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Essays in Financial Economics

by

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Abstracts

The thesis consists of three single-authored chapters. First chapter is related to the field of market microstructure, second chapter is about more on retail traders and the last chapter focuses on liquidity provision. All chapters use the data set from Borsa Istanbul which consists intraday trade-level data for benchmark index BIST30 stocks for the year of 2019, directly taken from the Exchange's database. The individual chapters are summarized in the following abstracts.

Chapter 1: The Role of Small Traders in the Stock Market

In cases of liquidity imbalances in the market, I examine the role of small traders in liquidity provision at different frequencies and whether they have a role in leaning against the imbalance. Using data from the benchmark Turkish BIST30 index from Borsa Istanbul for 2019, this paper examines the liquidity imbalance and returns with different levels of frequencies and different type traders categories, especially small traders. I find that small traders may have an important role in providing liquidity not only at a daily level but also at an intraday level. I show that small traders, especially those classified as passive (i.e., those who transact mostly via limit orders) provide liquidity of higher magnitude compared to those classified as aggressive (i.e., those who transact mostly via market orders). More active aggressive small traders are liquidity takers from the market by chasing trends, whereas less active aggressive small traders enter the market later and provide liquidity with a delay at an intraday level. The passive small traders seem to profit more from the liquidity provision than those classified as aggressive in my sample.

Chapter 2: Trading Patterns of Small Traders

This paper investigates the trading patterns of small traders, specifically their buying and selling activities over different time horizons for one stock from the benchmark Turkish BIST30 index in 2019. The main focus of the paper is the active small traders, and I show that they are likely to remain active if they were active during previous time interval. Additionally, these traders tend to buy when price is falling and sell when prices are rising, but there seems to be an asymmetry in their buying and selling patterns, where they buy more easily than they sell. At a daily level, active small traders tend to make reversals in their buy and sell patterns, whereas at an intraday level, they tend to keep momentum by continuing to buy or sell if they had already bought or sold

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previously. Furthermore, active small traders react to the stock-related news and buy more, both at the daily and intraday level. Their contemporaneous reaction to stock related news for the case of buying is higher in magnitude than the case of selling.

Chapter 3: How do intraday intermediaries react to shocks?

This paper investigates the trading patterns of intraday intermediaries in an automated stock market before and during a period of temporary liquidity shock in the form of large selling pressure. The study focuses on 30 stocks under the benchmark index BIST30 of Borsa Istanbul. In order to classify accounts as intraday intermediaries, a data-driven approach based on the accounts' trading activity and inventory pattern is adopted. I analyze minute-by-minute comovement between inventory changes and price changes to determine if there is any trading pattern change during the selling pressure period. I find that the trading pattern of intraday intermediaries classified as high frequency traders changed during the selling pressure period. Furthermore, the results indicate that this change mostly resulted from their aggressive holdings, which suggests a reduction in their liquidity removal (an increase in liquidity provision) and a preference to trade less aggressively during the liquidity shortage.

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1.1 Introduction

The main friction in the stock market is that buyers and sellers don't arrive simultaneously. As the markets become more automated, intermediation has increasingly been provided by market participants without formal requirements. Especially when institutional liquidity dries up or when conventional liquidity providers are constrained, the question of who steps into the market to provide liquidity becomes crucial. In these turbulent trading days, it is important to understand who meets in the market or who prefers to take on the role of a liquidity provider instead of the traditional market makers, as it influences the price formation in the market.

The direct participation of individual traders has always played an important role in well-functioning markets. There is substantial academic evidence showing that retail participation may contribute positively to market liquidity and to the depth of the order book (Kaniel et al., 2012), including periods of market instability (Barrot et al., 2016). This is due to the observation that retail traders tend to sell when prices increase and tend to buy or refrain from selling when prices decrease. A recent survey report (Gurrola-Perez et al., 2022) from World Federation Exchange (WFE) indicates an increasing trend of participation[1] among retail traders across exchanges.

A longstanding literature has considered the individual investors as "noise" traders for a long time, starting from Black (1986) and Shleifer and Summers (1990), who are pushing prices away from fundamentals and destabilize markets. In contrast to this literature, recent empirical evidence suggests that individual investors' trades provide liquidity to meet the demand for immediacy of other market participants (Kaniel et al., 2007; Kaniel et al., 2012; Kelley and Tetlock, 2013). While retail investors may be less sophisticated than their institutional counterparts, they also face lower agency costs and liquidity constraints relative to institutional investors such as mutual funds (Chevalier and Ellison, 1999; J. Coval and Stafford, 2007). Retail traders could thus have some ability to act as market makers, especially when institutional liquidity dries up, as was the case during the recent financial crisis. After financial crises in 2008, there has been increasing precautionary regulation that restricts the risk capacity of institutional traders who are acting as market makers in the stock markets.

[1]Trend graphs for retail trades across Exchanges are given in the Appendix.

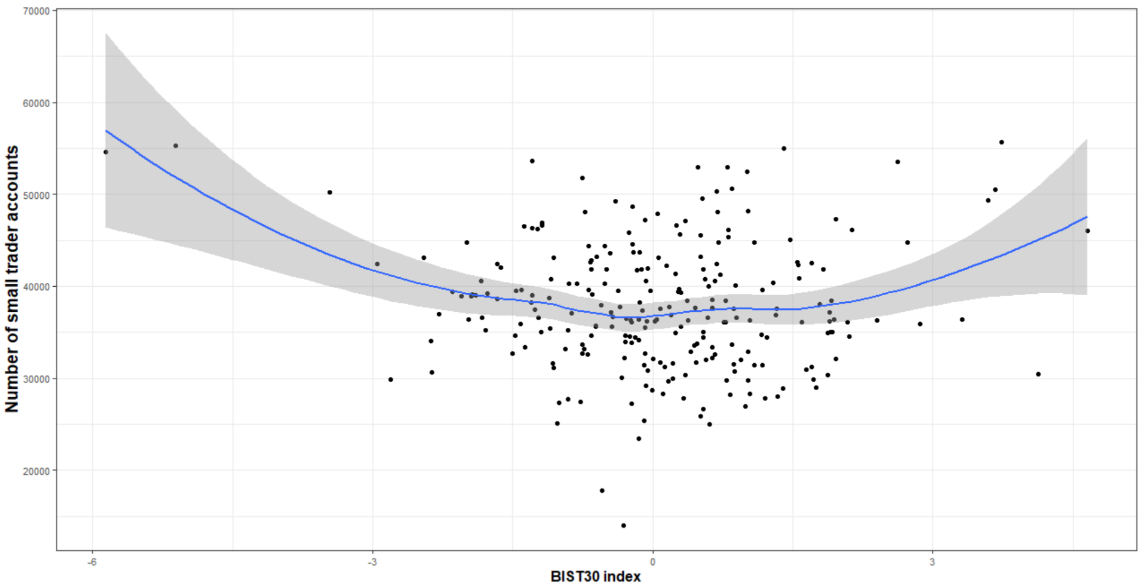

Figure 1.1: **Number of Small Traders vs BIST30 Index**

This figure presents number of small trader trading accounts versus BIST30 index for each of the trading days over the year 2019.

Figure 1.1 illustrates the number of small traders' trading accounts versus BIST30 index for each of the trading days for the year of 2019. This U shaped line in Figure 1.1 indicates that during volatile times of the BIST30 index, the number of small traders increases, highlighting the importance of these retail traders for the efficiency of financial markets which serves suggestive evidence for this research paper. This U-shaped line suggests that in absolute terms, high stock price changes – both increases and decreases - are associated with a high number of small traders actively trading on that specific trading day. However, it is crucial to consider that this relationship can be driven by multiple factors and might operate in both directions. On one hand, the U-shaped pattern may indicate that high stock price changes or volatility in the stock may result in an increase in the number of small trader accounts. This can be attributed to the attractiveness of the market when significant price fluctuations occur, prompting more individuals to engage in trading activities. The increased participation of small traders can further contribute to driving the stock price upwards or downwards, creating a positive feedback loop. On the other hand, increased participation of small traders can further contribute to driving the stock price upwards or downwards and result in market volatility. Recognizing the advantages of retail investors' participation in equity markets is crucial for both the markets and the investors themselves, there exists limited academic consensus regarding the overall impact of retail investors on stock markets (Eaton et al., 2022; Friedman and Zeng, 2022). This lack of consensus is not surprising given the heterogeneous nature of retail investors, characterized by variations in diligence, risk appetite, and motivations. From one point of these views, retail investment entails certain risks and warrants cautionary consideration. Retail trading has the potential to heighten correlated trading activity, which in turn may amplify systemic risk (Kumar and Lee, 2006). Furthermore, in the absence of sufficient levels of financial literacy and education, retail investors can be vulnerable to deceptive investment strategies. Inadequate protection exposes investors to the risk of falling victim to financial scams. As a recent research by Lyócsa et al. (2022), investor movement which was likely initiated by retail investors mostly happened around the social media is investigated. They explore the price variation of four stocks: GameStop, AMC Entertainment Holdings, Blackberry and Nokia for the year of 2020-2021. These four stocks were subject to a decentralized short squeeze that exploited the short positions of institutional investors. They demonstrate that part of the next day's price variation can be explained by an increase in the number of retail traders and the stock-related activity on the social media. The emergence of the GameStop like phenomenons have drawn significant attention to stock markets, specifically shedding light on the increased participation of retail investors and the influential role of news and social media on their trading activities.

In this paper, I investigate the role of the trader categories in terms of liquidity provision then I focus on the role of small traders in the market. This study leverages a data set comprising intraday trade-level data for the 30 stocks in the benchmark index BIST30 for the year of 2019. Utilizing trading account level data set, traders are categorized based on observed individual inventory and trading volume patterns. I observe all the transactions from the tradebook data for the year of 2019 and see the trading activity of each account IDs. This data set enables me to track the orders of a large sample of account IDs from January 2019 to December 2019 at a high frequency level. I categorize the traders entirely based on directly observed individual inventory and trading volume patterns, and then I empirically examine the dynamics between each trader category's imbalance which is calculated as the net position over the corresponding stock's volume from the daily to intraday level, and contemporaneous market returns to lagged returns. Since there is heterogeneity in small traders subset, I further analyze the reaction of market returns to the imbalances, especially for small traders in detail, and I separate trading accounts of the small traders' subset by looking at the proportion of their aggressive transactions - those incurred when traders submit marketable orders into the order book and immediately matched - versus passive transactions - those incurred via the traders' resting orders being executed by a marketable order. I uncover four main findings.

First, small traders play an important role in providing liquidity, not only at a daily level but also at an intraday level. This finding is in line with the findings of Barrot et al. (2016) which suggests that retail traders indeed provide liquidity to the stock market at a daily level. This paper adds findings at an intraday level and shows that this liquidity provision also holds at an intraday level. Furthermore, unlike in the given retail trader labels in their data set, I managed to observe their trading activity and see the whole traders universe, labeling them by looking at their empirically observed trading patterns, so that I can compare the trader categories. I find that liquidity provision is mostly done by small traders and not by the big neutral traders at an intraday level. This paper adds to the ongoing debate on the contribution of retail trades to stock market efficiency. Several papers have found that individual trades positively predict short-term returns. A first body of work has interpreted this as evidence of noise trading pushing prices away from fundamentals. Barber et al. (2009) finds that stocks that individual investors are buying (selling) during one week have positive (negative) abnormal returns that week and in the subsequent two weeks. These returns then reverse over the next several months. Although, Barber et al. (2009) interpret their results as evidence of noise trading, they are also consistent with individual investors providing liquidity to institutional investors. Kaniel et al. (2007) identify individual investor trades using the NYSE Consolidated Audit Trail Data files, which contain detailed information on all orders executed on the exchange, including a field that identifies whether the order comes from an individual investor. They show that the top decile of stocks heavily bought by individuals outperform those heavily sold by individuals, a result again consistent with retail traders providing liquidity to institutions that require immediacy. Kaniel et al. (2012) also find evidence that stocks purchased by individual investors prior to earnings announcement outperform those that they sell, and that compensation for risk-averse liquidity provision accounts for approximately half of this over performance. Finally, Kelley and Tetlock (2013) argue that retail traders provide liquidity to the market and benefit from the reversal of transitory price movements. My contribution to this body of work is twofold with the richness of the data set. As an intraday evidence, I add to this literature and mainly to Barrot et al. (2016) and find that small traders may have an important role in providing liquidity not only at a daily level but also at an intraday level. Furthermore, I manage to subset the small traders category by looking their activeness - in terms of the number of active trading days - and aggressiveness - in terms of having more aggressive transactions than their passive transactions - since small traders are so heterogeneous in terms of their trading activity.

Second, I take advantage of the richness of the data to further dissect of the small traders by looking at the data field for the transaction basis, whether they are aggressive or passive. For each transaction in the trade book, I have a column taking values as "A" - stands for aggressive or "P" stands for passive. I calculate a ratio from these labels (called as A/P ratio, A stands for aggressive, P stands for passive) which shows whether their transactions are mostly resulting from aggressive acquisitions or obtained via passive acquisitions. By using this ratio, I further label small traders as passive or aggressive. I find that small traders, especially the ones classified as passive, provide liquidity higher in magnitude compared to those classified as aggressive traders. This can be considered a robustness check to see if their trading patterns are in line with the liquidity provision and removal behaviour.

Third, in order to investigate more on aggressive small traders, I used further features of the data set and analyzed how active they are in terms of active trading days in 2019. I separated the aggressive small traders subset into two groups by looking their activeness in the market. Activeness is defined by looking at the number of days they are actively trading in the market. I find that more active aggressive small traders are momentum traders, whereas less active aggressive small traders come in late and provide liquidity with a delay. Thus, the overall delayed liquidity provision of small traders is driven by such less active participants becoming active.

Fourth, I analyze whether small traders make profits from liquidity provision, but my results are ambiguous. I tried to calculate the profits from three approaches due to data limitations. The issue with my data set is, it starts by January 2, 2019, so I can not see if the traders start selling before I see them buying. For this reason, I measured three types of profit calculation approaches and found that small traders seem to have profit per account, especially the passive - liquidity providing - ones, in two of the three approaches. I provide a possible explanation for this result. This may be due to the low speed of the small traders at which they reverse their trades. Individuals cannot benefit from liquidity provision unless they reverse their trades quickly enough thereafter, before the benefits are dissipated. This result also relates to the literature on individual investors' performance. The average household trades in excess of what liquidity and hedging motives would command and loses money in the process (Odean, 1998; Barber and Odean, 2000; Barber et al., 2009; Grinblatt and Keloharju, 2000) especially when going online (Barber and Odean, 2000). This is generally attributed to behavioral biases such as overconfidence or gambling (Statman et al., 2006; Glaser and Weber, 2007; Grinblatt and Keloharju, 2000; French, 2008). A small selected group of retail traders however manage to generate absolute performance (Barber et al., 2014) with some persistence (J. D. Coval et al., 2021). Linnainmaa (2010) finds losses on limit orders and gains on market orders in Finland, for portfolios long (short) in stocks that individuals on aggregate net bought (sold). I add to this body of work by showing that they fail to reverse their trades soon enough. Retail investors do not trade fast enough to collect the benefits from their liquidity provision.

The rest of the paper proceeds as follows. I introduce the institutional background, data and some descriptive statistics in Section 1.2. In Section 1.3, I present my trader categorization approach, methodology, and findings. Section 1.4 concludes the paper.

1.2 Institutional Background and Data

1.2.1 BIST Stock Market

Borsa Istanbul Group (BIST) was established in 1873 and now consists of four main markets: the Stock Market, Debt Securities Market, Derivatives Market, and Precious Metals and Diamond Markets. The Stock Market facilitates the trading of various financial instruments, including shares, pre-emptive rights, exchange-traded funds, intermediary institutions' warrants and certificates, lease certificates, real estate investment funds, real estate certificates, and venture capital investment funds. With a total traded value of 2.130 trillion Turkish Lira (TL), the BIST stock market ranks 21st globally, with a daily average traded value of 8.5 billion TL. The share turnover velocity in the BIST stock market is the 3rd highest in the world, standing at an impressive 227%. According to statistics from the World Federation Exchanges, the stock market boasts 402 listed companies, with foreign shares accounting for 61% of the free float market capitalization in 2019.

The stock market operates under a "price-time priority" matching algorithm, which prioritizes orders with more favorable prices over those with less favorable prices. In the case of orders with the same prices, they are executed based on the sequence in which they were received by the matching engine. It is worth noting that there are no formal liquidity providers for BIST30 stocks.

1.2.2 Data

The data set consists of intraday trade-level data for benchmark index BIST30 stocks for the year of 2019, directly taken from the Exchange's database. From the trade-level data, all regular transactions occurring during the 420-minute period where continuous trading occurs between 10:00-13:00 and 14:00-18:00 are examined for the year of 2019. For each transaction, I use fields from trade book data with account IDs for the buyer and the seller, the price and quantity transacted, the date and time (to the nearest minute), a matching ID number that sorts trades into chronological order within one minute and a field for an aggressiveness indicator stamped by the matching engine as "P" for a resting order and "A" for an order that executed against a resting orders. Account IDs are the IDs of the trading accounts which can possibly used by a single or multiple traders, by the financial intermediary for their portfolio management purposes or by mutual funds. Further information for the data set is given at the Appendix.

1.3 Methodology

In this section, I introduce my trader categorization approach then methodology and regression results for daily and intraday frequencies.

1.3.1 Trader Categories

In this subsection, I introduce my trader classification methodology. I categorize traders based on their directly observed individual inventory and trading volume patterns. For each trading day and stock in BIST30, I calculate each trader's end-of-day net position holding, normalized by their trading volume, as well as the ratio of their specific trading volume to the market volume. Figure 1.2 illustrates this categorization approach, where each dot represents a single trading account for one stock. To classify traders, I use two criteria: the trader volume relative to market volume on the y-axis and the end of day net position holding relative to trader volume on the x-axis of Figure 1.2. For each of the trading day, I took each account's initial net position as zero. The horizontal bold line represents the cut off for trader volume relative to market volume criteria, indicating how big or small the trading account in terms of their trade volume compared to the market volume. The cutoff is set as 0.1%[2] and trading accounts having larger volume by market volume are classified as

[2]The corresponding trade value in terms of dollars for the cutoff across 30 stocks in BIST30 index is given in the Appendix.

big and below as small.

In this research, I focus on small traders, specifically small non-neutral traders (green dots) who corresponds to the small traders except the neutral ones who maintain an average[3] levels of inventory within the -0.10 and 0.10 window in terms of the net position scaled by the trader volume on the x-axis over the year. This criteria indicates whether the trader is willing to carry end of day positions over the day and the small neutral accounts are inside this window, while the non-neutral traders fall outside this window on the x-axis.

The trading accounts on the x-axis equals one and minus one are mainly buyers or sellers who accumulate a significant portion of buy or sell position on a given day, most likely reflecting institutional investors with longer horizons. Traders between absolute values of 1 and 0 are mostly several trader accounts merged into a single account, likely brokerage accounts trading through a broker or hedge funds, and I label them as intermediate accounts. For the upcoming regressions, I use four distinct groups: those who exhibit neutrality in their end-of-day net position holdings pattern differentiating between big and small traders, and those displaying non-neutral behavior, again classified by size. To simplify terminology, I refer to the non-neutral traders simply as traders. These four groups are composed of big traders (encompassing big intermediates, big buyers, and big sellers), small traders, large neutrals, and small neutrals.

For each of the trading day in 2019, I measure two criteria for each account, for each stock and then I took the average of these criteria over the year, then I labelled them as their average category[4]. My classification strategy is entirely based on their directly observed individual end of day net position and trading volume patterns of traders in the data set.

[3]This averaging is done in absolute terms for the ratio of net position scaled by trader volume.

[4]See the robustness check for the stability of the traders categorization for small trader and neutral in the Appendix.

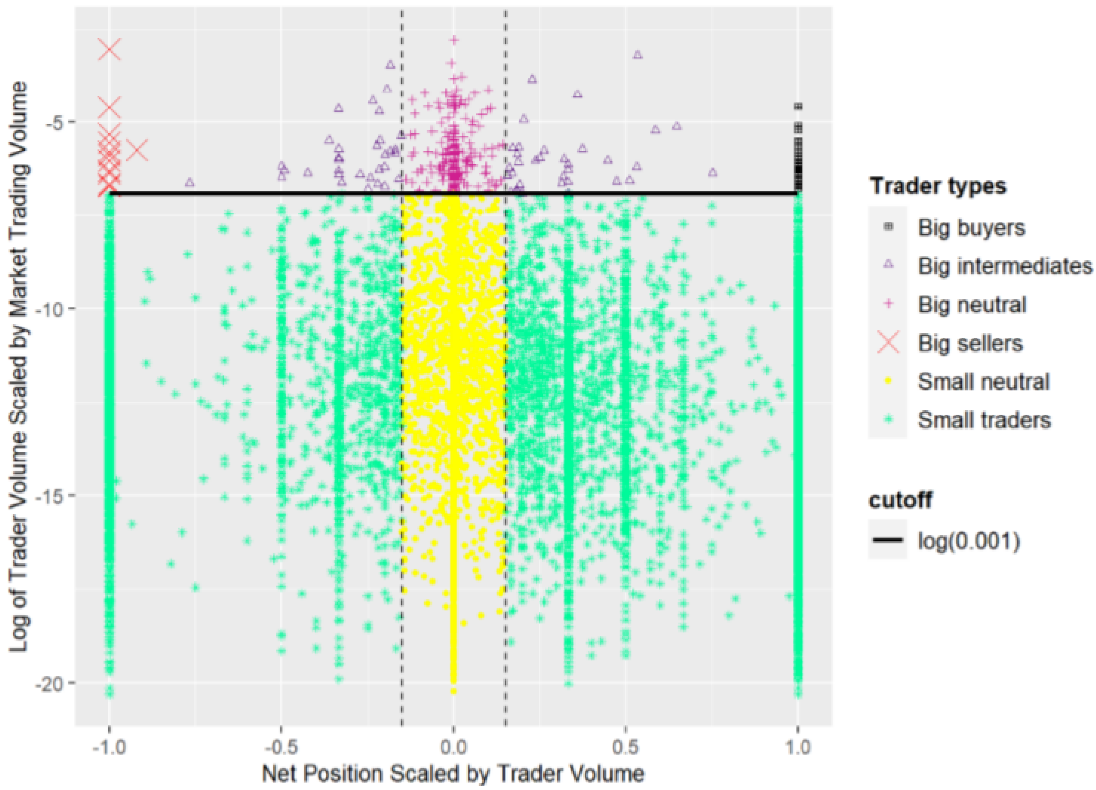

Figure 1.2: **Representative Categorization Approach**

This figure presents the representative categorization approach for each trading account for one stock. End of day net position scaled by trader volume - x-axis and trader volume scaled by related stock's total market volume - y-axis is calculated for each trading account. Trading accounts' x-axis value within the -0.10 and 0.10 window shows the neutral trading accounts where as horizontal cutoff of 0.1% for trader volume normalized by market volume shows how big or small the trading account is.

Descriptive statistics for the trader categories are presented in Table 1.1. First column is the average trader categories such as big traders (big buyers, big sellers and big intermediates), big neutrals, small traders and small neutrals. Second column shows the share of daily trade volume for each category per stock in BIST30 universe. Almost 15% of the average daily trade volume per stock is realized by the small traders altogether which signals that small trading accounts have an important role in the market. Neutral traders - big and small traders together - which are possibly behaving as liquidity providers in the market make almost 21% of of the average daily trade volume per stock. Third column shows the number of unique trading accounts ever seen for BIST30 stocks universe in 2019. The number of active accounts per day is dramatically high for the small traders.

Fourth column shows the number of active accounts per day. Fifth column shows the number of active days per account for each category. The number of active days per account is relatively low for the group of small traders. It could be interpreted as even there is high number of small traders account trading in the market, their number of active day is so low which fifth column signals how active the trader categories are in this given year.

Table 1.1: **Descriptive Statistics for the Trader Categories**

This table presents descriptive statistics for the trader categories. The first column presents average trader categories such as big traders (big buyers, big sellers and big intermediates are merged), big neutrals, small traders and small neutrals. Second column gives the number of unique trading accounts ever seen for BIST30 stocks universe in 2019. Third column shows the share of daily trade volume for each category per stock in BIST30 universe. Fourth column shows the number of active accounts per day for each category and the last column shows the number of active days for each account in in BIST30 universe.

Trader Category	% in trade volume	Number of trading accounts	Number of avg. active accounts per day	Number of avg. active days per account
Big traders	65	23 779	3393	74
Big neutrals	20	10 102	691	17
Small traders	13	601 040	57 815	24
Small neutrals	1.5	108 604	2002	5

1.3.2 Daily Approach

This paper investigates the role of small traders in providing liquidity across different time frequencies. The primary methodology aims to empirically examine the dynamics between each trader category's imbalance and contemporaneous returns, as well as the effect of lagged imbalances, ranging from daily to intraday levels. The question here is whether aggregate retail buy and sell imbalances exhibit contrarian behavior and positively predict stock returns across different frequencies. The definition of imbalance used here is similar to the one employed in (Kelley and Tetlock, 2013). It is computed on a daily basis as the difference between the number of shares bought and sold by retail investors, divided by the sum of shares bought and sold. The study utilizes a dynamic panel setting including 30 stocks and 248 days. In this particular section, the focus is on the daily frequency of the model. The baseline holdings and price regression can be summarized as follows:

$$Imb_{i,t,c} = \beta_1 R_{i,t} + \beta_2 R_{i,t-1} + \beta_3 R_{i,t-2} + \beta_3 R_{i,t-3} + \beta_4 R_{i,t-4} + \epsilon_{i,t} \tag{1.1}$$

where $Imb_{i,t,c}$ is the outcome variable and denotes the imbalance of the corresponding trader category c for the stock i and for the corresponding time frequency. t is day for the daily approach. $R_{i,t}$ stands for the daily contemporaneous and lagged market returns which are computed on a daily basis by calculating the difference between a stock's closing price on a given trading day and its closing price on the preceding trading day, divided by the closing price on that preceding trading day.

In Equation 1.1, parameters of interest are β_i shows the reaction of corresponding trader category's imbalance to the daily market returns. Before the introduction of the regression results, Table 1.2 shows the descriptive statistics for the daily observations of imbalance and returns for each trader category.

Table 1.2: **Descriptive Statistics for Regression Variables**

This table presents the descriptive statistics of the daily observations for BIST30 stocks for the year of 2019. The first column presents the trader categories' imbalance which is used as a left hand side variable in Equation 1.1 and daily return, second column is the number of observations in the data set. The third and the rest columns represent the mean, standard deviation and minimum, 25th and 75th percentile and maximum values of the given variables in the first column.

Trader category	N	Mean	St. dev.	Min.	Pctl. 25	Pctl. 75	Max.
Small traders imbalance	7440	0.002	0.03	−0.116	−0.017	0.019	0.155
Small neutral imbalance	7429	0	0	−0.002	0	0	0.002
Big traders imbalance	7440	−0.002	0.031	−0.161	−0.019	0.017	0.118
Big neutrals imbalance	7416	0	0.004	−0.104	−0.001	0.001	0.09
Daily Return, t	7440	0.001	0.022	−0.163	−0.012	0.014	0.148

Table 1.3 presents the daily regression results for the trader groups of small neutrals, big neutrals, small traders and big traders respectively. In Table 1.3, second column shows coefficient estimates for the daily regression for the category of small neutral trading accounts. The coefficient estimate for contemporaneous return as an explanatory variable with stock and trading day fixed effects, beta is -0.00106 and significant however, its low in magnitude. This finding is in line with the fact that small neutral traders are the ones between -0.1 and 0.1 on the y-axis which shows the net position scaled by trader volume in Figure 1.2. By construction, these accounts are not willing to carry positions over the days and weakly significant relationship between the returns and imbalance simply confirms this finding. In other words, on a daily level, neutral trading accounts close most of their positions by the end of day, so they are less likely to able to lean against price changes or market returns.

In Table 1.3, third column presents the coefficient estimates for the daily regression of big neutral trading accounts. The coefficient estimate for contemporaneous return as an explanatory variable with stock and trading day fixed effect, beta is 0.00553 and statistically insignificant. This finding is in line with the fact that big neutral traders are the ones between -0.1 and 0.1 on the y-axis which represents the net position scaled by trader volume in Figure 1.1. By construction, these accounts are not willing to carry positions over the days and weakly significant relationship between the returns and imbalance simply confirms this finding. In other words, on a daily level, neutral trading accounts close most of their positions by the end of day, so they are less likely to able to lean against price changes or market returns.

