatient traders increases or the order arrival rate decreases. Roşu (2009) develop a model in continuous time and allows for instantaneous adjustments of submitted order where it is optimal. So limit order traders can endogenously enter price competition by undercutting its price. Resulting equilibrium is competitive and imply that higher volume and competition between traders lower the spreads and the price impact in the market. Roşu (2009) model also implies that as the probability of large market orders increase, limit orders tend to cluster away from the spread and resulting in a "hump"-shaped limit order book.

As described above, theoretical models of limit book are solved under certain (and generally restrictive) assumptions. Closed form solution of an equilibrium in a "complete" model is still lacking. This is mainly due to high number of state variables in limit order trading. However, Goettler et al. (2005) simulate a stochastic sequential game to obtain a stationary Markov-perfect equilibrium of a dynamic limit order market. In this framework, one risk neutral trader arrives to the market at each period, observes the state of the book and consensus value and strategically chooses the vector of order sizes for each price from a finite set of possible prices. Market orders execute immediately and limit orders enter the book. Each previously submitted limit order has an exogenous probability of cancellation. At the end of the period the state of book is updated according to the order of the current trader and realizations of the cancellation probabilities. Asymmetric information drives order choices, i.e. orders reflect the private valuations of the traders. In equilibrium, average book depths are highest at the best bid and ask prices and decay gradually at the further price levels. Their results suggest that market orders from one side of the market are more likely to be followed by similar market orders or aggressive limit orders from the same side. They relate this result to the picking-off effect of the shocks to the consensus value or persistence of in the states of nature. Also, higher volatility of the consensus value leads to more aggressive limit orders and lower the transaction costs of market orders.

Intraday Behaviour of Trading Activity and Liquidity

Patterns of intraday trading activity has been observed in many markets. Although one can not claim existence of a uniform pattern among various exchanges, concentration of trading at the open and/or close of the trading frequently observed. Admati and Pfleiderer (1988) model this observation by allowing for discretionary liquidity traders in the adverse selection framework similar to Kyle (1985), who assumes the liquidity traders are noise traders, such that their arrival rate is random. By removing this restriction, they allow liquidity traders to time their trades. Their model concludes that the discretionary liquidity trading is concentrated and also informed traders are more active in these "thick" periods. Foster and Viswanathan (1990) model long-lived private information in a similar framework, where discretionary traders have the option of delaying their trades to the next trading day.

Admati and Pfleiderer (1988) model does not explicitly explain trading concentration at the open and the close of the market. However, they argue that *nondiscretionary* liquidity at the open and the close is higher (since it is impossible to trade before and after these periods, respectively) and as a result discretionary traders have incentives to trade in these periods. Another explanation for the trading concentration at the close is the settlement rules which does not differentiate the time of the trade in a given day, therefore the closing period is the intersection of intervals of different discretionary traders, in which they are willing to trade. Madhavan et al. (1997) relate concentration of trading at the start of the day to the market maker's transaction costs. They argue that since market maker's transaction costs increase during the day, it is optimal for discretionary liquidity traders to trade in the open where these costs are minimal.

There is extensive empirical research on intraday patterns of stock market liquidity. Foster and Viswanathan (1993) show that the trading volume is significantly higher for the first hour of trading in NYSE. Lee et al. (1993) find a reverse J-shaped intraday pattern in trading volume and spread. Hasbrouck (1991a), Hasbrouck (1991b) , McInish and Wood (1992) and Chan et al. (1995a) report U-shaped patterns in bid-ask spread in NYSE. However, Chan et al. (1995b) and Chung and Ness (2001) report that bid-ask spreads in the NASDAQ market decline during the day. This deviation from NYSE pattern is attributed to the structural differences between specialist and dealer markets.

Intraday patterns of liquidity in limit order markets is analyzed by various studies. Biais et al. (1995) and Fan and Lai (2006) find a U-shaped pattern in Paris Bourse and Taiwan Stock Exchange, respectively, where there are no trading halts. In London Stock Exchange (LSE), which also has no trading halts, Abhyankar et al. (1997) find that the volume follow an M-shaped pattern, which is quite unusual. However, after introduction of electronic trading platform, Cai et al. (2004) find the volume in LSE follow a reverse-L shaped pattern with a spike immediately after the opening of U.S. markets and this spike is more prominent in " more international" stocks. They relate the lack of trading in the opening periods to the existence of overnight trading. Hamao and Hasbrouck (1995) find volume in Tokyo Stock Exchange has a U-shaped pattern in the morning and L-shaped pattern in the afternoon session. Brockman and Chung (1998) and Ahn and Cheung (1999) analyze relative spread and trading volume, respectively, in Hong-Kong Stock Exchange and find that they follow a reverse-J shaped pattern in the morning and J-shaped pattern in the afternoon session.

For ISE, Tezölmez (2000) analyzes intraday behaviors of returns and volatility of six different market indices and finds that volatility (measured by absolute return) is higher during opening periods of morning and afternoon sessions. Bildik (2001) analyzes the intraday behavior of ISE100 index. He observes a W-shaped pattern for index returns and L-shaped pattern for stock volatility in morning and afternoon sessions. Ekinci (2004) finds that, for a single stock (SAHOL), volume follows a reverse J-shaped pattern in the morning and J-shaped pattern in the afternoon sessions. He also reports repeating a similar analysis for 17 large and 19 medium-sized stocks without statistical tests and suggests that smooth liquidity patterns disappear as firm size gets smaller. Ekinci (2008), using order level data for a single stock (KCHOL), finds that liquidity is mostly supplied in the day opening and market orders follow W-shaped pattern through the day. He also provides evidence that investors tend to wait until the last period of the day to convert their limit orders to market orders to obtain execution. Küçükkocaoğlu (2008) analyzes intraday returns and focus on possible close end price manipulations in ISE.

Commonality in Trading Activity and Liquidity

Commonality in liquidity can be defined as co-movement of liquidity of individual assets across the market. Combined with the evidence that liquidity and liquidity risk are reflected in security prices, commonality in liquidity provides a basis for incorporating liquidity in asset pricing models (Pastor and Stambaugh (2003), Acharya and Pedersen (2005) and Bekaert et al. (2007)).

Early theoretical and empirical studies of market microstructure focus on behavior of a single asset. Specifically, transaction costs and their sources of an individual asset and their behavior over time was the main subject matter. Based on empirical observations, cross-sectional behavior of liquidity was first investigated by Chordia et al. (2000) and Huberman and Halka (2001) using daily data and Hasbrouck and Seppi (2001) using intraday data for NYSE.

Chordia et al. (2000) use market models to estimate the effects of changes to the aggregate market liquidity to the liquidity of an individual security to establish existence of commonality in liquidity in NYSE. They find commonalities in quoted spread, quoted depth and effective spread over a large sample of 1169 stocks. While they do not provide exact determinants of commonality in liquidity, they argue that inventory risk of specialists and asymmetric information are the driving factors. As a result of commonality in liquidity, they argue, besides the previously established (Amihud and Mendelson (1986) and Brennan and Subrahmanyam (1996)) static channel by which the trading costs affect asset pricing of securities, there may also exist a dynamic channel, if liquidity shocks to the market can not be diversified away. In other words, while higher average trading costs of an individual asset require higher expected return, investors may require additional premium for the stocks which have higher sensitivities to the liquidity shocks in the market. Coughenour and Saad (2004) provide evidence from NYSE which indicates that in addition to the market-wide commonality, the liquidity of specialist's portfolio also affects commonality of the stocks in that portfolio.

Huberman and Halka (2001) estimate autoregressive time series models for quote and depth variables for the portfolios of 60 randomly selected stocks from each size-based quartile. They provide evidence of correlations between estimated residuals across size-based portfolios. They also can not identify the source of commonality and relate this phenomenon to the the shifts in the amount of noise trading in the market.

Hasbrouck and Seppi (2001) perform principal component and canonical correlation analysis for returns, order flows and liquidity for 30 Dow stocks using 15-minute interval data. While they find common factor characterizations returns and order flows, they could not identify significant common factors for liquidity variables.

Brockman and Chung (2002), Fabre and Frino (2004), Domowitz et al. (2005) and Martìnez et al. (2005) provide evidence of commonality in liquidity in various non-U.S. exchanges.

Liquidity also exhibits commonality between different stock exchanges across the world. Brockman et al. (2009), using spread and depth variables from 47 exchanges -including ISE-, analyze commonality in liquidity both within and across exchanges. They find significant evidence of commonality in spreads and depths in Asian exchanges but do not observe such effect in Latin American markets. They also show evidence that changes in liquidity of exchanges are significantly dependent on global and regional liquidity fluctuations . Their data set includes 59 stocks from ISE. They find that an average coefficient of 0.4611 for the exchange-level spread regressions. These coefficients are positively significant for 83 percent of the firms from the sample. Their estimated coefficents for depth regressions for ISE are positively significant for 88 percent and have a mean of 0.8078.

Also, studies find evidence for commonality of liquidity between markets of different asset classes. Chordia et al. (2005) provide evidence of liquidity comovements across equity and fixed-income markets. Subrahmanyam (2007) shows similar linkages between NYSE stocks and real estate investment trusts.

Institutional Structure of ISE

Istanbul Stock Exchange is a pure (with no market makers) order-driven, continuous auction market.[9] There are two trading sessions in ISE: morning and afternoon sessions. Morning session starts at 9:30 am and ends at 12:30 pm. Afternoon session starts at 2:00 pm and ends at 17:30 pm.

First 20-minutes of each session (9:30 am - 9:50 am and 2:00 pm - 2:20 pm) is called the "opening session". This period is a call market where buy and sell orders are accumulated in the system and at the end of this period these orders are matched by a trading algorithm to find a price which yields the maximum value. This price becomes the opening price of the day. Unmatched orders from the opening session remain in the order book for the continuous auction session. After the opening session, regular trading (continuous auction) starts and lasts until the end of the session. So, in ISE, continuous auction periods are 9:50 am - 12:30 pm in the morning session and 2:20 pm - 5:30 pm in the afternoon session. The data set used in this study consists of observations from these periods.

[9] While a small set of the securities (i.e. exchange traded funds and small-cap mutual funds) in ISE are traded with a market maker, these companies are excluded from the data.

In ISE, price improvement in submitted limit orders is possible, such that a limit buy (sell) order can be improved by increasing (decreasing) order price. Historically order cancellation was disallowed during continuous auction session, however, as of October 8, 2010, ISE allows for the cancellation of limit orders at a slight cost (2.5 millionths of the order volume).

CHAPTER 3

INTRADAY BEHAVIOR OF TRADING ACTIVITY AND LIQUIDITY

I investigate intraday patterns in trading activity and (il)liquidity for ISE in this chapter. Additionally, similarities and distinctions of intraday behaviors of trading activity and liquidity measures between different size and volume quintiles are examined. Also, I discuss implications of zero observations in the dataset.

Data

In this study, five-minute interval data for ISE for the period between May 28, 2010 and November 2, 2010 is used. Each observation contains following variables: Stock's symbol, date, time, open price, highest price, lowest price, closing price, number of stocks traded and total Turkish Lira volume (turnover). If a stock has no trades within a five-minute interval, this interval is missing from the data. Data is obtained from Matriks, a local financial data provider.

Also, data for free float ratios and total number of shares for each stock are obtained from ISE web site. Free float and size data are available for each day. However, these variables are not expected to change significantly in short periods. Therefore, for the purpose of this study these variables held constant (as of November 3, 2010) for each stock.

Data for two trading days is excluded because of half-day trading sessions due to holidays and data for one trading day is excluded because of uniform irregularities for that day across data set. Observations for the intervals outside trading hours are excluded. Also, stocks which are not included in ISE-TUM (ISE-ALL) index and the stocks offered to public in this period are excluded from data set. Also, I filtered for too few observations (less than five) for a given day for each stock, however no such occurrence is observed.

After applying filters, final data set consists of 1,457,268 firm-interval-day observations of 254 stocks over 106 trading days. There are seventy five-minute intervals for each day. 26,922 firm-day observations (out of a possible 26,924) exist.[10] Average Turkish Lira volume per interval over all stocks and trading days is given at Figure 1.

