HIGH-FREQUENCY TRADING AND MARKET QUALITY: CASE OF A "SLIGHTLY EXPOSED" MARKET

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Abstract

Impacts of high-frequency trading (HFT) on market quality and on other agents have been broadly studied in recent years. However, what happens when HFT is not a prominent figure in a market is a relatively unexplored question. This paper seeks to answer this question focusing on 30 blue chip stocks in an emerging market, BIST through Dec 2015 to Mar 2017. Despite a low share in the overall activity (3.2% in number of orders and 2% in volume of orders), HFT has observable effects. Liquidity provision by non-HFT traders has significantly reduced. HFT activity on sell side induces higher volatility. HF traders generate profits on both positive and negative days. These findings support the concerns regarding the effects of HFT with a different perspective, i.e. potential externalities are not special to the markets with HFT dominance.

Keywords: high-frequency trading (HFT), liquidity provision, volatility, returns

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1. Introduction

If a person spending eight hours in sleep on an average day could alter this with just 0.03 second without any side effects, this would be considered as a huge cut. Days when a person can make a round trip between Oslo and Cape Town in 0.1 second will definitely be much more different than today. Being capable of doing another activity in one millionth of the time we used to spend two decades ago is what many researchers broadly examine today.

Thanks to new microchips, orders can now be submitted in 740 billionth of a second (O'Hara, 2015). High-frequency trading (HFT) is an algorithmic trading (AT) type, which involves in heavy order submission activity within low latencies, i.e. as low as nanoseconds. As of 2008 and 2009, HFT accounted for 42% of trading volume in the large cap stocks listed in NASDAQ and NYSE (Brogaard et al., 2014). By then, 26 HFT firms participated in 73.8% of all trades in U.S. equity market (Brogaard, 2010). Hagströmer and Norden (2013) report 25% to 50% HFT participation in the trading activity of 30 most traded stocks in Sweden. Based on the rest of the literature, Menkveld (2014) concludes on 30% to 70% HFT involvement in developed markets. Excessive order cancellation is a phenomenon brought by HFT. O'Hara (2015) reports that more than 98% of all orders are cancelled. Moreover, 23% of orders are cancelled within 50 milliseconds (ms), much faster than 400-500 milliseconds, a time period it takes for the human eye to respond to a visual stimulus. The ability to trade fast is gained after heavy investments. A 3 ms reduction in the information transmission time between Chicago and New York markets costs an estimated $500m (Laughlin et al., 2014). In response to heavy investments, estimated profits of HFT are suggested to be large. Brogaard (2010) estimates a total annual profit of $3 billion for the U.S. stock market activity of 26 HFT firms in 2008-2009. However, being the fastest trader promises much more, i.e. the opportunity to enter and exit more favorable positions than the rest of the market and obtain the lion's share in the overall profits (Baron et al., 2012).

Based on this figure, various research questions arise. Is HFT beneficial or harmful for the markets? Relatedly, are non-high-frequency traders (nonHFTrs) better off in speedy markets?[3] More generally, how is the welfare of the society affected?

While there exist branches of literature focused on each of these questions, they are highly interrelated. Vast majority of the related research is recent and examine developed markets with large HFT participation. Findings being mostly concentrated on the last decade of developed markets brings an additional question for consideration. *What are the implications of fast trading when the market is dominated by slow traders?* This paper aims to provide answers regarding this central question.

Chordia et al. (2013) stress that "Hasbrouck and Saar (2013) do not claim that a market dominated by HFTs is inherently better than a market dominated by human traders. … The findings are limited to the current market environment in which HFTs dominate the scene. … The question of whether financial markets before the advent of HFTs were better or worse than today's HFT-dominated markets remains unanswered."