In Table 1.3, fourth column presents the coefficient estimates for the daily regression of small traders trading accounts. The coefficient estimate for contemporaneous return as an explanatory variable with stock and trading day fixed effect, beta is -1.10217 and statistically significant. A one standard deviation decrease in contemporaneous return leads to an increase of about 1 percentage point in imbalance which represents the 35% the sample deviation of the small trader's imbalance. This suggests small traders' imbalance seems to react strongly to the contemporaneous returns and decaying from the high of 1.10217 to the past returns. This estimate stays almost same by the addition of stock fixed effects which suggests the time invariant stock level characteristics are not responsible for the cross-sectional correlation between the imbalances and past returns. Overall, small traders' pattern of buying and selling reversals seems to be similar to the liquidity providers who are supposed to take the opposite positions of the rest of the market. These estimates are comparable with the ones obtained by (Barrot et al., 2016).

In Table 1.3, fifth column presents the coefficient estimates for the daily regression of the big traders trading accounts. The coefficient estimate for contemporaneous return as an explanatory variable with stock and trading day fixed effect, beta is 1.09764 and statistically significant. A one standard deviation increase in contemporaneous return leads to an increase of about 1 percentage point in imbalance which represents the 32% the sample deviation of the big trader's imbalance. Here, big traders imbalance as a left hand side variable on market returns may be an issue of endogeneity since almost 85% of the market trading volume is made by big traders. It is not clear whether market returns affect their imbalance or vice versa.

Table 1.3: **Daily Regression for Trader Groups**

This table presents estimated coefficients for the regression in Equation 1.1. The dependent variable is the imbalance for each trader categories which is defined as the net position over the total market trade volume for each stock, trading days. The sampling frequency is daily. Standard errors are clustered at stock level. Models include stock and trading day fixed effect.

	Small Neutrals	Big Neutrals	Small Traders	Big Traders
Return, t	-0.00106 ***	0.00553	-1.10217 ***	1.09764 ***
	(0.00027)	(0.00526)	(0.07020)	(0.06807)
Return, t-1	0.00067 ***	0.00090	-0.06281 **	0.06136 ***
	(0.00016)	(0.00293)	(0.02562)	(0.02651)
Return, t-2	-0.00011	0.00031	-0.08486 ***	0.08452 ***
	(0.00016)	(0.00224)	(0.01957)	(0.01971)
Return, t-3	-0.00002	-0.00326	-0.08265 ***	0.08630 ***
	(0.00011)	(0.00318)	(0.01981)	(0.02003)
Return, t-4	0.00017	-0.00250	-0.06542 ***	0.06712 ***
	(0.00010)	(0.00348)	(0.02111)	(0.02092)
N	7263	7250	7274	7274
R2	0.05584	0.04056	0.54631	0.53920
Adj.R2	0.01840	0.00244	0.52835	0.52096
Stock FE	Yes	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

1.3.3 Intraday Approach

As it is indicated in the previous section, the main idea of the methodology is empirically examine dynamics between each trader category's imbalance for different frequencies. Previous section shows the results for daily regressions. In this section, the same methodology is applied to imbalances and contemporaneous and lagged market returns measured for each ten minutes. Imbalance here is defined by the number of stock shares bought minus the number of stock shares sold by the trader category normalized by the market volume of the given stock for each 10 minutes. The baseline holdings and price regression is given as below:

$$Imb_{i,t,c} = \alpha_1 R_{i,d-1} + \sum_{k=0}^{s} \beta_k R_{i,t-k} + \epsilon_{i,t} \tag{1.2}$$

where $Imb_{i,t,c}$ is the outcome variable and denotes the 10 minutes imbalance for stock i, for each ten minutes shown as t for the corresponding trader category c. $R_{i,d}$ stands for previous day market return for stock i, $\beta_k R_{i,t-k}$ stands for contemporaneous and lagged 10 minutes returns until time k which are simply the price changes calculated as the difference between the stock's price and ten minutes lagged price over its ten minutes lagged price. From the tradebook, price is calculated as the mean of the prices for the transactions realized in that specific ten minutes. In Equation 1.2, parameters of interest are α_1 shows the reaction of corresponding trader category's imbalance to the previous days' return whereas β_k shows the reaction of corresponding trader category's imbalance to the contemporaneous and lagged ten minutes market returns. In these section, (Barrot et al., 2016) methodology which has results only daily level is reproduced from intraday data and the intraday mechanism is investigated.

Table 1.4 presents the coefficient estimates for the intraday regression for the the trader categories of small traders, small neutral, big traders and big neutrals respectively. In Table 1.4, second column presents the intraday coefficient estimates for small traders. It starts with previous day's return, contemporaneous and lagged market returns until ten minutes with stock fixed effect, alpha is -0.88600 and statistically significant and negative which is in line with the daily findings on Table 1.3. The beta standing for the contemporaneous return for the corresponding ten minute is -4.29587 and statistically significant. A one standard deviation decrease in contemporaneous return leads to an increase of about 4 percentage point in imbalance. This suggests small traders' imbalance seems to react strongly to the contemporaneous returns and decaying from the high of 4.29587 to the past returns. The fact that the first reaction is high results mostly from the limit orders they placed. By adding the lag returns, I find a significant and negative stock returns. Overall, small traders' pattern of buying and selling reversals seems to be similar to the liquidity providers not only for the daily but also intraday level.

In Table 1.4, third column presents the intraday coefficient estimates for small neutrals. As it is mentioned before, neutral traders are the ones between -0.1 and 0.1 on the y-axis which represents the net position scaled by trader volume in Figure 1.2. By construction, these accounts are not willing to carry positions over the days and weakly significant relationship between the returns and imbalance on a daily level (Table 1.3) simply confirms this finding. The coefficient estimate beta standing for the contemporaneous return for the corresponding ten minute is -0.10868 and statistically significant, then the sign of the lagged return is reversed staying still significant. They are not providing liquidity at an intraday level at all.

In Table 1.4, fourth column presents the intraday coefficient estimates for the category of big traders. Big traders' imbalance as a left hand side variable on market returns may be an issue of endogeneity since almost 85% of the market trading volume is made by big traders. It is not clear their imbalance results from the price changes or they trade in the direction of the price movement.

In Table 1.4, fifth column presents the coefficient estimates for the intraday regression for the category of big neutrals. As its discussed before, neutral traders are the ones between -0.1 and 0.1 on the y-axis which represents the net position scaled by trader volume in Figure 1.2. By construction, these accounts are not willing to carry positions over the days and weakly significant relationship between the returns and imbalance on a daily level (Table 1.3) simply confirms that. However, beta standing for the contemporaneous return for the corresponding ten minute is 0.70262 and statistically significant, then the sign of the lagged return is flipped after 30 minutes. This positive and significant coefficients may be interpreted as momentum trading or liquidity takers for the category of big neutrals. Interestingly, they do not provide liquidity.

Table 1.4: **Intraday Regression for Traders Groups**

This table presents estimated coefficients for the regression in Equation 1.2. The dependent variable is the imbalance for each trader categories which is defined as the net position over the total market trade volume for each stock, trading days, ten minutes. $\alpha_1 R_{i,d}$ stands for the previous day return whereas $R_{i,t}$ stands for contemporaneous and lagged 10 minutes returns. The sampling frequency is ten minutes. Standard errors are clustered at stock level. Models include stock, trading day and ten minutes fixed effect.

	Small Traders	Small Neutrals	Big Traders	Big Neutrals
Previous day return	-0.88600 ***	-0.00308	0.93386 ***	-0.04145 ***
	(0.05069)	(0.00309)	(0.05190)	(0.01090)
Return, t	-4.29587 ***	-0.10868 ***	3.48084 ***	0.70262 ***
	(0.40218)	(0.03661)	(0.35373)	(0.24667)
Return, t-1	-1.50122 ***	0.03694 **	1.51935 ***	0.00731
	(0.12811)	(0.01456)	(0.12524)	(0.09497)
Return, t-2	-1.25567 ***	-0.01887	1.12157 ***	0.19404 ***
	(0.12285)	(0.01219)	(0.11511)	(0.06500)
Return, t-3	-0.99881 ***	0.00240	0.97055 ***	-0.00300
	(0.10644)	(0.01408)	(0.11375)	(0.05817)
Return, t-4	-0.82837 ***	-0.02904 **	0.82241 ***	0.01051
	(0.07583)	(0.01394)	(0.07652)	(0.06314)
Return, t-5	-1.06842 ***	-0.02455	1.01057 ***	-0.01070
	(0.09300)	(0.01505)	(0.09305)	(0.05689)
Return, t-6	-0.78674 ***	-0.01758	0.87478 ***	-0.04086
	(0.07054)	(0.01053)	(0.07100)	(0.07114)
Return, t-7	-0.67515 ***	-0.00894	0.69342 ***	-0.04478
	(0.07627)	(0.01331)	(0.06398)	(0.05107)
Return, t-8	-0.66718 ***	-0.01216	0.64593 ***	0.05698
	(0.08302)	(0.01206)	(0.08612)	(0.05510)
N	340720	268094	340951	311266
R2	0.07751	0.05167	0.05345	0.01003
Adj.R2	0.07658	0.05045	0.05250	0.00894
Stock FE	Yes	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes	Yes
Ten min FE	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

1.3.4 Aggressive vs Passive Small Traders

In order to further analyze the reaction of imbalances to the market returns especially for small traders in detail, trading accounts of the small traders subset are separated by looking the proportion of their aggressive transactions versus passive transactions. I calculate a ratio (called as A/P ratio, A stands for aggressive, P stands for passive) which shows whether their transactions resulted via aggressive acquisitions or obtained via passive acquisitions. The data set allows me to observe each of the transaction whether they are passive or aggressive directly. This separation is important in signalling the behaviour of the trader group if their trading pattern shows liquidity provision or removal. In general, aggressive transactions are incurred when traders submit marketable orders into the order book and immediately matched. This means that they trade aggressively in the same direction as the prices are moving, thus, taking liquidity from the market. Passive transactions are those incurred via the traders' resting orders' being executed by a marketable order. This means, they trade passively against price movements and, thus, provide liquidity. My daily results from Table 1.3 and intraday results from Table 1.4 suggest that small traders' pattern of buying and selling reversals seems to be similar to the liquidity providers who are supposed to take the opposite positions of the rest of the market at a daily and intraday level. With this further subset, I have the opportunity if this fact holds especially for the passive subset of small traders group who are supposed to provide liquidity and how this small trader subsets result unfolds in terms of the coefficients across aggressive and passive small traders subset.

I define this ratio for each account, stock and trading day, calculate their aggressive and passive transactions then I calculate the ratio of aggressive transactions over the total transactions which is the total of aggressive and passive transactions. Then, I label the accounts as aggressive if they have a ratio higher than the mean of this ratio for the whole small traders' trading account universe. The mean of this ratio is 47% for my data set. Table 1.5 shows the descriptive statistics for the aggressive and passive small trader subsets. Mean of this ratio for aggressive and passive small traders is 0.72 and 0.22 respectively. Average daily total volume for these subsets are 4068 and 5257 and their share in total volume is 44% and 56% respectively. These closer number of average daily positions and share in total position across the subsets help me to make a reasonable comparison.

Table 1.5: **Descriptive Statistics for A/P Ratio**

This table presents the descriptive statistics of the subsets of the small traders category. The first column presents the trader categories whether they are passive or aggressive. Second column shows the mean of the A/P ratio for the corresponding subset of small traders category. Third column shows the number of accounts ever seen over the year 2019 in this categories. Total volume is the average total volume of the trader categories and fourth column shows the corresponding average share in total volume of the small traders subset.

Trader category	Mean of A/P ratio	Number of accounts	Total volume	Avg share in total volume
Aggressive Small Traders	0.72	427 754	4068	44 %
Passive Small Traders	0.22	379 933	5257	56 %

1.3.5 Daily Approach

The same methodology in Section 1.3.2 is applied here for the subsets of the small traders. The idea is to understand how the previous parameters of interest for the small traders category unfolds for different subsets of the small traders in terms of their transactions mostly being aggressive versus passive.

Table 1.6 presents the coefficient estimates for the daily regression of passive and aggressive small traders category. In Table 1.6, second column presents the coefficient estimates for the daily regression for passive small traders category. The coefficient for contemporaneous return is -0.79462 and statistically significant. A one standard deviation decrease in contemporaneous return leads to an increase of about 0.7 percentage point in imbalance which represents about 21% of the sample deviation of small trader's imbalance. This suggests passive small traders' imbalance seems to react to the contemporaneous returns and decaying from the high of 0.79462 to the past returns. In Table 1.6, third column presents the coefficient estimates for the daily regression for aggressive small traders category. The coefficient for contemporaneous return is -0.30755 and statistically significant for aggressive small traders. A one standard deviation decrease in contemporaneous return leads to an increase of about 0.3 percentage point in imbalance which represents the 10% the sample deviation of the small trader's imbalance. By adding the lag returns, I still find a significant and negative stock returns. This suggests aggressive small traders' imbalance seems to react to the contemporaneous returns and decaying from the high of 0.30755 to the past returns. This finding is in line with the results in Table 1.3.

To sum up, when I compare the magnitude of the contemporaneous return's coefficients in Table 1.6, it is higher for the passive subset of small traders than the aggressive subset of small traders, which is compatible with definition of the passive transactions given in the beginning of this section.

Table 1.6: **Daily Regression for Passive and Aggressive Small Traders**

This table presents estimated coefficients for the regression in Equation 1.1 for the subsets of passive and aggressive small traders. The dependent variable is the imbalance which is defined by the number of stock shares bought minus the number of stock shares sold by the trader category normalized by the market volume of the given stock. The sampling frequency is daily. Standard errors are clustered at stock level. Models include stock, trading day and ten minutes fixed effect.

	Passive Small Traders	Aggressive Small Traders
Return, t	-0.79462 ***	-0.30755 ***
	(0.04820)	(0.02511)
Return, t-1	-0.01683	-0.04598 ***
	(0.01557)	(0.01111)
Return, t-2	-0.03181 **	-0.05306 ***
	(0.01200)	(0.00864)
Return, t-3	-0.03707 ***	-0.04558 ***
	(0.01198)	(0.00877)
Return, t-4	-0.02904 **	-0.03637 ***
	(0.01229)	(0.00985)
N	7274	7274
R2	0.59522	0.35678
Adj.R2	0.57919	0.33131
Stock FE	No	Yes
Trading Day FE	Yes	Yes
Clustered SE	Yes	Yes

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

1.3.6 Intraday Approach

The same methodology in Section 1.3.3 is applied here. The idea is to understand how the previous parameters of interest for the small traders category unfolds for different subsets of the small traders in terms of their aggressiveness behaviour at an intraday level.

Table 1.8 presents the coefficient estimates for the intraday regression of aggressive small traders category. Second column of Table 1.8 starts with previous day return, contemporaneous return and its lag until 10 minutes with stock, trading day and ten minutes fixed effect, alpha is -0.70962 and statistically significant and negative in line with the daily level findings on Table 1.6. The beta standing for the contemporaneous return for the corresponding ten minute is 3.17991 and statistically significant. A one standard deviation increase in contemporaneous return leads to an increase of about 3 percentage point in imbalance. This suggests aggressive small traders' imbalance seems to react strongly to the contemporaneous returns and decaying from the high of 3.17991 to the past returns. It is interesting that aggressive small traders' contemporaneous return is significantly positive, then it flips to negative with ten minutes lag. In order to investigate more on this aggressive small traders, I used further feature of the data set and analyze how active they are in terms of active trading days over the year. I separated the aggressive small traders subset into two groups by looking their activeness in the market. Activeness is defined by looking the number of days they are actively trading in the market. The mean of active trading days across the small traders' accounts are 29 days over 248 trading days. Trading accounts under small traders category who have higher than 29 days of active trading days are classified as more active[5], the rest is less active[6].

Table 1.7: **Descriptive Statistics for the Small Traders**

This table presents the descriptive statistics for the small traders category for the features of aggressiveness and passiveness. First column is for the trader categories. Second column shows the number of active trading days of the subsets. Third column shows the mean of A/P ratio which gives an idea about how aggressive their transactions are. Fourth column shows the number of accounts ever seen in the data set. Fifth column shows the mean of total position for the corresponding trader category. Sixth column shows the average share of the categories in total position of the small traders.

Trader category	Number of active trading days	Mean of AP ratio	Number of accounts	Total position	Avg share in total position
Aggressive Small Traders - More Active	68	70 %	17 881	4921	25 %
Passive Small Traders - More Active	77	23 %	22 118	6700	34 %
Aggressive Small Traders - Less Active	10	73 %	426 348	3775	19 %
Passive Small Traders - Less Active	11	22 %	377 489	4490	23 %

In Table 1.8, third and fourth column presents the coefficient estimates of the intraday regression for aggressive and more or less active traders. Third column shows the coefficient estimates for more active aggressive small traders. The coefficient estimate for previous day return is 0.20441 and statistically significant and positive. The beta standing for the contemporaneous return for

[5]Indicated as MA in Table 1.8.
[6]Indicated as LA in Table 1.8.

the corresponding ten minute is 3.67875 and statistically significant. This suggests aggressive and more active small traders' imbalance seems to react strongly to the contemporaneous returns - high mostly from the limit orders they placed - and decaying from the high of 3.67875 to the past returns immediately. Interesting finding for the aggressive small traders unfolds here and seems that contemporaneous liquidity taking behaviour is mostly coming from the more active small traders subset. They behave as liquidity takers when I look into the contemporaneous and lagged market returns and they seem to taking liquidity from the market by chasing trends. In Table 1.8, fourth column shows the coefficient estimates for less active aggressive small traders. Model starts with previous day's return, contemporaneous return and its lag until 10 minutes with stock, trading day and ten minutes fixed effect, alpha is -0.91041 and statistically significant and negative in line with my findings on Table 1.6. The beta standing for the contemporaneous return for the corresponding ten minute is -0.73450 and insignificant. Ten minutes lagged coefficients are higher in magnitude and significant suggesting that aggressive and less active small traders' are staying slow in reaction with a lag of ten minutes but their imbalance seems to react to the ten minutes lag and decaying from the high of 2.27967 to the past returns as well. Less active small traders seems to come in late and give liquidity with a delay. Thus, the overall delayed liquidity provision of small traders is driven by such less active participants becoming active, some react only with a delay of 1 or 2 hours.

In Table 1.8, fifth column presents the coefficient estimates for the intraday regression of passive small traders category. Model starts with previous day's return, contemporaneous return and its lags until 10 minutes with stock, trading day and ten minutes fixed effect, alpha is -0.18606 and statistically significant and negative in line with my findings on Table 1.4. The beta standing for the contemporaneous return for the corresponding ten minute is -6.92139 and statistically significant. A one standard deviation decrease in contemporaneous return leads to a increase of about 6 percentage point in imbalance. This suggests passive small traders' imbalance seems to react strongly to the contemporaneous returns - high mostly from the limit orders they placed - and decaying from the high of 6.92139 to the past returns immediately. It seems from their contemporaneous return that their reaction is automatic due to the limit orders they sent. They just give contemporaneous liquidity but there is no significant reaction afterwards.

Table 1.8: **Intraday Regression for Aggressive and Passive Small Traders**

This table presents estimated coefficients for the regression in Equation 1.2. The dependent variable is the imbalance for small traders categories and its subsets which is defined as the net position over the total market trade volume for each stock, trading days, ten minutes. $\alpha_1 R_{i,d}$ stands for the previous day return whereas $R_{i,t}$ stands for contemporaneous and lagged 10 minutes returns. Standard errors are clustered at stock level. Models include stock, trading day and ten minutes fixed effect.

	Aggressive Small Traders	Aggressive Small Traders MA	Aggressive Small Traders LA	Passive Small Traders
Previous day return	-0.70962 ***	0.20441 ***	-0.91041 ***	-0.18606 **
	(0.08901)	(0.02711)	(0.09281)	(0.07530)
Return, t	3.17991 ***	3.67875 ***	-0.73450	-6.92139 ***
	(0.70945)	(0.35871)	(0.51864)	(0.65805)
Return, t-1	-1.48737 ***	0.91966 ***	-2.27967 ***	-0.30196
	(0.22792)	(0.11922)	(0.25458)	(0.20564)
Return, t-2	-1.03075 ***	0.59034 ***	-1.62993 ***	-0.17522 *
	(0.13553)	(0.09253)	(0.15762)	(0.09122)
Return, t-3	-1.09181 ***	0.28134 ***	-1.34675 ***	0.05815
	(0.11437)	(0.09120)	(0.14598)	(0.08853)
Return, t-4	-0.86913 ***	0.21378 **	-1.08504 ***	-0.00924
	(0.13308)	(0.08118)	(0.13704)	(0.09450)
Return, t-5	-0.70413 ***	0.23663 **	-0.98551 ***	-0.25001 **
	(0.11551)	(0.10358)	(0.11220)	(0.10460)
Return, t-6	-0.78912 ***	0.14670 *	-0.91458 ***	-0.03523
	(0.09775)	(0.08310)	(0.10831)	(0.07937)
Return, t-7	-0.66167 ***	0.08257	-0.75847 ***	0.01099
	(0.09738)	(0.07045)	(0.09920)	(0.07999)
Return, t-8	-0.74972 ***	0.00422	-0.73150 ***	0.10581
	(0.08129)	(0.06553)	(0.08464)	(0.06252)
N	341109	341291	341220	341263
R2	0.02964	0.02581	0.05270	0.03751
Adj.R2	0.02867	0.02483	0.05174	0.03655
Stock FE	Yes	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes	Yes
Ten min FE	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes

*** p < 0.01; ** p < 0.05; * p < 0.1.

1.3.7 Profits and Losses

In order to calculate the daily profits, for each trading account denoted as ”k”, the calculations are conducted for each trading day ”t” and each stock ”i” using marked-to-market accounting. It is assumed that each trading account begins each day with a zero inventory position. Specifically, the end-of-day profits for each trader are computed by summing the cash received from selling short positions and subtracting the cash paid for buying long positions. Additionally, the value of any outstanding positions at the end of the day is included, which is determined by marking these positions to the market price at the close for the stocks they are trading in. This is then adjusted by subtracting the value of any outstanding positions from the previous day. To obtain the cumulative daily profits for each trading account, the profits are summed over time. These cumulative profits are then normalized by dividing each cumulative profit by the maximum total position that the trading account has ever held throughout the year. This normalization is performed for each trading account individually.

Lastly, the accounts are aggregated based on their corresponding trader groups, and mean profit for each trader category is calculated.

$$\pi_{k,t} = \sum_{n=1}^{N_{k,T}} p_n y_{k,n} + p_T y_{k,T} - p_{T-1} y_{k,T-1}, \tag{1.3}$$

where $n = 1...N_{k,T}$ indexes the trades for trader k between the start of the trading day (t=0) and the end of the trading day ($t = T$), p_n is the price of the trade, $y_{k,n}$ is the quantity of the nth trade by trader k, and $p_T y_{k,T}$ is the value of any end-of-day positions outstanding for every stocks they have minus $p_{T-1} y_{k,T-1}$ is the value of previous days' end-of-day positions outstanding for every stocks they have in BIST30 stocks.

There is a potential limitation in this approach used for calculating profits. Since the available data set begins on January 2, 2019, it does not provide visibility into whether traders initiated selling before their buying activities. To address this issue, three different approaches were employed while acknowledging their respective limitations.

The first approach involves disregarding trading accounts that exhibit a cumulative negative net position over the entire sample period. This decision was made due to the inability to determine when these accounts made their initial purchases. Approximately 17% of the total number of unique trading accounts fell into this category. In the second approach, it is assumed that trading accounts purchased their maximum ever seen negative net position over the sample on the first trading day of 2019. This assumption allows for a consistent starting point in calculating profits for these accounts, despite the absence of precise timing information. The third approach, which does not address the aforementioned issue, simply involves calculating profits without taking any specific measures to handle it.

While these approaches were implemented to mitigate the challenge of the potential limitations, it is important to recognize that each approach has its own limitations and may not fully capture the actual buying and selling sequence of traders.

Table 1.9: **Profit for Trader Categories**

This table presents the profits per trader categories. The first column shows the trader category. Second column shows the corresponding A/P ratio of the category.First profit calculation approach is the version with disregarded trading accounts whoever seen cumulative negative net position over the sample. Second profit approach is the version with the assumption of the trading accounts has bought the maximum ever seen negative net position over the sample on the first trading day, so I include this purchases into the profit calculation. Third profit approach is the one calculated with the inclusion of all accounts and no assumption of purchase on the first trading day.

Trader Category	A/P ratio	Profit per account - First approach	Profit per account - Second approach	Profit per account - Third approach
Big traders	Aggressive	5.28%	21.52%	26.81%
Big traders	Passive	0.31%	10.31%	16.49%
Big neutrals	Aggressive	−0.72 %	−0.73 %	−0.72 %
Big neutrals	Passive	−0.26 %	−0.27 %	−0.26 %
Small neutrals	Aggressive	−0.56 %	−0.57 %	−0.56 %
Small neutrals	Passive	1.85%	1.84%	1.85%
Small traders	Aggressive	−0.30 %	9.99%	14.27%
Small traders	Passive	−1.64 %	12.25%	16.17%

Table 1.9 presents the cumulative profits per account for each trader category, along with their corresponding aggressiveness ratio. The third column of the table represents the profit calculation approach where trading accounts with a cumulative negative net position over the sample are disregarded. The fourth column displays the profit approach that includes the assumption of trading accounts purchasing the maximum ever seen negative net position on the first trading day. This assumption is applied to incorporate these purchases into the profit calculation. The fifth column represents the profit calculated according to Equation 1.3, where all accounts are included, and no additional inclusion of purchases is made. When examining the neutral traders, the percentages remain relatively consistent across the different profit calculation approaches. This consistency can be attributed to the fact that neutral trading accounts tend to close most of their positions by the end of the day at the daily level. As a result, they appear to be less affected by the profit calculation issue mentioned earlier in this section. On the other hand, small traders, particularly those categorized as passive liquidity providers, tend to exhibit higher profits per account in the

second and third profit calculation approaches. In contrast, big traders demonstrate profits across all the profit calculation approaches, highlighting their consistent performance. Given the mentioned limitation, the differences seem to be a level effect which is similar between trader groups so that it may be economically less important.

Overall, the variations observed in cumulative profits per account shed light on the different profit calculation approaches and their impact on trader categories. Small traders, especially passive liquidity providers, tend to benefit from the alternative approaches, while big traders consistently generate profits across all approaches.

1.4 Conclusion

In the evolving nature of the stock markets, a big challenge is that buyers and sellers don't always act at the same time. With the growing automation of markets, there's a rising role for non-traditional intermediaries who don't have formal prerequisites in terms of liquidity provision. This becomes particularly pertinent when institutional liquidity vanishes or conventional liquidity providers face constraints. The crucial question revolves around identifying those who step into market to provide liquidity during turbulent trading periods, as this choice significantly impacts price formation in the market.

Despite the prior views of individual traders as noise traders, recent empirical evidence suggests that they contribute liquidity, particularly during times of market stress. This research focuses on small traders and their role in liquidity provision. The study utilizes intraday trade data for the benchmark BIST30 index in 2019, categorizing traders based on observed inventory and trading volume patterns. It examines the relationship between trader categories' imbalances and market returns. The study also highlights the U-shaped relationship between small traders' activity and stock price changes, suggesting their importance during market turbulence.

This paper investigates the role of small traders in providing liquidity in stock market, focusing on various aspects. I uncover four main findings. From the point of liquidity provision view, I find that small traders contribute significantly to liquidity provision, not only on a daily basis but also intraday basis. This finding aligns with previous research (Barrot et al., 2016) and extends it to intraday levels. The study emphasizes that small traders are major liquidity providers compared to big neutral traders.

To address the significant heterogeneity in the trading behavior of small traders, I have taken a more granular approach. To do so, I have categorized them into subsets based on their trading patterns such as their level of activeness in terms of active trading days and whether they exhibit more aggressive or passive transactions. I find that passive small traders contribute more substantial liquidity compared to their aggressive counterparts, verifying the alignment of their trading patterns with liquidity provision. Also, I show that highly active aggressive traders exhibit momentum trading strategies, while less active ones delay entry and provide liquidity.