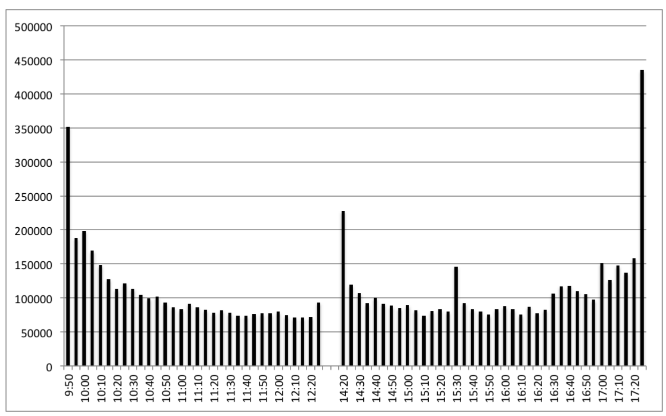


Figure 1: Average Turkish Lira volume per interval over all firms and trading days

Individual Stock Behavior

In this section, I analyze intraday patterns for trading activity and liquidity for 254 stocks trading in ISE. I utilize Turkish Lira volume (turnover) to measure trading activity and components of Amihud (A) and Hui-Heubel(HH) illiquidity measures to measure price impact. These measures are defined below:

[10]The list of stocks used in the data set is provided in Appendix A.

- $V_t = \sum_{j=1}^{N_t} p_j.q_j$, where N_t is the number of shares traded between time t-1 and t, p_j is price for trade j and q_j is the number of shares traded in trade j.
- $A_t = \dfrac{|r_t|}{V_t}$, where r_t is the open-to-close return for the interval t.
- $HH_t = \dfrac{\dfrac{p_{max,t} - p_{min,t}}{p_{min,t}}}{\dfrac{V_t}{F.p_t}}$, where p_{max} and p_{min} are maximum and minimum prices in the interval t, respectively; p_t is the closing price and F is the free float of the company.

Amihud measure estimates the price impact of the unit volume. On the other hand, Hui-Heubel measure takes price range into account and therefore less sensitive to closing price manipulations. Hui-Heubel measure also takes free-float of the stocks into consideration. However, Amihud measure is more commonly used in literature, possibly because of the lack of the intraday high/low price data. Also, in the cases where price range is close to absolute value of the difference of open and close prices, Hui-Heubel measure can be considered as free float adjusted Amihud measure. Mianbi and Langnan (2007) compare several price impact measures with a high frequency benchmark and conclude that Hui-Heubel measure performs best among other measures. For both of these measures, liquidity decreases as measure increases.

I examine the intraday behavior of these measures using a regression with dummy variables for each stock in the data. I assign a dummy variable for each time period and control for the interday effects using a fixed effects model. The following models are estimated for each of the 254 stock in the data set:

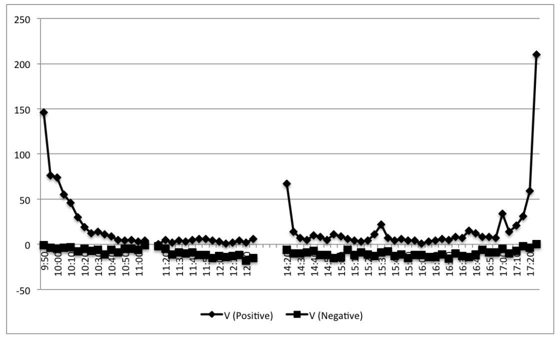
$$\begin{aligned}
&V_{t,i} = \alpha + \beta_t + \textstyle\sum_i \delta_{V,i}.D_i + \epsilon_{t,i},\\
&A_{t,i} = \alpha + \beta_t + \textstyle\sum_i \delta_{A,i}.D_i + \epsilon_{t,i},\\
&HH_{t,i} = \alpha + \beta_t + \textstyle\sum_i \delta_{HH,i}.D_i + \epsilon_{t,i},\\
&i \in \{1, 2, ..., 16, 18, ..., 70\}
\end{aligned} \tag{1}$$

where $V_{t,i}$, $A_{t,i}$ and $HH_{t,i}$ are the volume, Amihud measure and Hui-Heubel measure in day t and time period i, respectively, and D_i is the dummy variable assigned to period i. Dummy variables are assigned in ascending order, i.e D1 represents first 5-minute period and D70 represents last 5-minute period of the trading day. D17 (midpoint of the morning session) is excluded from the regression to eliminate singularity and therefore is the benchmark period. β_t is the fixed effect parameter of each day.

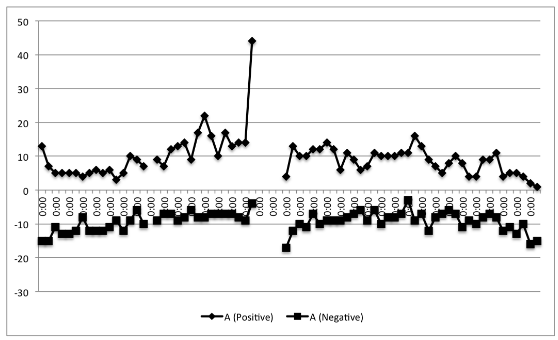
In this model, we are interested in coefficients of the dummy variables. A positive (negative) significant coefficient implies that the liquidity measure for that period is significantly higher (lower) than the measure for the benchmark period (midpoint of the morning session). β_t controls for the day-to-day fluctuations in a given liquidity measure. Summary results are reported in Figure 2. Intentionally, all figures show a gap to differentiate between morning and afternoon sessions.

It is important to note that the results given in Figure 2 disregard the magnitude of coefficients in the single-firm regression, but show total number of stocks which have significantly positive or negative coefficients for a given time interval.

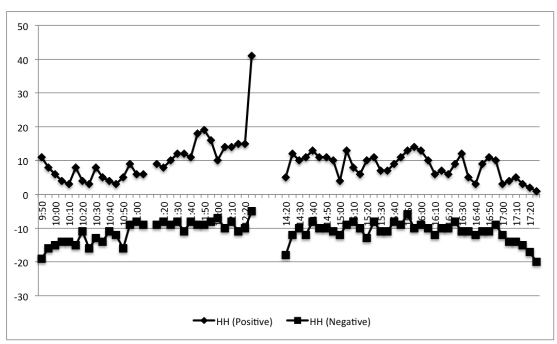
Individual regressions on volume (V) indicate that, for about 60 percent of the stocks, trading volume during first period of the day is significantly higher than the benchmark interval, however this ratio decays to close to zero within 40 minutes of



(a) Dependant Variable: V



(b) Dependant Variable: A



(c) Dependant Variable: HH

Figure 2: Number of Regressions with Significant Dummy Coefficients by Intraday Intervals. *Note*: The figures above represent the total number of individual stock regressions where coefficients of dummies are significant at 2.5 percent level ($|t| > 1.96$) for each interval. Total number of positive (negative) significant coefficients are reported in positive (negative) vertical axis. Total number of stocks is 254.

the morning session and remains steady until the end of the session. For about 25 percent of the stocks, trading activity is significantly higher than the benchmark period at the first interval of afternoon session. However, after this interval, for almost all stocks, the trading volume is not significantly higher than the benchmark interval, until the last 30 minutes of trading. During the last 5 minutes of trading, more than 80 percent of stocks have higher volume than the benchmark period.

Regressions of Amihud (A) and Hui-Heubel (HH) measures yield relatively close results. Since these regressions are individual stock regressions and size of the firms are constant for each firm, the regression results only differentiate between the return per trading volume (for Amihud measure) and the range per trading volume (for Hui-Heubel measure). For these liquidity measures, in general, the coefficients of interval dummies are not significantly different than the benchmark interval. However, I observe that in the last period of the morning session, these measures are higher than the benchmark for about 20 percent of the stocks, indicating lack of liquidity in this interval.

Aggregate Analysis

In the previous section, I analyzed patterns of the liquidity measures for each stock in the data set. In this section, I perform an aggregate analysis of liquidity patterns for the whole data set. To do this, I extend the model given in Equation 1 and estimate the following multi-level fixed effects models, for all $s \in S$, where S is the set of stocks included in analysis:

$$
\begin{aligned}
&V_{s,t,i} = \alpha + \beta_t + \gamma_s + \textstyle\sum_i \delta_i.D_i + \epsilon_{s,t,i}, \\
&A_{s,t,i} = \alpha + \beta_t + \gamma_s + \textstyle\sum_i \delta_i.D_i + \epsilon_{s,t,i}, \\
&HH_{s,t,i} = \alpha + \beta_t + \gamma_s + \textstyle\sum_i \delta_i.D_i + \epsilon_{s,t,i}, \\
&i \in \{1, 2, ..., 16, 18, ..., 70\}
\end{aligned}
\tag{2}
$$

where $V_{s,t,i}$, $A_{s,t,i}$ and $HH_{s,t,i}$ are the volume, Amihud measure and Hui-Heubel measure for firm s in day t and time period i, respectively, D_i is the dummy variable assigned to period i and γ_s is the stock-specific dummy variable. β_t represents fixed effects dummy for a given day.

I also divide the set of stocks in the data into size and volume quintiles. Size quintiles are generated by using market capitalizations of the firms and volume quintiles are generated by using average daily Turkish Lira volume of stocks calculated from the data. Daily volume of a given stock is found by:

$\overline{DV_s} = \sum_t \frac{DV_{s,t}}{T}$,

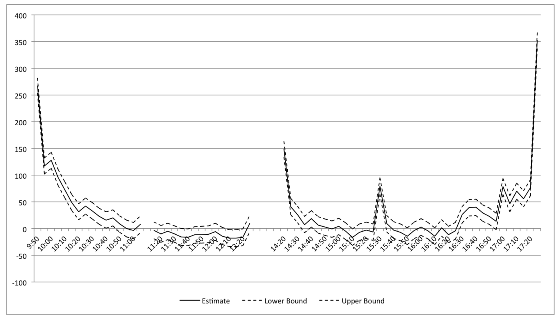
where $DV_{s,t} = \sum_i V_{s,t,i}$. Market capitalizations are calculated by multiplying total number of shares outstanding by the average of volume weighted average prices (VWAP) of each day. I perform further analyses for the whole data set and for each size and volume quintile. Summary statistics for the complete dataset and each quintile are given in Table 1. Distribution of stocks across size and volume quintiles is provided in Appendix B.

Figures 3, 4 and 5 provide estimated interval dummy coefficients for all liquidity measures, for the whole data, size quintiles and volume quintiles, respectively.

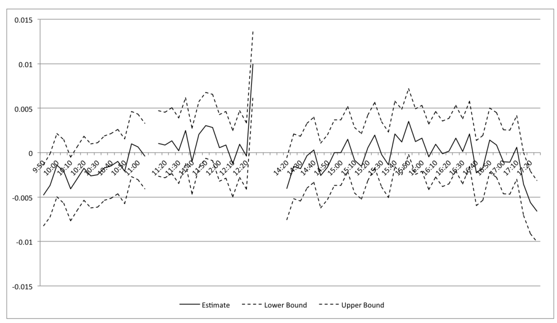
Table 1: Summary statistics for the Stocks Included in the Dataset.

$\overline{DV}$ is the average daily volume of a given stock. Mkt. Cap. is the market capitalization. Free Float is the market value of shares which are available to trade. All values are in million Turkish Liras. N is the number of firms in a given subsample.