The raised question is important with respect to several aspects. First, possible alternative mechanisms for financial markets and potential regulations and restrictions against HFT are increasingly discussed. In response to suggested drawbacks of ultra-fast trading environment, several researchers argue for high-frequency series of batch auctions, continuous order submission accompanied with discrete clearing periods of one second or less (see e.g. Menkveld, 2014 and Budish et al., 2015). A few restrictive actions include the change in regulatory fees in Canada (Malinova et al., 2013), introduction of an order-to-trade ratio (OTR) fee in Italy (Friederich and Payne, 2015) and introduction of fees on high OTRs in Norway (Jorgensen et al., 2017). From this perspective, the attempt to address this question can be considered as futuristic. Second, it aims to provide insight in the introduction phase of HFT in emerging markets. HFT activity in emerging markets is currently low, but rising. Haldane

[3] HFTrs, fast traders and low latency traders are used interchangeably throughout the paper. Similarly, nonHFTrs and slow traders are used in place of each other.

(2012) estimates 5-10% HFT share in total volume in Asian markets. Ekinci and Ersan (2018) report HFT accounts for 2.9% (1.2%) of the orders submitted in 30 largest cap (overall) stocks listed in Borsa Istanbul (BIST) in a 2015 dataset. Thus, the exploration of the issue is essential for a healthy transition and/or preservation of a robust financial system.

Regarding several properties, current status of Borsa Istanbul (BIST) is a well-suited environment for inquiring the issue. First, HFT activity is available and observable. Recent improvements and technological upgrades including the introduction of BISTECH platform and colocation service allow for HFT activity. Besides, the activity is evident and detectable from order and trade data. Second, it is documented that recent level of HFT is considerably low, clearly far from dominating the market. Third, the exchange represents one of the largest emerging markets with significant trading activity and potential[4].

We examine the impacts of HFT activity on several market characteristics such as liquidity provision by nonHFTrs, stock price volatility and excess returns. By these specifications, we aim to address ongoing discussions on HFT, i.e. the concerns about its effects regarding crowding out of other traders, deteriorating market quality, significant HFT profits against the incurred costs to nonHFTrs.

Our main findings are threefold. First, liquidity provided by nonHFTrs is lower when HFT involvement in orders is higher. Thus, we argue that HFT, despite its low participation rate, may still have a crowding out effect imposed on other traders. Second, we provide evidence for the excess returns generated by HFT. On days with large buy (sell) side HFT share, excess returns are substantially higher (lower). We do not have an account-based dataset disabling a detailed profit analysis. However, HFTrs are more likely to be on the right side of the market. These two findings on nonHFT liquidity provision and excess returns together imply that HFTrs maintain benefits on the cost of other traders.

[4] Boehmer et al. (2015) report that in terms of median number of messages per stock, Borsa Istanbul is 6th among 42 countries (following NYSE, Shanghai, NASDAQ, Shenzhen and Euronext Amsterdam) by 2011. For the period of our study, Dec. 2015 – Mar. 2017, daily average number of orders submitted in total of 30 blue chip stocks is 223,207. Therefore, our findings may equally have implications for developed markets with similar large trading activity, regarding the researchers' suggestions on realizing restrictions and/or barriers to HFT.

Our third finding regards price volatility in the examined stocks. We do not observe a consistent and strong relationship between overall HFT activity and volatility. An exception is the worsening impact of sell side HFT, i.e. a stock's price is more volatile on days with larger HFT activity on sell side order volume. This fact is in line with increased uncertainty arising from sell side pressure by sophisticated traders (see e.g.). Two findings, namely, lower liquidity provision by nonHFTrs and occasionally higher volatility, together reflect a potential deterioration in market quality.

The paper provides new ground for the pronounced concerns, that is, negative externalities of HFT is not special to developed markets with HFT dominance. Instead, these impacts may arise even in a market where HFT activity is considerably low. This proposition suggests that restrictions on HFT activity targeting a narrower HFT involvement may not fully cancel potential drawbacks of HFT. On the other hand, structural changes such as introduction of discrete call auctions may be better alternatives.

The rest of the paper is organized as follows. In a review of the literature, Section 2 presents relevant issues about HFT. Section 3 explains the data, variables and methodology. Section 4 reports the findings and Section 5 concludes.