Lastly, when considering the aspect of profitability, I investigate whether small traders gain profits from providing liquidity. Nevertheless, the results present a mixed picture owing to constraints related to data availability. In essence, the disparities observed in cumulative profits per account offer insights into the diverse approaches used for profit calculation and their impact on trader categories. Notably, small traders, particularly those engaged in passive liquidity provision, tend to benefit from the alternative approaches, while larger traders consistently generate profits across all approaches. The possible explanation may be that the relatively slower reversal of trades by small traders may impede their ability to fully capitalize on liquidity provision.

The research contributes insights into the behavior of small traders, shedding light on their role in liquidity provision. As I conclude this study, I should point out that the results are valid for the stock market of Borsa Istanbul and subject to external validity constraints. Future research should further explore the heterogeneity of small traders and their role to continually evolving stock markets.

2 Chapter 2: Trading Patterns of Small Traders

2.1 Introduction

The active involvement of retail investors has consistently played a significant role in the effective functioning of financial markets. In World Federation Exchange's (WFE) report on enhancing liquidity in emerging markets, Gurrola-Perez et al. (2022) emphasized the significance of establishing a diverse investor base encompassing both retail and institutional investors, each with unique time horizons and investment perspectives. This diversification is crucial for ensuring the robustness and vitality of financial markets. The participation of retail investors in the market holds several benefits for the economy. By diversifying their savings and gaining access to improved opportunities, retail participants can secure long term returns that outpace inflation. Moreover, retail investment infuses additional liquidity into the market, particularly benefiting small and mid-cap stocks, by introducing new and cost-effective sources of funding. This, in turn, enables the allocation of capital towards innovation and development, which serves as a catalyst for economic growth. The involvement of retail trading can increase stock return volatility (Foucault et al., 2011). Notably, substantial academic evidence supports the notion that retail participation contributes favorably to market liquidity and the depth of the order book (Kaniel et al., 2012; Kaniel et al., 2007; Kelley and Tetlock, 2013), even during periods of market instability (Barrot et al., 2016). While retail investors may have less sophistication compared to institutional counterparts, they encounter lower agency costs and liquidity constraints relative to institutional investors like mutual funds (Chevalier and Ellison, 1999; J. Coval and Stafford, 2007). Consequently, retail traders possess the potential to act as market makers, particularly when institutional liquidity diminishes, as seen during the 2008-2009 financial crisis. In fact, there is an emerging body of literature indicating that individual traders are stepping into the market and providing liquidity when institutional and conventional liquidity providers face constraints (Barrot et al., 2016). Unlike the professional traders, small traders do not engage in trading as a primary occupation, but in aggregate, the importance of their role is increasing.

Recognizing the advantages of retail investors' participation in stock markets is crucial for both the markets and the investors themselves. While there exists limited academic consensus regarding the overall impact of retail investors on equity markets (Eaton et al., 2022; Friedman and Zeng, 2022), this lack of consensus is not surprising given the heterogeneous nature of retail investors, characterized by variations in diligence, risk appetite, and motivations. The divergent behavior of retail investors, both compared to institutional investors and among themselves, can prove particularly valuable during periods of market stress. For instance, in scenarios where institutional liquidity diminishes, retail trading can contribute to reducing bid-ask spreads and mitigating the price impact of trades (Ozik et al., 2021). Notably, retail investors demonstrated their potential as a stabilizing force in the market during the market crash induced by the COVID-19 pandemic in March 2020. By maintaining their investment positions and strategically purchasing stocks during price declines, retail investors played a role in stabilizing the market (Ozik et al., 2021; Welch, 2022). This behavior persisted throughout the pandemic, with individual investors tending to increase their share purchases when the market was down by 1 percent compared to when it was up by the same amount (Banerji, 2021).

On the other hand, retail investment entails certain risks and warrants cautionary consideration. Retail trading has the potential to heighten correlated trading activity, which in turn may amplify systemic risk (Kumar and Lee, 2006). Furthermore, in the absence of sufficient levels of financial literacy and education, retail investors can be vulnerable to deceptive investment strategies. Inadequate protection exposes investors to the risk of falling victim to financial scams. The emergence of the GameStop like phenomenons have drawn significant attention to stock markets, specifically shedding light on the participation of retail investors and the influential role of news and social media on their trading activities.

This paper investigates the trading patterns of active small traders, specifically their buying and selling activities over different time horizons for one stock from the benchmark Turkish BIST30 index in 2019. Furthermore, their reaction to stock-related news is explored both at the daily and intraday level. The main focus of the paper is the active small traders. Figure 2.1 shows the suggestive evidence for this research paper. This figure presents the number of small trading accounts and the corresponding change in the stock price. This U-shaped line suggests that in absolute value, high stock price changes – both increases and decreases - are associated with a high number of small traders actively trading on that specific trading day. The U-shaped pattern may indicate that high stock price changes or volatility in the stock may result in an increase in the number of small trader accounts. This can be attributed to the attractiveness of the market when significant price fluctuations occur, prompting more individuals to engage in trading activities. The increased participation of small traders can further contribute to driving the stock price upwards or downwards, creating a positive feedback loop. Further analysis confirms the intuition conveyed by the Figure 2.1.

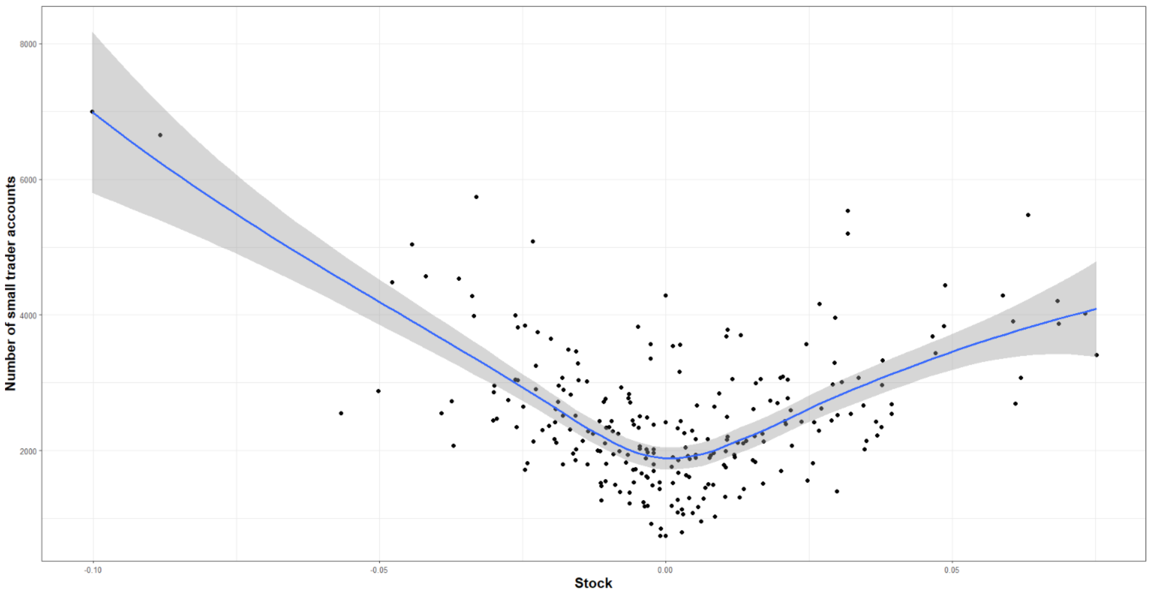

Figure 2.1: **Number of Small Traders vs the Change in the Stock Price**

This figure illustrates the number of small trading accounts alongside the corresponding change in the stock price. The x-axis of the figure represents the price change in the stock, while the y-axis represents the number of small trader accounts. Each point on the graph represents the daily number of small trader accounts and the corresponding daily change in the stock. Therefore, each dot represents one of the trading days throughout 2019.

The broader question of this research is to add knowledge about the trading patterns of the small traders and understand if there are any differences between their buying and selling patterns from daily to intraday levels. The reason for focusing especially the small traders subset is the nature of their heterogeneity. Since there is still limited research in the literature, I believe the richness of my data set can add knowledge on their trading patterns. In order to understand this, a trader-by-trader analysis is performed, and the trading activity, such as buying and selling patterns, of these traders is examined over different time horizons such as daily, hourly and fifteen minutes. The novelty of this research compared to previous works is twofold. Firstly, transaction level data set allows for the examination and comparison of patterns from daily to intraday at a trader-by-trader level. Secondly, instead of a given subset of individual traders universe, the entire universe of traders is observed, and small traders are grouped based entirely on directly observed volume patterns. Due to data constraints and the resulting challenges in obtaining and processing data for all 30 stocks in the BIST30 index, I decide to focus the analysis on a single stock. The exponential increase in the size of the data matrix and the associated computational constraints posed significant limitations on running regressions and interpreting results. By selecting a representative stock out benchmark BIST30 index, I believe the research objectives could still be achieved. This approach allows for in-depth analysis and meaningful insights into the selected stock's behavior and performance, which can be generalized to a broader context. I uncover three main findings.

First, I show that active small traders - who have on average have higher number of trading days in the data set - who are likely to be price stabilizers as they buy when prices fall, sell them when they rise. Several papers have found that individual trades positively predict short-term returns. A first body of work has interpreted this as evidence of noise trading pushing prices away from fundamentals. Barber et al. (2009) find that stocks that individual investors are buying (selling) during one week have positive (negative) abnormal returns that week and in the subsequent two weeks. These returns then reverse over the next several months. Although Barber et al. (2009) interpret their results as evidence of noise trading, they are also consistent with individual investors providing liquidity to institutional investors. Kaniel et al. (2007) identify individual investor trades using the NYSE Consolidated Audit Trail Data files, which contain detailed information on all orders executed on the exchange, including a field that identifies whether the order comes from an individual investor. They show that the top decile of stocks heavily bought by individuals outperform those heavily sold by individuals, a result again consistent with retail traders providing liquidity to institutions that require immediacy. Dorn et al. (2008) show that correlated limit orders predict subsequent returns in a manner consistent with executed limit orders receiving compensation for accommodating liquidity demands. Kaniel et al.(2012) also find evidence that stocks purchased by individual investors prior to earnings announcement outperform those that they sell, and that compensation for risk-averse liquidity provision accounts for approximately half of this overperformance. Finally, Kelley and Tetlock (2013) argue that retail traders provide liquidity to the market and benefit from the reversal of transitory price movements. I contribute to this literature by showing the price stabilization holds not only at the daily level but also at an intraday level. This finding aligns with the observation that retail traders tend to sell when prices rise and buy (or refrain from selling) when prices decline.

Second, I show that there is an asymmetry between buying and selling decisions, as they buy more easily than they sell. Their trading patterns make a reversal at a daily level, whereas they keep momentum at intraday levels. As noted in Barber and Odean (2008), in formal models, the decisions to buy and to sell often differ only by a minus sign. However, recent empirical evidence show that this is not so. Barber and Odean (2013) show that there is reason to suspect that selling and buying decisions involve different psychological processes. Recent work from the lab is consistent with this discrepancy: Buying decisions appear to be more forward-looking and belief-driven than selling decisions in an experimental asset market (Grosshans et al., 2018; Akepanidtaworn et al., 2021) add this by analyzing a unique data set and discover that institutional investors, with an average portfolio size of $573 million, exhibit systematic and costly heuristics in their decision making process. They find that, interestingly, while they demonstrate skill in buying, their selling decisions consistently underperform, even when compared to random selling strategies. I contribute to this literature by showing that small traders buy more easily than sell not only at daily level but also at an intraday level.

Third, I introduce stock-related news variable to further investigate the effect of the stock related news on the trading behaviour of active small traders at daily and intraday levels. I find that active small traders react positively to the stock-related news and buy more at both daily and intraday level. Contemporaneous reactions in buying to the stock-related news are higher in magnitude compared to the selling. I use stock related news as an attention grabbing factor. In theory, investors encounter a similar search challenge when selling as they do when buying. However, there are factors that alleviate this search problem for individual investors during the selling process. Firstly, individual investors typically have a relatively small number of common stocks in their portfolios. Secondly, individual investors primarily engage in selling stocks that they already own, as opposed to engaging in short selling (Barber and Odean, 2008). They proposed that investors address the challenge of selecting from numerous potential stock purchases by narrowing their search to stocks that have recently captured their attention. Although investors do not purchase all attention-grabbing stocks, they tend to buy stocks that have caught their attention. Conversely, the selling process does not present the same search problem, as investors typically sell only the stocks they already own. The authors argue that attention significantly influences individual investors' buying decisions, as they face a substantial search problem when choosing stocks to buy. Rather than conducting a systematic search, many investors may only consider stocks that have initially captured their attention, such as those making news headlines or experiencing significant price movements. This leads to a tendency for individual investors to heavily invest in attention-grabbing stocks. Since most individual investors own a limited number of stocks and sell only those they possess, the selling process involves less of a search problem and is less influenced by attention effects. By using abnormal trading volume, previous day's return, and news coverage as proxies for attention, Barber and Odean (2013) discover that individual investors execute a higher proportion of buy orders for stocks that attract more attention. Engelberg and Parsons (2011) find that individual investors are more likely to trade an S&P 500 index stock subsequent to an earnings announcement if that announcement was covered in the investor's local newspaper. Both buying and selling increase, though buying somewhat more than selling. Engelberg and Parsons (2011) look at overnight market reaction to buy and sell recommendations on the television show Mad Money. They find that the market reaction is greater following recommendations made when viewership—based on Nielson ratings—is higher. Furthermore, consistent with Barber and Odean's hypothesis that attention matters more for buying than selling. Engelberg and Parsons (2011) use Google search frequency as a measure of investor attention to analyze whether investor attention can cause price pressure effects as described in Barber et al. (2008). Using data from 2004 to 2008, they document that increases in search frequency predict higher returns in the ensuing two weeks and an eventual reversal within the year. I contribute to this literature by showing that small traders buying pattern differs from selling and they tend to buy more easily than sell not only at daily level but also at an intraday level. Furthermore, news which may attract the attention of traders are indeed important and buying pattern reacts more to the stock related news compared to selling pattern.

The paper is organized as follows: In Section 2.2 provides a description of the institutional background and data used in this research. The methodology employed and the results obtained are presented in Section 2.3. The findings and implications are discussed in Section 2.4, where I conclude the paper.

2.2 Institutional Background and Data

2.2.1 BIST Stock Market

Borsa Istanbul Group (BIST) was established in 1873 and now consists of four main markets: the Stock Market, Debt Securities Market, Derivatives Market, and Precious Metals and Diamond

Markets. The Stock Market facilitates the trading of various financial instruments, including shares, pre-emptive rights, exchange-traded funds, intermediary institutions' warrants and certificates, lease certificates, real estate investment funds, real estate certificates, and venture capital investment funds. With a total traded value of 2.130 trillion Turkish Lira (TL), the BIST stock market ranks 21st globally, with a daily average traded value of 8.5 billion TL. The share turnover velocity in the BIST stock market is the 3rd highest in the world, standing at an impressive 227%. According to statistics from the World Federation Exchanges, the stock market boasts 402 listed companies, with foreign shares accounting for 61% of the free float market capitalization in 2019.

The stock market operates under a "price-time priority" matching algorithm, which prioritizes orders with more favorable prices over those with less favorable prices. In the case of orders with the same prices, they are executed based on the sequence in which they were received by the matching engine.

This paper focuses on Garanti BBVA (GARAN.E), a prominent banking sector stock traded in the BIST Stars Market under the benchmark index BIST30. It is worth noting that there are no formal liquidity providers for BIST30 stocks. Garanti BBVA initially went public in 1990 on the Borsa Istanbul, becoming the first Turkish company to offer its shares on international markets in 1993. Additionally, Garanti BBVA's Depository Receipts are listed on the Over-The-Counter (OTC) Markets in the USA. In 2012, Garanti BBVA joined the prestigious tier of the U.S. Over-The-Counter (OTC) market, specifically the OTCQX International Premier, where participating companies must meet stringent financial standards and adhere to an effective disclosure process. Trading among 56 leading global companies, Garanti BBVA established itself as one of the top Depository Receipts traded on the OTCQX marketplace, ranking 30th in terms of Market Capitalization, 20th in terms of Dollar Volume, and 41st in terms of Volume in 2019.

As of the end of 2019, Garanti BBVA had a market capitalization of TL 46.8 billion (USD 7.9 billion) and a free float ratio of 50.07%, amounting to TL 23.4 billion in floating market capitalization. Notably, Garanti BBVA possesses the highest free float in the BIST 100 index. Among all banking stocks traded on the Borsa Istanbul, Garanti BBVA's shares (GARAN) have the highest average daily turnover of TL 881 million (USD 156 million) and account for an 11% market share in BIST 100 turnover. In 2019, GARAN was the most traded stock by foreign investors, with a total foreign transactions turnover of USD 29 billion. Moreover, as of the end of 2019, GARAN held the highest weightage in both the BIST 100 and BIST 30 indices. Impressively, 89% of Garanti BBVA's shares in the free float are owned by foreign investors, hailing from approximately 33 countries.

2.2.2 Data

The exchange data set consists of intraday trade-level data for the GARAN.E stock, which is in the benchmark index of BIST30 stocks for the year of 2019. The data set is directly taken from the Exchange's database. From the trade-level data, I examine all regular transactions occurring during the 420-minute period where continuous trading occurs between 10:00-13:00 and 14:00-18:00 for the whole year. For each transaction, I use fields from trade book data with account IDs for the buyer and the seller, the price and quantity transacted, the date and time (to the nearest minute), a matching ID number that sorts trades into chronological order within one minute. Account IDs are the IDs of the trading accounts that can possibly used by a single or multiple trader, by the financial intermediary for their portfolio management purposes, or by mutual funds.

To measure the effect of the news of the stock on the trading behaviour of the small traders, news data is collected from *Bloomberg News*. Any news including GARAN.E stock is searched, and a data matrix is created for daily, hourly and intraday frequencies. The news variable is binary and takes a value of 0 or 1. It takes 1 if there is any news for the stock at that specific time interval and 0 otherwise. News that appeared outside of the trading hours are counted for the following trading day.

2.2.3 Trader Categories

The concept of a "retail" investor is generally understood as an individual, trading in a personal account for his or her own benefit. However, it is hard to identify them correctly if the Exchange does not label them directly. Exchanges can identify retail orders in different ways since, in general, retail investors do not have direct access to the exchange, but can only access through an intermediary (a broker), the identification can happen in different ways. The exchange can identify individual investors. In some cases, exchanges can identify a retail investor directly, as when opening an account, an investor is required to provide personal information (ID number and tax report) which is available to the exchange directly or through the broker. Alternatively, the exchange identifies retail orders through the broker. In many cases, brokers label and register some of their clients as "retail". However, there is often no mandate for them to share the investment profile of their clients with the exchanges. The order submitted by the exchange member to the trading platform bears only a trading code, which can correspond to "retail", but the profile of the investor behind the trading code is only known to the member. In other cases, the identification may happen at a later stage of the trade life cycle, when the investor is required to identify himself to operate with an individual account at the Central Securities Depository. Finally, they can be identified through their observed trading patterns. Some exchanges rely on individual trade characteristics (e.g. trade quantity, trade value, and originating broker) to identify these trades as retail. In my data set, retail trades are not labelled directly and I rely on the observed trading pattern of the traders over a longer period.

Recent empirical studies have utilized data sets that provide labels for small traders or retail traders sourced from large discount brokerage firms or full-service brokers. Prior to the availability of these data sets, researches such as Lee (1992); Hvidkjaer (2008) and Barber et al. (2009) inferred the trading behavior of individual investors in the US using signed small trades from the TAQ database. However, the accuracy of this signing algorithm can be misleading for several reasons. One factor is the increasing prevalence of algorithmic and other trading practices, resulting in small trades being executed by institutional or high-frequency traders, making it difficult to determine their origin and reducing the reliability of this measure. O'Hara et al. (2012) further support these suspicions by using small trades as a proxy for the behavior of individual investors post-2001. In my research, I examine the entire universe of traders and classify them as small or big traders based on their observed overall trading pattern over a longer period for the benchmark index. To determine the category of each trader, I calculate their volume-to-market-volume ratio on a daily basis in the BIST30. Traders with a ratio below a predetermined cutoff of 0.1% are labeled as small traders, while those above are classified as big traders. By averaging the daily categorizations throughout the year, I establish the average trade category for each trader. The data appendix provides evidence of the stability of my categorization method across multiple trading days for each stock. Specifically, for the stock of interest, traders who are consistently classified as small on average remain in the small trader category for approximately 92% of their active trading days. It is important to note that this research specifically focuses on small traders.

Table 2.1: **Descriptive Statistics for the Big vs Small Traders**

This table provides descriptive statistics for the trader categories in the BIST30 stocks universe for the year 2019. The first column displays the average trader categories, including big traders and small traders. The second column shows their respective shares within the BIST30 stocks universe during the same period. In the third column, the number of unique trading accounts ever observed in the data set is presented. Fourth column shows the number of active accounts per day for each category. Lastly, the last column displays the number of active trading days for each account within the BIST30 universe.

Trader Category	Share in trade volume	Number of trading accounts	Number of active accounts per day	Number of active days per account
Big traders	83 %	25 121	4084	40
Small traders	17 %	616 359	59 818	24

Table 2.1 shows the average daily statistics for trader groups to see the general picture of the market for the whole stocks under the benchmark index. 17 % percent of the whole trade volume comes from small traders. There is unique 25,000 accounts for big traders whereas more than 600,000 accounts for small traders. Per day on average, approximately 60,000 accounts are counted as small traders whereas it is 4,000 accounts for big traders. The number of active days per account is 24 trading days for small traders whereas a bit higher for big traders which is 40.

Given the extensive data set comprising over 600,000 small trader accounts, the focus of this analysis is specifically on the GARAN.E stock, which is one of the stocks outside the index. The sheer size of the data matrix and the resulting computational challenges presented notable limitations for conducting regressions and interpreting the outcomes effectively. Table 2.2 shows the statistics for GARAN.E stock. For this stock, I selected the small traders subset based on the criteria explained in the trader categories section. I determine the median number of actively trading days for this subset, which is 14 trading days. Using this information, I divided the small traders into two groups: more active and less active. Table 2.2 presents the descriptive statistics for these two subsets of small traders for GARAN.E stock. It can be observed that the more active small traders have an average of 61 active trading days and a higher number of unique trading accounts, close to 9,000. Their average total position is three times larger than that of the less active subset, and they contribute approximately 70% of the total volume coming from active small traders. Approximately 12% of the total trading volume is contributed by the subset of highly active small traders, which is the primary focus of this paper.

Table 2.2: **Descriptive Statistics for the Small Traders**

This table presents descriptive statistics for the small traders in the GARAN.E stock for the year 2019. The first column categorizes the small traders into two groups: more active and less active. Activeness is determined based on whether the traders have a higher number of active trading days than the median (14 days) of the small traders' set in the BIST30 index traders universe. The second column provides the number of active trading days for each category. The third column indicates the unique number of accounts in each subset. The fourth column shows the total number of unique trading accounts observed in the data set. The fifth column displays the number of active accounts per day for each category. Finally, the last column shows the average number of active days for each account in the BIST30 universe.

Trader category	Number of active trading days	Number of accounts	Total volume	Share in total volume
More Active Small Traders	61	8852	16 987	71 %
Less Active Small Traders	7	84 086	6947	29 %

2.3 Methodology

This section introduces the methodology and regression results for daily and intraday (hourly and 15 minutes) frequencies. The empirical methodology aims to examine the relationship between the buying and selling patterns of small traders and market returns across different frequencies, ranging from daily to intraday. In the buy regressions, the left-hand side variable is binary, taking a value of 1 if the trader buys in a specific time interval and 0 otherwise. Similarly, in the sell regressions, the left-hand side variable is binary, indicating whether the trader sells in that specific time interval. The right hand side variables in the regressions include the trader's previous trading behavior, such as whether they bought or sold in the previous time interval, in order to understand their trading pattern. Additionally, other variables incorporated are the foreign share in the total volume for that specific time interval, the logarithm of the stock's contemporaneous and lag market volume, and price changes that reflect the market return. The market return is calculated as the ratio of the average price of the transactions compared to the previous average price of the transactions, minus one. The reason I use the average price instead of the last transaction price in the corresponding time interval is to avoid the extreme transaction prices. The unit of observation is a single trading account for each type of time frequency for the GARAN.E stock. The research design adopts a linear probability model with robust standard errors. Equation 2.1 presents the buy regression for analyzing buying patterns, while Equation 2.2 presents the sell regression for studying selling patterns

$$B_{i,t} = \alpha_1 B_{i,t-1} + \alpha_2 S_{i,t-1} + \theta F_t + \gamma_0 V_t + \gamma_1 V_{t-1} + \gamma_2 V_{t-2} + \sum_{k=0}^{s} \beta_k R_{t-k} + \epsilon_t \tag{2.1}$$

$$S_{i,t} = \alpha_1 B_{i,t-1} + \alpha_2 S_{i,t-1} + \theta F_t + \gamma_0 V_t + \gamma_1 V_{t-1} + \gamma_2 V_{t-2} + \sum_{k=0}^{s} \beta_k R_{t-k} + \epsilon_t \tag{2.2}$$

where $B_{i,t}$ and $S_{i,t}$ are the binary outcome variable and denotes whether the small trader bought or sold in that specific time interval and R_t stands for the daily contemporaneous and lagged market returns of the stock which are simply the price changes. In Equation 2.1 and 2.2, parameters of interest are α_1 and α_2 show the previous trading pattern of the small trader how their lag buy and sell behaviour changes, γ shows the reaction to the share of foreign traders in the market volume and β_k shows the reaction to the contemporaneous and lagged market returns. Table 2.3 shows the descriptive statistics for the daily and intraday observations of buy, sell and market return variables.

Table 2.3: **Descriptive Statistics for the Regression Variables**

This table presents descriptive statistics for the regression's left hand side variable of buy and sell and right hand side variable of market return for the daily, hourly and 15 minutes frequencies. Unit of observation is trader level.

Variables	# of observation	Mean	St. Dev.	Min	Pctl.25	Pctl.75	Max
Daily buy		0.138	0.345	0	0	0	1
Daily sell		0.130	0.337	0	0	0	1
Daily return		0.02	0.025	−0.1	−0.012	0.015	0.201
Hourly buy		0.033	0.178	0	0	0	1
Hourly sell		0.029	0.169	0	0	0	1
Hourly return		0	0.007	−0.031	−0.003	0.004	0.234
15 mins buy		0.011	0.106	0	0	0	1
15 mins sell		0.01	0.099	0	0	0	1
15 mins return		0	0.003	−0.024	−0.01	0.01	0.017

There are 8,852 trading accounts classified as more active small traders in the GARAN.E stock. At the daily level, there are 248 trading days, resulting in approximately 1.7 million observations. Considering seven hours of continuous trading in a day, the hourly level yields around 12 million observations. Furthermore, with 28 fifteen-minute intervals in a day, there are approximately 49 million observations at the fifteen-minute level. The unconditional mean for buying is 0.138 at the daily level and 0.130 for selling. At the hourly level, the unconditional mean for buying is 0.033, and for selling, it is 0.029. Lastly, at the fifteen-minute level, the unconditional mean is 0.011 for buying and 0.010 for selling. The standard deviation is higher for buying compared to selling.

2.3.1 Daily Approach

In this section, the time frequency of the variables used in Equation 2.1 and 2.2 is daily. Table 2.4 presents the regression results for both buying and selling behavior at the daily level. The regression utilizes over 1.7 million observations and employs a linear probability model with robust standard errors. As explained in the methodology section, the left-hand side variable is binary, indicating whether the small trader buys or sells on a specific day. The 'Daily Buy' column of the table shows the regression results for buying, while the 'Daily Sell' column shows the regression results for selling.

The results for the daily buy regression indicate that traders are 0.24640 points more likely to buy if they bought the previous day, and 0.17812 more likely to sell if they bought the previous day. The magnitudes of the coefficients suggest that contemporaneous buying is more likely if the trader bought the previous day compared to when they sold. The coefficient for foreign share in volume appears to be negatively related to traders' buying behavior, while the contemporaneous log of stock volume shows a positive relationship. The contemporaneous market return and its lag returns are negatively related to buying decisions and the coefficient of β_1 is -1.30201 and statistically significant. A one standard deviation decrease in contemporaneous return leads to an increase of approximately 1.3 percentage points in the buying decision, representing around 52% of the sample deviation of the small trader's daily return. The market return coefficients exhibit a negative decay from -1.30201 to -0.20992 which suggests that they trade with a delay.