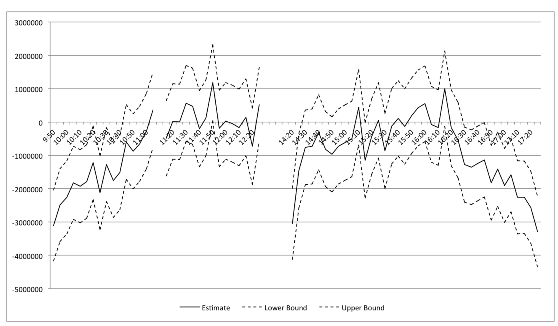
	Variable	N	Min	Mean	Max	St. Dev.
All Data	$\overline{DV}$	254	0.158	7.702	228.198	19.161
	Mkt. Cap.	254	9.818	1617.365	33345.416	4445.740
	Free Float	254	5.950	526.926	18037.424	1764.604
Size Quintile 1	$\overline{DV}$	51	0.587	23.397	228.198	38.000
	Mkt. Cap.	51	1306.722	6905.013	33345.416	7997.471
	Free Float	51	13.067	2192.338	18037.424	3483.938
Size Quintile 2	$\overline{DV}$	51	0.278	5.678	39.607	7.646
	Mkt. Cap.	51	407.167	731.323	1306.389	255.097
	Free Float	51	23.439	234.718	1205.424	200.241
Size Quintile 3	$\overline{DV}$	51	0.224	5.256	18.253	4.834
	Mkt. Cap.	51	162.248	271.692	399.417	71.393
	Free Float	51	7.799	132.139	377.183	93.113
Size Quintile 4	$\overline{DV}$	51	0.239	2.387	7.617	1.752
	Mkt. Cap.	51	66.513	106.617	161.949	25.139
	Free Float	51	13.525	43.716	159.092	27.848
Size Quintile 5	$\overline{DV}$	50	0.158	1.676	7.839	1.497
	Mkt. Cap.	50	9.818	41.274	65.691	15.454
	Free Float	50	5.950	21.813	61.495	13.174
Volume Quintile 1	$\overline{DV}$	51	8.893	28.690	228.198	35.773
	Mkt. Cap.	51	176.169	5651.151	33345.416	8486.094
	Free Float	51	66.204	2019.192	18037.424	3524.796
Volume Quintile 2	$\overline{DV}$	51	3.592	5.373	8.749	1.321
	Mkt. Cap.	51	26.427	972.952	9104.256	1717.329
	Free Float	51	13.742	326.831	4096.915	625.567
Volume Quintile 3	$\overline{DV}$	51	1.735	2.483	3.580	0.582
	Mkt. Cap.	51	21.451	392.323	2759.940	536.541
	Free Float	51	13.067	97.973	592.022	121.202
Volume Quintile 4	$\overline{DV}$	51	0.906	1.238	1.689	0.226
	Mkt. Cap.	51	11.900	434.032	4019.520	710.563
	Free Float	51	5.950	100.395	1004.880	168.634
Volume Quintile 5	$\overline{DV}$	50	0.158	0.588	0.898	0.188
	Mkt. Cap.	50	9.818	616.746	10067.813	1827.342
	Free Float	50	6.176	81.504	503.391	117.101



(a) Dependant Variable: V



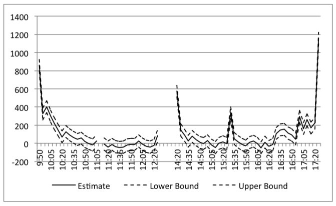
(b) Dependant Variable: A



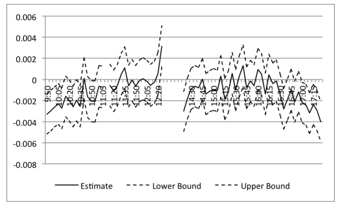
(c) Dependant Variable: HH

Figure 3: Coefficients of interval dummies for the model given in Equation 2 for the complete dataset. Dashed lines represent 95 percent confidence interval.

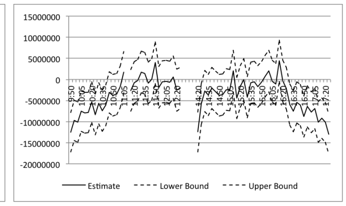
Size Quintile 1 (Larger)



(a) Dependant Variable: V

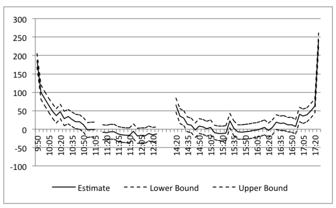


(b) Dependant Variable: A

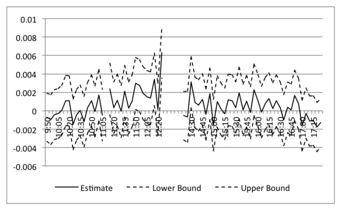


(c) Dependant Variable: HH

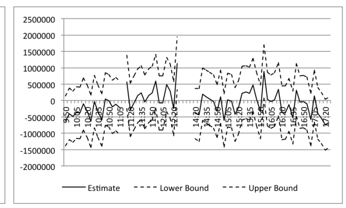
Size Quintile 2



(d) Dependant Variable: V

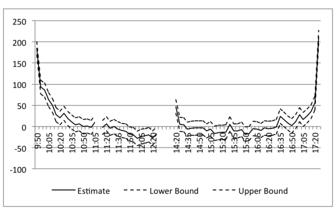


(e) Dependant Variable: A

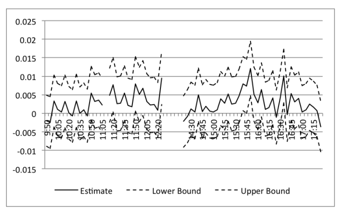


(f) Dependant Variable: HH

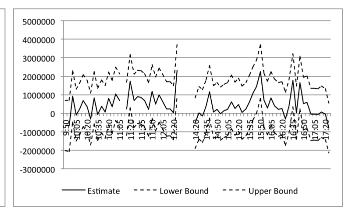
Size Quintile 3



(g) Dependant Variable: V

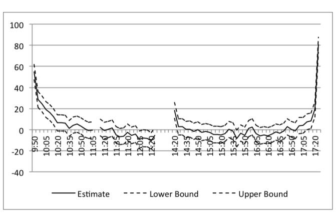


(h) Dependant Variable: A

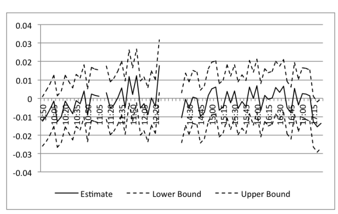


(i) Dependant Variable: HH

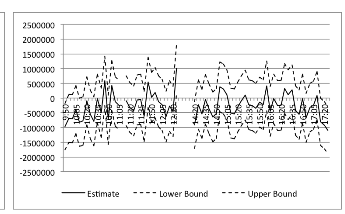
Size Quintile 4



(j) Dependant Variable: V

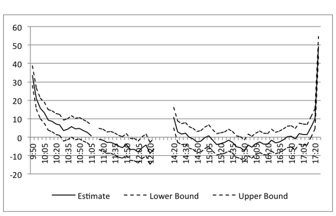


(k) Dependant Variable: A

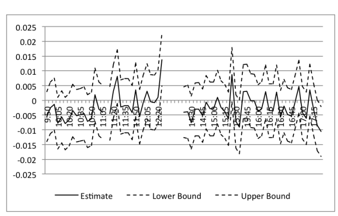


(l) Dependant Variable: HH

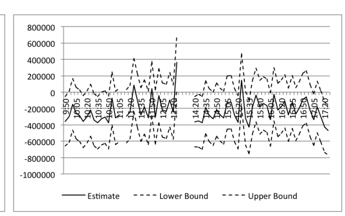
Size Quintile 5 (Smaller)



(m) Dependant Variable: V



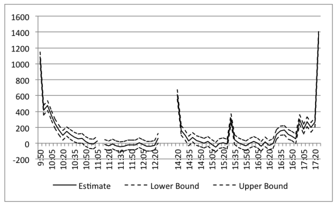
(n) Dependant Variable: A



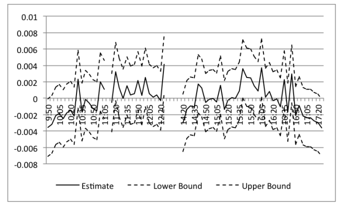
(o) Dependant Variable: HH

Figure 4: Coefficients of interval dummies for the model given in Equation 2 by size quintiles. Dashed lines represent 95 percent confidence interval.

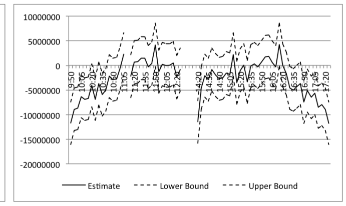
Volume Quintile 1 (Higher Volume)



(a) Dependant Variable: V

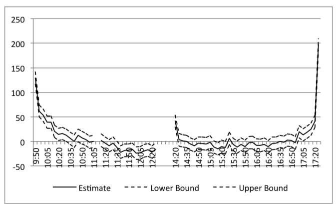


(b) Dependant Variable: A

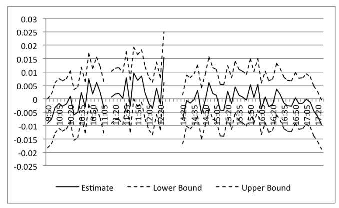


(c) Dependant Variable: HH

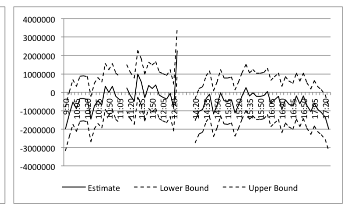
Volume Quintile 2



(d) Dependant Variable: V

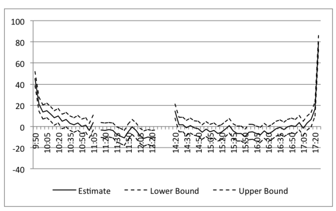


(e) Dependant Variable: A

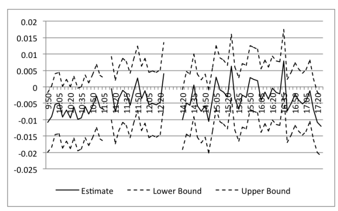


(f) Dependant Variable: HH

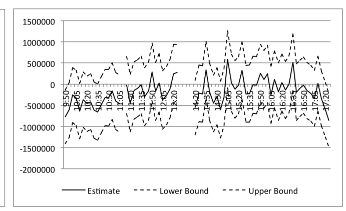
Volume Quintile 3



(g) Dependant Variable: V

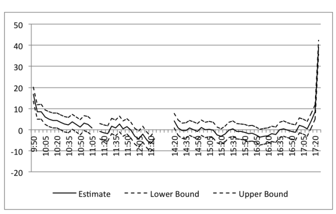


(h) Dependant Variable: A

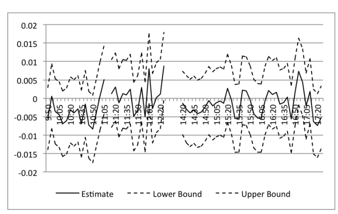


(i) Dependant Variable: HH

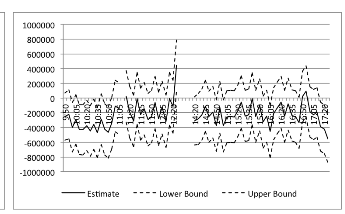
Volume Quintile 4



(j) Dependant Variable: V

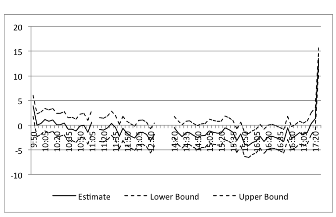


(k) Dependant Variable: A

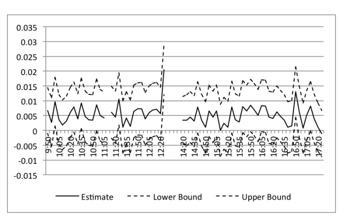


(l) Dependant Variable: HH

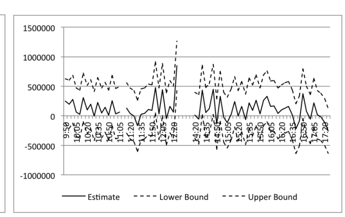
Volume Quintile 5 (Lower Volume)



(m) Dependant Variable: V



(n) Dependant Variable: A



(o) Dependant Variable: HH

Figure 5: Coefficients of interval dummies for the model given in Equation 2 by volume quintiles. Dashed lines represent 95 percent confidence interval.

All Data

Analysis of the whole dataset indicates that trading volume is significantly higher than the benchmark period during first 20 intervals of trading in the morning session, first two intervals of afternoon session, one interval immediately after 3:30 pm and last 12 interval of afternoon session. Trading volume decays during the opening hours of the day and increases during as the close approaches. The highest periods of trading volume are the last and the first period of the day. Therefore estimation results suggest that trading volume follows a reverse-J shaped curve in the morning session and a U-shaped pattern in the afternoon session.

These results are consistent with related literature. High amounts of trading activity during opening hours are generally associated with the information accumulation during the periods when markets are closed and increased trading during the closing hours are related to the incentives of trades to close their positions, since settlement rules does not differentiate the time of the trades. Closing periods can also be seen as intersections of time intervals during which different discretionary traders are willing to trade.

Also, existence of call markets (pre-opening sessions) before both morning and afternoon sessions creates incentives for traders during the first periods of respective sessions, since the liquidity (limit orders) during call auction periods carry over to the regular session. So as suggested by Admati and Pfleiderer (1988), traders have incentives to concentrate their trades to benefit from increased liquidity and as a result, liquidity carrying over from call auctions provide incentives to trade immediately after these pre-opening sessions. I believe the question of how much of the trading volume during opening period is due to the liquidity generated in call markets deserves further research.