2. Review of Literature

There is a broad literature embodied in the last decade on HFT and its impacts on financial markets. While there exists ample evidence, both empirical and theoretical, there is large dispersion among studies, leading to disagreements and ongoing debates. Several discussion papers have been released and surveys have been conducted surrounding various aspects of HFT in financial markets (See O'Hara, 2015; Stiglitz, 2014; and Biais and Foucault, 2014 for discussions, and Jones, 2013; Goldstein et al., 2014; and Chung and Lee, 2016 for surveys). Besides, a number of studies examine the effects of algorithmic trading on market quality.[5] However, this paper mainly deals with the speed advantage in

[5] See for example Hendershott et al. (2011), Hendershott and Riordan (2013), Chaboud et al. (2014) and Frino et al. (2014) among others.

financial markets and its consequences. Therefore, studying the investor type, whether human or computer, is not our primary focus.

How HFT affects market quality is studied with respect to changes in various market quality measures and to other exogenous factors. Asked by many agents, liquidity is a main component for a financial market. Several papers suggest that HFT improves overall market liquidity. For example, Brogaard (2010) analyzes whether high-frequency traders (HFTrs) provide better inside quotes more frequently than nonHFTrs and whether the price impact of trades in the presence of HFT limit orders, reaching the conclusion that HFT plays an essential part in liquidity provision. Similarly, Jarnecic and Snape (2014) observe that HFTrs submit orders at multiple prices, mostly at or within the quote, leading to continuous liquidity provision to the market. It is also suggested that HFT remedies for temporal liquidity imbalances. Hasbrouck and Saar (2013) find that increased levels of HFT yield increased liquidity indicated by lower bid-ask spreads. Moreover, positive effect of HFT on liquidity is larger in amount through more stressful market conditions with high economic uncertainty.

Most of the relevant studies examining liquidity utilize bid-ask spreads. On the other hand, as a measure of liquidity, changes in bid-ask spread may not fully represent the liquidity impact of HFT on market participants. Jovanovic and Menkveld (2016) show that spreads are lower following the entry of better informed middlemen, HFTrs, however this time, prices sent by market participants are strategically picked off by middlemen resulting in a push towards the loss of spread.

Literature reveals other fields for objection to the positive impact of HFT on liquidity. Hasbrouck and Saar (2009) inquire the quality of HFT liquidity provision in response to the “fleeting nature” of short-lived limit orders of HFTrs. Egginton et al. (2014) provide evidence on worsened liquidity when there is excessive quoting activity. Baron et al. (2012) report that HFT firms consuming liquidity most aggressively earn the largest profits. According to Kirilenko et al. (2017), HFTrs consumed large amount of liquidity through the further stages of 2010 Flash Crash.

Price discovery (and price efficiency) is another aspect in the realized impacts of HFT on financial markets. For example, Brogaard et al. (2014) show that HFT plays significant role in price discovery. Brogaard (2010) documents that HFTs add more to price discovery process when compared to non-HFTs. Martinez and Rosu (2013) suggest that HFT makes news incorporate into prices faster, resulting in increased price efficiency. On the contrary, Zhang (2010) claims that HFT plays a negative role in the incorporation of firm-specific news to the prices through overreaction to news. Similarly, Lee (2015) reports that HFT deteriorates price discovery in Korean index futures market. In the theoretical model of Foucault et al. (2016), two effects of the trading of fast speculator, i.e. negative (positive) effects of HFT with anticipation of short run (long run) price changes, offset each other, resulting in unaltered speed of price discovery.

Also related to the price discovery process, whether HFT dampens or boosts volatility in prices is another discussion topic. Hasbrouck and Saar (2013) suggest that HFT decreases stock price volatility, the relation being stronger in worsened market conditions. Hagströmer and Norden (2013) find that market making activity of HFT decreases price volatility. On the other hand, Dichev et al. (2014) and Ye et al. (2013) provide evidence for the fact that HFT exacerbates intraday volatility. Finally, several papers do not observe an HFT impact on volatility (See e.g. Groth, 2011; Gsell, 2008).