In Table 2.4, the daily sell column shows the regression results for selling as the left-hand side variable. The coefficients for lag buy and sell variables suggest that traders are 0.28594 points more likely to buy if they bought the previous day, and 0.16733 more likely to sell if they bought the previous day. Similarly, the magnitudes of the coefficients indicate that contemporaneous selling is more likely if the trader bought the previous day compared to when they sold. The coefficient for foreign share in volume appears to be negatively related to traders' selling behavior, while the contemporaneous log of volume shows a positive relationship. The contemporaneous market return and its lag returns are positively related to selling decisions, β_1 is 0.97211 and statistically significant. A one standard deviation increase in contemporaneous return leads to an increase of about 1 percentage point in the selling decision, representing approximately 38% of the sample deviation of the small trader's daily return. The market return coefficients exhibit a positive decay from 0.97211 to 0.05683 which again confirms that they trade with a delay.

In summary, Table 2.4 reveals that active small traders exhibit daily reversals at the daily level, as they are more likely to buy or sell if they sold or bought the previous day. Furthermore, it seems that daily buy pattern is more like momentum trading compared to sell patterns as the lag buying coefficient is larger that on past selling. This finding aligns with the notion of inventory risk as a contributing factor to daily reversals in the market, as supported by Hvidkjaer (2008); Barber et al. (2008); Kaniel et al. (2007) and Kelley and Tetlock (2013). Additionally, at the daily level from the signs of price changes, active small traders appear to act as price stabilizers. They are buying when prices fall and selling when they rise, in line with the findings of Barber et al. (2008), Kaniel et al. (2007) and Kelley and Tetlock (2013).

Table 2.4: **Daily Regression Results for Buy and Sell Behaviour**

This table presents the estimated coefficients for the regression shown in Equations 2.1 and 2.2. In Equation 2.1, the dependent variable is the buy variable, which is binary and takes the value of 1 if the trader buys on that specific day, and 0 otherwise. This regression is represented in the 'Daily Buy' results for the active small trader. In Equation 2.2, the dependent variable is the sell variable, which is binary and takes the value of 1 if the trader sells on that specific day, and 0 otherwise. This regression is represented in the 'Daily Sell' results for the active small trader. The regression includes several control variables, such as lag buy and sell behavior, foreign share in market volume, contemporaneous and lagged market returns. A linear probability model with robust standard errors is used to estimate the coefficients.

	Daily Buy	Daily Sell
Constant	-0.58664 ***	-0.46320 ***
	(0.00754)	(0.00744)
Lag buy	0.24640 ***	0.28594 ***
	(0.00119)	(0.00120)
Lag sell	0.17812 ***	0.16733 ***
	(0.00119)	(0.00119)
Foreign share in volume	-0.14082 ***	-0.04718 ***
	(0.00837)	(0.00786)
Log of Stock Volume, t	0.05700 ***	0.06742 ***
	(0.00064)	(0.00059)
Log of Stock Volume, t-1	-0.02350 ***	-0.04431 ***
	(0.00081)	(0.00077)
Log of Stock Volume, t-2	0.00278 ***	0.00515 ***
	(0.00066)	(0.00061)
Price change, t	-1.30201 ***	0.97211 ***
	(0.01114)	(0.01078)
Price change, t-1	-0.11654 ***	0.28214 ***
	(0.01100)	(0.01039)
Price change, t-2	-0.20992 ***	0.05683 ***
	(0.01057)	(0.00988)
N	1701645	1701645
R2	0.15533	0.17817
Adj.R2	0.15533	0.17817

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

2.3.2 Intraday Approach

In this section, the time frequency of the variables used in Equations 2.1 and 2.2 is examined at the hourly and 15 minutes intervals to analyze the intraday patterns. Table 2.5 presents the regression results for the buy and sell behavior at the hourly level in the first two columns, and at the 15 minutes level in the third and fourth columns. The hourly regression utilizes over 12 million observations, while the 15-minute regression utilizes over 40 million observations. Both regressions employ a linear probability model with robust standard errors.

In the results for the hourly buy behavior, the left-hand side variable indicates whether the small trader buys or not in a specific hour. The coefficients for the lag buy and sell variables suggest that they are 0.22184 points more likely to buy if they bought in the previous trading hour, and 0.14911 more likely to sell if they bought in the previous trading hour. The magnitudes of the coefficients indicate that their contemporaneous buying is more likely if they bought in the previous hour compared to when they sold. The coefficient for foreign share in volume shows a positive relationship with small traders' buying behavior, and the contemporaneous log of volume is also positively related to buy behavior. As expected, contemporaneous market return and its lag returns are negatively related to their buy decisions. β_1 is -1.26014 and statistically significant. A one standard deviation decrease in contemporaneous return leads to an increase of about 1.26 percentage points in the buying decision, representing approximately 55% of the sample deviation of the small trader's daily return. This means that their contrarian trading is economically important. Market return coefficients decay from the high of -1.26014 to -0.18637.

The second column presents the results for the hourly sell pattern. The left hand side variable indicates whether the small trader sells or not in a specific hour. The coefficients for the lag buy and sell variables suggest that they are 0.19437 points more likely to buy if they bought in the previous hour, and 0.18336 more likely to sell if they bought in the previous hour. The magnitudes of the coefficients indicate that their contemporaneous selling is equally likely if they bought in the previous hour compared to when they sold. The coefficient for foreign share in volume shows a positive relationship with both the buy and sell behaviors of traders. The contemporaneous log of volume is positively related to buy behavior, and contemporaneous market return and its lag returns are positively related to their sell decisions and β_1 is 1.22995, statistically significant. A one standard deviation increase in contemporaneous return leads to an increase of about 1.22 percentage points in the selling decision, representing approximately 56% of the sample deviation of the small trader's daily return. Market return coefficients decay from the high of 1.22995 to 0.19808. These strong lags may result in delayed contrarian strategy. In sum, the hourly buy and sell results indicate that active small traders tend to maintain momentum at the hourly level, continuing their previous patterns.

In the third column, the results for the 15 minutes buy pattern are shown. The left hand side variable indicates whether the small trader buys or not in a specific 15 minutes. For this regression, over 41 million observations are used in a linear probability model with robust standard errors. The coefficients for the lag buy and sell variables suggest that they are 0.23554 points more likely to buy if they bought in the previous 15 minutes, and 0.12902 more likely to sell if they bought in the previous 15 minutes. The magnitudes of the coefficients indicate that their contemporaneous buying is more likely if they bought in the previous 15 minutes compared to when they sold. The coefficient for foreign share in volume shows a positive relationship with small traders' buying behavior, and the contemporaneous log of volume is also positively related to buy behavior. As expected, contemporaneous market return and its lag returns are negatively related to their buy decisions, and β_1 is -1.60489, statistically significant. A one standard deviation decrease in contemporaneous return leads to an increase of about 1.60 percentage points in the buying decision, representing approximately 18% of the sample deviation of the small traders' 15 minutes return. Market return coefficients decay from the high of -1.60489 to -0.23731.

In the fourth column, the results for the 15 minutes sell pattern are shown. The left-hand side variable indicates whether the small trader sells or not in a specific 15 minutes. The coefficients for the lag buy and sell variables suggest that they are 0.14343 points more likely to buy if they bought in the previous hour, and 0.20844 more likely to sell if they bought in the previous hour. The magnitudes of the coefficients indicate that their contemporaneous selling is more likely if they sold in the previous 15 minutes compared to when they bought. The coefficient for foreign share in volume shows a positive relationship with both the buy and sell behaviors of traders. The contemporaneous log of volume is positively related to buy behavior, and contemporaneous market return and its lag returns are positively related to their sell decisions, β_1 is 1.19592 and statistically significant. A one standard deviation increase in contemporaneous return leads to an increase of about 1.19 percentage points in the selling decision, representing approximately 25% of the sample deviation of the small trader's 15 minutes return. Market return coefficients decay from the high of -1.19592 to 0.13965. The 15-minute buy and sell results indicate that active small traders seem to maintain momentum at the 15 minutes level, meaning they continue their previous patterns.

From the intraday results, more active small traders are likely to be active if they were active at previous period. Based on this finding, it appears that small traders who were active in the previous period are more likely to remain active in subsequent periods. This observation raises an interesting question regarding the factors that drive their market participation. While the median number of active trading days for the subset of small traders is relatively low at 14 days, this persistence in intraday momentum suggests a potential link to their decision to enter the market. Once these traders decide to engage in trading on a particular day, they tend to sustain their momentum trading.

The intraday analysis reaffirms the role of small traders as price stabilizers, as they consistently exhibit buying behavior during price declines and selling behavior during price increases, both at hourly and 15 minutes intervals. This finding further supports the conclusions of previous studies by Barber et al. (2008), Kaniel et al. (2007) and Kelley and Tetlock (2013), which demonstrate that the daily patterns observed also hold true at intraday frequencies.

Regarding trading patterns, there appears to be an asymmetry between buying and selling decisions, with buying being easier than selling. Barber et al. (2008) initially suggested that buying and selling decisions in formal models are similar, differing only by a minus sign. However, recent empirical evidence, including the work of Barber and Odean (2013) and Akepanidtaworn et al. (2021), suggests that buying and selling decisions involve distinct psychological processes. Notably, institutional investors demonstrate skill in buying but consistently underperform in selling, even when compared to random strategies. Adding to this body of research, my contribution demonstrates that small traders exhibit a greater inclination to buy than to sell, both at a daily and intraday level.

Table 2.5: **Intraday Regression for Buy and Sell Behaviour**

This table presents the estimated coefficients for the regression shown in Equations 2.1 and 2.2. In Equation 2.1, the dependent variable is the buy variable, which is binary and takes the value 1 if there was a buy activity by the active small trader during the specific hour and 15 minutes, otherwise 0. Equation 2.2 focuses on the sell variable, which is binary and takes the value 1 if there was a sell activity by the active small trader during the specific hour and 15 minutes, otherwise 0. The regression models include controls such as lagged buy and sell behavior, foreign share in market volume, contemporaneous and lagged market returns. The analysis employs a linear probability model with robust standard errors.

	Hourly Buy	Hourly Sell	15 minutes Buy	15 minutes Sell
Constant	-0.14831 ***	-0.12266 ***	-0.04453 ***	-0.03848 ***
	(0.00094)	(0.00088)	(0.00024)	(0.00022)
Lag buy	0.22184 ***	0.19437 ***	0.23554 ***	0.14343 ***
	(0.00070)	(0.00067)	(0.00067)	(0.00056)
Lag sell	0.14911 ***	0.18336 ***	0.12902 ***	0.20844 ***
	(0.00068)	(0.00071)	(0.00060)	(0.00069)
Foreign share in volume, t	-0.01618 ***	-0.01426 ***	-0.00435 ***	-0.00249 ***
	(0.00087)	(0.00080)	(0.00019)	(0.00017)
Log of Volume, t	0.01956 ***	0.01809 ***	0.00593 ***	0.00572 ***
	(0.00007)	(0.00007)	(0.00002)	(0.00002)
Log of Volume, t-1	-0.00862 ***	-0.00874 ***	-0.00221 ***	-0.00234 ***
	(0.00008)	(0.00007)	(0.00002)	(0.00002)
Price change, t	-1.26014 ***	1.22995 ***	-1.60489 ***	1.19592 ***
	(0.00935)	(0.00911)	(0.00844)	(0.00734)
Price change, t-1	-0.35253 ***	0.21760 ***	-0.15003 ***	0.22327 ***
	(0.00773)	(0.00711)	(0.00722)	(0.00631)
Price change, t-2	-0.21647 ***	0.20748 ***	-0.32989 ***	0.23587 ***
	(0.00708)	(0.00658)	(0.00698)	(0.00621)
Price change, t-3	-0.18637 ***	0.19808 ***	-0.23731 ***	0.13965 ***
	(0.00723)	(0.00688)	(0.00684)	(0.00610)
N	12546030	12546030	40755857	40755857
R2	0.09919	0.10881	0.08604	0.08504
Adj.R2	0.09919	0.10881	0.08604	0.08504

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

2.3.3 The Effect of News on the Trading Patterns of Small Traders

In this section, I examine the impact of stock-related news on the trading behavior of active small traders, both on a daily and intraday (15 minutes) basis. My contention is that news holds significant influence over the attention of small traders, thereby affecting their trading patterns. According to Barber and Odean (2008), individual investors tend to focus on stocks that capture their initial attention, particularly those featured in the news or experiencing notable price movements. Moreover, empirical evidence suggests that real investors are influenced by media coverage, exhibiting a tendency to buy stocks that are currently in the news rather than selling them (Barber and Odean, 2013).

To delve deeper into this phenomenon, I incorporate news data into my analysis to observe its impact on traders' trading patterns. The stock-related news data is sourced from Bloomberg News, with a specific focus on any news related to the GARAN.E stock. This process results in the creation of a binary variable (0 or 1), indicating the presence or absence of news during specific time intervals. It is important to note that the content of the news is not taken into consideration. Throughout the year 2019, there were 46 trading days with GARAN.E-related news.

Empirically, I examine the relationship between the buying and selling patterns of small traders and the stock-related news. For the buy regressions, the dependent variable is binary, taking a value of 1 if the trader buys in a specific time interval and 0 otherwise. Similarly, for the sell regressions, the dependent variable is binary, taking a value of 1 if the trader sells and 0 otherwise. The independent variables in both regressions include contemporaneous and lagged news variables. Equation 2.3 represents the buy regression for the buying pattern, while Equation 2.4 represents the sell regression for the selling pattern. The unit of observation is a single trading account's buy or sell decision for each time frequency type concerning the GARAN.E stock. The research design employs a linear probability model with robust standard errors to account for uncertainties.

$$B_{i,t} = \alpha + \sum_{k=0}^{s} \beta_k News_{t-k} + \epsilon_t \tag{2.3}$$

$$S_{i,t} = \alpha + \sum_{k=0}^{s} \beta_k News_{t-k} + \epsilon_t \tag{2.4}$$

where $B_{i,t}$ and $S_{i,t}$ is the outcome variable and denotes whether the small trader bought or sold in that specific time interval and $News_{t-k}$ stands for the contemporaneous and lagged news. Previous control variables such as the market share of foreign traders in the market volume, log of the market volume and market returns are not used since they are highly correlated with the news variable.

Table 2.6 presents the regression results for the buying and selling behavior on a daily level. In the daily buy results, the left-hand side variable takes a value of 0 or 1, indicating whether the small trader buys or not on that specific day. The coefficients of the lag buy and sell variables indicate that small traders are 0.03119 points more likely to buy when there is contemporaneous news, with the estimated coefficients gradually decreasing from 0.03119 for contemporaneous news to 0.01121 for news four days prior. Contrast to the unconditional probability of daily buy 0.138 shown in Table 2.3, 0.03119 points is quite large. As for the daily sell results, the left-hand side variable also takes a value of 0 or 1, representing whether the small trader sells or not on that specific day. From the coefficient of contemporaneous news, it can be observed that the selling behavior does not react immediately as it does in the case of daily buying. This finding aligns with the conclusions of Barber and Odean (2008) and Barber and Odean (2013), suggesting an asymmetry between the selling and buying behavior of individual investors. This asymmetry implies that investors face different constraints and challenges when searching for buying and selling opportunities. While they may have limitations when selling due to short selling constraints, they appear to react positively with a lag.

Table 2.7 displays the regression results for the buy and sell behavior on a 15 minutes level. For the intraday buy results, the coefficients of contemporaneous news indicate that small traders are 0.00923 points more likely to buy when there is contemporaneous news. Similar to the daily results, the estimated coefficients gradually decline from 0.00923 for contemporaneous news to 0.00063 for news, seven 15 minutes prior. For the intraday sell results, the coefficients of contemporaneous news suggest that small traders are 0.00795 points more likely to sell when there is contemporaneous news. Contrast to the unconditional mean of 15 minutes selling 0.010 shown in Table 2.3, contemporaneous reaction is quite large. The estimated coefficients also decay positively, ranging from 0.00795 for contemporaneous news to 0.00302 for news three 15 minutes prior. It seems that there are lots of delays in selling to the news, 15 minutes to 30 minutes lags are roughly the same as the contemporaneous news coefficient.

To summarize, both Table 2.6 and 2.7 demonstrate that active small traders' buying behavior responds positively to stock-related news at both daily and intraday levels. However, their contemporaneous selling reaction appears to be limited and shows a lag. This finding confirms the existing literature, indicating an asymmetry between the selling and buying behavior of individual investors. The magnitudes of the contemporaneous reactions in buying to stock-related news are higher compared to selling at both frequency levels. These results contribute to the literature by extending the asymmetry findings to the intraday level, suggesting that this trading pattern persists throughout different time frames.

Table 2.6: **Daily Regression Results for Buy and Sell Behaviour**

This table presents estimated coefficients for the regression shown in Equation 2.3 and 2.4. The dependent variable in the daily buy model is the daily buy variable, which is binary and takes a value of 1 if the small trader buys on that specific day, and 0 otherwise. Similarly, in the daily sell model, the dependent variable is the daily sell variable, which is binary and takes a value of 1 if the small trader sells on that specific day, and 0 otherwise. The controls in both models are the news variable and lagged news variable. The observations are recorded on a daily basis. A linear probability model with robust standard errors is used to analyze the data.

	Daily Buy	Daily Sell
Constant	0.12890 ***	0.12710 ***
	(0.00036)	(0.00036)
News, t	0.03119 ***	0.00064
	(0.00075)	(0.00069)
News, t-1	0.00181 **	0.00776 ***
	(0.00072)	(0.00070)
News, t-2	0.00342 ***	0.00179 **
	(0.00073)	(0.00070)
News, t-3	0.00526 ***	0.00622 ***
	(0.00072)	(0.00071)
News, t-4	0.01121 ***	-0.00223 ***
	(0.00071)	(0.00068)
News, t-5	0.00022	0.00672 ***
	(0.00070)	(0.00069)
N	1683943	1683943
R2	0.00154	0.00024
Adj.R2	0.00154	0.00024

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 2.7: **15 minutes Regression Results for Buy and Sell Behaviour**

This table presents estimated coefficients for the regression shown in Equation 2.3 and 2.4. In the intraday buy results, the dependent variable is the buy variable, which is binary and takes a value of 1 if the small trader buys in that specific 15 minutes interval, and 0 otherwise. Similarly, in the intraday sell results, the dependent variable is the sell variable, which is binary and takes a value of 1 if the small trader sells in that specific 15 minutes interval, and 0 otherwise. The controls in both models are the news variable and lagged news variable. The observations are recorded at 15 minutes interval. A linear probability model with robust standard errors is used to analyze the data

	Intraday Buy	Intraday Sell
Constant	0.01121 ***	0.00973 ***
	(0.00002)	(0.00001)
News, t	0.00923 ***	0.00795 ***
	(0.00023)	(0.00022)
News, t-1	0.00815 ***	0.00957 ***
	(0.00022)	(0.00022)
News, t-2	0.00330 ***	0.00480 ***
	(0.00020)	(0.00020)
News, t-3	0.00276 ***	0.00302 ***
	(0.00019)	(0.00018)
News, t-4	0.00133 ***	0.00006
	(0.00018)	(0.00016)
News, t-5	0.00114 ***	-0.00067 ***
	(0.00018)	(0.00016)
News, t-6	0.00254 ***	0.00087 ***
	(0.00019)	(0.00017)
News, t-7	0.00063 ***	0.00070 ***
	(0.00018)	(0.00017)
News, t-8	-0.00128 ***	0.00067 ***
	(0.00016)	(0.00017)
N	49319786	49319786
R2	0.00012	0.00014
Adj.R2	0.00012	0.00014

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

2.4 Conclusion

The active involvement of retail investors is crucial for the effective functioning and vitality of financial markets. Retail investors, along with institutional investors, contribute to establishing a diverse investor base, ensuring market robustness and liquidity. The participation of retail investors brings several benefits to the economy, including long-term returns, liquidity infusion, and capital allocation towards innovation and development. While retail investors may have less sophistication compared to institutional counterparts, they possess lower agency costs and liquidity constraints, enabling them to act as market makers, particularly during times of institutional liquidity constraints. Notably, retail investors have demonstrated their potential as stabilizing forces in the market, as seen during the 2008-2009 financial crisis and the COVID-19 pandemic. However, it is important to acknowledge the risks associated with retail investment, such as the potential for correlated trading activity and vulnerability to deceptive investment strategies. Financial literacy and investor protection play crucial roles in mitigating these risks.

The research primarily focuses on investigating the trading patterns of active small traders and their reactions to stock-related news. It involves analyzing individual-level buy and sell patterns at daily and intraday levels using a unique data set for the year 2019, specifically focusing on one of the BIST30 benchmark index stocks, GARAN.E. Since the term "retail" investor typically refers to individuals trading in personal accounts for their own benefit, it becomes challenging to accurately identify them without direct labeling from the Exchange. To address this, I label small traders based solely on directly observed trading patterns from the entire traders data set of the benchmark index. The primary emphasis is on the subset of active small traders. In the first part of the methodology section, I empirically examine the relationship between buying and selling patterns of small traders and market returns across various frequencies, ranging from daily to intraday. Then I focus on the reaction of the trading patterns of active small traders to the stock-related news.

The findings reveal that active small traders tend to stabilize prices by buying when prices fall and selling when prices rise. There is an asymmetry between buying and selling decisions, as buying tends to be more prevalent than selling. Additionally, active small traders demonstrate positive reactions to stock-related news, particularly in buying, indicating the influence of attention on their trading behavior.

In summary, this research contributes to the understanding of retail investors' role in financial markets by examining their trading patterns and reactions to news. The findings highlight the importance of considering the behavior of small traders and their impact on market dynamics.

3 Chapter 3: How do intraday intermediaries react to shocks?

3.1 Introduction

The periods of temporary high selling or buying pressures provides an opportunity to investigate the functioning of the markets, the role of different type of traders and even gain a better understanding of market crashes. Huang and Wang (2009) proposed theory suggesting that a period of large and temporary selling pressure can trigger a market crash even when there is no change in the fundamentals of the stocks. In these times, the role of the market intermediation becomes substantial. Intermediation is the essential function of any market where buyers and seller do not arrive simultaneously. Traders, known as intraday intermediaries[7], behave as an intermediaries to minimize frictions arising from the imperfect synchronization of the timing of buyers and sellers. As the markets become more automated, intermediation has been increasingly ensured by market participants without formal requirements. An important question is how these endogenously arisen intraday intermediaries behave during periods of large and temporary buying or selling pressure in automated financial markets.

This paper focuses on an episode of extreme illiquidity in the Turkish stock market on March 27, 2019. This episode started with a temporary government measure[8] which was taken by the government to stop local banks from facilitating deals on the swap market to prevent further depreciation in Turkish currency (TL) just before the local elections in March 2019. The Turkish lira overnight swap rate in London rose from their initial level of 24% to 1300% all-time-high on March 27, effectively making it impossible for foreign traders to short the lira after this measure. This TL shortage in the swap market indirectly affected Borsa Istanbul (BIST) stock market. Foreign traders in need of TL for speculative purposes or those who already had an open position wanted to get out of their TL position and started to sell their TL-denominated stocks in stock market, which caused temporary selling pressure, mostly by foreign traders who needed TL. This selling pressure and resulting imbalance is represented in Figure 3.1. This figure presents the liquidity imbalance that occured in BIST30 stocks with the origin of the account detail. I aggregate the buy and sell positions of each trading account by the trading day and origin, which means the trading account

[7] I use the term intraday intermediaries instead of market makers or liquidity providers because the former has become more associated with traders formally obligated to provide two sided quotes and receive rebates from Exchange fee in return, the latter may become confusing since I have a shorter time period in my data set to categorize daily liquidity providers.

[8] Details are given in Section 3.1.

has domestic or foreign intermediary origin, and I define imbalance ratio as the net buy position scaled by total volume. The average of this value across 30 stocks is plotted for each day with the corresponding account origin class. Each dots below zero in the x-axis shows the excess selling while the dots above show the excess buying. It can be seen that the gap between excess selling and buying was the highest on March 27 and the selling pressure came from the foreign accounts.

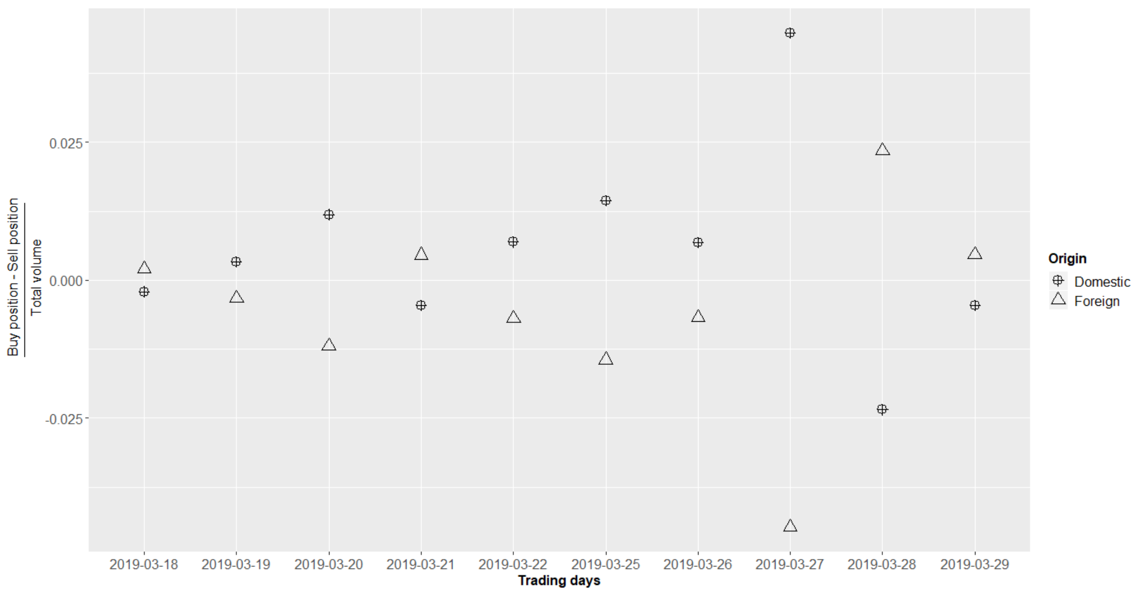

Figure 3.1: **Liquidity Imbalance Graph for BIST30 Stocks.**

This figure presents the liquidity imbalance for BIST30 stocks with the account origin detail. For each of the stock, trading day and account in the sample, buy and sell positions are calculated. For each of the stock, total volume is calculated for everyday. Then, buy and sell positions are aggregated by account origin level and the imbalance ratio which is net buy position scaled by total volume is calculated for account level. The average of this value across stocks is plotted for each day with the corresponding account origin class. The dots below zero in the x-axis shows the excess selling whereas above ones shows the excess buying. In these graph, all of the trading accounts in the sample are included.

Figure 3.2 represents the intraday average net position change for BIST30 stocks for average of March 18 to March 26 versus March 27. It confirms that the selling on March 27 was much larger than previous trading days' averages and came from foreign-originated accounts. Around \$168 million valued BIST30 stocks sold by the foreigners which makes 0.1% of stock market value, and this selling pressure led to a fall of 5.86% in benchmark index BIST30, the second-highest fall seen after Coup d'etat attempt in 2016.

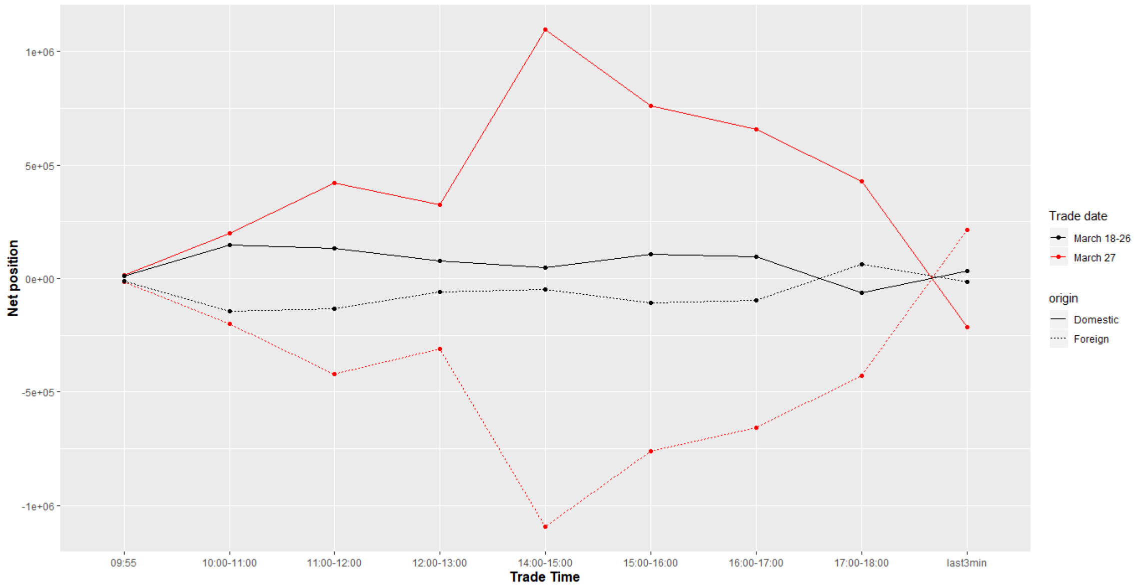

Figure 3.2: **Intraday Net Position Change**

This figure presents the intraday average net position for BIST30 stocks with the account origin and connection type detail. Dashed line is for the foreign accounts whereas solid line is for domestic accounts. Red line is calculated with March 27 data, black line stands for the average intraday net position change for the trading days before March 27.