Another interesting observation is the temporarily high trading volume immediately after 3:30 pm. I believe that this is related to macroeconomic data announcements (especially U.S. data) at this time of the day. Since foreigners' share in the ISE is quite significant, their trading activity due to portfolio balancing is likely to increase immediately after the announcements.

Estimation results for both of the price impact measures over all data indicate that the price impacts of trades are significantly lower during the opening periods of both sessions and during the close of the day. Additionally, coefficient of Amihud (A) measure is significantly higher than the benchmark for the last period of the morning session, providing evidence for illiquidity during this interval.

Overall, most active periods of trading during a given day are the opening periods for both sessions and closing period of the afternoon session in ISE. As in other stock exchanges trading is especially concentrated in the first and last periods of the day. This result is in line with the theoretical models of intraday trading. While the trading volume is significantly higher during these periods, price impact measures are also significantly lower. Lower price impact in the opening period of the day, in combination with the high volume observation in this period, suggest that sufficient amount of liquidity for the relatively high amount market orders is supplied either in call market or in this period. This result is consistent with Ekinci (2008) who finds that liquidity is mostly supplied before or in the first period of the day.[11]

[11] Ekinci (2008) uses a data set from a period before call market mechanism is introduced.

Size Quintiles

I partition the data to observe whether intraday trading behavior vary in different levels of trading activity or firm size. I divide the data set into quintiles by firms' market capitalization and by their average daily turnover. Then for each size and volume quintile equation 2 is estimated.

An analysis of the trading behavior in different size quantiles (Figure 4) suggest that, in general, intraday trading patterns are consistent with the results found in analysis of overall data.

Trading volume is significantly higher than benchmark during opening periods of both sessions and closing periods of the day. However, we observe that the duration of these intervals shorten (especially during the closing periods of the day) as market capitalization of the firms get smaller. Also, the phenomenon which is observed at 3:30 pm in the analysis of overall data, persists only for the largest two size quintiles.

The estimates Amihud and Hui-Heubel measures also have a tendency to behave as in the analysis of the whole dataset. Amihud measure is significantly higher during the last period of morning session for all quintiles. The opening period of the morning session is significantly lower for the largest and the fourth size quintiles, the opening period of afternoon session is significantly lower for the largest quintile and the closing period of the day is significantly lower for the largest, fourth and the smallest quintile.

The estimates of Hui-Heubel measure, compared to the benchmark period, are significantly lower for all size quintiles except third quintile for the opening period of the day; significantly higher for all size quintiles except the largest quintile for the closing period of the morning session; significantly lower for the largest, fourth and the smallest size quintiles for the opening of the afternoon session and significantly lower for all size quintiles except third size quintile.

Different size quintiles in general follow similar intraday patterns to the overall data. One exception is the announcement effect in trading volume observed at 3:30pm. It is more prominent in the largest size quintile, which mostly contains active stocks. Estimates of all three measures indicate that there are three periods (opening periods of the day, opening period of the afternoon session and closing period of the day) where liquidity is significantly higher and one period (opening period of the afternoon session) where it is lower.

Volume Quintiles

Analysis of volume quintiles yields results similar to previous findings(Figure 5). Trading volume is again significantly higher during the opening periods of both sessions and closing of the day. However, durations of the periods where volume is significantly higher gradually diminish as trading activity decreases. For example, for the highest volume quintile, trading volume is significantly higher for first and last 60 minutes of the trading day; whereas these durations are 5 minutes for the lowest volume quintile.

Also 3:30 pm effect is only significant for most active stocks, providing evidence that international macroeconomic announcements have significant impact only for these stocks. This also implies that international funds tend to adjust their positions to new information by trading in most active stocks in order to minimize their trading costs.

Easley et al. (1996) show that probability of informed trading is lower in high volume stocks. They find that even though high volume stocks have more frequent information events and higher arrival rates of informed traders, these effects are offset by the higher arrival rates of uninformed traders. They argue that since less active stocks have higher risks of informed trading they have higher spreads. They also find that while high volume stocks have lower probabilities of informed trading than medium volume stocks, there is no significant difference between medium and low volume stocks.

While Easley et al. (1996) relate higher spreads (lower liquidity) in less active stocks to the small number of uninformed traders, they also emphasize the "free option" property of limit orders. Since informed trading is higher in inactive stocks, limit order traders demand higher rent to supply limit orders, increasing the bid-ask spread. On the other hand, recent models of limit order book provide other possible reasons of higher spreads. Foucault et al. (2005) and Roşu (2009) argue that higher ratio of patient traders and higher probabilities of large market orders can lead to higher spreads.

In the light of these arguments, a comparison of the coefficients of the first and the last periods of the day for different volume quintiles can be a basis for an argument for the "free option" issue. For the highest volume quintile, the coefficient for the last period is about 15 percent higher than the first period. This ratio monotonically increases up to 300 percent for the lowest volume quintile. Note that, for the most of part our data set, order cancellation was not available in ISE. Therefore limit order traders could not independently choose both timing and duration of their orders, facing higher risks related to limit order trading (winner's curse). If they were trying to minimize the duration of their orders, they would postpone the submission of limit orders to the closing periods, therefore creating higher amounts of depth during these periods. I think a detailed analysis of this issue using quote level data warrants further research.

Price impact measures for volume quintiles exhibit similar intraday patterns compared to the whole data set. They indicate lower price impacts during opening and closing of the day and opening of the afternoon session and higher price impacts at the end of the morning session. I observe that these effects are more prominent for the highest volume, however these tendencies are persistent for all quintiles.

Impact of Order Cancellation Mechanism on Intraday Behavior

Starting from October 8, 2010, ISE introduced "order cancellation mechanism". Before this date limit order traders were unable to cancel their orders and therefore a limit order, once submitted, stayed in the order book until the end of the session.[12]

Order cancellation mechanism gives the limit order traders the option of canceling their outstanding orders by incurring a small fee. I explore possible impacts of this structural change by estimating following regressions for all subsets of data defined in previous section:

$$\begin{aligned}
&V_{s,t,i} = \alpha + \beta_{OC,t} + \gamma_{OC,s} + \textstyle\sum_i \delta_{OC,i}.D_i + \sum_i \theta_{OC,i}.(D_{OC}.D_i) + \epsilon_{s,t,i},\\
&A_{s,t,i} = \alpha + \beta_{OC,t} + \gamma_{OC,s} + \textstyle\sum_i \delta_{OC,i}.D_i + \sum_i \theta_{OC,i}.(D_{OC}.D_i) + \epsilon_{s,t,i},\\
&HH_{s,t,i} = \alpha + \beta_{OC,t} + \gamma_{OC,s} + \textstyle\sum_i \delta_{OC,i}.D_i + \sum_i \theta_{OC,i}.(D_{OC}.D_i) + \epsilon_{s,t,i},\\
&i \in \{1, 2, ..., 16, 18, ..., 70\}
\end{aligned} \tag{3}$$

[12]For limit orders submitted in morning session, traders can choose to extend this duration until the end of the trading day.

where D_{OC} is zero before October 8, 2010 and one otherwise. These models are unrestricted versions of the models provided in Equation 2. That is, if we impose the restrictions $\theta_{OC,i} = 0$, for all i, these models reduce to the models estimated in previous section. I examine whether there are significant changes in intraday patterns after introduction of order cancellation mechanism by using F-test for restrictions. The null and alternate hypotheses are:

$H_0 : \theta_{OC,i} = 0$ for all i.

$H_a : \theta_{OC,i} \neq 0$ for some i.

The test statistic is given by:

$$\frac{(R^2_{ur} - R^2_r)/J}{(1 - R^2_{ur})/N - K} \sim F[J, N - K],$$

where R^2_{ur} and R^2_r are R^2's of the unrestricted and restricted regressions, respectively, J is the number of restrictions, N is the number of observations and K is the number estimated coefficients in the unrestricted regression. $F[J, N - K]$ is the F distribution with J degrees of freedom in numerator and N-K degrees of freedom in denominator.

The p-values of test statistics for each dependent variable and for each subset of data used are provided in Table 2. F-test statistics indicate that we cannot reject the null hypothesis for price impact measures, A and HH, for all subsets at 5 percent significance level. Therefore, there is no significant change in dummy coefficients for these variables after the introduction of order cancellation.

For trading volume, V, we reject the null hypothesis for most subsets of data at 5 percent and for all subsets at 10 percent level of significance. This implies that there exist at least one $\theta_{OC,i}$ that is not equal to zero , i.e, there is a change in at least some of the dummy coefficients after the introduction of order cancellation mechanism.

Table 2: P-values of Test Statistics for Restrictions

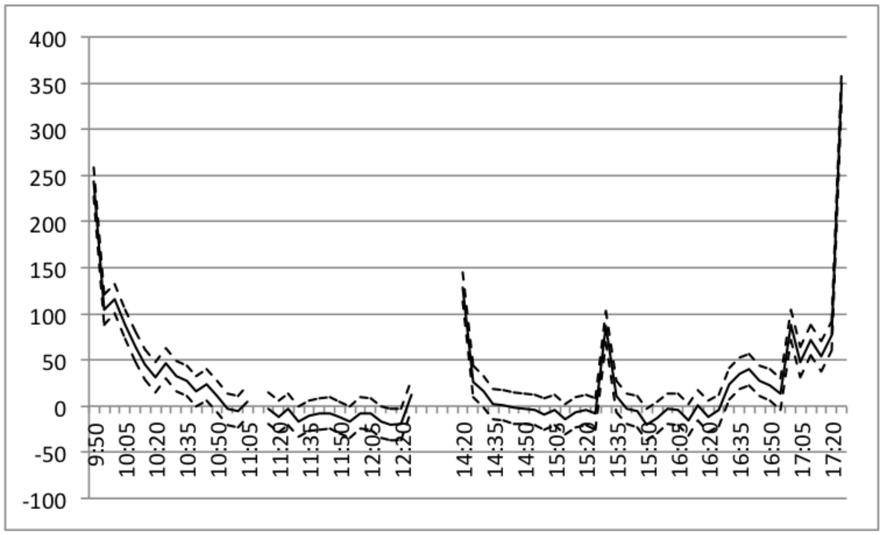
P-values of F statistics for testing the hypothesis $H_0 : \theta_{OC,i} = 0$ for all i, are provided below, for each dependent variable, V, A and HH and for a given subset of data. V is Turkish Lira volume and A and HH are price impact measures defined in previous sections.

	Dependent Variable		
	V	A	HH
All Data	0.0000	0.9878	0.3790
Size Quintiles			
Larger	0.0000	0.9951	0.5573
Size 2	0.0199	0.9634	0.9999
Size 3	0.0000	0.9987	0.9997
Size 4	0.0000	0.9979	0.9847
Smaller	0.0000	0.8196	0.1199
Volume Quintiles			
Higher Volume	0.0000	0.9999	0.6442
Volume 2	0.0000	0.9982	0.9996
Volume 3	0.0000	0.6797	0.3986
Volume 4	0.0000	0.9689	0.0529
Lower Volume	0.0742	0.9980	0.8199

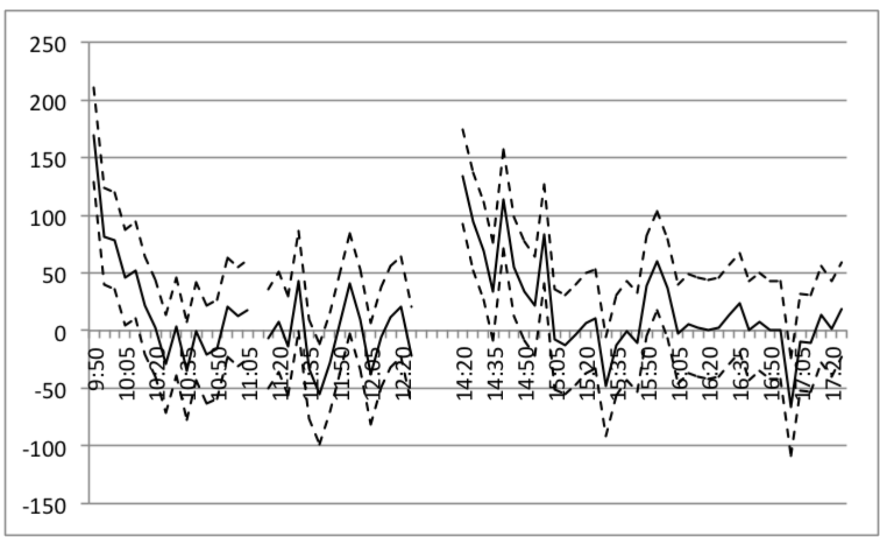
I provide the estimates of $\delta_{OC,i}$ and $\theta_{OC,i}$ for trading volume in Figures 6, 7 and 8 for the whole data, size quintiles and volume quintiles, respectively. It is important to note that the estimates of $\delta_{OC,i}$ are common to the periods both before and after the introduction of order cancellation mechanism. On the other hand, estimates of $\theta_{OC,i}$ show how the estimates of $\delta_{OC,i}$ are changed after the introduction of this mechanism.