Study of unfavorable market conditions are essential in evaluating the impact of HFT. Whether HFT ameliorates or exaggerates these conditions is important for the well-functioning of financial markets. Examining the surrounding of Flash Crash event, Kirilenko et al. (2017) suggest that on the contrary to the market makers, HFTrs played an important role by liquidating large positions. In a related study with a broader focus, Brogaard et al. (2016) analyze extreme price movements. Detected liquidity provision from HFTrs to nonHFTrs is shown to mitigate trade imbalances around extreme price movements (EPMs). However, when multiple stocks experience EPMs simultaneously, HFT's liquidity demand is higher than its supply. Brogaard et al. (2017) study trading activity in U.S stocks through 2008 short sale ban period characterized by high volatility. They find that liquidity reduction is larger for the large cap stocks in which HFT activity is much more substantial. Similarly, Gao and Mizrach (2016) suggest that HFT significantly increases the market breakdown frequency. In a recent study, Hautsch et al. (2017) study HFT activity around effective macroeconomic news arrivals and around turbulent periods such as Brexit announcement in 2016 and Greek debt crisis in 2015. The authors argue towards a mixed effect of HFT around announcements. Specifically, HFTrs seem to act as market makers providing liquidity following the announcements while they widen spreads shortly preceding these events resulting in liquidity shortage. Additionally, in case of turbulent periods, HFTrs mostly alter their market making activities with aggressive strategies having a distorting effect on the market.

The fact that HFTrs obtain significant profits in their trading activities is supported by the evidence regarding the relationship between HFT and asset returns. Brogaard et al. (2014) report that HFT orders predict price changes in short run and they are correlated with market-wide returns. Hirschey (2017) shows that anticipatory trading of HFTrs ahead of nonHFTrs is profitable. The stocks aggressively bought (sold) by HFTrs yield positive (negative) future returns. Mahmoodzadeh and Gençay (2017) provide similar evidence on how HFTrs absorb the benefits of a reduction in tick size by front running slow traders.

HFT strategies such as anticipatory trading, can result in excess profits for HFTrs and incur costs to nonHFTrs, such as adverse selection. Brogaard (2010) documents that HFTrs trade with other HFTrs (nonHFTrs) less (more) than expected. McInish and Upson (2011) show that in the U.S. HFTrs adversely select slower traders who submit at inferior prices, generating substantial annual profits. Biais et al. (2015) theoretically explain the increased adverse selection cost for the rest of the market when a group of traders get extra speed and so the ability to search for better quotes in fragmented markets. 'Algorithmic trading adverse selection risk' is named after higher adverse selection costs due to liquidity supplying algorithmic traders' strategic management of resting orders in a multi-market trading environment (Upson and Van Ness, 2017). The analysis of HFT profits in Baron et al. (2012) reveals that HFTrs earn most of their profits from their trades with opportunistic traders.[6]

Consequently, a central negative externality of HFT is its crowding out effect on other traders. Breckenfelder (2013) shows that HFT competition results in increased HFT volume but no significant change in total volume. Non high-frequency liquidity providers are considered as potential traders to be crowded out. Similarly, Biais et al. (2015) suggest that adverse selection induced by HFT may cause lower rate of market participation by crowding out slow traders.

Since even marginal differences in speed matter, Baron et al. (2017) propose that HFT activity will always be dominated by few firms and there will be one firm that will be able to imply adverse selection costs for all the remaining. In line with this, Biais et al. (2015) and Budish et al. (2015) show that HFT competition may result in market concentration. Breckenfelder (2013) provides evidence on the fact that HFT competition may impair market quality in terms of liquidity and short-term volatility.