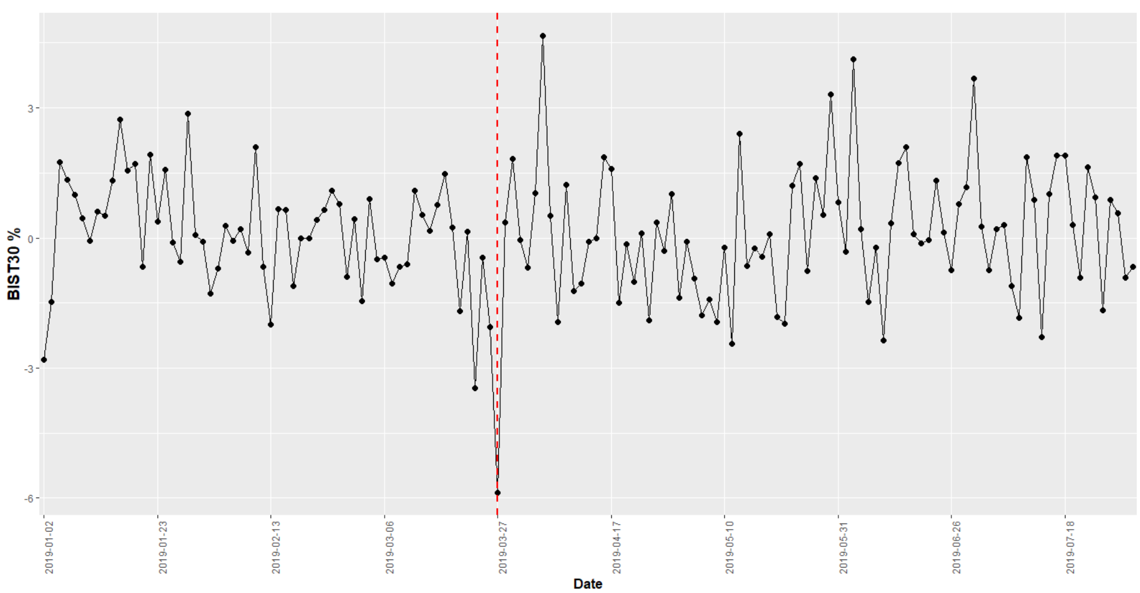

Figure 3.3: **BIST30 Daily Return**

This figure presents BIST30 daily return rates for the sample period from January to July 2019. See March 27 fall with the red dashed line.

Figure 3.3 presents BIST30 daily return rates from January to July 2019. The red dashed line shows the March 27 fall. All of the 30 stocks under the BIST30 index experienced different levels of fall on this specific day.

In this paper, I empirically analyze the role intraday intermediaries who provide intraday market intermediation in the market before and during a period of large and temporary selling pressure. I use account-level transaction data for the 30 stocks under the benchmark index BIST30 in the stock market over the period of March 18 to 29, 2019. There are no formal market maker obligations for BIST30 stocks, and high frequency traders[9] (HFTs) have no obligation to stabilize the prices in the market. In order to identify the trading accounts behaving as intraday intermediaries, I use data driven approach guided by the literature O'Hara (1995) and Hasbrouck and Sofianos (1993). I classify the trading accounts by looking at their observed trading patterns, whether they accumulate large directional positions or they continuously buy and sell during March 18 to 26 as intraday intermediaries. If an account is classified as an intraday intermediary over March 18-26, 2019, I keep it in the same category on March 27. Thus, this approach does not require that intraday intermediaries maintain low inventory on the liquidity shortage day. I further separate the intraday intermediaries into HFT and non-HFT subsets. I can directly observe each trading account's technical connection type to the exchange from the data set.

In order to examine the risk bearing capacity of intraday intraday intermediaries, I empirically study the minute-by-minute comovement of their inventory changes and price changes over March 18 to 27. I find that both aggressive and passive holdings of non-HFT intraday intermediaries exhibit a statistically significant relationship with contemporaneous and lagged price changes, and this relationship did not change when prices fell during the selling pressure. However, the statistical relationship between HFT intraday intermediaries' aggressive holdings and price changes did change during the selling pressure compared with the previous seven days, and they seem to reverse the direction of their trading significantly. This change may be due to a reduction in their liquidity removal (increase in liquidity provision) and a preference to trade less aggressively during the liquidity shortage.

The rest of the paper proceeds as follows. I discuss the literature review and how this paper

[9]Servers for these users are located at co-location. Total latency of their connections is less than 1 milliseconds. Trading accounts sending order from this connection type have to report themselves as high frequency trader and they have further responsibilities in using risk management tools and they are subject to order to trade fees for order updates and cancellation.

is positioned in the literature in section 3.2. I introduce the historical background, data and some descriptive statistics in Section 3.3. In Section 3.4, I present my trader categorization approach, methodology, and findings. In section 3.5, I conclude.

3.2 Literature Review

The provision of liquidity and the leading role of the intermediaries[10] are key topics in the market microstructure theory. Intermediation is an essential function in any market where buyers and sellers do not arrive simultaneously. As technological changes transform the way financial assets are traded, intermediation has increasingly been provided by market participants without formal obligations. The term "intraday intermediation" is used for the market participants who do not have duties of entailing designated market making or mandatory liquidity provision. Intraday intermediation can be provided by any of the market participants. In the following subsections, related theoretical and empirical papers studying intermediation are introduced, respectively.

3.2.1 Theory

Market crashes refer to large, sudden drops in asset prices in the absence of a change in fundamentals. There are several distinct features of crashes, such as being mostly one-sided, less likely to experience market surges, typically accompanied by large selling pressures in the market, and slow recovery in price (Huang and Wang, 2009). Even though there is no consensus on what constitutes a market crash, the lack of liquidity is generally considered as an essential symptom of such events. In case of abnormal trading pressure, only a limited supply of liquidity is available to accommodate the trades, and hence prices have to shift significantly (Shleifer and Summers, 1990 and Grossman and Miller, 1988). As seen in most market crashes, with a limited supply of liquidity in the market, these sudden surges of endogenous liquidity needs lead to large price drops when market presence is costly.

Huang and Wang (2009) develop an equilibrium model that captures two important aspects of the stock market liquidity: the need to trade and the cost of trading and their impact on asset prices. This model seeks to answer how the need for liquidity arises endogenously and how it behaves. The model suggests that even in the case of perfectly matched desires of the trading agents, costly market presence prevents them from synchronizing their trades and gives rise to endogenous order

[10] Here, the term refers intraday intermediaries and not the financial intermediation term.

imbalances and the need for liquidity. Since the provision of continuous market presence is costly, intraday intermediaries choose to maintain equilibrium risk exposures that are too low to offset large but temporary liquidity imbalances. In the event of a large enough sell order, the liquidity on the buy side can only be obtained after a price drop that is large enough to compensate increasingly reluctant intraday intermediaries for taking on additional risky inventory.

Weill (2007) presents optimal dynamic liquidity provision in a theoretical market setting with large and temporary selling pressure and order execution delays. The model suggests that intraday intermediaries provide liquidity by absorbing external selling pressures and buy when the pressure is large, accumulate inventories and sell when the pressure alleviates. As intraday intermediaries anticipate that the marginal utilities of some outside investors begin to increase and the selling pressure subsides, they find it optimal to dynamically accumulate a long position, during which time market prices rise. They then unwind their inventory just as market prices reach their initial level.

The main takeaway taken from the theoretical literature is that how the risk bearing capacity of intermediaries changes and how they adjust their inventories in times of stress such as selling pressure, extreme price movements, or volatile periods is important since their preferences may affect the equilibrium price realized in the market. If intermediaries' risk bearing capacity is overwhelmed, they may become unwilling to accumulate more inventory without large price concessions, and they may play a role in the extent of the price fall. From this point of view, this paper aims to provide empirical findings on the key role of intraday intermediaries.

3.2.2 Empirical Evidence

The focus of this study is the trading pattern of intraday intermediaries before and during a large selling pressure in the stock market with the focus of HFT and non-HFT intermediaries. In modern markets, high frequency traders (HFTs) play a pivotal role in providing liquidity (Hasbrouck and Saar, 2013, Menkveld, 2013, Malinova et al., 2018, Conrad et al., 2015). Nevertheless, liquidity provision by HFTs is endogenous as they are typically not obligated to stabilize markets in periods of stress. A growing literature finds that endogenous liquidity providers (ELPs) often withdraw from the market during such periods (Bongaerts and Van Achter, 2016; Cespa and Vives, 2013; Korajczyk and Murphy, 2019; Anand and Venkataraman, 2016).

Kirilenko et al. (2017) studied intraday market intermediation during the fully automated Emini S&P 500 Futures market before and during the Flash Crash, a period of large and temporary selling pressure. Their results are consistent with the theory of limited risk-bearing capacity in that intraday intermediaries did not take on large risky inventories relative to the crash, and the most active intraday intermediaries classified as HFTs did not significantly alter their inventory dynamics when faced with large liquidity imbalances. Contrast to this finding, I find that trading pattern changed especially for HFT intraday intermediaries during the selling pressure period on March 27. This changed pattern results from their aggressive holdings and suggest a reduction in their liquidity removal and preference to trade less aggressively during stress times. On the other hand, I show that non-HFT intraday intermediaries do no significantly change in their trading patterns during March 27. This finding is inline with the main findings of Brogaard et al. (2017) which suggests that on average, HFTs trade in the opposite direction of extreme price movements and supply liquidity to non-HFTs by absorbing their trade imbalances.

Second, I find that HFT intraday intermediaries buy if immediate prices are rising whereas non-HFT intraday intermediaries sell when immediate prices are rising. This finding is inline with the Kirilenko et al. (2017) and Hendershott and Menkveld (2014) which suggests that inventory changes of non-HFT intraday are negatively related to contemporaneous price changes, consistent with theories of traditional market making. In contrast to this pattern, inventory changes of High Frequency Traders are positively related to contemporaneous price changes. Foucault et al. (2011), Menkveld (2013), and Budish et al. (2015) provide theoretical mechanisms through which the inventories of intermediaries may positively co-move with price changes at high frequencies. These studies suggest that if certain traders can react marginally faster to a signal, they can adversely select stale quotes of marginally slower market makers, engaging in stale quote sniping or latency arbitrage. Consequently, faster traders are able to trade ahead of price changes at short time horizons. Inline with these, I show that HFT intraday intermediaries buy if immediate prices are rising.

Third, the pursuit of inventory management objective of intraday intermediaries may lead them to trade aggressively in the same direction as the prices are moving, thus taking liquidity. At other times, in order to achieve their target inventory levels, they may trade passively against the price movements and, thus, providing liquidity. With the help of the novelty of my detailed data set, I can follow for every single trading account and I have the opportunity to separate the transactions of each trader whether it is aggressive or passive and then, I show that aggressive holdings change confirms liquidity taking behaviour, whereas passive holdings change confirms liquidity providing behaviour[11].

3.3 Historical Background and Data

3.3.1 Historical Background of Liquidity Shock

In this section, I introduce the background of TL shortage in the swap market as mentioned in the introduction. Turkey experienced a long credit-led economic boom accompanied by strong domestic demand, mostly financed with capital inflows from abroad more than ten years. These inflows and ongoing political conjuncture led to a deterioration of the current account deficit, and sudden capital withdrawals, mainly aftermath of Coup d'etat attempt on July, 2016 resulted in a constant depreciation in TL against the US currency (USD). The loss of credibility for TL grew due to a rising doubt over the ability of the Central Bank of Turkey (CBRT) to conduct proper monetary policy under political pressure. This fragile nature of the currency made the economy vulnerable to speculative attacks, and had adverse effects on the asset quality of the major financial lenders and major Turkish corporations.

The government took a temporary government measure[12] to stop local banks from facilitating deals on swap market to prevent further depreciation in TL just before the local elections on March, 2019. The reason for this temporary measure was the news released on March 27th, claiming that foreign currency reserves[13] of CBRT had fallen by around $10 billion dollars in the sole month of March, suggesting that the remaining reserve was being used to prop up the TL in case of sharp depreciation, which mainly created further depreciation expectation in TL.

To understand the effect of this measure to the stock market, the mechanism of the London swap market should be clearly understood. The players of the London swap market are usually the local banks and foreign traders who want to short (sell) TL and long (buy) USD in expectation of further depreciation in TL for speculative purposes. Since foreign traders do not have TL, they first need to borrow TL in the market. Everyday at 5 pm, the market rolls over and investor is credited

[11] Aggressive transactions are incurred when traders submit marketable orders into the order book and immediately matched. This means that they trade aggressively in the same direction as the prices are moving, thus, taking liquidity from the market. Passive transactions are those incurred via the traders' resting orders' being executed by a marketable order. This means, they trade passively against price movements and, thus, provide liquidity.

[12] https://uk.reuters.com/article/uk-turkey-currency/turkey-to-shore-up-lira-via-tight-supply-through-elections-sources-idUKKCN1R81VF

[13] https://www.ft.com/content/9718e75e-611d-11e9-b285-3acd5d43599e

(or debited) based on the rollover rate[14] of the operation. The gain for the investor is up to the difference between interest rate of the foreign currency and domestic currency. In normal times, such interest rates are similar to overnight interbank rates, as national banks provide liquidity to the market.

However, Turkish lira overnight swap rate in London rose from their initial level of 24% to 1300% all-time-high on March 27, effectively making it impossible for foreign traders to short the lira after this measure was implemented. Figure 3.5 presents TRYUSD swap rates for the period between March 18 and March 29, 2019. The jump in the swap rate was due to the restriction on the amount of TL provided by the national banks, making it nearly impossible to find a counterparty willing to lend TL to short bets. Since banks were warned by the government to comply with this measure immediately.

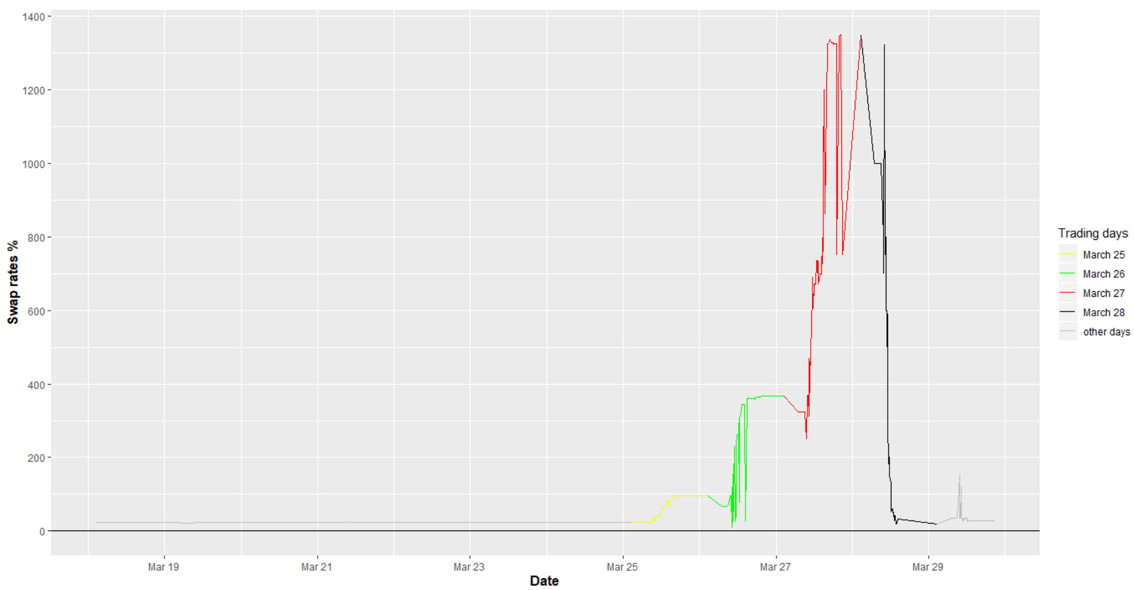

Figure 3.4: **TRYUSD Swap Rates**

This figure presents TRYUSD swap rates from March 18 to March 29, 2019. Interest rates on swaps rose from their initial level of 24% to 300% on March 26 and then to 1300% an all- time high on March 27. Rates of March 27 is shown in red. *Source: Bloomberg*

[14]Rollover Rate $= \frac{\text{Base Currency Interest Rate} - \text{Quote Currency Interest Rate}}{365 * \text{Exchange Rate}}$

3.3.2 BIST Stock Market

Borsa Istanbul Group (BIST) was established in 1985 and consists of four main markets: the Stock Market, Debt Securities Market, Derivatives Market, and Precious Metals and Diamond Markets. The Stock Market facilitates the trading of various financial instruments, including shares, pre-emptive rights, exchange-traded funds, intermediary institutions' warrants and certificates, lease certificates, real estate investment funds, real estate certificates, and venture capital investment funds. With a total traded value of 2.130 trillion Turkish Lira (TL), the BIST stock market ranks 21st globally, with a daily average traded value of 8.5 billion TL. The share turnover velocity in the BIST stock market is the 3rd highest in the world, standing at an impressive 227%. According to statistics from the World Federation Exchanges, the stock market boasts 402 listed companies, with foreign shares accounting for 61% of the free float market capitalization.

The stock market operates under a "price-time priority" matching algorithm, which prioritizes orders with more favorable prices over those with less favorable prices. In the case of orders with the same prices, they are executed based on the sequence in which they were received by the matching engine. It is worth noting that there are no formal intraday intermediaries for BIST30 stocks.

3.3.3 Data

The data set used in this study consists of intraday trade and order level data for benchmark index BIST30 stocks for the sample period spanning from March 18 to 29, 2019. The data is directly sourced from the Exchange's database. The trade level data includes all regular transactions occurring during the 420-minute continuous trading period between 10:00-13:00 and 14:00-18:00 for each of the ten days. For each transaction, fields from trade book data are used, including account IDs for the buyer and the seller, transacted price and quantity, date and time (to the nearest minute), a matching ID number to sort trades into chronological order within one minute, a field indicating whether the trade resulted from a limit or market order, an aggressiveness indicator stamped by the matching engine as "P" for a resting order and "A" for an order that executed against a resting order, and a field for user connection type indicating whether the user connection is high frequency [15] or not. Account IDs are the IDs refer to trading accounts that may be used by a single or multiple trader, by financial intermediaries for portfolio management purposes or by

[15] Total latency is less than 1 milliseconds.

mutual funds.

Order level data, which includes every messages in microseconds recorded in BIST30 stocks trading on the stock market, is used for descriptive purposes in this research. From the order level data, the field for account IDs for the buyer and the seller, transacted price and quantity, timestamps in microseconds, and user connection type of the account are used.

Interest rate data in the TRYUSD swap market at five-minute frequency is obtained from Bloomberg. This data provides information about changes in the cost of borrowing in the market and is used to investigate the mechanism of the liquidity shortage.

Trading accounts that submits order to BIST through foreign intermediaries that have no retail banking operation in Turkey are labeled as foreign. Access to these intermediaries is significantly limited for the average retail investor in Turkey as they charge the highest commissions (Borsa Istanbul, 2016) compared to domestic intermediaries. Local institutional investors, such as pension funds and mutual funds that operate in Turkey, typically prefer domestic intermediaries as most of them also have a brokerage license or have a sister company that has a brokerage license.

3.3.4 Descriptive Statistics

In this section, market level statistics for BIST30 index is presented in Table 3.1. I report the statistics for each trading day from March 18 to 29, 2019. First column presents the corresponding trading day. Second column presents the number of trading accounts actively traded on that specific day and it is the highest on March 27. Third column gives the total trade volume. Fourth columns shows the foreign share in total trade volume. It is around 11% on average whereas its the highest of 15.67% for March 27. BIST30 index changes are shown in the fifth column. Last column shows the average volatility for the corresponding trading days. I calculate volatility of each stock for every trading day by taking the standard deviation of the transaction prices, then I normalize the value by the average volatility of the each stock, then I took the average of 30 stock for every single trading day. Volatility is more than double on March 27 compared to the rest trading days.

Table 3.1: **Descriptive Statistics for BIST30 Stocks**

This table presents summary statistics of BIST30 stocks for March 18 to 29, 2019. The first column presents the trading days of the data set, second the number of actively trading accounts. The third column presents the statistics of the total number of contracts traded. Fourth column gives the share of foreign trading accounts trade volume in total. BIST30 index change is given in the fifth column. Last column stands for the average volatility which is calculated for each stock for every trading day by taking the standard deviation of the transaction prices, then normalized by the average volatility of the each stock, then averaged for 30 stocks for each trading day.

Trade date	Number of trading accounts	Trade volume	Foreign share in trade volume	BIST30 change	Average volatility
2019-03-18	47.472	2.0B	8.47%	1.47%	71.48%
2019-03-19	49.014	2.6B	9.22%	0.25%	79.81%
2019-03-20	44.973	3.0B	7.19%	−1.68 %	82.77%
2019-03-21	44.448	2.4B	10.85%	0.15%	80.67%
2019-03-22	52.514	2.8B	12.32%	−3.46 %	127.51 %
2019-03-25	45.987	2.6B	12.65%	−0.46 %	89.08%
2019-03-26	41.084	2.4B	12.23%	−2.05 %	91.72%
2019-03-27	57.226	3.3B	15.67%	−5.87 %	205.86 %
2019-03-28	49.385	3.4B	14.16%	0.35%	95.58%
2019-03-29	43.927	2.0B	12.20%	1.83%	75.52%

Descriptive statistics for the subset of intraday intermediaries are presented in Table 3.2. Features of the HFT and non-HFT subset of intraday intermediaries are given in the rows of the first column. Number of trading accounts labelled as intraday intermediaries is given in the first row. This is the number of unique accounts classified as intraday intermediaries. An account can be classified as an intraday intermeidary for multiple stocks. Average number of trades per minute given in the second row are computed by dividing the total number of transactions that a trader makes in a given time period by the total number of minutes in a trading day. Average number of trades per minute is indicative of the decision horizons and execution strategies for different intraday intermediary subsets. It is higher for HFT subsets, showing HFTs are more active in terms of transactions on tradebook. Average intertrade duration is the time in seconds until the next trade realized and its very shorter for the HFT subsets. Share of the trade volume done by intraday intermediaries are approximately 30% of the total market volume. Average order duration shows the time in seconds until the next order sent and its shorter for the HFTs. Average number of orders per minute is ten times higher for HFTs. Average share of limit order shows almost all orders are limit by HFTs whereas it is %98 for the non-HFTs. Average mean reversion coefficient is closer in both subsets whereas its a bit smaller for the HFT subset of intraday intermediaries.

Table 3.2: **Descriptive Statistics for Intraday Intermediaries**

This table presents summary statistics for HFT and non-HFT intraday intermediaries calculated for the period of March 18 to 29, 2019. The first row presents the connection type of the subsets, second shows the number of unique trading accounts. The third row presents the average number of trades per minute and per trading account. Fourth row gives the duration passed within trades in seconds. The share of average trade volume realized by each of the subsets is given in the fifth row. Sixth row shows the average order duration in seconds. Seventh row shows the average number of orders per minute. Eighth row shows their preference of order price type. Last row shows their average mean reversion coefficient.

	HFT	**non-HFT**
Number of trading accounts	66	725
Average number of trades per minute (per account)	11.03	1.96
Average intertrade duration (seconds)	198	1601
Average trade volume scaled by average daily volume	9.6%	19.3%
Average order duration (seconds)	347	702
Average number orders per minute (per account)	4.37	0.41
Average share of limit order	100%	98%
Average mean reversion coefficient	0.08	0.11

3.4 Methodology and Results

3.4.1 Trader Categories

There are more than 167,000 trading accounts across BIST30 stocks in my data set. Traders in these stocks do not have formal liquidity provision requirements such as market makers, dealers, or specialists in this market. The focus of this study is the group of traders acting as an intraday intermediaries or liquidity providers in the market. The reason for using of "intraday intermediaries" term instead of a broader liquidity provider definition is the limited number of trading days in my data. Otherwise, it would be reasonable to expect that intraday intermediaries may also prefer to provide liquidity not only intraday but also at a daily level, such as bridging the trading days.

Intraday intermediaries in automated stock markets can be broadly defined as "traders who are behaving as an intermediary and try to minimize the frictions resulting from the fact that buyers and sellers don't arrive simultaneously (Grossman and Miller, 1988, p.617). This definition implies that intermediaries are often involved in a significant amount of transactions (see Glosten and Milgrom, 1985, Kyle, 1985) and that intermediaries' inventories are mean-reverting at a relatively high frequency (Garman, 1976; Amihud and Mendelson, 1980 and Ho and Stoll, 1983 among others). Empirically, the most salient characteristics of intraday intermediaries from literature are consistently buying and selling throughout a trading day, being involved in a relatively high trading volume, and maintaining low levels of end-of-day inventory (Hasbrouck and Sofianos, 1993 and

Madhavan and Smidt, 1993).

To identify the subset of intraday intermediaries, I adopt a data driven approach based on the observed trading activity and inventory patterns of each trading account across the 30 stocks. I define intraday intermediaries as traders who follow a strategy of consistently buying and selling throughout a day while maintaining low levels of inventory and being involved in relatively high trading volume. To meet this definition, the end-of-day net positions relative to its daily trading volume are calculated for each trading account for the trading days between March 18–26. Then, those accounts whose end-of-day net position relative over its trading volume is between -0.15 and 0.15 for at least 5 out of 7 trading days for each stock are considered. From the subset of accounts, those whose average trade volume is higher than the median of all accounts and average trade per minute is higher than the median of all accounts are labelled as intraday intermediaries on March 27. Figure 3.5 illustrates the timeline of event and liquidity shock that happened on March 27. The seven trading days just before the liquidity shortage are used for the trader categorization and the upcoming baseline regressions in this section.

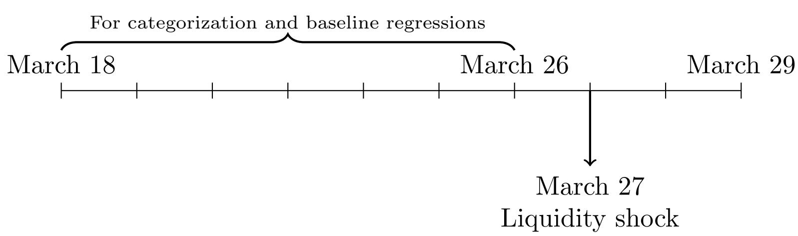

Figure 3.5: **Timeline for the Analysis**

The data set consists of ten trading days. Since there is no formal intraday intermediaries in the market, I identify the intraday intermediaries via data driven approach. For this identification, trading statistics of the trading accounts are calculated with the data between March 18 and March 26 irrespective of their trading behaviour on March 27. The identified intraday intermediary accounts kept in the same category on March 27.

A growing literature on the most active intraday intermediaries variously defines them as fast traders, high-frequency traders, or high-frequency market makers (Biais et al., 2015; Aıt-Sahalia and Saglam, 2016; Jovanovic and Menkveld, 2016), as well as empirical studies by Carrion (2013), Menkveld (2013) and Brogaard et al. (2014). The novelty of the data set is that information about the technical connection of the traders to the Exchange can be directly observed. Thus, I can further classify the intraday intermediaries based on whether they have an HFT or non-HFT connection to the Exchange. Having an HFT connection does not necessarily mean that these accounts are behaving as an high frequency trader, but this type of connection is costly to stand idle. I believe it is still informative to have the HFT and non-HFT intraday liquidity subsets separately if there are any differences in terms of trading behaviour.