The estimates of $\theta_{OC,i}$ for the whole data indicate significantly higher trading volume during the opening periods of both morning and afternoon sessions after introduction of order cancellation. This changes persist in all size quintiles except second quintile. Also in the three lowest size quintiles, there is significant increase in volume during the last period of the day. Observed changes in the estimates for the whole data also exist in the two highest volume quintiles. Additionally, I observe higher volume for the second and third volume quintiles during the last period of the day.

In this section, I examine possible effects of order cancellation to intraday patterns in ISE. While patterns established in the previous section remains the same, my findings indicate a significant increase in trading volume during opening periods of both sessions after introduction of order cancellation.



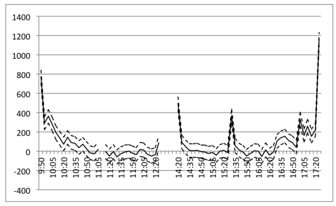
(a) Estimates of $\delta_{OC,i}$



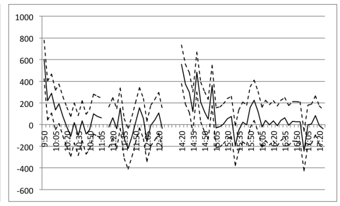
(b) Estimates of $\theta_{OC,i}$

Figure 6: Estimated values of $\delta_{OC,i}$ and $\theta_{OC,i}$ for the model given in Equation 3 for dependent variable V for the complete dataset. Dashed lines represent 95 percent confidence interval.

Size Quintile 1 (Larger)

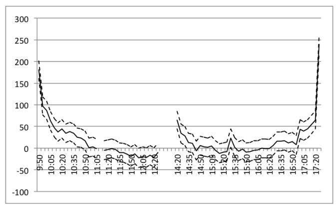


(a) Estimates of $\delta_{OC,i}$

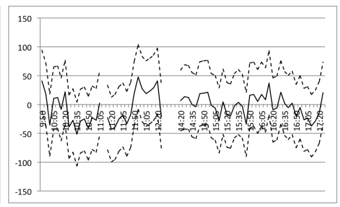


(b) Estimates of $\theta_{OC,i}$

Size Quintile 2

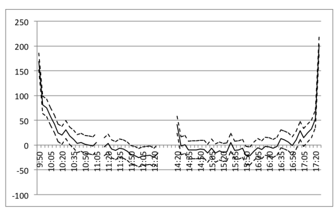


(c) Estimates of $\delta_{OC,i}$

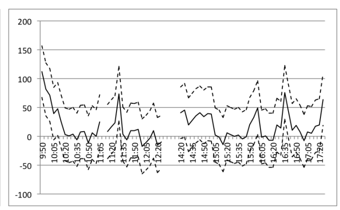


(d) Estimates of $\theta_{OC,i}$

Size Quintile 3

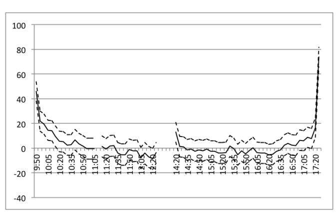


(e) Estimates of $\delta_{OC,i}$

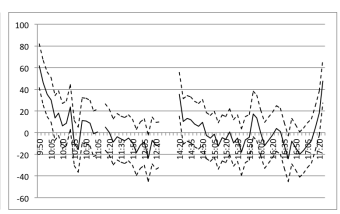


(f) Estimates of $\theta_{OC,i}$

Size Quintile 4

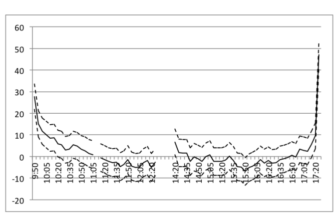


(g) Estimates of $\delta_{OC,i}$

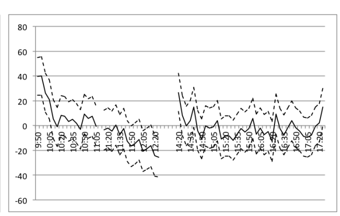


(h) Estimates of $\theta_{OC,i}$

Size Quintile 5 (Smaller)



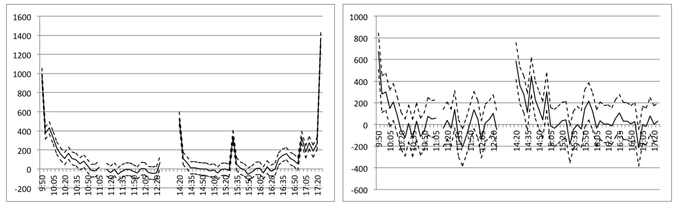
(i) Estimates of $\delta_{OC,i}$



(j) Estimates of $\theta_{OC,i}$

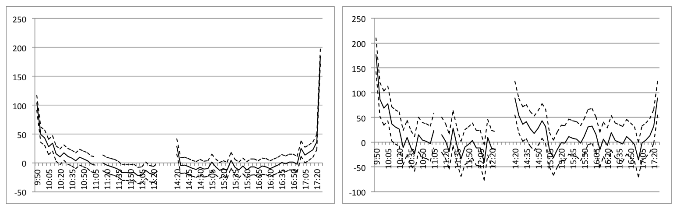
Figure 7: Estimated values of $\delta_{OC,i}$ and $\theta_{OC,i}$ for the model given in Equation 3 for dependent variable V by size quintiles. Dashed lines represent 95 percent confidence interval.

Volume Quintile 1 (Higher Volume)



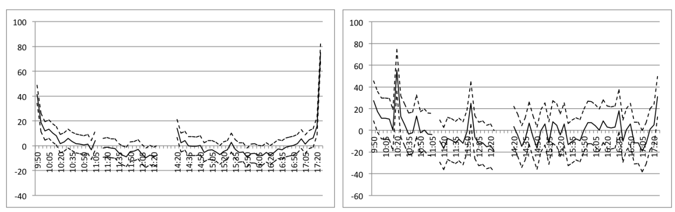
(a) Estimates of $\delta_{OC,i}$ (b) Estimates of $\theta_{OC,i}$

Volume Quintile 2



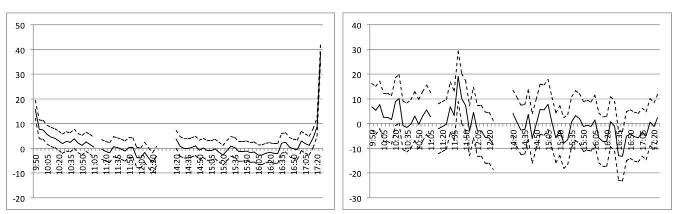
(c) Estimates of $\delta_{OC,i}$ (d) Estimates of $\theta_{OC,i}$

Volume Quintile 3



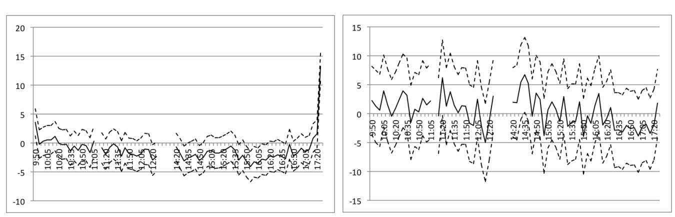
(e) Estimates of $\delta_{OC,i}$ (f) Estimates of $\theta_{OC,i}$

Volume Quintile 4



(g) Estimates of $\delta_{OC,i}$ (h) Estimates of $\theta_{OC,i}$

Volume Quintile 5 (Lower Volume)



(i) Estimates of $\delta_{OC,i}$ (j) Estimates of $\theta_{OC,i}$

Figure 8: Estimated coefficients of $\delta_{OC,i}$ and $\theta_{OC,i}$ for the model given in Equation 3 for dependent variable V by volume quintiles. Dashed lines represent 95 percent confidence interval.

Zeros

In this section I will slightly digress from the topic of this chapter to discuss another intraday phenomenon, zeros, in the data.

Lesmond et al. (1999) show that days with zero returns within a month is positively correlated with spread and negatively correlated with firm size. They argue that price movements occur when the amount of accumulated information exceeds the transaction cost. So, less liquid stocks (stocks with high spreads) would have higher numbers of zero returns and larger firms would have fewer numbers of zero returns.

In intraday setting, zero volume periods indicate lack of trading activity and can be thought as a proxy measure of illiquidity. I will argue that periods that have zero price ranges fall into a similar category.

Using zero measures, especially for return series, comes with the disadvantage of identification problem. This is because an observed zero return does not necessarily imply a zero change in efficient price, and also conversely one can observe a non-zero return while the efficient price had not changed.[13] This is mainly due to the bid-ask bounce.

Bid-ask bounce refers to the change in observed trade prices because of the direction of last trade. As an example, let, at a certain time t, the best bid price for a stock is b_t and the best ask price is $a_t(b_t < a_t)$, therefore the efficient price of the stock is between b_t and a_t. Also assume that no new information and no new limit order arrives between t and t+1. If a unit market buy order arrives at t and a unit market sell order arrives t+1, then the trade price at time t (t+1) is $a_t(b_t)$. So, even

[13]Lesmond et al. (1999) discuss possible scenarios where there is an identification problem.

though the efficient market price remains unchanged, trade prices reflect a price change due to the direction of the order.

On the other hand, "zero range" observations have less severe identification problems. An observed equality of the highest and lowest price in a given period implies three distinct theoretical possibilities of underlying market order behavior in a given interval:

- Unidirectional order(s) which does not exhaust liquidity: These orders have a total size less than amount of depth at a price level (which can either be at bid or ask side).
- Unidirectional order(s) which exhaust liquidity: These orders consume all available liquidity at a price level and result in an increase in the bid-ask spread.
- Bidirectional orders: These types of market orders consume all available liquidity at a price level and become limit buy or sell order at that price depending on the type of the market order. Then other market orders of opposite direction are executed at that price.

While we can not identify which one of these possibilities is the case for a given interval observation, I assume that first case is the most common one. Therefore, in terms of trading activity, zero range observations are similar to the zero volume observations, since in an *active* trading environment we expect to observe both buy and sell side market orders. So, it can be argued that the periods with zero volume or zero range observations are the periods where there is no active bidirectional trading.

One exception to the above arguments is the aggressive market orders which "walk the book", which can yield observations of positive price range with unidirectional market orders . These are the market orders which consumes the liquidity of at least one price level and portions of which execute at different price level, thus causing multiple price observations by unidirectional trades. However, these orders are not common. For ISE, Ekinci (2004), for a single stock (SAHOL) finds no price changes larger than one tick and Booth and Yuksel (2006) find that only 0.03 percent of the transactions result in a price change of at least two ticks in a dataset of 28 stocks over 14 months. [14]

Table 3 provides a summary of distributions of zeros in the ISE data set for all data, size and volume quintiles. First column provides the total number of intervals for all firms and trading days. Second column is the total number of intervals trading occurred. Third and fourth columns provide total number zero return (where opening price equals closing price) and zero range (where highest price equals lowest price) intervals, respectively. The last two columns provide the total number of zero volume and zero range observations and the total number of positive volume and non-zero range observations for a given subset. All percentages are relative to the total number of intervals.

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[14]These studies utilize data sets of active stock(s) for the periods in which the price ticks were more discrete. Therefore, the frequency of such orders may be higher after reduction in tick sizes or for the stocks with medium or low levels of activity.

Table 3: Zeros

Note: Percentages are relative to total numbers of intervals in a given subset.