Whether social welfare is deteriorated by HFT is closely related to incurred adverse selection costs and crowding out effect. Cartea and Penalva (2013) and Hoffmann (2014) theoretically show that welfare of the liquidity traders and slow traders are worsened by the speed advantage of HFTrs. Menkveld (2014) suggests that aggressive strategies of HFTrs to pick off slow investors' quotes based on marginally earlier access to information dampens welfare. Goldstein et al. (2017) point out the welfare externality arising from the fact that nonHFT limit orders are crowded out by HFT. Stiglitz (2014) argues against faster price discovery and HFT in the context of social welfare.

Another dimension in discussing the welfare effects of HFT is the substantial technological investments. Budish et al. (2015) report that median duration of SP-SPY arbitrage opportunities declined from 97 milliseconds in 2005 to 5 milliseconds in 2011, as a consequence of heavy

[6] The authors define opportunistic traders as "medium-sized traders who either take large directional positions (but are not large enough to be classified as Fundamental traders) or who move in and out of positions throughout the day but with significantly larger fluctuations and persistence in their positions than HFTs and Non-HFT market makers. This group likely captures brokerage firms, hedgers, small institutional investors, hedge funds, and other hard-to-identify traders."

investments. Biais et al (2015) report Tabb Group estimates on 2013 investments in high speed trading technologies, i.e. $1.5 billion, twofold the investment amount in 2012. The authors underline the gap between privately and socially optimal levels of investments in an arms race of HFT firms to be the fastest. Hoffmann (2014) suggests that gaining extra speed is accompanied with market power and results in investments that are socially wasteful.

To summarize the literature, the impact of HFT on liquidity, price discovery, volatility, unfavorable market conditions such as market breakdowns and EPMs have been broadly studied. Moreover, the literature intensively inquires closely related topics such as high HFT profits, costs incurred by nonHFTrs, large technological investments for marginal speed jumps and consequent welfare implications. However, a general consensus in the literature about these effects is missing. Besides, vast majority of literature solely deal with developed markets already dominated by HFT activity, leaving room for a higher marginal contribution of findings on markets that are in the early phase of HFT.

3. Data and Methodology

3.1. Data and Market

We examine HFT activity in Borsa Istanbul (BIST) between December, 2015 and March, 2016. BIST is among the largest emerging markets with high growth potential. Daily average turnover in the equity market is 4.07 billion Turkish Lira (TL) for the examined time period. Daily traded value record was broken on July 18, 2016 with 7.43 billion TL.[7] By the end of 2016, the share of foreign investors in free-floating market capitalization was 63.4%, while the free-float rate was 41% (2016 annual report of BIST).

[7] Dollar/TL exchange rate varies between 2.79 and 3.89 throughout the study period.

Trading in BIST equity market is continuous between 10:00 – 13:00 and 14:00 – 18:00. There are three call auctions, i.e. at opening, midday and closing. Orders are collected between 09:40 – 09:55, 13:00 – 13:55 and 18:01 – 18:05; while price determination and matching take place between 09:55 – 10:00, 13:55 – 14:00 and 18:05 – 18:08. Trades at closing price are between 18:08 – 18:10.[8] There is a daily price limit of 20% for the stocks listed in the market. BIST is a limit order market. Apart from a few stocks with low turnover, there is no registered market maker. Thus the blue chip stocks in our focus do not have market maker activity. While there does not exist any identified HFT firm in Turkey, firms can make HFT activity through brokerage houses. Reported in 2016 annual report of BIST, 85 brokerage houses are authorized to trade in the equity market and 33 of these have spots in colocation.

We restrict our analysis to 30 largest cap stocks listed in BIST 30 index. The purpose of focusing on large-cap stocks is twofold. First, HFT activity is mostly concentrated in large-cap stocks, i.e. daily average of HFT rate in large-cap stocks is 2.24 times the rate in mid-cap stocks and almost 30 times the rate in small-cap stocks. Second, HFT activity is substantially low in the market, providing us with many days of zero HFT activity for small and mid-cap stocks. Brogaard et al. (2014) and Hagströmer and Norden (2013) show that HFT activity in U.S. and Sweden are also concentrated in large-cap stocks. Limiting the scope of analysis to the HFT activity in largest cap stocks is in line with studies such as Hagströmer and Norden (2013) and Baron et al. (2017). In our study, the blue chip stocks listed in BIST 30 index constitute 72% of total turnover in BIST through the specified time span. The index level at the starting and ending dates of our study are 94,147 and 109,014, respectively. Through the sixteen-month period, lowest and highest values for the index are 88,120 and 112,005, respectively.