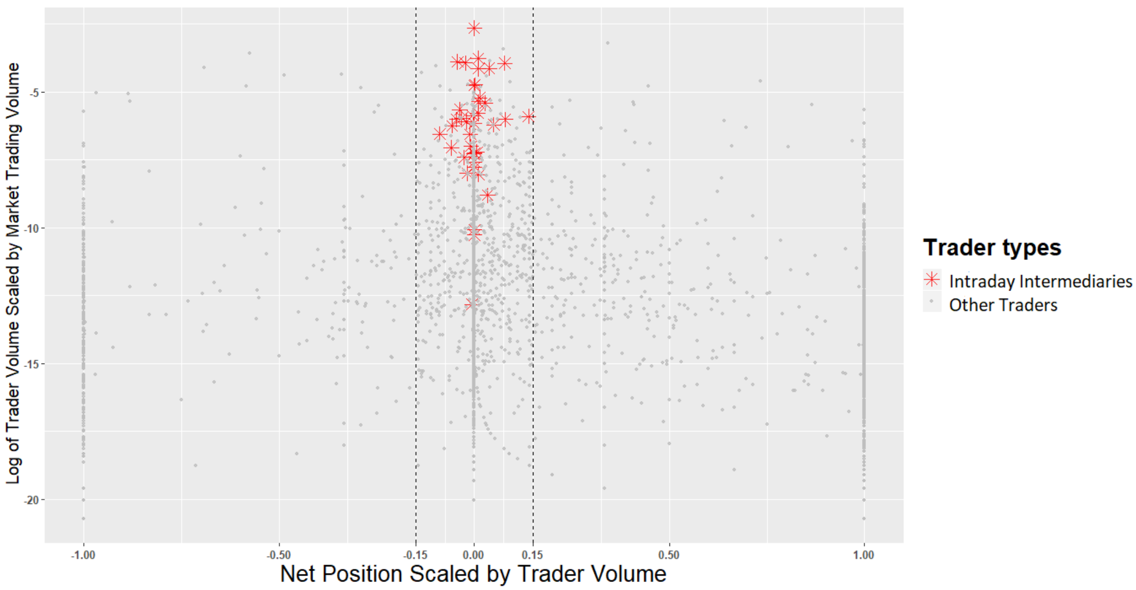

Figure 3.6: **Representative Categorization Approach**

This figure presents the average statistics for each trading account for one stock. End of day net position scaled by trader volume is shown on the x-axis and log of the trader volume scaled by related stock's total market volume is shown on the y-axis. Trading accounts' having x-axis value within the -0.15 and 0.15 window at least 5 out of 7 trading days is subsetted and then those having average trade volume higher than the median of all accounts' and average trade per minute higher than the median of all accounts' is labelled as intraday intermediaries and shown in red.

Figure 3.6 provides a sample representation of my trader classification methodology for one stock by using the trading statistics from March 18 and March 26. Each dot on the figure represents a single trading account. The dimensions of the figure are the log of trader volume scaled by market trading volume of that stock and end-of-day net positions scaled by trader's volume for all accounts. To identify the accounts as intraday intermediaries, I subsetted the trading accounts falling to the window between -0.15 and 0.15 for x-axis for at least 5 out of 7 trading days of the sample period of March 18 and 26. Then, I labeled accounts that had an average trade per minute higher than the median of all accounts' and average trade volume higher than the median of all accounts' as intraday intermediaries, shown in red within the window and directly labelled as intraday intermediaries for March 27. The remaining accounts are categorized as other traders for this research.

3.4.2 Intraday Intermediation

The main idea of the methodology is empirically examine the minute-by-minute comovement of holdings changes and price changes before and during March 27. For this purpose, inventory statistics of the intraday intermediaries are aggregated with respect to their connection types such as HFT or non-HFT. I simply examine the comovement of intraday intermediaries' holdings and price changes without making causal inferences, since prices and holdings are jointly determined. I employ the below baseline analysis shown in Equation 3.1 separately for the identified HFT and non-HFT intraday intermediaries for 30 stocks under BIST30. The baseline holdings and price regression is given as below:

$$\Delta y_{i,t} = \alpha_i + \phi \Delta y_{i,t-1} + \delta y_{i,t-1} + \sum_{k=0}^{s} [\beta_k \Delta p_{i,t-k}/c] + \epsilon_{i,t} \tag{3.1}$$

where $\Delta y_{i,t}$ is the outcome variable and denotes the change in holdings (in stocks) and $\Delta y_{i,t-1}$ and $y_{i,t-1}$ stands for the lagged change in holdings (in stocks) and lagged holdings level (in stocks) for each minute of a trading day, t=0 the opening minute of continuous trading on the BIST at 10:00 am and t=420 denotes the closing minute of continuous trading and $\Delta p_{i,t-k}/c_i$ denotes the price change in each stock scaled by the stock's tick size[16] c_i represents tick size which shows minimum price increment. Prices are calculated for each minute as the average of trade prices in the tradebook. i is for the stocks and c_i is the tick size of the ith stock. Moreover, parameters of interest are δ and β_k which denote long term mean reversion coefficient and the relationship of contemporaneous and lagged price changes with the holding changes respectively. Equation 3.1 introduces the baseline regression, I stack observations between March 18 and March 26 in order to analyze the statistical relationship between inventory changes and price changes of HFT and non-HFT intraday intermediaries separately and then, in order to test whether this relationship significantly changed during the selling pressure, I estimate the below Equation 3.2. For this regression, D_t dummy is added as an interaction term for the March 27 observations which basically corresponds to the selling pressure day. The interaction term measure differences between the coefficient estimates for the respective periods of selling pressure period and not that period.

[16] I choose to standardize the price changes of stocks by normalizing with the tick size, facilitating a more readily comprehensible interpretation as its in Kirilenko et al. (2017).

$$\Delta y_{i,t} = \alpha_i + \phi \Delta y_{i,t-1} + \delta y_{i,t-1} + \sum_{k=0}^{s} [\beta_k \Delta p_{i,t-k}/c_i] + D_t \left[\alpha_i^d + \phi^d \Delta y_{i,t-1} + \delta^d y_{i,t-1} + \sum_{k=0}^{s} [\beta_k^d \Delta p_{i,t-k}/c_i] \right] + \epsilon_{i,t}^d \tag{3.2}$$

In this research, the estimation methodology employed is instrumental variables (IV) estimation for equation 3.2. The rationale for selecting this approach is due to the presence of the net position change variable as the dependent variable, and its lagged version as an independent variable. It becomes evident that without employing IV estimation, the strict exogeneity assumption cannot be upheld, as the error terms display correlation with the lagged net position change variable, which is essentially a lagged version of the dependent variable. To resolve this endogeneity concern, I introduce the lagged net position (as a level, not its change) as an instrumental variable. By incorporating this instrument, I can effectively mitigate the endogeneity issues arising from the correlation of the error terms and the lagged net position change variable. IV results for HFT and non-HFT intraday intermediaries are presented in Table 3.3.

In table 3.3, second column presents the coefficient estimates for HFT intermediaries and non-HFT one is in the third column. As for the HFT intermediaries, the long-term mean reversion parameter δ is -0.741 and is statistically significant. This suggests that HFTs reduce 74% of their position in one minute. This long term mean reversion coefficient corresponds to an estimated half-life of inventory period of 56 seconds[17]. Changes in net holdings of HFTs are statistically positively related to changes in prices for the contemporaneous price and the first four lags. The estimated coefficients are positively decaying from the high of 1.892 for the contemporaneous price to the low of 0.224 for the price 4 minutes prior. This can be interpreted as follows: one tick price increase in the current price corresponds to an increase the contracts in the net holdings of HFTs by 1.8 standard deviations. Moreover, one tick price increase in the current price corresponds to an increase of up to 3.8 standard deviations during the next 4 minutes. HFTs appear to trade in the same direction as the contemporaneous prices and prices of the past four minutes. In other words, they buy if immediate prices are rising. These results suggest that, possibly due to their speed advantage or ability to predict price changes, HFTs are able to buy right as the prices are about

[17]I calculate estimated half-life of the inventory holding period as $\frac{ln(0.5)}{\delta}$

to increase. These finding of inventory changes of HFTs are positively related to contemporaneous price changes is inline with the findings of Foucault et al. (2011); Menkveld (2013 and Budish et al. (2015). They provide theoretical mechanisms through which the inventories of intermediaries may positively co-move with price changes at high frequencies. These studies suggest that if certain traders can react marginally faster to a signal, they can adversely select stale quotes of marginally slower market makers, engaging in stale quote sniping or latency arbitrage. Consequently, faster traders are able to trade ahead of price changes at short time horizons. In order to see if their trading pattern significantly changed during March 27, interaction terms is interpreted as follows: For HFT intraday intermediaries, the interaction terms for contemporaneous and lagged price changes until 4 minutes are negative and significant. This result may suggest that HFT intraday intermediaries reversed the direction of their trading significantly. It may be due to a reduction in their liquidity removal (increase in liquidity provision) and prefer to trade less aggressively during the liquidity shortage on March 27. These changed behaviour is different than the Kirilenko et al. (2017) which finds that trading pattern of the most active HFT intraday intermediaries not change when prices fell during the Flash Crash.

As for the non-HFT intermediaries, the coefficient estimate for the long-term mean reversion parameter Δ is -0.702 and is statistically significant. This suggests that non-HFTs reduce 70% of their position in one minute. This long term mean reversion coefficient corresponds to an estimated half-life of inventory period of 59 seconds.[18] In contrast to the HFTs, changes in net holdings of non-HFTs are statistically negatively related to changes in prices for the contemporaneous price (less significant coefficients for 2nd and 3rd minutes). non-HFT intraday intermediaries sell when immediate prices are rising. This is inline with the findings of Kirilenko et al. (2017) suggesting that inventory changes of Market Makers are negatively related to contemporaneous price changes, consistent with theories of traditional market making (see Hendershott and Menkveld, 2014). non-HFT intraday intermediaries sell when immediate prices are rising. Price coefficients can be interpreted as follows: one tick price decrease in the current price corresponds to an increase in the net holdings of non-HFTs by 1 standard deviation during the next 3 minutes. The reason of lagged price coefficients' for 2 or 3 minutes' being less significant may be a signal of non-HFTs having more likely longer term strategies. In order to see their trading pattern during March 27, interaction terms is

[18]It is significantly smaller than the specialist inventory half life measures of Hendershott and Menkveld (2014) who employ NYSE data set from 1994-2005.

checked. However, there is no significant change in their trading patterns during March 27 since there is no significant interaction terms for non-HFT intraday intermediaries.

Table 3.3: **Intraday Intermediaries**

This table presents estimated regression coefficients for both HFT and non-HFT intermediaries shown in Equation 3.2. The dependent variable is the change in holdings (in stocks) of HFT and non-HFT intraday intermediaries respectively. Both changes in holdings, $\Delta y_{i,t-1}$ and $y_{i,t-1}$ are in stocks. Price changes, $\Delta p_{i,t}$, are in ticks. The sampling frequency is one minute. Observations are stacked from May 18 through 27. IV model estimators are indicated and model includes both stock and trading days and trading hours fixed effects.

VARIABLES	HFT	Non - HFT
lagged net position change	0.0162***	0.00826***
	(0.00541)	(0.00693)
lagged net position	-0.741***	-0.702***
	(0.00437)	(0.00547)
contemporaneous price	1.892***	-0.577***
	(0.387)	(0.137)
lagged price change - 1 min	0.969***	0.227
	(0.226)	(0.139)
lagged price change - 2 min	0.561***	-0.211*
	(0.158)	(0.118)
lagged price change - 3 min	0.229**	-0.282**
	(0.116)	(0.125)
lagged price change - 4 min	0.224**	0.0683
	(0.105)	(0.0911)
lagged price change - 5 min	-0.00917	-0.0911
	(0.0884)	(0.0745)
March 27- lagged net position	-0.0276***	-0.000407
	(0.00786)	(0.00733)
March 27- contemporaneous price change	-1.261**	0.384
	(0.573)	(0.233)
March 27- lagged price change - 1 min	-1.085***	0.123
	(0.258)	(0.201)
March 27- lagged price change - 2 min	-0.638***	0.170
	(0.209)	(0.164)
March 27- lagged price change - 3 min	-0.605**	0.268
	(0.265)	(0.182)
March 27- lagged price change - 4 min	-0.511***	0.234
	(0.171)	(0.146)
March 27- lagged price change - 5 min	-0.00548	0.128
	(0.224)	(0.140)
Observations	99,120	95,403
R-squared	0.537	0.484
Stock FE	-	-
Stock*Trading day FE	Yes	Yes
Trading Hours FE	Yes	Yes

Standard errors clustered by stock level in Model 1, by stock*trading day level in Model 2 and 3.
*** p<0.01, ** p<0.05, * p<0.1

3.4.3 Intraday intermediaries: Liquidity Provision or Removal

In this section, I focus on intraday intermediaries holdings with a focus of whether they are passive or aggressive. Intraday intermediaries are a category of very short-term investors characterized by their swift adjustment of positions and rapid reversion to target inventory levels. The trading activity of these intraday intermediaries encompasses several key aspects. By definition, these traders do not hold positions over long periods of time and revert their target inventory level quickly. Firstly, it is observed that intraday intermediaries emerge endogenously within the market and exhibit aggressive trading behavior, seemingly anticipating price changes in either direction. This raises the question of whether they genuinely function as intraday intermediaries. Secondly, these traders submit orders based on their price expectations, aligning their trades with these anticipated price movements. Thirdly, due to their limited risk-bearing capacities, intraday intermediaries engage in trading activities to maintain their inventories within predefined target levels. The pursuit of this inventory management objective may influence and interact with their price anticipation strategies. In other words, inventory management considerations of intraday intermediaries may lead them to aggressively trade in the same direction as the prices are moving, thus taking liquidity. At other times, in order to achieve their target inventory levels, they may trade passively against the price movements and, thus, providing liquidity.

In practice, I find that intraday intermediaries exhibit two distinct liquidity provision/removal behaviors, which are crucial to understand their role in the market. To analyze their liquidity provision and removal behavior further, I segregate the changes in their holdings into two categories; aggressive changes and passive changes, directly observed from my data set. Aggressive changes occur when intraday intermediaries submit marketable orders into the order book, leading to immediate matching. This implies that they trade aggressively in alignment with the prevailing price movements, effectively extracting liquidity from the market. On the other hand, passive changes are observed when the traders' resting orders are executed by marketable orders. This indicates that they trade passively against price movements, thereby providing liquidity to the market.

Analyzing aggressive and passive changes helps me understand how intraday intermediaries provide or take liquidity. These insights contribute to a better understanding of how they influence market dynamics and liquidity conditions. In order to analyze further the liquidity provision/removal behaviour of intraday intermediaries, I separate their changes in holdings into aggressive changes (those resulted via aggressive acquisitions) and passive (those obtained via passive acquisitions) which I observe directly the field from transactions whether they are aggressive or passive from the data set. Aggressive changes are incurred when traders submit marketable orders into the order book and immediately matched. This means that they trade aggressively in the same direction as the prices are moving, thus, liquidity taking from the market. Passive changes are those incurred via the traders' resting orders' being executed by a marketable order. This means they trade passively against price movements and thus, provide liquidity.

Table 3.4 presents the regression results of the two components of change in - respectively aggressive and passive - holdings on lagged holdings, lagged change in holdings and lagged price changes over one minute intervals both for HFT and non-HFT intraday intermediaries. Second column shows the regression results for change in aggressive holdings of HFT intraday intermediaries. The long term mean reversion coefficient as -0.734 which is statistically significant and negative. This means, HFTs aggressively reduce 73% of their holdings in one minute. The coefficient estimates for price changes are positive for the contemporaneous and first 5 lagged prices, decaying from 3.215 to 0.236. One tick increase in current price corresponds to an increase of 3.2 standard deviation aggressive increase in the holdings by HFTs. Moreover, a one tick increase in the current price corresponds to an 8.3 standard deviation aggressive in the holdings by HFTs up to five minutes. In order to see their trading pattern during March 27 for contemporaneous and lagged price changes are checked, they are significantly negative and decaying from -2.037 to -0.773 during next four minutes. When all the significant price coefficients added - increase in the aggressive holdings with respect to price increase is decreased from 8.3 to 5.2 standard deviations. This finding suggests that HFTs are decreasing their liquidity removal during the liquidity shortage on March 27 which is consistent with the findings in Table 3.3. Third column presents the regression results for the changes in passive holdings of HFTs from May 18 to May 27. The long term mean reversion estimate is -0.707, which is less smaller than the corresponding one in Table 3.3. The coefficients for contemporaneous and lagged price changes are negative and statistically significant; ranging from -1.990 for the current price change to -0.447 for the 5th lagged price change. They indeed provide liquidity. The coefficient estimates for contemporaneous and lagged price changes for March 27 implies that they do not change their liquidity provision pattern during the liquidity shortage on March 27. The larger coefficient for the aggressive long term mean reversion parameter suggests that HFTs quickly reduce their inventories by submitting marketable orders and they also aggressively trade when prices are about to change. Over slightly longer time horizons, however, HFTs sometimes act as providers of liquidity.[19]

[19]See Appendix Table C.6, when sampling frequency is 5 minutes, the relationship between the holdings and contemporaneous and first lagged price changes become statistically negative for HFT intraday intermediaries.

Table 3.4: **Intraday Intermediaries - Aggressive and Passive Positions**

This table presents estimated regression coefficients for both HFT and non-HFT intermediaries' aggressive and passive holdings shown in Equation 3.2. The dependent variable is the change in aggressive and passive holdings (in stocks) of HFT and non-HFT intraday intermediaries. Both changes in holdings, $\Delta y_{i,t-1}$ and $y_{i,t-1}$ are in stocks. Price changes, $\Delta p_{i,t}$, are in ticks. The sampling frequency is one minute. Observations are stacked from May 18 through 27. IV model estimators are indicated and model includes both stock and trading days and trading hours fixed effects.

VARIABLES	Agressive HFT	Passive HFT	Agressive non-HFT	Passive non-HFT
lagged net position change	0.00881*	0.00522	0.00964	-0.00668
	(0.00504)	(0.00617)	(0.00712)	(0.00703)
lagged net position	-0.734***	-0.707***	-0.706***	-0.680***
	(0.00426)	(0.00533)	(0.00629)	(0.00571)
contemporaneous price	3.215***	-1.990***	0.986***	-1.847***
	(0.489)	(0.223)	(0.214)	(0.305)
lagged price change - 1 min	1.890***	-1.396***	0.820***	-1.087***
	(0.272)	(0.168)	(0.170)	(0.216)
lagged price change - 2 min	1.425***	-1.408***	0.742***	-0.995***
	(0.190)	(0.169)	(0.177)	(0.200)
lagged price change - 3 min	0.839***	-1.032***	0.445***	-0.802***
	(0.160)	(0.159)	(0.147)	(0.169)
lagged price change - 4 min	0.708***	-0.806***	0.417***	-0.453***
	(0.121)	(0.140)	(0.106)	(0.128)
lagged price change - 5 min	0.236**	-0.447***	0.137*	-0.238**
	(0.101)	(0.0891)	(0.0774)	(0.0994)
March 27- lagged net position	-0.0287***	-0.00956	0.00801	-0.00336
	(0.00877)	(0.00580)	(0.00713)	(0.00731)
March 27- contemporaneous price change	-2.037**	0.581	-0.408	0.846*
	(0.861)	(0.572)	(0.311)	(0.489)
March 27- lagged price change - 1 min	-1.565***	0.266	-0.430	0.493
	(0.379)	(0.480)	(0.318)	(0.354)
March 27- lagged price change - 2 min	-1.008***	0.132	-0.215	0.429
	(0.255)	(0.562)	(0.309)	(0.277)
March 27- lagged price change - 3 min	-0.858***	0.0518	-0.101	0.498**
	(0.194)	(0.381)	(0.256)	(0.217)
March 27- lagged price change - 4 min	-0.773***	0.197	-0.0262	0.407**
	(0.139)	(0.292)	(0.178)	(0.173)
March 27- lagged price change - 5 min	-0.0838	0.0529	-0.0340	0.233
	(0.166)	(0.218)	(0.113)	(0.171)
Observations	99,120	98,707	94,164	95,403
R-squared	0.536	0.498	0.491	0.472
Stock FE	-	-	-	-
Stock*Trading day FE	Yes	Yes	Yes	Yes
Trading Hours FE	Yes	Yes	Yes	Yes

Standard errors clustered by stock level in Model 1, by stock*trading day level in Model 2 and 3.
*** p<0.01, ** p<0.05, * p<0.1

Fourth and fifth column presents the regression results of the two components of change in - respectively aggressive and passive - holdings on lagged holdings, lagged change in holdings and lagged price changes over one minute intervals for non-HFT intraday intermediaries. As for the fourth column, the long term mean reversion coefficient is -0.706, statistically significant and negative. The coefficient estimates for the contemporaneous and first 5 lagged prices are positive and decaying from 0.986 to 0.137. A one tick increase in current price corresponds to an increase of 0.98 standard deviation aggressive increase in the holdings by non-HFTs. Moreover, a one tick increase in the current price corresponds to an 3.5 standard deviation increase in aggressive holdings by non-HFTs during the next five minutes. These estimates are smaller than HFTs counterparts. This may be considered as an evidence that non-HFTs are slower than HFTs in responding to anticipated price changes. The interaction coefficient estimates for contemporaneous and lagged price changes for March 27 are not significant and suggesting that non-HFTs do not change their liquidity removal pattern during the liquidity shortage on March 27. Fifth column presents the regression results for the change in passive holdings of non-HFTs from May 18 to May 27. The long term mean reversion estimate is -0.680, which is smaller than the coefficient from the aggressive holdings change regression. The contemporaneous and first lagged price changes are negative and statistically significant; ranging from -1.847 for the contemporaneous price change to -0.238 for the 5th lagged price change. The interaction coefficient estimates for contemporaneous and lagged price changes for March 27 are not significant and suggesting that non-HFTs do not change their liquidity provision pattern during the liquidity shortage on March 27.

In sum, aggressive holdings change with respect to price changes are positive and significant, consistent with liquidity taking behaviour and passive holdings change with respect to price changes are negative and significant, consistent with liquidity providing behaviour for both HFT and non-HFT intraday intermediary subsets. From the liquidity provision point of view, non-HFT's reaction is higher in magnitude compared to HFT counterparts (See Table 3.4 passive results for non-HFTs.). From the liquidity taker point of view, HFT's reaction is higher in magnitude compared to HFT counterparts (See Table 3.4 aggressive results for HFTs.). In order to understand whether these intraday intermediaries significantly change their trading patterns on March 27, I check the interaction terms for price coefficients on March 27 from the Table 3.4. In the second column of Table 3.4, interaction terms for the relationship between contemporaneous (and lagged) prices and aggressive holdings turn to be significantly negative for HFT intraday intermediaries in line with the findings from Table 3. This suggests that trading pattern change of HFTs on March 27 stems mostly from the changes in their aggressive holdings pattern. However, there is no significant change in these coefficients for the passive holdings in Table 3.4. Moreover, there is not a significant change in interaction terms for the relationship between contemporaneous and lagged prices and both type of holdings for non-HFT intraday intermediaries as seen in Table 3.4.

3.4.4 Intraday intermediaries: Profits and Losses

After examining their trading patterns, it is interesting to see whether intraday intermediaries earns profit or not. The daily profits for each trading account, i, is calculated for each trading day, t, according to marked-to-market accounting, assuming that each trading account starts each day with a zero inventory position. More precisely, for each trader, I calculate the end-of-day profits as the cumulative cash received from selling short positions minus the cash paid from buying long positions, plus the value of any outstanding positions at the end-of-day, marked to the market price at close for the stocks they trade in and then took the average of this in case the trading account is labeled as a intraday intermediary for more than one stock.

$$\pi_{i,t} = \sum_{n=1}^{N_{i,T}} p_n y_{i,n} + p_T y_{i,T}, \tag{3.3}$$

where $n = 1...N_{i,T}$ indexes the trades for trader i between the start of the trading day (t=0) and the end of the trading day ($t = T$), p_n is the price of the trade, $y_{i,n}$ is the quantity of the nth trade by trader i, and $p_T y_{i,T}$ is the value of any end-of-day positions outstanding for every stocks they have in BIST30 stocks.

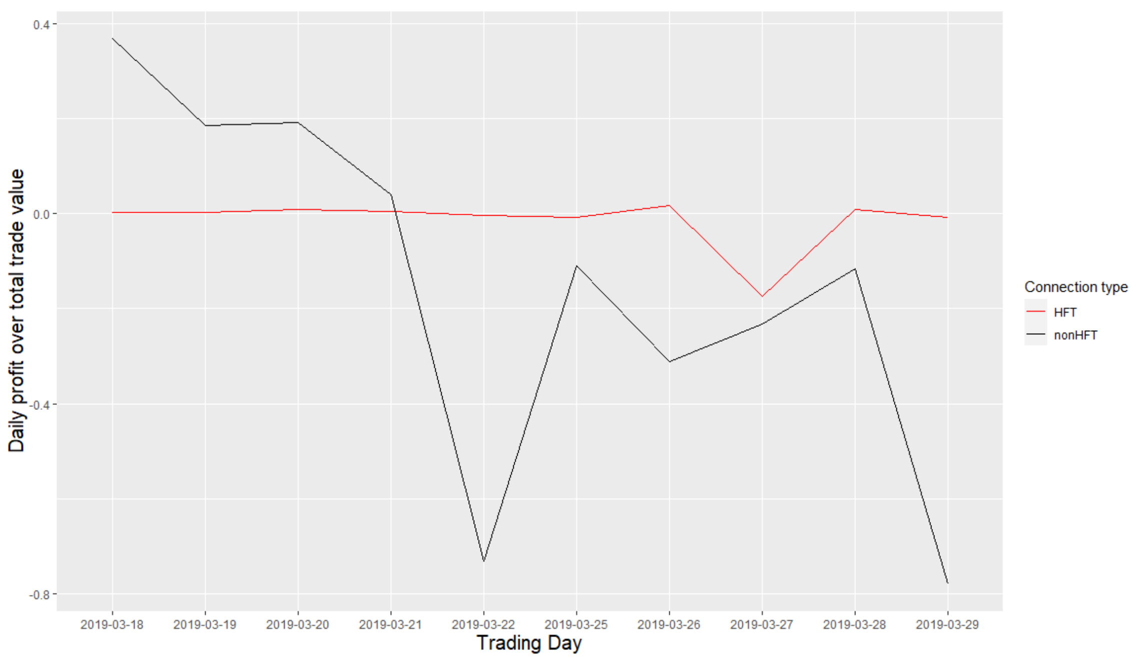

Figure 3.7: **Daily Profit over Total Trade Value %**

Profit calculation approach is composed of two parts. First part is the net trade value which is the difference between the number of sold and bought shares multiplied with the corresponding transaction prices. Second part is the value of any outstanding positions at the end-of-day, marked to the market price at close for the stocks they trade in and then took the average of this in case the trading account is labeled as intraday intermediary for more than one stock. For each classified accounts, I aggregate their average profits for the subsets of HFT and non-HFT intraday intermediaries.

Figure 3.7 shows the aggregated profits for HFT and non-HFT subset of intraday intermediaries. HFTs have loss of around 0.5% of their total trade value where non-HFTs have loss around 4.9% of their total trade value on average for the period of March 18-29. However, HFTs are having on average profit around 0.1% of their total trade value where non-HFTs have loss around 1.7% of their total trade value for the period before March 27, 2019.

In order to have more specific approach, I used the aggressive and passive categorization approach from Baron et al. (2012). I broke down HFTs into three subcategories which are aggressive, mixed, and passive. The definition of this grouping is based on how frequently the HFT initiates a transaction. To be considered as an aggressive HFT, trading account has to initiate at least 60% of the trades it enters into; to be considered as a passive HFT, trading account has to initiate fewer than 20% of the trades it enters into; those HFTs that meet neither the aggressive nor the passive definition are labeled as mixed HFTs. The number of aggressive, mixed and passive accounts are respectively 23, 33 and 10 for HFTs, 166, 385 and 174 for non-HFTs.