	Total Number of Intervals	Number of Intervals with Positive Volume	Number of Intervals with Zero Return	Number of Intervals with Zero Range	Number of Intervals with Zero Range or Zero Volume	Number of Intervals with Positive Volume and Non-zero Range
Panel A. All data						
All Data	1,884,680	1,457,268	984,350	709,971	1,137,383	747,297
(N=254)		*77.32%*	*52.23%*	*37.67%*	*60.35%*	*39.65%*
Panel B. Size Quintiles						
Larger	378,420	315,438	207,728	131,139	194,121	184,299
(N=51)		*83.36%*	*54.89%*	*34.65%*	*51.30%*	*48.70%*
2	378,420	287,573	200,187	151,972	242,819	135,601
(N=51)		*75.99%*	*52.90%*	*40.16%*	*64.17%*	*35.83%*
3	378,420	292,385	197,026	139,350	225,385	153,035
(N=51)		*77.26%*	*52.07%*	*36.82%*	*59.56%*	*40.44%*
4	378,420	286,844	195,088	146,893	238,469	139,951
(N=51)		*75.80%*	*51.55%*	*38.82%*	*63.02%*	*36.98%*
Smaller	371,000	275,028	184,321	140,617	236,589	134,411
(N=50)		*74.13%*	*49.68%*	*37.90%*	*63.77%*	*36.23%*
Panel C. Volume Quintiles						
Higher Volume	378,420	357,678	217,997	105,389	126,131	252,289
(N=51)		*94.52%*	*57.61%*	*27.85%*	*33.33%*	*66.67%*
2	378,420	317,444	211,524	150,022	210,998	167,422
(N=51)		*83.89%*	*55.90%*	*39.64%*	*55.76%*	*44.24%*
3	378,420	295,997	202,949	156,017	238,440	139,980
(N=51)		*78.22%*	*53.63%*	*41.23%*	*63.01%*	*36.99%*
4	378,420	265,675	188,500	155,665	268,410	110,010
(N=51)		*70.21%*	*49.81%*	*41.14%*	*70.93%*	*29.07%*
Lower Volume	371,000	220,474	163,380	142,878	293,404	77,596
(N=50)		*59.43%*	*44.04%*	*38.51%*	*79.08%*	*20.92%*

For the whole dataset, we observe positive volume in 77.32 percent of all intervals. For size quintiles, this ratio decays slowly as firms get smaller from 83.36 percent to 74.13 percent of all respective intervals. This decay is more prominent in volume quintiles. For the most active quintile, there exist a trade in 94.52 percent of the cases. This ratio monotonically decreases to 59.43 percent for the least active quintile. This implies that as total trading volume in stocks increases the number of periods where this trading occurs also increases. This is consistent with the results obtained in previous sections, where I find that the duration of significantly higher periods of trading is longer for more active stocks.

I observe zero range in 37.67 percent of the observations in the whole data set. This ratio varies between 34.65 percent and 40.16 percent for different size quintiles. For the most active volume, the percentage of zero range observation is 27.85 percent and it jumps to levels close 40 percent for the remaining quintiles.

It is important to note that if an observation has a zero range value, it also has a zero return value. Since, as discussed above, one expects to observe multiple prices in an active trading period, when analyzing intraday returns this must be taken into consideration.

The last column of Table 3 provides the total number periods where there is active bidirectional trading. For the whole data, bidirectional trading occurs for 39.65 percent for all possible intervals. For the largest size quintile, bidirectional trading exists in 48.7 percent of the cases and for remaining quintiles this ratio drops to a range of 35.83 - 40.44 percent. For volume quintiles, the number of periods where stocks are actively traded diminishes rapidly as volume decrease. For the stocks with highest trading volume, I observe bidirectional trading in 66.67 percent of observations, whereas this ratio falls to 20.92 percent for the stocks with lowest volume.

It is natural to expect high number of zero return observations in financial return series, especially since they are known to exhibit leptokurtic behavior. However, common market trading mechanisms imply existence of multiple price observations in actively traded stocks. My findings indicate that in 60.35 percent of all intervals included in this study there is either no trading or trades that result in zero range observations. While this ratio is 33.33 percent for the quintile that includes most active stocks, it is higher than 55 percent for the remainder of the data.

The analysis of zeros, in addition to the findings of previous sections, indicate that active intraday trading in ISE mostly occurs in the stocks with high Turkish Lira turnover. Also, as trading activity decreases the trading tends to concentrate at the opening periods of the sessions and at the closing periods of the day. Therefore especially for the stocks which have medium to low levels of activity, trades executed in such period have minimal price impact.

Also, international macroeconomic announcements seem to affect the trading only for most active stocks. Effects of different types of announcements to trading activity and magnitudes of these effects require further research. Nonetheless increased trading activity occurring immediately after macroeconomic announcements suggests that funds, even if they hold less active stocks, tend to adjust their portfolio to the news by trading in more liquid stocks. This supports the evidence from other exchanges that investors have preferences to trade in more liquid stocks. It is also established in literature that investors expect lower returns from more liquid stocks (liquidity premium), since they have lower transaction (such as liquidation or price impact) costs. The question of whether liquidity premia exist in ISE requires further research.

CHAPTER 4

COMMONALITY IN TRADING ACTIVITY AND LIQUIDITY

In this chapter, I will explore whether cross-sectional commonality in trading activity and liquidity exists in Istanbul Stock Exchange. Daily aggregations of volume and liquidity variables are used to capture the intertemporal fluctuations of these variables. Panel data estimations are utilized to test the effects of changes in market volume and liquidity to the individual stock trading volume and liquidity.

To analyze commonality in liquidity in ISE, I aggregate the interval data used in the previous chapter to obtain following daily measures of trading activity and liquidity for each stock:

$$\begin{aligned} DV_{s,t} &= \textstyle\sum_i V_{s,t,i}, \\ ILLIQ_{s,t} &= \textstyle\sum_i^{N_{s,t}} \frac{A_{s,t,i}}{N_{s,t}}, \end{aligned} \tag{4}$$

where $DV_{s,t}$ is the total trading volume of stock s in day t, $N_{s,t}$ is the number of intervals for which $A_{s,t,i}$ is defined and $ILLIQ_{s,t}$ is the Amihud (2002) illiquidity measure for stock s in day t.

Market trading volume is calculated by summing each stock's volume for a given day. Market illiquidity for each day t is the mean of each individual stock's ILLIQ measure.

$$\begin{aligned} MDV_t &= \textstyle\sum_s DV_{s,t} \\ MILLIQ_t &= \textstyle\sum_s \frac{ILLIQ_{s,t}}{S} \end{aligned} \tag{5}$$

I explore, for each measure, the impact of a percentage change in the market measure on percentage change in firm-specific measures. For the whole data set and size and volume quintiles defined in previous chapter, I estimate the following fixed effects models:

$$\begin{aligned} \Delta DV_{s,t} &= \alpha_s + \beta \Delta MDV_t + \varepsilon_{s,t}, \\ \Delta ILLIQ_{s,t} &= \alpha_s + \beta \Delta MILLIQ_t + \varepsilon_{s,t}, \end{aligned} \tag{6}$$

where α_s is the firm fixed effects and Δ is the percentage change from previous period. Regression results are provided in Table 4.

Regression results provide evidence of commonality in both trading activity and liquidity in ISE. Expected impact of one percent change in market volume is 1.34 percent for a given stock. This positive relationship also persists in different size and volume quintiles, however the magnitude of these coefficients diminish as firms sizes decrease. While such a decaying pattern does not exist in volume quintiles, the marginal impact of unit change in market volume is relatively smaller for the smallest volume quintile. All coefficients of commonality in trading activity are significant at 1 percent level.

Changes in market liquidity also exhibit commonality in ISE. A unit increase (decrease) in market (il)liquidity increase (decrease) (il)liquidity a stock by a factor of 6.62 in average. However, deeper analysis of size quintiles yield significant coefficients only for the largest and two smallest quintiles. Regressions with different volume quintiles yield positively significant coefficients for all but the second most active quintile at least at 10 percent level.

One interesting observation from illiquidity regressions is that as firms get less active, marginal impacts of changes in market liquidity tend to get larger. Or, equivalently, active stocks are less sensitive to liquidity shocks and have lower liquidity risks attached to them, which in turn creates additional incentives to trade in these stocks.

Next, market capitalization is added as an additional variable to Equation 6 to control for possible firm size effects. Then the following models are estimated for previously defined sets of stocks:

$$\begin{aligned}\Delta DV_{s,t} &= \alpha_s + \beta \Delta MDV_t + \Gamma X_{i,t} + \varepsilon_{s,t},\\ \Delta ILLIQ_{s,t} &= \alpha_s + \beta \Delta MILLIQ_t + \Gamma X_{i,t} + \varepsilon_{s,t},\end{aligned} \tag{7}$$

where $X_{i,t} = log(MarketCap)_{i,t}$ is the logarithm of market capitalization of firm i at time t. Regression results are provided in Table 5.

Further robustness checks are performed by setting $X_{i,t} = \{log(MarketCap)_{i,t}, p_{i,t}, MR+_t, MR-_t, MRMA5+_t, MRMA5-_t, |MR|MA5_t\}$, where for a given time t, $log(MarketCap)_{i,t}$ is the logarithm of market capitalization of firm i, $p_{i,t}$ is the closing price of stock i; $MR+_t$ is the size weighted market return if it is positive, otherwise zero; $MR-_t$ is the size weighted market return if it is negative, otherwise zero; $MRMA5+_t$ is the five-day moving average of size weighted market return if it is positive, otherwise zero; $MRMA5-_t$ is the five-day moving average of size weighted market return if it is negative, otherwise zero and $|MR|MA5_t$ is the five-day moving average of absolute value of size weighted market return. Table 6 and 7 provide estimation results where dependent variable is ΔDV and $\Delta ILLIQ$, respectively.

For the whole sample, coefficient of market capitalization is positively significant in trading activity and negatively significant in (il)liquidity regressions. While this is consistent with expectations, using market capitalization and other market variables as control variables has very little effect on commonality coefficients.

My findings provide evidence for commonality in trading activity and liquidity of stock in ISE. Trading activity is measure by daily volumes of stocks and (il)liquidity is measured by ILLIQ measure suggested by Amihud (2002). Further research using market-wide depth data would provide better estimates of commonality in liquidity in ISE. Also, this analysis utilizes a data set with daily frequency over 106 trading days. An analysis using monthly or lower frequencies over longer time horizons would allow incorporating various macroeconomic indicators as possible common factors as determinants of liquidity.

Table 4: Summary Results for the Models in Equation 6

Estimation results for the models in Equation 6 are provided below. DV and ILLIQ are the daily volume and ILLIQ measure for each stock in a given day, respectively. MDV and MILLIQ are the market volume and market ILLIQ measure for each day. Δ indicates percentage change from previous period.

Dependent Variable	ΔDV			$\Delta ILLIQ$		
	ΔMDV	R^2	N	$\Delta MILLIQ$	R^2	N
Panel A. All Data						
	1.3360	0.0177	26668	6.6231	0.0193	26610
	(13.23)			*(3.88)*		
Panel B. Size Quintiles						
Larger	1.6111	0.0345	5355	8.1190	0.0278	5347
	(8.39)			*(2.19)*		
Size 2	1.3965	0.0245	5355	-3.6758	0.0188	5348
	(8.76)			*(-1.36)*		
Size 3	1.2201	0.0193	5355	2.3261	0.0206	5325
	(6.46)			*(0.89)*		
Size 4	1.3716	0.0116	5354	14.8739	0.0154	5350
	(4.60)			*(2.61)*		
Smaller	1.0757	0.0095	5249	11.5359	0.0172	5240
	(4.10)			*(3.27)*		
Panel C. Volume Quintiles						
Higher	1.3451	0.0332	5355	2.8859	0.0253	5355
Volume	*(10.02)*			*(2.08)*		
Volume 2	1.7968	0.0177	5354	5.6808	0.0278	5352
	(6.71)			*(1.52)*		
Volume 3	1.2509	0.0145	5355	5.0929	0.0221	5351
	(4.93)			*(2.28)*		
Volume 4	1.4497	0.0156	5354	11.8495	0.0144	5347
	(6.84)			*(2.09)*		
Lower	0.8280	0.0113	5250	7.6479	0.0143	5205
Volume	*(3.51)*			*(1.70)*		

Table 5: Summary Results for the Models in Equation 7

Estimation results for the models in Equation 7 are provided below. DV and ILLIQ are the daily volume and ILLIQ measure for each stock in a given day, respectively. MDV and MILLIQ are the market volume and market ILLIQ measure for each day. $\log(MarketCap)$ is the logarithm of market capitalization of each stock in a given day. Δ indicates percentage change from previous period.