We employ two datasets, i.e. order and trade data, in monthly basis provided by Borsa Istanbul. Order data list all the electronic messages submitted to the system including ticker, order ID number, date, submission time in seconds, trade direction (buy/sell), price, quantity and order type. Similarly, trade data include ticker, trade ID number, date, execution time in seconds, buy order ID and sell order ID,

[8] On November 14, 2016, trading hours are modified in line with changes in daylight savings. In the period prior to the modification, opening call auction started at 09:15 and closing call auction ended at 17:40.

price and quantity. We combine these two datasets for each stock on daily basis. We chronologically store electronic messages in each order so that all orders start with a submission and finalize with a cancel message (cancellation either submitted by the owner of order or done automatically by the system following the close) or execution (or partial cancellation and partial execution). We clean orders on daily basis since order validity is limited to one day in BIST.

We work with roughly 76 million orders and 102 million messages (excluding execution notifications). Table 1a provides descriptive statistics on the orders submitted in 30 blue chip stocks for 339 trading days of our study. Represented by the last row, daily average number of submitted orders in all examined stocks is 223,207. Daily average turnover of the orders in these stocks is around 9.1 billion TL, ranging from 1.5 billion TL to 20.3 billion TL in the studied time span. Stock based overview reveals daily variations in trading environment are substantially high. For example, in most stocks, number of orders in the days with the highest submission is 20 to 30 times higher than the days with the lowest submission. On daily basis, the most frequent order submission is observed in Halkbank stock (HALKB) with 89,575 orders. Largest order volume on a specific day is in Garanti Bank stock (GARAN) with approximately 5.7 billion TL.

3.2. Variables

3.2.1. Detecting HFT from the message flow and the 'HFT rate' variable

Literature applies various approaches in determining HFT activity. These can be listed as, utilizing an algorithmic trading proxy as a proxy for HFT (Boehmer et al., 2015; Frino et al., 2014); focusing on a structural change or system upgrade as a proxy for HFT (Boehmer et al., 2015); utilizing special datasets (account-level or aggregate) on the trading of a subset of HFT firms (Baron et al., 2012; Brogaard et al., 2014; Kirilenko et al., 2017); and inferring HFT from commonly observable electronic messages data (Hasbrouck and Saar, 2013; Ekinci and Ersan, 2016, 2017).[9]

[9] See Biais and Foucault (2014) and Ekinci and Ersan (2017) for more detailed discussions on the positive and negative sides of the applied approaches.

In this paper, we follow the approach of inference from electronic messages data. Specifically, we apply the methodology suggested in Ekinci and Ersan (2017). Based on the methodology, we label certain orders as HFT orders in a two-step approach. In the first step, we perform an order-level analysis where we seek at least two sequential messages of an order arriving within low latency of one second or less. This suggests two separate actions of a trader occurring within a latency which is too short for a human trader to do so.[10] Types of orders labelled as HFT orders in this step include orders submitted and cancelled; submitted and modified; modified and cancelled; and modified more than once within the same second. In the second step, we inquire the exact arrival times of electronic messages in the HFT orders of the first step. Observing orders of same size with messages arriving at these specific seconds, we label additional orders as HFT orders. Examples for HFT orders and linkages, empirical evidence from BIST for an earlier time period and robustness on the reliability of the methodology can be found in Ekinci and Ersan (2018).

While the methodology provides a relatively narrower set of orders when compared to Hasbrouck and Saar (2013) and Ersan and Ekinci (2016), accuracy in the inference is much stronger with the two step approach. Our main purpose in this study is to investigate the effects of HFT on market quality, for which we strictly require the observation of variations in a reliable and representative HFT variable.