Figure 3.8 and 3.9 shows the daily profits scaled by total trade value for the subgroups of HFTs. From Figure 3.8, It is seen that the group of passive HFTs having profits on March 27 whereas the rest have losses. For the trading days before March 27, on average aggressive HFTs have profits of 1% of their total trade value whereas mixed and passive ones have losses 0.5% and 0.1% of their total trade value respectively. The fact that aggressive HFTs earn substantially higher profits than passive HFTs suggests that there is a strong profit motive for liquidity taking rather than liquidity providing. Figure 3.9 shows the daily profits scaled by total trade value for the subgroups of non-HFTs. It is seen that only the group of aggressive non-HFTs having profits on March 27 whereas the rest have losses. For the trading days before March 27, on average aggressive non-HFTs have a loss around 6% of their total trade value whereas mixed and passive ones have losses 2% and 0.3% of their total trade value respectively.

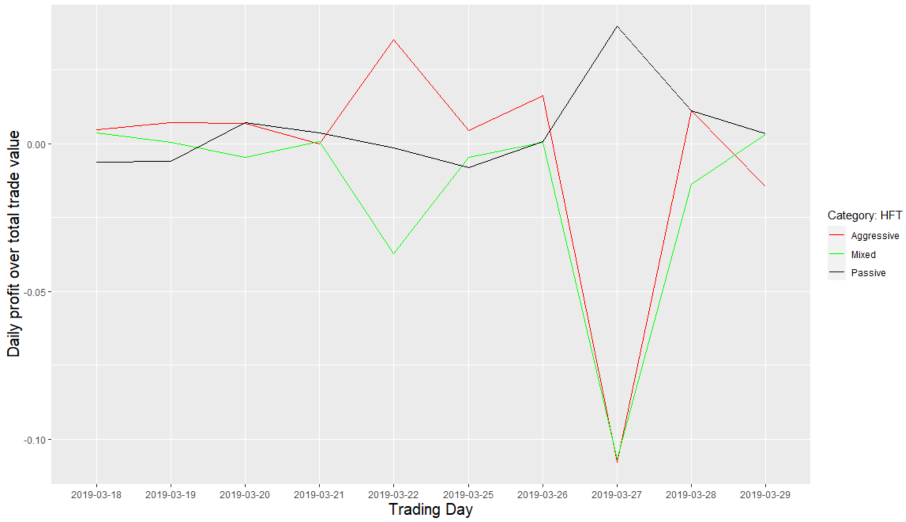

Figure 3.8: **Daily Average Profit - HFT Intraday Intermediaries**

Daily profits scaled by total trade value for the subgroup of HFTs is given in this figure. Red line is for aggressive group, mixed are green and passives are in black.

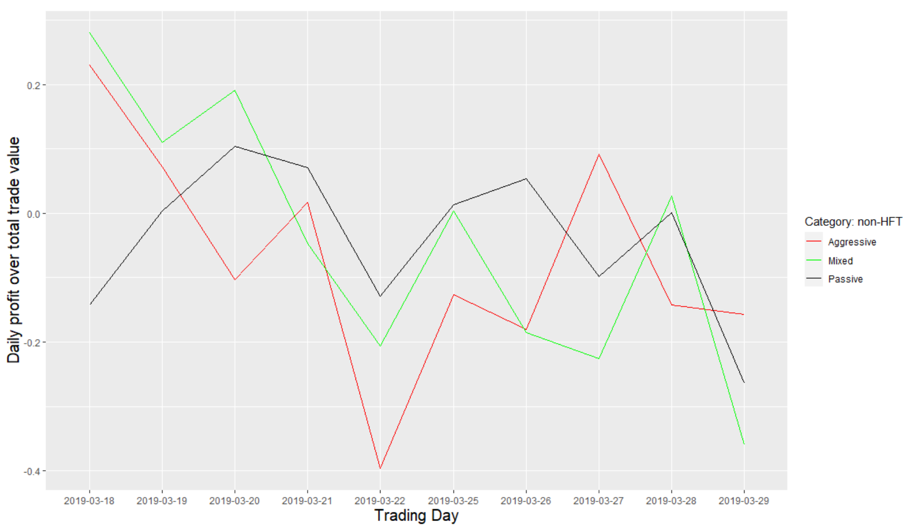

Figure 3.9: **Daily Average Profit - non-HFT Intraday Intermediaries**

Daily profits scaled by total trade value for the subgroup of non-HFTs is given in this figure. Red line is for aggressive group, mixed are green and passives are in black.

3.4.5 The Mechanism of the Liquidity Shortage

The current analysis and its outcomes appear to offer some insights into the underlying mechanism driving the liquidity shortage observed on March 27. The liquidity shortage observed on March 27 might stem from various mechanisms. One possible explanation is that stocks sold on March 27 are subsequently repurchased on March 28, resembling a circular trading pattern. Alternatively, the situation could be attributed to a reconfiguration of stock ownership, or perhaps the identified pattern pertains to all trading days I have in my data set. Broadly speaking, a critical economic query emerges: Is this liquidity shortage a transient, short-term occurrence akin to friction, or does it signify a more enduring trend involving the redistribution of ownership? The complexity is compounded by the constraint of limited available trading days for analysis, which poses challenges to this investigation.

Nonetheless, initial observations reveal some noteworthy facts. Among the 30 stocks comprising the BIST30, 20 were sold on March 27 and subsequently repurchased on March 28, constituting an average repurchase ratio of 87%. This suggests that, on average, 87% of the aforementioned stocks were bought back. However, 8 out of the 30 stocks that were sold on March 27 continued to be sold on March 28, while 2 of the 30 stocks purchased on March 27 continued to be held on March 28. In aggregate, the data indicates that, on average, approximately 20% of the volume of stocks sold on March 27 were bought back on March 28.

In order to understand better the mechanism of the liquidity shortage, I conduct additional empirical analysis for March 28. From Figure 3.1, excess selling on March 27 by foreign accounts seems to be reversed to some extent on March 28 and turn to be an excess buying of foreign trading accounts on March 28. In order to see the trading patterns of the intraday intermediaries on March 28, equation 3.2 is estimated and Table 3.5 present the results for HFT and non-HFT intermediaries.

Second column in Table 3.5 presents the coefficient estimate for the long-term mean reversion parameter as -0.746 for HFT intraday intermediaries and is statistically significant. Changes in net holdings of HFTs are statistically positively related to changes in prices for the contemporaneous price and the first two lags. These are similar findings I have in Table 3.3. Here, the question is whether there is any trading pattern change ongoing after March 27, I check the interaction terms standing for March 28 and some of the lagged price changes until 4 minutes seems to be negative and significant. This result may suggest that on March 28, HFT intraday intermediaries continue to reduce their liquidity removal and prefer to trade less aggressively as happened on March 27 but in a lesser degree than the case of liquidity shortage day. From the second column in Table C.1 in the Appendix, it is seen that this effect is mostly coming from the significantly negative interaction terms for price coefficients in the aggressive holdings change which confirms the reduction in the liquidity removal of HFT intraday intermediaries. Third column in Table C.1 in the Appendix confirms that this effect is not coming from the pattern change in passive holdings.

Third column in Table 3.5 results for non-HFT intraday intermediaries. The coefficient estimate for the long-term mean reversion parameter as -0.700 and is statistically significant for non-HFT intraday intermediaries. This suggests that non-HFTs reduce 70% of their position in one minute. In contrast to the HFTs, changes in net holdings of non-HFTs are statistically negatively related to changes in prices for the current price as in the previous cases. When I check if trading pattern change during March 28, it seems that there is an increase in the liquidity provision of non-HFT intraday intermediaries since there are significant and negative price coefficients. When all the significant price coefficients added - holdings are increase (decreased) from 1 to 2 standard deviations when there is one tick price decrease (increase). This finding suggests that non-HFTs possibly increasing their liquidity provision during the day after liquidity shortage on March 28, this may be due to the market recovery purposes. From Table 6 in Online Appendix, this effect is mostly coming from the significantly negative interaction terms for price coefficients in the aggressive holdings change which confirms the reduction in the liquidity removal of non-HFT intraday intermediaries. Results in fifth column of table C.1 in the Appendix confirms that this effect is not coming from the pattern change in passive holdings.

In order to check the identified pattern pertains to all trading days or not, placebos for different trading days are run in the Appendix, Table C.2- C.3-C.4. It is seen that there is not a significant trading pattern change in the other days.

Table 3.5: **Intraday Intermediaries - March 28**

This table presents estimated coefficients for the regression in Equation 3.2. The dependent variable is the change in the holdings (in stocks) of HFT and non-HFT intraday intermediaries. Both changes in holdings, $\Delta y_{i,t-1}$ and $y_{i,t-1}$ are in stocks. Price changes, $\Delta p_{i,t}$, are in ticks. The sampling frequency is one minute. Observations are stacked from May 18 through 28. IV model estimators with three model specifications are indicated. Model has both stock and trading days and trading hours fixed effects.

VARIABLES	HFT	non - HFT
lagged net position change	0.0182***	0.00610
	(0.00514)	(0.00638)
lagged net position	-0.746***	-0.700***
	(0.00420)	(0.00509)
contemporaneous price	1.521***	-0.471***
	(0.366)	(0.128)
lagged price change - 1 min	0.653***	-0.192*
	(0.199)	(0.108)
lagged price change - 2 min	0.401***	-0.171*
	(0.116)	(0.0900)
lagged price change - 3 min	0.0650	-0.208**
	(0.0923)	(0.0958)
lagged price change - 4 min	0.0746	-0.000240
	(0.0916)	(0.0713)
lagged price change - 5 min	-0.000645	-0.0615
	(0.0951)	(0.0620)
March 28- lagged net position	-0.0210***	-0.00838
	(0.00785)	(0.00678)
March 28- contemporaneous price change	-0.752	-0.413*
	(0.633)	(0.237)
March 28- lagged price change - 1 min	-0.912***	-0.377**
	(0.317)	(0.151)
March 28- lagged price change - 2 min	-0.608***	-0.179
	(0.191)	(0.171)
March 28- lagged price change - 3 min	-0.229	-0.258**
	(0.150)	(0.127)
March 28- lagged price change - 4 min	-0.345***	-0.211
	(0.112)	(0.197)
March 28- lagged price change - 5 min	-0.141	-0.164
	(0.139)	(0.108)
Observations	111,097	107,380
R-squared	0.540	0.485
Stock FE	-	-
Stock*Trading day FE	Yes	Yes
Trading Hours FE	Yes	Yes

Standard errors clustered by stock level in both models.
*** p<0.01, ** p<0.05, * p<0.1

3.5 Conclusion

The research on the periods marked by temporary surges in buying or selling activities presents a valuable opportunity to understand more about market dynamics, the roles played by various types of traders, and even to enhance our understanding of market crashes. Notably, Huang and Wang (2009) proposed a theory suggesting that abrupt and substantial selling pressures can trigger market crashes, even in the absence of fundamental stock changes. Within such contexts, the function of market intermediaries becomes substantial. These intermediaries assume a critical role in markets where buyers and sellers do not interact simultaneously, working to mitigate frictions arising from imperfect synchronization in trading timing. As markets grow increasingly automated, intermediation has progressively transitioned to being managed by market participants without formal requirements.

In this paper, I study the trading patterns of intraday intermediaries in an automated stock market before and during a period of temporary liquidity shock in the form of large selling pressure. The origins of this pressure trace back to a government intervention aimed at halting local banks from facilitating swap market transactions, seeking to curtail further depreciation of the Turkish currency (TL) just prior to local elections in March 2019. The sudden surge in overnight swap rates in London, elevating from an initial 24% to an unprecedented 1300% on March 27, rendered shorting the lira unfeasible for foreign traders. This indirectly reverberated into the Borsa Istanbul (BIST) stock market, where foreign traders, compelled to exit TL positions, triggered a bout of temporary selling pressure. I studied the effect of this pressure on 30 stocks under the benchmark index BIST30 of Borsa Istanbul. In order to classify accounts as intraday intermediaries, I adopt a data driven approach based on trading activity and inventory patterns. I further separate intraday intermediaries into two subsets depending their connection type: HFT and non-HFT.

First, the data shows that HFT intraday intermedires buy when immediate prices are rising, suggesting that they are able to buy right as prices are about to increase, posiibly due to their speed advantage or ability to predict price changes. In contrast to the HFTs, changes in net holdings of non-HFTs are statistically negatively related to changes in prices for the contemporaneous price, suggesting that non-HFT intraday intermediaries sell when immediate prices are rising. There is no significant relationship between lagged prices and net holdings, which may indicate that non-HFTs have longer-term strategies than a one-minute frequency. This finding is inline with Kirilenko et al. (2017) and Hendershott and Menkveld (2014) which suggests that inventory changes of non-HFT intraday are negatively related to contemporaneous price changes, consistent with theories of traditional market making. In contrast to this pattern, inventory changes of HFTs are positively related to contemporaneous price changes.

Second, my results suggest that trading patterns changed especially for intraday intermediaries classified as HFTs, during the selling pressure period on March 27 compared to the previous trading days. Moreover, my findings show that changed patterns result from their aggressive holdings, suggesting a reduction in their liquidity removal (an increase in liquidity provision) and a preference to trade less aggressively during the liquidity shortage. In contrast to HFTs, there is no significant change - neither in aggressive nor passive holdings - in trading patterns for non-HFT intraday intermediaries during March 27. Contrast to the growing literature suggesting that endogenous liquidity providers often withdraw from the market during stress periods (Bongaerts and Van Achter, 2016; Cespa and Vives, 2013; Korajczyk and Murphy, 2019; Anand and Venkataraman, 2016), I showed that their trading pattern is suggesting a reduction in their liquidity removal - an increase in liquidity provision - and a preference to trade less aggressively during the liquidity shortage.

Third, in order to further analyze the liquidity provision and removal behaviour of intraday intermediaries, I separate their changes in holdings into aggressive and passive changes, which I observe directly from the data set. For both HFT and non-HFT subsets, aggressive holdings change with respect to price changes are positive and significant, compatible with liquidity-taking behaviour. Passive holdings change with respect to price changes are negative and significant, compatible with liquidity providing behaviour.

Fourth, I conduct additional empirical analyses for March 28 - the day after the liquidity shortage - in order to better understand the mechanism of the shortage. My results suggest that on March 28, HFT intraday intermediaries continue to reduce their liquidity removal and prefer to trade less aggressively, as they did on March 27 but to a lesser degree than during the liquidity shortage. Moreover, I find that non-HFTs also increase their liquidity provision during the day after liquidity shortage on March 28, this may be due to the market recovery purposes.

By analyzing the patterns of these intermediaries, this study offers key insights. Keeping in mind the external validity issues, this paper substantiates the adaptability of HFTs in response to liquidity imbalances, while non-HFT intermediaries adhere more closely to established traditional market making patterns. Additionally, the analysis uncovers the nuanced relationship between inventory changes and price movements, revealing distinct behaviors between HFTs and non-HFTs. In sum, this study sheds light on the intricate dynamics of intraday intermediaries during times of substantial market stress.

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A Appendix for Chapter 1

A.1 Exchange data

For the analysis, I use intraday tradebook data for benchmark index BIST30 stocks for the year of 2019. It is directly taken from the Exchange's database. From this data, I examine all regular transactions occuring during the 420-minute period where continuous trading occurs between 10:00-13:00 and 14:00-18:00 for each of the ten days. I exclude all other sessions except continuous trading. I use following fields from tradebook data;

- field for the abbreviation (3 digits) of the financial intermediary. Financial intermediaries are usually the subsidiaries of banks operating in Turkey. They have been serving domestic and foreign customers who wants trade in stock market by opening an account and providing connection to the Exchange.
- field for username is the merged column of financial intermediary and its user connection name such ABC_FIX1
- account IDs for the buyer and the seller, these are numbers.
- the price and quantity transacted,
- the date and time in microseconds, rounded up to the nearest minute.
- a matching ID number that sorts trades into chronological order within one minute.
- field indicating whether the trade resulted from a limit or market order.
- field for aggressiveness indicator stamped by the matching engine as "P" for a resting order and "A" for an order that executed against a resting orders.

A.1.1 Imbalance Variables

$Imb_{i,t,c}$ is the outcome variable of Equation 1.1. It is calculated as the following: For each trading account and stock and the trading frequency (daily or ten minutes), the number of stock shares bought minus the number of stock shares sold normalized by the market volume of the given stock. net positions for one minute is calculated and then, they aggregated accordingly to the subset of which trading account belongs.

A.1.2 Price Variables

$\Delta R_{i,t-k}$ denotes the price change in the stock or market return for the stock. Daily contemporaneous and lagged market returns are simply the price changes calculated on a daily level as the difference between the stock's closing price on a trading day and its closing price on the previous trading day over its closing price on the previous trading day. As for the case of intraday, price changes calculated as the difference between the stock's price and ten minutes lagged price over its price. From the tradebook, price is calculated as the mean of the prices for the transactions realized in that specific ten minutes.

A.2 Robustness Check for the Trader Categorization

In order to maintain a robust categorization approach, stability of the average trading categories are also calculated especially for the focus trader categories; small traders and neutrals. Stability ratio shows how stable the trading accounts in terms of daily categories vs average categories across stocks. This may be an important issue mostly for the small trading accounts as they may act differently over the days. For this reason for each stock on the y axis on Figure 1.3, stability rate is calculated for the trading accounts classified as small neutrals. It seems stability rate for the average category of small neutrals are almost higher than 98 % for each stock under BIST30 index. In Figure A.1, stability rate is calculated for the trading accounts classified as small traders as well and it seems that average category of small traders are almost higher than 91 % for each stock under BIST30 index.

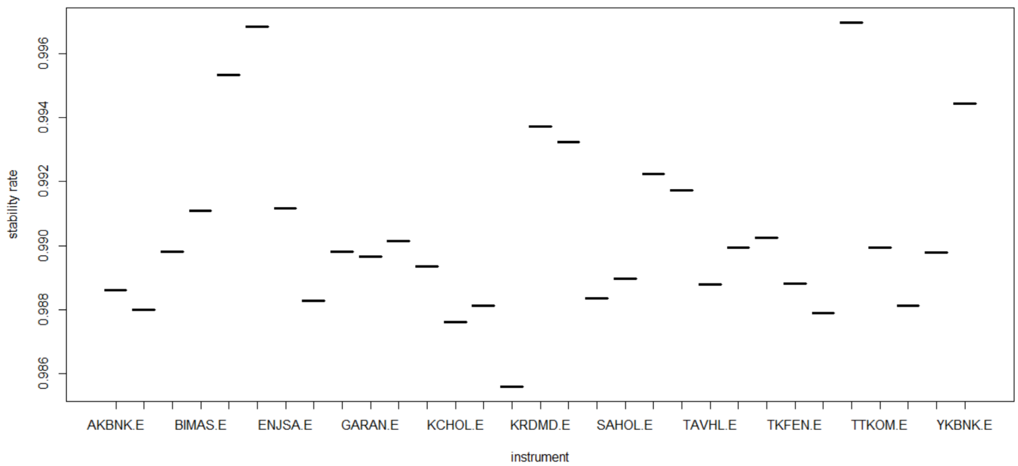

Figure A.1: **Stability Ratio of Average Small Neutral Accounts**

This figure shows the stability of the small neutrals' categorization. The categorization approach of the traders are averaged over the whole trading year. This figure shows the ratio of their trading category stable over the year. On the y-axis, stability rate is indicated and the x-axis is the names of the stock's in the benchmark BIST30 index. Stability rate is calculated as the numbers of the days when the trader is actually categorized as small trader on a daily level divided by the total number of the trading days in 2019.

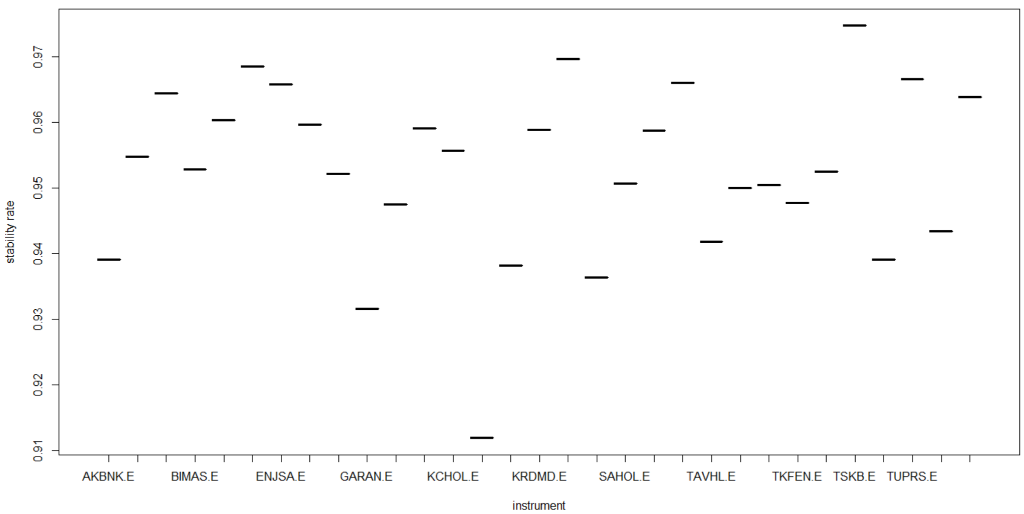

Figure A.2: **Stability Ratio for Average Small Non-neutral Accounts**

This figure shows the stability of the small traders' categorization. The categorization approach of the traders are averaged over the whole trading year. This figure shows the ratio of their trading category stable over the year. On the yaxis, stability rate is indicated and the xaxis is the names of the stock's in the benchmark BIST30 index. Stability rate is calculated as the numbers of the days when the trader is actually categorized as small trader on a daily level divided by the total number of the trading days in 2019.

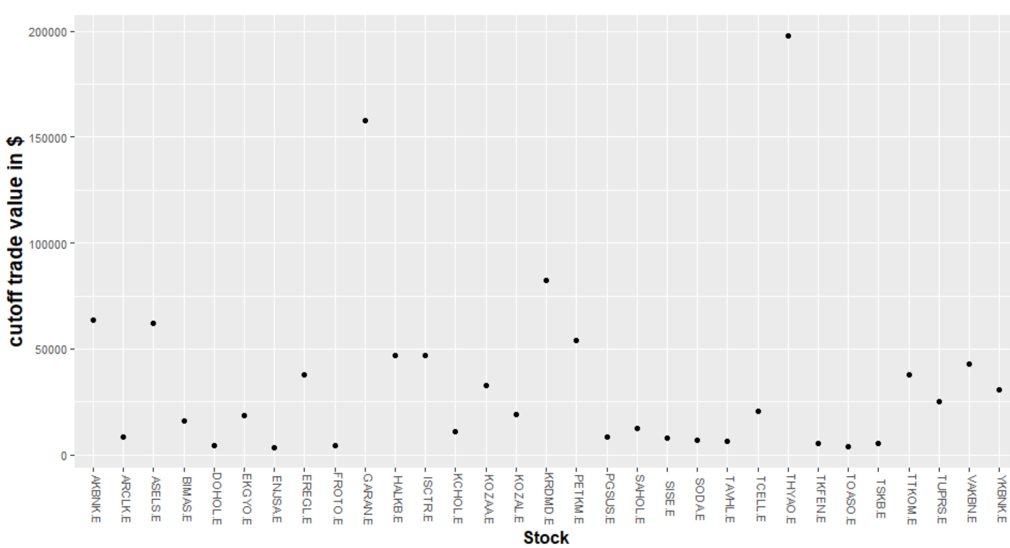

Figure A.3: **Cutoff Trade Value across BIST30 Stocks**

This figure shows the corresponding average cutoff value in US dollars for 30 stocks in BIST30 Index.

A.3 Further Analysis for Small Neutrals

Table A.1: **Daily Regression for Aggressive and Passive Small Neutrals**

This table presents estimated coefficients for the regression in Equation 1.1 for the subsets of passive and aggressive small neutral traders. The dependent variable is the imbalance which is defined by the number of stock shares bought minus the number of stock shares sold by the trader category normalized by the market volume of the given stock The sampling frequency is daily. Standard errors are clustered at stock level. Models include stock, trading day fixed effect.

	Passive Small Neutrals	Aggressive Small Neutrals
Return, t	-0.00095 ***	-0.00012
	(0.00025)	(0.00008)
Return, t-1	0.00056 ***	0.00013
	(0.00016)	(0.00008)
Return, t-2	0.00001	-0.00014 *
	(0.00011)	(0.00008)
Return, t-3	-0.00005	0.00006
	(0.00006)	(0.00008)
Return, t-4	0.00012	0.00005
	(0.00010)	(0.00006)
N	7223	7195
R2	0.05639	0.03875
Adj.R2	0.01875	0.00025
Stock FE	Yes	Yes
Trading Day FE	Yes	Yes
Clustered SE	Yes	Yes

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table A.2: **Intraday Regression for Aggressive and Passive Small Neutrals**

This table presents estimated coefficients for the regression in Equation 1.1. The dependent variable is the imbalance for aggressive and passive small neutrals category which is defined as the net position over the total market trade volume for each stock, trading days, ten minutes. $\alpha_1 R_{i,d}$ stands for the previous day return whereas $R_{i,t}$ stands for contemporaneous and lagged 10 minutes returns. The sampling frequency is 10 minutes. Standard errors are clustered at stock level. include stock, trading day and ten minutes fixed effect.

	Passive Small Neutrals	Aggressive Small Neutrals
Previous day return	0.18073 **	-0.19407 **
	(0.07691)	(0.07548)
Return, t	-7.37595 ***	7.78487 ***
	(0.77185)	(0.79076)
Return, t-1	-0.11082	-0.12659
	(0.23141)	(0.23992)
Return, t-2	0.11219	-0.05960
	(0.10323)	(0.11314)
Return, t-3	0.37020 ***	-0.39879 ***
	(0.09144)	(0.09049)
Return, t-4	0.30289 **	-0.30950 **
	(0.11900)	(0.12940)
Return, t-5	0.04900	-0.02813
	(0.11334)	(0.11578)
Return, t-6	0.26485 ***	-0.31189 ***
	(0.08964)	(0.09470)
Return, t-7	0.33175 ***	-0.35197 ***
	(0.09088)	(0.09201)
Return, t-8	0.39726 ***	-0.38855 ***
	(0.06104)	(0.06091)
N	341154	340893
R2	0.04002	0.04381
Adj.R2	0.03905	0.04285
Stock FE	Yes	Yes
Trading Day FE	Yes	Yes
Ten min FE	Yes	Yes
Clustered SE	Yes	Yes

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

A.4 Price Momentum

R_t indicates the contemporaneous and R_t shows the lagged price changes to time k which stands for the market return calculated as the ratio of average price of the transactions compared to previous average price of the transactions minus one. Equation A.1 shows the price momentum regression where the contemporaneous price is the left hand side variable and the lagged prices are shown on the left hand side.

$$R_t = \alpha + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \beta_5 R_{t-5} + \epsilon_t \tag{A.1}$$

Momentum here is defines as the rate of acceleration of stock's price which gives an idea about the speed at which the price is changing. It shows the rate of change in price movement over a period of time to help the traders determine the strength of a trend. Results for the regression shown in Equation A.1 is given below at daily and intraday - 10 minutes levels. Table 24 shows the regression results for the daily frequency. It seem that there is no significant price momentum for BIST30 index level over the year of 2019.

Table A.3: **Daily Price Momentum**

This table presents estimated coefficients for the regression shown in Equation A.1. The dependent variable is contemporaneous return for the stock. The controls are the lag market returns. The frequency of the market return is daily.

	Return, t
Return, t-1	-0.00507
	(0.00987)
Return, t-2	-0.01359
	(0.02518)
Return, t-3	-0.00172
	(0.01472)
Return, t-4	-0.01441
	(0.01356)
N	7894
R2	0.34841
Adj.R2	0.32374
Stock FE	Yes
Trading Day FE	Yes
Clustered SE	Yes

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table 25 shows the intraday price momentum for 10 minutes frequency. There is standard up and downs in 15 minutes decaying from 5 basis points to 1 points. This is consistent with the finding of Heston et. al. 2010 which documents pronounced intraday return reversals due to bid-ask bounce, and these reversals last for several trading days.

Table A.4: **Intraday Price Momentum**

This table presents estimated coefficients for the regression shown in Equation A.1. The dependent variable is contemporaneous return for the stock. The controls are the lag market returns. The frequency of the market return is ten minutes.