Dependent Variable	ΔDV				$\Delta ILLIQ$			
	ΔMDV	$\log(MarketCap)$	R^2	N	$\Delta MILLIQ$	$\log(MarketCap)$	R^2	N
Panel A. All Data								
	1.3241	0.8201	0.0183	26668	6.5108	-12.2858	0.0195	26610
	(13.12)	*(4.10)*			*(3.81)*	*(-2.32)*		
Panel B. Size Quintiles								
Larger	1.5964	0.8214	0.0351	5355	8.0454	-6.6100	0.0279	5347
	(8.31)	*(1.90)*			*(2.17)*	*(-0.51)*		
Size 2	1.3823	0.8531	0.0257	5355	-3.7103	-3.4658	0.0188	5348
	(8.67)	*(2.62)*			*(-1.37)*	*(-0.40)*		
Size 3	1.2152	0.3104	0.0194	5355	2.2498	-8.1232	0.0209	5325
	(6.44)	*(0.87)*			*(0.87)*	*(-1.06)*		
Size 4	1.3507	1.5978	0.0127	5354	14.5912	-32.4779	0.0160	5350
	(4.53)	*(2.49)*			*(2.56)*	*(-1.69)*		
Smaller	1.0693	0.7153	0.0100	5249	11.4540	-12.5721	0.0175	5240
	(4.08)	*(1.59)*			*(3.25)*	*(-1.33)*		
Panel C. Volume Quintiles								
Higher	1.3446	0.0209	0.0332	5355	2.8459	-2.5377	0.0254	5355
Volume	*(10.01)*	*(0.09)*			*(2.05)*	*(-0.70)*		
Volume 2	1.7802	1.1296	0.0185	5354	5.6211	-7.0585	0.0279	5352
	(6.65)	*(2.11)*			*(1.51)*	*(-0.60)*		
Volume 3	1.2412	0.7565	0.0150	5355	4.9888	-13.1665	0.0229	5351
	(4.89)	*(1.63)*			*(2.23)*	*(-2.06)*		
Volume 4	1.4377	0.9980	0.0165	5354	11.6242	-33.0733	0.0150	5347
	(6.79)	*(2.30)*			*(2.05)*	*(-1.83)*		
Lower	0.8071	2.3619	0.0136	5250	7.5834	-9.6267	0.0144	5205
Volume	*(3.42)*	*(3.50)*			*(1.68)*	*(-0.48)*		

Table 6: Robustness Checks - Dependent Variable: ΔDV

Robustness check results for the dependent variable ΔDV is given below. DV is the daily volume for each stock in a given day. MDV is the market volume for each day. For a given day, $log(MarketCap)$ is the logarithm of market capitalization and $p_{i,t}$ is the closing price of a given stock. For a given day, $MR{+}_t$ is the size weighted market return if it is positive, otherwise zero; $MR{-}_t$ is the size weighted market return if it is negative, otherwise zero; $MRMA5{+}_t$ is the five-day moving average of size weighted market return if it is positive, otherwise zero; $MRMA5{-}_t$ is the five-day moving average of size weighted market return if it is negative, otherwise zero and $|MR|MA5_t$ is the five-day moving average of absolute value of size weighted market return. Δ indicates percentage change from previous period.

Dependent Variable	ΔDV									
	ΔMDV	$\log(MarketCap)$	p	MR+	MR-	MRMA5+	MRMA5-	$\|MR\|MA5_t$	R^2	N
Panel A. All Data										
	1.3318	0.8418	-0.0014	1.6769	8.8629	-0.9104	46.3660	-17.8878	0.0196	25906
	(11.82)	*(3.77)*	*(-0.31)*	*(0.30)*	*(1.60)*	*(-0.08)*	*(3.11)*	*(-1.72)*		
Panel B. Size Quintiles										
Larger	1.6257	-0.5425	0.1885	4.1001	10.5073	-24.2681	77.3778	-3.9760	0.0415	5202
	(7.60)	*(-0.96)*	*(4.51)*	*(0.39)*	*(1.00)*	*(-1.16)*	*(2.73)*	*(-0.20)*		
Size 2	1.3502	1.1485	-0.0045	12.1354	11.4964	-6.9953	35.7861	-5.8287	0.0291	5202
	(7.61)	*(2.89)*	*(-1.21)*	*(1.37)*	*(1.31)*	*(-0.41)*	*(1.52)*	*(-0.35)*		
Size 3	1.2333	0.2168	0.0019	-5.6710	12.1132	-3.8089	58.2554	-39.9169	0.0229	5202
	(5.88)	*(0.52)*	*(0.16)*	*(-0.54)*	*(1.17)*	*(-0.19)*	*(2.10)*	*(-2.05)*		
Size 4	1.3594	1.6434	0.0129	17.4535	-4.7760	-53.4070	63.7603	-12.3397	0.0139	5201
	(4.07)	*(2.21)*	*(0.25)*	*(1.05)*	*(-0.29)*	*(-1.66)*	*(1.44)*	*(-0.40)*		
Smaller	1.0881	0.4889	0.0363	-20.2358	14.7938	80.2771	3.7570	-21.6396	0.0124	5099
	(3.72)	*(0.73)*	*(0.31)*	*(-1.39)*	*(1.03)*	*(2.88)*	*(0.10)*	*(-0.80)*		
Panel C. Volume Quintiles										
Higher	1.3884	-0.0999	0.0007	-6.3748	4.7506	24.2306	37.5258	-14.9368	0.0364	5202
Volume	*(9.33)*	*(-0.38)*	*(0.23)*	*(-0.86)*	*(0.65)*	*(1.67)*	*(1.91)*	*(-1.09)*		
Volume 2	1.9095	0.7176	0.0462	-2.3497	5.6267	-43.5475	120.0017	-22.4534	0.0219	5201
	(6.38)	*(1.09)*	*(1.71)*	*(-0.16)*	*(0.38)*	*(-1.51)*	*(3.02)*	*(-0.81)*		
Volume 3	1.1521	1.0048	-0.0297	15.8345	8.2330	-27.3966	37.3212	-41.2682	0.0167	5202
	(4.06)	*(1.58)*	*(-0.46)*	*(1.12)*	*(0.59)*	*(-1.01)*	*(1.00)*	*(-1.57)*		
Volume 4	1.5274	0.6066	0.0667	-17.3135	18.8713	41.4433	12.8689	10.5449	0.0184	5201
	(6.44)	*(0.94)*	*(0.71)*	*(-1.47)*	*(1.61)*	*(1.82)*	*(0.41)*	*(0.48)*		
Lower	0.6735	2.8346	-0.1420	18.9812	6.8831	-0.1835	27.7828	-18.2542	0.0147	5100
Volume	*(2.57)*	*(2.42)*	*(-0.64)*	*(1.45)*	*(0.53)*	*(-0.01)*	*(0.80)*	*(-0.75)*		

Table 7: Robustness Checks - Dependent Variable: $\Delta ILLIQ$

Robustness check results for the dependent variable $\Delta ILLIQ$ is given below. ILLIQ is the ILLIQ measure for each stock in a given day. MILLIQ is the market ILLIQ measure for each day. For a given day, $log(MarketCap)$ is the logarithm of market capitalization and $p_{i,t}$ is the closing price of a given stock. For a given day, $MR{+}_t$ is the size weighted market return if it is positive, otherwise zero; $MR{-}_t$ is the size weighted market return if it is negative, otherwise zero; $MRMA5{+}_t$ is the five-day moving average of size weighted market return if it is positive, otherwise zero; $MRMA5{-}_t$ is the five-day moving average of size weighted market return if it is negative, otherwise zero and $|MR|MA5_t$ is the five-day moving average of absolute value of size weighted market return. Δ indicates percentage change from previous period.

Dependent Variable	$\Delta ILLIQ$									
	$\Delta MILLIQ$	$\log(MarketCap)$	p	MR+	MR-	MRMA5+	MRMA5-	$\|MR\|MA5_t$	R^2	N
Panel A. All Data										
	6.5356	-14.3168	0.0748	86.4762	89.8078	126.6450	-160.5389	-545.0210	0.0200	25848
	(3.69)	*(-2.43)*	*(0.63)*	*(0.61)*	*(0.61)*	*(0.44)*	*(-0.41)*	*(-2.01)*		
Panel B. Size Quintiles										
Larger	7.5609	-2.4574	-0.1215	-121.5411	415.9158	-433.9699	-39.0255	-650.4884	0.0296	5194
	(1.96)	*(-0.14)*	*(-0.10)*	*(-0.40)*	*(1.30)*	*(-0.68)*	*(-0.05)*	*(-1.10)*		
Size 2	-3.9547	-4.9897	0.0190	-178.9847	204.9359	150.7705	102.4561	-187.0788	0.0191	5195
	(-1.41)	*(-0.47)*	*(0.19)*	*(-0.80)*	*(0.88)*	*(0.33)*	*(0.16)*	*(-0.44)*		
Size 3	2.4060	-11.9596	0.0835	-140.0020	56.4684	498.6081	-93.6801	-131.7322	0.0218	5172
	(0.89)	*(-1.32)*	*(0.32)*	*(-0.65)*	*(0.25)*	*(1.13)*	*(-0.16)*	*(-0.32)*		
Size 4	15.2550	-37.6697	0.5043	995.7584	-180.2273	622.2001	-845.2506	-739.2111	0.0175	5197
	(2.59)	*(-1.71)*	*(0.33)*	*(2.12)*	*(-0.37)*	*(0.65)*	*(-0.65)*	*(-0.82)*		
Smaller	11.4977	-18.0209	1.4618	-128.9654	-46.7274	-271.8441	103.3593	-996.7397	0.0191	5090
	(3.13)	*(-1.28)*	*(0.58)*	*(-0.44)*	*(-0.15)*	*(-0.46)*	*(0.13)*	*(-1.78)*		
Panel C. Volume Quintiles										
Higher	2.6247	-2.3201	0.0129	-78.9394	166.6346	-131.5010	-71.1778	-131.4336	0.0262	5202
Volume	*(1.83)*	*(-0.54)*	*(0.27)*	*(-0.69)*	*(1.40)*	*(-0.56)*	*(-0.22)*	*(-0.60)*		
Volume 2	4.6433	-3.1788	-0.0894	-328.9191	343.9731	-313.6285	136.5583	-929.4522	0.0302	5199
	(1.21)	*(-0.22)*	*(-0.15)*	*(-1.08)*	*(1.08)*	*(-0.51)*	*(0.16)*	*(-1.58)*		
Volume 3	4.4600	-20.5502	0.9027	-124.4213	134.2678	287.8434	-857.1191	-103.7015	0.0242	5198
	(1.92)	*(-2.34)*	*(1.01)*	*(-0.67)*	*(0.70)*	*(0.77)*	*(-1.67)*	*(-0.29)*		
Volume 4	13.2419	-54.8772	2.9387	1267.7144	-684.6592	663.3864	-1580.2066	-1267.4897	0.0174	5194
	(2.25)	*(-2.04)*	*(0.75)*	*(2.70)*	*(-1.40)*	*(0.70)*	*(-1.21)*	*(-1.41)*		
Lower	7.8733	-2.0051	-1.2964	-315.3407	491.5290	88.1441	1628.3721	-244.2400	0.0160	5055
Volume	*(1.68)*	*(-0.06)*	*(-0.20)*	*(-0.85)*	*(1.27)*	*(0.12)*	*(1.57)*	*(-0.34)*		

CHAPTER 5

CONCLUSION

In this dissertation, I analyze trading activity and liquidity in Istanbul Stock Exchange using intraday interval data for a large sample of 254 stocks. Trading activity and (il)liquidity are measured by trading volume and price impact measures, respectively. I find that trading activity is concentrated during opening and closing hours of the day. Additionally, I observe higher trading activity during the opening period of the afternoon session. For the most active stocks, trading concentration also exists during the period immediately after 3:30 pm. Trading activity follows L-shaped pattern during morning sessions and J-shaped pattern during afternoon session.

Trading concentration during opening and closing periods is a commonly observed phenomenon in various stock exchanges. A call market mechanism is practiced in ISE before both sessions of the day and remaining liquidity is carried over to the regular session. This structural mechanism may create additional motives for liquidity demanders to trade immediately after market opens.