In order to obtain a cross sectionally comparable measure, we obtain an HFT rate which is the number of HFT labeled orders divided by total number of orders submitted in a stock and time, represented below.

$$HFTrate_{i,t} = \frac{Order_{i,t}^{HFT}}{Order_{i,t}^{All}} \tag{1}$$

[10] One second can be considered long for identifying low latency trading. However, we observe that it is a suitable time period to differentiate fast traders from slow traders in BIST. First, tests on order submission speed yields 600 ms difference between two conditional orders in 2017 (Ekinci and Ersan, 2018). Second, in a stock-based analysis for an 2015 dataset, Ekinci and Ersan (2018) report that only 2.58% of the trades follow the preceding trade on the same second.

Buy side HFT rate and sell side HFT rate are calculated in the same way, where number of HFT labelled buy (or sell) orders is in the numerator and total number of buy (or sell) orders are in the denominator this time.

3.2.2. Market Quality

Once a person decides to trade an asset, she would like to do that in the shortest time and with lowest additional costs, ceteris paribus. Similarly, for a risk averse individual, less of the variations is preferred for any level of expected return in an investment. Relatedly, higher returns are associated with larger risks as explained by the risk-return tradeoff framework.

We inquire whether HFT is a determinant in the observed levels of liquidity and volatility in the examined equity market, Borsa Istanbul. Furthermore, we study potential effects of HFT on the excess returns.

3.2.2.1. Liquidity

Overall liquidity provision to the market is the sum of liquidity provided by HFTrs and nonHFTrs. While overall liquidity in the market rises, liquidity provided by nonHFTrs may still shrink in a market with increased HFT. This fact represents a dilemma in which slow traders are reluctant to trade in a more liquid market (Hoffmann, 2014). On one hand, HFT share reaching to more than half of the trading volume in developed markets, some researchers advocate that HFT provides liquidity to the market (Hasbrouck and Saar, 2013; Jarnecic and Snape, 2014). On the other hand, a more challenging but a more intriguing question might be how the liquidity provision from nonHFTrs is affected by HFT. Several papers perform detailed analyses on HFT and nonHFT liquidity. These studies employ readily available datasets of HFT firms that enable the categorization of HFT and nonHFT liquidity demand and supply (Brogaard, 2010; Brogaard et al., 2014).

Most of the literature utilizes bid-ask spread as the measure for liquidity, in examining the impacts of HFT (see e.g. Hasbrouck and Saar, 2013; and Frino et al., 2014). Instead, we construct and use a liquidity provision variable.[11] This is because, bid-ask spread is representative of the overall liquidity observed in the market. Thus, it may not fully serve to the aforementioned discussion on the benefits of liquidity to market participants. For example, Mahmoodzadeh and Gençay (2017) show how bid-ask spread gets smaller following a tick size reduction while the consequent benefits are mostly absorbed by HFTrs. This fact is also related to the arguments of increased adverse selection costs incurred by nonHFTrs and strategic quote picking (sniping) performed by HFTrs (McInish and Upson, 2012; Hoffmann, 2014; Upson and VanNess, 2017).

Our liquidity provision variable incorporates volume of submitted orders as well as each order's lifetime. We multiply the volume of each order by the length of time it remains in the market. Summing up the resulting values for all orders at a stock on a given day, we obtain the liquidity provision variable. This is represented below.

$$Liq.Prov_{i,t} = \sum_{j=1}^{N} Vol_{i,j,t} * (Duration_{i,j,t}/Duration_{Total}) \quad (2)$$

where $Liq.Prov_{i,t}$ is the liquidity provision variable for stock *i* on day t; $Vol_{i,j,t}$ and $Duration_{i,j,t}$ are order volume and pending period of order *j* at stock *i* on day t; $Duration_{Total}$ is the total trading hours on day t.