	Return, t
Return, t-1	0.05890
	(0.03488)
Return, t-2	-0.04323 ***
	(0.00589)
Return, t-3	-0.01273 ***
	(0.00321)
Return, t-4	-0.00841 **
	(0.00348)
Return, t-5	-0.01293 ***
	(0.00276)
Return, t-6	-0.01100 **
	(0.00454)
Return, t-7	-0.02077 ***
	(0.00251)
Return, t-8	-0.01469 ***
	(0.00306)
N	276263
Stock FE	Yes
Trading Day FE	Yes
Ten min FE	Yes
Clustered SE	Yes
R2	0.04407
Adj.R2	0.04292

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

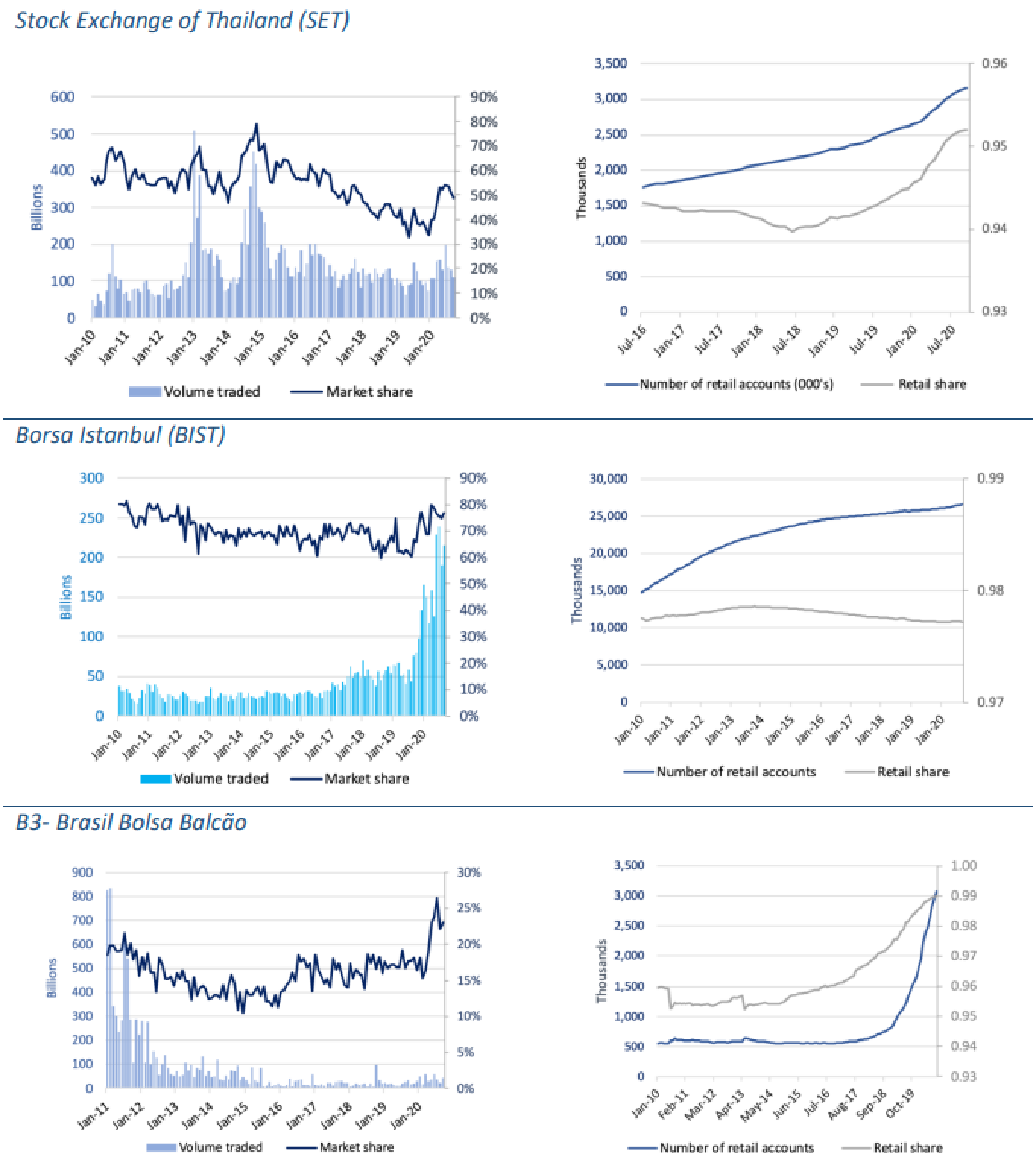

Figure A.4: **Patterns in the Evolution of Retail Traders across Exchanges**

B Appendix for Chapter 2

B.1 Exchange data

To examine the buy and sell patterns, I utilize intraday tradebook data for the stocks listed under the benchmark index BIST30 for the year 2019. This data is directly obtained from the Exchange's database. I focus specifically on regular transactions that occur during the continuous trading session, which spans a 420-minute period. Continuous trading takes place between 10:00-13:00 and 14:00-18:00 throughout the year, while all other types of trading sessions are excluded from the analysis:

- This three-digit code represents the financial intermediary involved in the transaction. These intermediaries are typically subsidiaries of banks operating in Turkey, facilitating stock market trading for domestic and foreign customers by providing account services and connections to the Exchange.
- This field combines the financial intermediary code with the user connection name, such as ABC_FIX1.
- account IDs are numerical identifiers for both the buyer and the seller.
- in order to define trading accounts, I merge the username with the account IDs and categorize them as either HFT (High-Frequency Trading) or non-HFT accounts. HFT accounts exclusively belong to individual investors or funds, whereas non-HFT accounts can be used by single or multiple investors, including portfolio accounts of financial intermediaries.
- the side variable variable indicates whether a transaction is a buy (B) or sell (A) transaction.
- the price and quantity transacted,
- the date and time in microseconds, rounded up to the nearest minute.
- a matching ID number is assigned to each trade and helps sort them chronologically within specific time intervals.

B.1.1 Buy and Sell Variables

The outcome variables, denoted as $B_{i,t}$ and $S_{i,t}$, represent whether the small trader bought or sold during a specific time interval. Specifically, $B_{i,t}$ takes the value of 1 if the trader bought during that time interval, and 0 otherwise. Similarly, $S_{i,t}$ takes the value of 1 if the trader sold during that time interval, and 0 otherwise.

To analyze the trading patterns of the small trader, we include the lagged buy and sell variables, denoted as $B_{i,t-1}$ and $S_{i,t-1}$, as controls. These variables capture the small trader's buying and selling behavior in the previous time interval, providing insights into their trading patterns.

B.1.2 Price Variables

The variable R_{t-k} represents both contemporaneous and lagged price changes up to time k, indicating the market return. It is calculated as the ratio of the average price of the transactions to the previous average price of the transactions, subtracted by one.

B.2 Price Momentum

R_t denotes the contemporaneous price changes, while R_{t-k} represents the lagged price changes up to time k. These variables are used in the price momentum regression, as shown in Equation 1. The left-hand side variable of the regression is the contemporaneous price, while the lagged prices are shown on the right-hand side.

$$R_t = \alpha + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_3 R_{t-3} + \beta_4 R_{t-4} + \beta_5 R_{t-5} + \epsilon_t \quad \text{(B.1)}$$

The results for the regression shown in Equation B.1 are presented below in Table B.1 for the daily level and Table B.2 for the intraday level.

In this study, momentum is defined as the rate of acceleration of a stock's price, providing insight into the speed at which the price is changing. It reflects the rate of price movement over a specific time period, assisting traders in assessing the strength of a trend. Table B.1 reveals that there is no significant price momentum observed for the GARAN.E stock on a daily level throughout the year 2019.

Table B.1: **Daily Price Momentum**

This table presents estimated coefficients for the regression shown in Equation B.1. The dependent variable is contemporaneous return for the stock. The controls are the lag market returns. The frequency of the market return is daily.

	Return, t
Return, t-1	0.01700
	(0.07090)
Return, t-2	-0.04926
	(0.06575)
Return, t-3	0.04831
	(0.07581)
Return, t-4	-0.02212
	(0.07822)
Return, t-5	-0.02565
	(0.06597)
N	242
R2	0.00614
Adj.R2	-0.01492

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table B.2 presents the intraday price momentum results at a 15 minutes frequency. The findings indicate a consistent pattern of standard ups and downs, with the magnitude decaying from 20 basis points to 2 points. These results align with the findings of Heston et al. (2010), who documented pronounced intraday return reversals attributed to bid-ask bounce. Furthermore, their research revealed that these reversals tend to persist for several trading days.

Table B.2: **15 minutes Price Momentum**

This table presents estimated coefficients for the regression shown in Equation B.1. The dependent variable is contemporaneous return for the stock. The controls are the lag market returns. The frequency of the market return is 15 minutes.

	Return, t
Return, t-1	0.20179 ***
	(0.01892)
Return, t-2	-0.09454 ***
	(0.01792)
Return, t-3	-0.04908 ***
	(0.01494)
Return, t-4	-0.05059 ***
	(0.01840)
Return, t-5	-0.06741 ***
	(0.01781)
Return, t-6	-0.02935 *
	(0.01702)
Return, t-7	-0.02516 *
	(0.01515)
Return, t-8	-0.03328 **
	(0.01393)
N	5511
R2	0.13867
Adj.R2	0.09722
Trading Day FE	Yes

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

B.3 Robustness Check for the Trader Categorization

Figure B.1 displays the stability of small traders' categorization throughout the trading year. The categorization approach of the traders is averaged over the entire year, and this figure illustrates the ratio of their trading category stability. The y-axis represents the stability rate, while the x-axis displays the names of the stocks in the benchmark BIST30 index. The stability rate is calculated by dividing the number of days when a trader is categorized as a small trader on a daily basis by the total number of trading days in 2019.

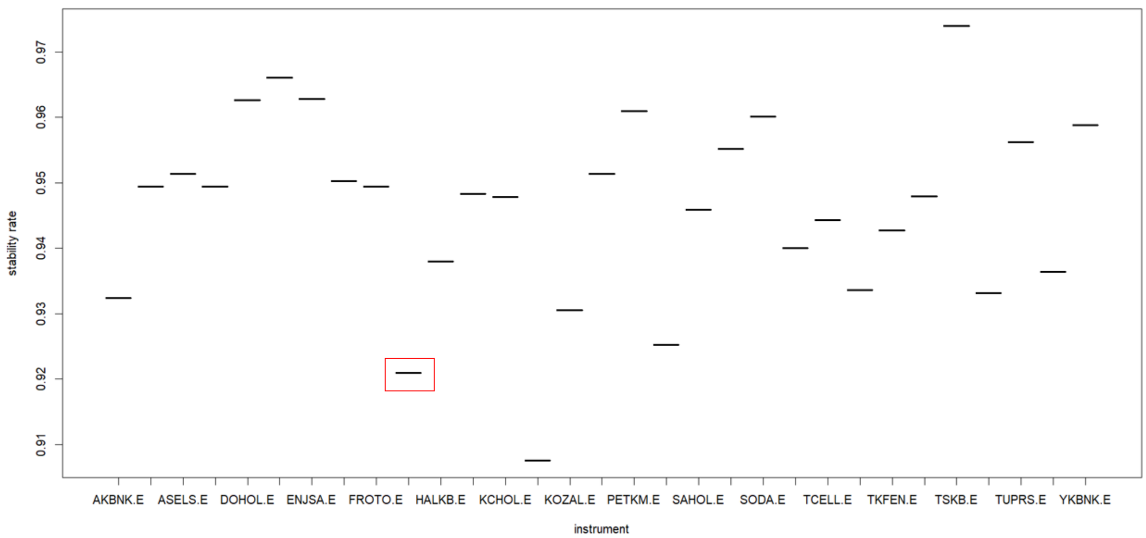

Figure B.1: **Stability of the Small Traders' Category across the Stock**

This figure presents number of small trader trading accounts versus BIST30 index for each of the trading day over the data sample.

The square with the red line represents the stability rate of the GARAN.E stock, which is approximately 92%. This suggests that on almost 92% of the trading days, small traders classified as average traders also remain classified as small traders on a day-specific level. This finding supports the stability of the categorization approach for small traders over time.

B.4 Trading Sessions

In the year 2019, there were 248 trading days, consisting of 7 hours, equates to 420 minutes continuous trading. This further breaks down into 28 fifteen-minute intervals of continuous trading.

C Appendix for Chapter 3

C.1 Exchange Data

For estimating the effect of price changes on changes in holdings, I use intraday tradebook data for benchmark index BIST30 stocks for the sample period spanning from March 18 to 29, 2019. It is directly taken from the Exchange's database. From this data, I examine all regular transactions occuring during the 420-minute period where continuous trading occurs between 10:00-13:00 and 14:00-18:00 for each of the ten days. I exclude all other sessions except continuous trading. Actually, there is an opening session where one minute trade is possible with one price at 09:55 and midday session at 13:55, also closing session at 18:05 and another session in which trades at closing/last price realized between 18:08-18:10. However, I exclude them since they are so few in numbers and not continuous trading in nature. I use following fields from tradebook data;

- field for the abbreviation (3 digits) of the financial intermediary. Financial intermediaries are usually the subsidiaries of banks operating in Turkey. They have been serving domestic and foreign customers who wants trade in stock market by opening an account and providing connection to the Exchange.
- a field for user connection type which reveals an information about the connection type of the user to the Exchange whether high frequency or not. There are three types of users in terms of connection protocols such as FIX[20], HFT types[21].
- field for username is the merged column of financial intermediary and its user connection name such ABC_FIX1
- account IDs for the buyer and the seller, these are numbers.
- In order to define trading accounts, I merge username with account IDs and label the ones having HFT connection type as HFT, and the rest as non-HFT. For the HFT accounts, it is mandatory to be used only one entity such as an individual investor or fund but for the

[20]**FIX:** Servers for these users can be either in colocation or not. This user type is the mostly used standard electronic protocol for pre-trade communications and trade execution.

[21]**HFT:** Servers for these users are located at colocation. These accounts are the ones that reports themselves as HFT to Exchange and they are subject to order to trade fees for order updates and cancellation and also have to commit that they use proper risk management tools.

non-HFT accounts, they can be either used by single or multiple investor, even as an portfolio account of a financial intermediary.

- the price and quantity transacted,
- the date and time in microseconds, rounded up to the nearest minute.
- a matching ID number that sorts trades into chronological order within one minute.
- field indicating whether the trade resulted from a limit or market order.
- field for aggressiveness indicator stamped by the matching engine as "P" for a resting order and "A" for an order that executed against a resting orders.

C.1.1 Holdings Variables

$\Delta y_{i,t}$, change in holdings (in stocks) in Equation 3.2 is the outcome variable of the analysis. Net position or holding changes of each subset of intraday intermediaries in terms of stocks for each stock and one minute interval. Net position means the difference between buy positions and sell position. For each trading account, net positions for one minute is calculated and then, they aggregated accordingly to the subset of which trading account belongs. $\Delta y_{i,t-1}$ stands for the lagged change in holdings (in stocks) for each minute of the trading day. $y_{i,t-1}$ is the lagged holding level (in stocks). All of the mentioned series of holding variables are standardized by the standard deviation of each stock and trading day in order to have a standard interpretation across different stocks.

C.1.2 Price Variables

$\Delta p_{i,t-k}/c_i$ denotes the price change in each stock scaled by the stock's tick size[22]. Price changes are calculated for each minute as the average of trade prices in the tradebook. c_i is the tick size of the ith stock. In order to interpret the effect of price changes on holding changes, I convert price changes into the number of ticks, I divide each price changes by the corresponding tick size of the stock.

[22]There are four different type of tick size in BIST30 stocks depending on the price interval of the stock

C.2 Additional Robustness Checks

Table C.1: **Intraday Intermediaries - March 28**

This table presents estimated coefficients for the regression in Equation 3.2. The dependent variable is the change in the holdings (in stocks) of HFT and non-HFT intraday intermediaries. Both changes in holdings, $\Delta y_{i,t-1}$ and $y_{i,t-1}$ are in stocks. Price changes, $\Delta p_{i,t}$, are in ticks. The sampling frequency is one minute. Observations are stacked from May 18 through 28. IV model estimators with three model specifications are indicated. Model has both stock and trading days and trading hours fixed effects.

VARIABLES	Agressive HFT	Passive HFT	Agressive non-HFT	Passive non-HFT
lagged net position change	0.0122**	0.00371	0.00875	0.00930
	(0.00491)	(0.00572)	(0.00649)	(0.00653)
lagged net position	-0.739***	-0.707***	-0.706***	-0.679***
	(0.00415)	(0.00492)	(0.00572)	(0.00529)
contemporaneous price	2.623***	-1.826***	0.868***	-1.612***
	(0.535)	(0.259)	(0.175)	(0.283)
lagged price change - 1 min	1.432***	-1.313***	0.693***	-0.945***
	(0.309)	(0.199)	(0.168)	(0.196)
lagged price change - 2 min	1.177***	-1.378***	0.682***	-0.885***
	(0.183)	(0.195)	(0.153)	(0.162)
lagged price change - 3 min	0.609***	-1.015***	0.420***	-0.665***
	(0.142)	(0.149)	(0.124)	(0.135)
lagged price change - 4 min	0.483***	-0.744***	0.407***	-0.332***
	(0.133)	(0.134)	(0.0870)	(0.0997)
lagged price change - 5 min	0.229**	-0.435***	0.129**	-0.183**
	(0.0885)	(0.0828)	(0.0610)	(0.0797)
March 28- lagged net position	-0.0147*	-0.00590	-0.00696	-0.0111
	(0.00857)	(0.00827)	(0.00553)	(0.00722)
March 28- contemporaneous price change	-1.332	0.272	-0.738**	0.329
	(0.928)	(0.604)	(0.309)	(0.523)
March 28- lagged price change - 1 min	-1.307***	0.108	-0.686***	0.278
	(0.481)	(0.407)	(0.238)	(0.242)
March 28- lagged price change - 2 min	-1.001***	0.234	-0.670***	0.433
	(0.348)	(0.466)	(0.195)	(0.283)
March 28- lagged price change - 3 min	-0.457*	0.123	-0.494***	0.150
	(0.249)	(0.340)	(0.160)	(0.187)
March 28- lagged price change - 4 min	-0.528***	0.0185	-0.444***	0.0776
	(0.159)	(0.244)	(0.123)	(0.256)
March 28- lagged price change - 5 min	-0.222	-0.0975	-0.222**	-0.0676
	(0.175)	(0.136)	(0.0979)	(0.143)
Observations	111,097	110,684	106,141	107,380
R-squared	0.537	0.498	0.491	0.474
Stock FE	-	-	-	-
Stock*Trading day FE	Yes	Yes	Yes	Yes
Trading Hours FE	Yes	Yes	Yes	Yes

Standard errors clustered by stock level in all models.
*** p<0.01, ** p<0.05, * p<0.1

Table C.2: **Intraday Intermediaries - March 25**

This table presents estimated coefficients for the regression in Equation 3.2. The dependent variable is the change in the holdings (in stocks) of HFT and non-HFT intraday intermediaries. Both changes in holdings, $\Delta y_{i,t-1}$ and $y_{i,t-1}$ are in stocks. Price changes, $\Delta p_{i,t}$, are in ticks. The sampling frequency is one minute. Observations are stacked from May 18 through 25. IV model estimators with three model specifications are indicated. Model has both stock and trading days and trading hours fixed effects.

VARIABLES	HFT	non-HFT
lagged net position change	0.0170***	0.00753
	(0.00649)	(0.00830)
lagged net position	-0.739***	-0.701***
	(0.00522)	(0.00652)
contemporaneous price	2.103***	0.551***
	(0.507)	(0.176)
lagged price change - 1 min	1.109***	-0.179
	(0.287)	(0.163)
lagged price change - 2 min	0.670***	-0.212
	(0.233)	(0.150)
lagged price change - 3 min	0.394***	-0.363**
	(0.127)	(0.159)
lagged price change - 4 min	0.329**	0.0535
	(0.140)	(0.125)
lagged price change - 5 min	0.0788	-0.175
	(0.114)	(0.110)
March 25- lagged net position	-0.00581	0.0118
	(0.00637)	(0.00824)
March 25- contemporaneous price change	-0.462	-0.102
	(1.036)	(0.419)
March 25- lagged price change - 1 min	0.00717	-0.243
	(0.492)	(0.418)
March 25- lagged price change - 2 min	-0.0353	0.0183
	(0.354)	(0.307)
March 25- lagged price change - 3 min	-0.199	0.184
	(0.218)	(0.368)
March 25- lagged price change - 4 min	-0.131	-0.130
	(0.283)	(0.255)
March 25- lagged price change - 5 min	-0.170	0.171
	(0.277)	(0.142)
Observations	74,340	71,449
R-squared	0.530	0.483
Stock FE	-	-
Stock*Trading day FE	Yes	Yes
Trading Hours FE	Yes	Yes

Standard errors clustered by stock level in both models.
*** p<0.01, ** p<0.05, * p<0.1

Table C.3: **Intraday Intermediaries - March 26**

This table presents estimated coefficients for the regression in Equation 3.2. The dependent variable is the change in the holdings (in stocks) of HFT and non-HFT intraday intermediaries. Both changes in holdings, $\Delta y_{i,t-1}$ and $y_{i,t-1}$ are in stocks. Price changes, $\Delta p_{i,t}$, are in ticks. The sampling frequency is one minute. Observations are stacked from May 18 through 26. IV model estimators with three model specifications are indicated. Model has both stock and trading days and trading hours fixed effects.

VARIABLES	HFT	non-HFT
lagged net position change	0.0191***	0.00868
	(0.00581)	(0.00749)
lagged net position	-0.741***	-0.700***
	(0.00458)	(0.00596)
contemporaneous price	2.001*	-0.565***
	(0.442)	(0.161)
lagged price change - 1 min	1.112**	-0.229
	(0.242)	(0.151)
lagged price change - 2 min	0.660**	-0.207
	(0.191)	(0.132)
lagged price change - 3 min	0.350***	-0.321**
	(0.104)	(0.149)
lagged price change - 4 min	0.308**	-0.0817
	(0.122)	(0.109)
lagged price change - 5 min	0.0373	-0.132
	(0.0987)	(0.0895)
March 26- lagged net position	-0.648	-0.0101
	(0.509)	(0.00750)
March 26- contemporaneous price change	-0.495	-0.0693
	(0.836)	(0.309)
March 26- lagged price change - 1 min	-0.648	0.00169
	(0.509)	(0.370)
March 26- lagged price change - 2 min	-0.460*	-0.0223
	(0.267)	(0.299)
March 26- lagged price change - 3 min	-0.559**	0.193
	(0.221)	(0.268)
March 26- lagged price change - 4 min	-0.383**	0.0727
	(0.176)	(0.183)
March 26- lagged price change - 5 min	-0.212	0.199*
	(0.138)	(0.118)
Observations	86,730	84,426
R-squared	0.532	0.484
Stock FE	-	-
Stock*Trading day FE	Yes	Yes
Trading Hours FE	Yes	Yes

Standard errors clustered by stock level in both models.
*** p<0.01, ** p<0.05, * p<0.1

Table C.4: **Intraday Intermediaries - March 29**

This table presents estimated coefficients for the regression in Equation 3.2. The dependent variable is the change in the holdings (in stocks) of HFT and non-HFT intraday intermediaries. Both changes in holdings, $\Delta y_{i,t-1}$ and $y_{i,t-1}$ are in stocks. Price changes, $\Delta p_{i,t}$, are in ticks. The sampling frequency is one minute. Observations are stacked from May 18 through 29. IV model estimators with three model specifications are indicated. Model has both stock and trading days and trading hours fixed effects.

VARIABLES	HFT	non-HFT
lagged net position change	0.0172***	0.00616
	(0.00485)	(0.00614)
lagged net position	-0.747***	-0.701***
	(0.00409)	(0.00489)
contemporaneous price	1.339***	-0.565***
	(0.317)	(0.116)
lagged price change - 1 min	0.429**	-0.283***
	(0.184)	(0.0993)
lagged price change - 2 min	0.241**	-0.223***
	(0.119)	(0.0726)
lagged price change - 3 min	-0.00566	-0.275***
	(0.0793)	(0.0783)
lagged price change - 4 min	-0.0131	-0.0563
	(0.0754)	(0.0633)
lagged price change - 5 min	-0.0353	-0.102*
	(0.0808)	(0.0536)
March 29- lagged net position	0.0124*	-0.000932
	(0.00651)	(0.00660)
March 29- contemporaneous price change	-0.396	-0.102
	(0.990)	(0.256)
March 29- lagged price change - 1 min	-0.361	0.0658
	(0.477)	(0.258)
March 29- lagged price change - 2 min	-0.142	-0.414
	(0.485)	(0.263)
March 29- lagged price change - 3 min	0.0910	0.0440
	(0.255)	(0.248)
March 29- lagged price change - 4 min	-0.417**	0.129
	(0.194)	(0.161)
March 29- lagged price change - 5 min	-0.315**	-0.0851
	(0.138)	(0.144)
Observations	123,487	118,944
R-squared	0.538	0.485
Stock FE	-	-
Stock*Trading day FE	Yes	Yes
Trading Hours FE	Yes	Yes

Standard errors clustered by stock level in both models.
*** p<0.01, ** p<0.05, * p<0.1

Table C.5: **Intraday Intermediaries - All trading days**

This table presents estimated coefficients for the regression in Equation 3.1. The dependent variable is the change in the holdings (in stocks) of HFT and non-HFT intraday intermediaries. Both changes in holdings, $\Delta y_{i,t-1}$ and $y_{i,t-1}$ are in stocks. Price changes, $\Delta p_{i,t}$, are in ticks. The sampling frequency is one minute. Observations are stacked from May 18 through 29. Models include both stock and trading days and trading hours fixed effects.

VARIABLES	HFT	non-HFT
lagged net position change	0.0173***	0.00622
	(0.00485)	(0.00615)
lagged net position	-0.746***	-0.701***
	(0.00410)	(0.00483)
contemporaneous price	1.303***	-0.574***
	(0.299)	(0.107)
lagged price change - 1 min	0.395**	-0.277***
	(0.171)	(0.0928)
lagged price change - 2 min	0.227*	-0.258***
	(0.117)	(0.0715)
lagged price change - 3 min	0.000388	-0.272***
	(0.0757)	(0.0741)
lagged price change - 4 min	-0.0498	-0.0455
	(0.0752)	(0.0593)
lagged price change - 5 min	-0.0644	-0.110**
	(0.0776)	(0.0512)
Observations	123,487	118,944
R-squared	0.537	0.485
Stock FE	-	-
Stock*Trading day FE	Yes	Yes
Trading Hours FE	Yes	Yes

Standard errors clustered by stock*trading day level in both models.
*** p<0.01, ** p<0.05, * p<0.1

Table C.6: **Intraday Intermediaries - 5 minutes**

This table presents estimated coefficients for the regression in Equation 3.1. The dependent variable is the change in holdings (in stocks) of HFT and non-HFT intraday intermediaries. Both changes in holdings, $\Delta y_{i,t-1}$ and $y_{i,t-1}$ are in stocks. Price changes, $\Delta p_{i,t}$, are in ticks. The sampling frequency is five minutes. Observations are stacked from May 18 through 29. IV estimators with three model specifications are indicated. Models include both stock and trading days and trading hours fixed effects.

VARIABLES	HFT	non-HFT
lagged net position change	0.0349***	0.0239**
	(0.0101)	(0.0108)
lagged net position	-0.787***	-0.727***
	(0.00913)	(0.00904)
contemporaneous price	-0.263***	-0.137*
	(0.0638)	(0.0731)
lagged price change - 5 min	-0.380***	-0.216*
	(0.0680)	(0.129)
lagged price change - 10 min	-0.438***	-0.297**
	(0.0894)	(0.126)
lagged price change - 15 min	-0.379***	-0.203
	(0.0831)	(0.133)
lagged price change - 20 min	-0.296***	-0.177**
	(0.0767)	(0.0756)
lagged price change - 25 min	-0.177**	-0.0452
	(0.0524)	(0.0466)
March 27- lagged net position	-0.0247***	0.00181
	(0.0106)	(0.0132)
March 27- contemporaneous price change	0.0534	-0.163
	(0.168)	(0.233)
March 27- lagged price change - 5 min	0.0439	0.0542
	(0.204)	(0.224)
March 27- lagged price change - 10 min	0.154	0.202
	(0.293)	(0.223)
March 27- lagged price change - 15 min	0.0305	0.0891
	(0.226)	(0.198)
March 27- lagged price change - 20 min	-0.00899	-0.0384
	(0.150)	(0.145)
March 27- lagged price change - 25 min	0.0279	-0.0417
	(0.0976)	(0.124)
Observations	23,023	22,099
R-squared	0.587	0.499
Stock FE	-	-
Stock*Trading day FE	Yes	Yes
Trading Hours FE	Yes	Yes

Standard errors clustered by stock level in both models.
*** p<0.01, ** p<0.05, * p<0.1