Analysis of different volume quintiles indicate that duration of trading concentration decreases as stocks become less active. For example, for the most active stocks, trading volume is significantly higher than the benchmark level during the first and the last hour of trading. This result is consistent with Ekinci (2004)'s findings on volume for a single (active) stock. However, I observe that for the least active stocks these durations diminish to 5 minutes. Also, volume during the last period of the day is higher than the first period for all cases. Additionally, this difference increases as total trading activity decreases.

I also test for possible impacts of introduction of order cancellation mechanism to intraday patterns. I find a significant increase in trading volume during opening periods of both sessions after introduction of order cancellation.

Intraday behavior of price impact measures suggest significantly lower price impacts during the opening and closing periods of the day. However, I observe significantly higher price impacts during the last period of morning session. Since this price impact impacts are generated by a similar volume levels, they are possibly due to closing price manipulations (probably within the bid-ask bounce).

Distributions of zero observations for different intraday variables indicate that stocks with high Turkish Lira turnover exhibit active trading throughout the day. For stocks with medium to low levels of average trading volume, zeros analysis provide additional evidence for concentration of trading activity during the open and the close of the trading day.

I also find evidence for commonality in liquidity and trading activity in ISE. Positive shocks to the market trading volume and liquidity have, on average, positive impact on individual stocks' volume and liquidity. Additionally, I find that more active stocks are less sensitive to the liquidity shocks than less active ones.

This dissertation, to the best of my knowledge, is first to analyze market-wide trading activity and liquidity in ISE. Specifically, it analyzes intraday trading patterns over all stocks in the data set and within size and volume quintiles. It also provides evidence for the commonality in trading activity and liquidity in ISE.

Market microstructure research analyzing ISE is still at its infancy. Most of the microstructure research on ISE focus on a single or a relatively small subset of stocks. Also, ongoing changes in trading mechanisms in ISE leads new research questions. There are various possible extensions of this dissertation, which I believe are quite relevant. First, a similar market-wide analysis based on quote data (which allow analysis of spread and depth based measures) would create a clearer picture of behavior of liquidity supply in stocks throughout the day and market-wide commonality of liquidity. An analysis of quote level data would also provide insights on effects of different tick-size regimes on quoted depth.

Also, further research on the effects of newly introduced order cancellation mechanism is worth pursuing. Specifically, frequency of canceled orders and given that frequency, durations of limit orders in the order book are important empirical questions.

An additional research topic may be the effect of call market mechanisms in ISE on trading activity during regular session. An analysis of trading volume during call markets or the contribution of liquidity supplied during the call markets to the amount of liquidity consumed during initial minutes of trading are relevant research questions.

APPENDIX A

List of Stocks Included in the Dataset

Table 8: List of Stocks Included in the Dataset

Stocks included in the dataset are provided below. Symbol is the stock's ticker symbol in ISE. Size Rank and Volume Rank columns indicate the rank of the stock when the stocks are sorted in descending order by market capitalization and average daily volume, respectively. Size Quintile and Volume Quintile columns show the quintile in which the stock is included.

Symbol	Size Rank	Volume Rank	Size Quintile	Volume Quintile
ACIBD	53	212	2	5
ADANA	99	221	2	5
ADBGR	133	253	3	5
ADEL	166	134	4	3
ADNAC	183	97	4	2
AEFES	13	80	1	2
AFMAS	157	76	4	2
AFYON	86	16	2	1
AGYO	175	244	4	5
AKALT	208	183	5	4
AKBNK	1	7	1	1
AKCNS	48	145	1	3
AKENR	50	35	1	1
AKFEN	47	176	1	4
AKGRT	84	25	2	1
AKMGY	79	160	2	4
AKSA	92	66	2	2
AKSEN	27	116	1	3

Table 8 – continued

AKSUE	229	141	5	3
ALARK	72	100	2	2
ALBRK	42	122	1	3
ALCAR	151	246	3	5
ALCTL	169	84	4	2
ALGYO	149	196	3	4
ALKA	192	208	4	5
ALKIM	145	211	3	5
ALNTF	94	251	2	5
ALTIN	120	216	3	5
ALYAG	238	55	5	2
ANACM	65	189	2	4
ANELT	197	132	4	3
ANHYT	57	157	2	4
ANSGR	85	67	2	2
ARCLK	20	36	1	1
ARENA	184	103	4	3
ARSAN	201	72	4	2
ASELS	43	49	1	1
ASUZU	153	231	3	5
ASYAB	25	14	1	1
ATEKS	200	252	4	5
AVIVA	82	232	2	5
AYEN	115	79	3	2
AYGAZ	34	90	1	2
BAGFS	112	41	3	1
BAKAB	206	107	5	3
BANVT	87	110	2	3
BFREN	104	47	3	1

Table 8 – continued

BIMAS	17	42	1	1
BJKAS	124	30	3	1
BOLUC	136	225	3	5
BOSSA	130	207	3	5
BOYNR	139	34	3	1
BRISA	73	81	2	2
BROVA	241	120	5	3
BRSAN	91	149	2	3
BRYAT	135	213	3	5
BSHEV	18	83	1	2
BSOKE	168	224	4	5
BTCIM	88	248	2	5
BUCIM	93	234	2	5
BURVA	253	182	5	4
CARFA	46	158	1	4
CARFB	55	138	2	3
CCOLA	22	174	1	4
CELHA	221	245	5	5
CEMTS	191	222	4	5
CIMSA	54	184	2	4
CLEBI	102	142	2	3
CMBTN	222	147	5	3
CMENT	74	235	2	5
COMDO	125	195	3	4
CRDFA	186	161	4	4
DENCM	212	162	5	4
DENIZ	14	227	1	5
DENTA	181	156	4	4
DERIM	248	163	5	4

Table 8 – continued

DESA	235	209	5	5
DEVA	89	104	2	3
DGGYO	170	186	4	4
DGZTE	119	144	3	3
DITAS	242	247	5	5
DMSAS	209	249	5	5
DOAS	63	93	2	2
DOBUR	223	180	5	4
DOHOL	28	13	1	1
DURDO	232	173	5	4
DYHOL	45	11	1	1
DYOBY	163	118	4	3
ECILC	49	29	1	1
ECYAP	121	128	3	3
ECZYT	111	92	3	2
EDIP	162	178	4	4
EGEEN	227	218	5	5
EGGUB	156	91	4	2
EGSER	180	82	4	2
EMKEL	246	137	5	3
EMNIS	226	254	5	5
ENKAI	10	31	1	1
ERBOS	216	210	5	5
EREGL	16	9	1	1
ERSU	231	187	5	4
ESCOM	247	217	5	5
FENER	52	10	2	1
FENIS	178	151	4	3
FFKRL	114	135	3	3

Table 8 – continued

FINBN	12	223	1	5
FMIZP	143	140	3	3
FORTS	37	99	1	2
FRIGO	252	242	5	5
FROTO	23	69	1	2
FVORI	244	113	5	3
GARAN	2	1	1	1
GARFA	164	146	4	3
GENTS	195	230	4	5
GEREL	250	243	5	5
GLYHO	155	85	4	2
GOLDS	193	71	4	2
GOLTS	96	112	2	3
GOODY	141	153	3	3
GSDHO	128	75	3	2
GSRAY	76	50	2	1
GUBRF	60	48	2	1
GUSGR	122	170	3	4
HALKB	7	8	1	1
HEKTS	182	102	4	2
HURGZ	66	40	2	1
HZNDR	237	233	5	5
IDAS	249	115	5	3
IHEVA	144	37	3	1
IHLAS	127	27	3	1
INDES	165	220	4	5
INTEM	239	250	5	5
IPMAT	100	22	2	1
ISCTR	3	2	1	1

Table 8 – continued

ISFIN	113	63	3	2
ISGSY	188	240	4	5
ISGYO	75	70	2	2
ISMEN	101	228	2	5
ISYHO	148	28	3	1
ITTFH	132	89	3	2
IZMDC	110	105	3	3
IZOCM	80	185	2	4
KAPLM	214	239	5	5
KAREL	185	238	4	5
KARSN	118	51	3	1
KARTN	106	46	3	1
KCHOL	8	19	1	1
KERVT	134	64	3	2
KIPA	59	136	2	3
KLBMO	204	205	4	5
KLMSN	174	148	4	3
KLNMA	51	108	1	3
KNFRT	233	202	5	4
KONYA	78	43	2	1
KORDS	83	206	2	5
KOZAA	68	21	2	1
KOZAL	31	39	1	1
KRDMA	147	59	3	2
KRDMB	187	73	4	2
KRDMD	107	23	3	1
KRSTL	211	123	5	3
KRTEK	198	86	4	2
KUTPO	190	150	4	3

Table 8 – continued

LATEK	154	57	4	2
LINK	243	172	5	4
LOGO	219	124	5	3
LUKSK	224	127	5	3
MAALT	199	121	4	3
MARTI	173	111	4	3
MERKO	236	203	5	4
METRO	138	26	3	1
MGROS	19	88	1	2
MIPAZ	179	154	4	4
MNDRS	172	106	4	3
MRDIN	64	226	2	5
MRSHL	123	53	3	2
MTEKS	251	155	5	4
MUTLU	158	164	4	4
NETAS	109	65	3	2
NTHOL	117	68	3	2
NTTUR	140	96	3	2
NUGYO	230	191	5	4
NUHCM	39	229	1	5
OLMKS	146	215	3	5
OTKAR	105	193	3	4
OZGYO	234	175	5	4
PARSN	171	152	4	3
PEGYO	213	129	5	3
PENGD	177	139	4	3
PETKM	33	6	1	1
PETUN	131	214	3	5
PIMAS	205	200	5	4

Table 8 – continued

PINSU	210	197	5	4
PKART	218	199	5	4
PNSUT	103	198	3	4
PRKAB	160	241	4	5
PRKTE	108	61	3	2
PTOFS	24	78	1	2
RAYSG	126	109	3	3
RHEAG	207	58	5	2
RYSAS	137	133	3	3
SAGYO	225	192	5	4
SAHOL	9	12	1	1
SANKO	159	179	4	4
SARKY	150	237	3	5
SASA	152	125	3	3
SELEC	44	188	1	4
SERVE	254	219	5	5
SISE	30	20	1	1
SKBNK	56	54	2	2
SKPLC	189	131	4	3
SKTAS	194	236	4	5
SNGYO	62	45	2	1
SODA	98	167	2	4
TATKS	95	171	2	4
TAVHL	29	33	1	1
TCELL	5	15	1	1
TEBNK	32	17	1	1
TEKFK	240	168	5	4
TEKST	97	101	2	2
TEKTU	142	87	3	2

Table 8 – continued

THYAO	21	5	1	1
TIRE	116	52	3	2
TKFEN	35	24	1	1
TOASO	26	56	1	2
TRCAS	70	130	2	3
TRKCM	41	117	1	3
TSGYO	161	201	4	4
TSKB	40	77	1	2
TSPOR	129	38	3	1
TTKOM	4	32	1	1
TTRAK	67	114	2	3
TUDDF	81	74	2	2
TUKAS	196	194	4	4
TUPRS	15	18	1	1
ULKER	58	44	2	1
UNYEC	90	190	2	4
USAK	245	98	5	2
VAKBN	11	3	1	1
VAKFN	176	94	4	2
VAKKO	167	166	4	4
VESBE	77	165	2	4
VESTL	69	60	2	2
VKGYO	202	119	4	3
VKING	215	159	5	4
YATAS	228	143	5	3
YAZIC	38	169	1	4
YKBNK	6	4	1	1
YKFIN	36	204	1	4
YKGYO	203	181	4	4

Table 8 – continued

YKSGR	61	126	2	3
YUNSA	220	177	5	4
YYGYO	217	95	5	2
ZOREN	71	62	2	2

APPENDIX B

Distribution of Stocks Across Size and Volume Quintiles

Table 9: Distribution of Stocks across Size and Volume Quintiles

		Volume Quintiles					
		Higher Volume	Quintile 2	Quintile 3	Quintile 4	Lower Volume	TOTAL
	Larger	28	9	5	6	3	51
Size	Quintile 2	11	11	10	9	10	51
Quintiles	Quintile 3	12	14	9	5	11	51
	Quintile 4	0	13	15	11	12	51
	Smaller	0	4	12	20	14	50
	TOTAL	51	51	51	51	50	254

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