In order to represent nonHFT liquidity provision, our final variable, we calculate the daily variable in Equation 2 only for the HFT orders. For this, initially, we exclude orders labelled as HFT orders based on the adapted methodology. Moreover, liquidity provision in buy and sell sides are calculated separately, with the use of orders in each direction.

Additionally, we employ two alternative variables, i.e. number of pending orders and volume of pending orders. We find the number of pending orders as total number of orders minus the number

[11] We could have used bid-ask spread as an alternative variable in examining the changes in overall liquidity. However, due to high tick sizes, the variations in the spreads are not frequent enough in Turkish stock market disabling a healthy analysis.

of orders executed and cancelled. Volume of pending orders is straightforward. It is just total volume of these orders. For any time period, pending orders are awaiting orders providing liquidity to the market. Again, we exclude HFT orders to calculate nonHFT variables. Volume of pending orders is a simpler version of our main variable, not incorporating the durations each order lives in the system. Number of pending orders also excludes the volume component, assigning equal importance to each order. As shown in Table 2, the correlation between volume of pending orders and our main liquidity provision variable is as high as 93.2%, suggesting that volume of orders that outstand until the end of trading day is a good proxy for the variable incorporating order lifetimes. The correlation between number of pending orders and our main liquidity provision variable is lower but at a significant level, 61.3%.

3.2.2.2. Volatility

In order to account for the volatility in the prices, we utilize a commonly applied measure of price range (see e.g. Hasbrouck and Saar, 2013; Boehmer et al., 2016; Kirilenko et al., 2017).

$$HighLow_{i,t} = \frac{High_{i,t} - Low_{i,t}}{(High_{i,t} + Low_{i,t})/2} \tag{3}$$

where $HighLow_{i,t}$ is the volatility in the prices of stock *i* on day *t*; $High_{i,t}$ and $Low_{i,t}$ are the highest and lowest transaction prices on that day.

3.2.2.3. Excess Returns

In line with studies examining HFT profits (Brogaard et al., 2014; Hirshey, 2017) and whether HFTrs are informed (Brogaard, 2010; McInish and Upson, 2012), we investigate the relationship between HFT and stock returns. We utilize daily excess stock returns over the market (BIST 100 index) return.

3.2.3. Control Variables

In the regression analysis of HFT impact on market quality, we include several control variables. Following Hasbrouck and Saar (2013), we incorporate stock trading intensity, market return and absolute value of market return. Moreover, we repeat our analyses with day of the week dummies and market capitalization variables. We alternatively use natural logarithm of market capitalization as well as a dummy variable that is equal to 1 for market capitalization values higher than the median value and 0 otherwise.

Table 1a and 1b report descriptives on the employed variables. While former table is stock based, Table 1b reports overall statistics from 11,700 observations in 30 stocks and on 339 trading days. Mean HFT rate in the number of submitted orders is 3.21% while HFT orders' volume constitutes 2% of total order volume. HFT rate within total volume being lower than the rate within total number of orders approves the fact that HFT is performed with relative smaller sized orders, e.g. split orders. HFT shares within buy orders and sell orders are very similar, indicating that HFTrs are equally likely to buy and sell as nonHFTrs do.

Daily average number of nonHFT orders not executed or cancelled, is 976.8. Lowest and highest observations are 138 and 27,877 representing a wide range. Daily average turnover of nonHFT awaiting orders is 43 million TL. Daily average volatility measured by price range ratio is 2.65%. Daily average return for the examined stocks and for the market are positive at 8 and 6 basis points, respectively.

3. 3 Methodology

Correlations between our HFT variables and market quality measures are shown in Table 2. HFT rate within total number of orders (total volume of orders) has a correlation of -16.8% (-19.8%) with our main nonHFT liquidity provision variable. HFT rates on buy side and on sell side are also negatively correlated with the nonHFT liquidity provision on each side of the market. The correlation between HFT rate within total number of orders and daily volatility is much lower (-4%), but still significant. Volume based HFT rate does not have a significant correlation with volatility. Finally, buy side (sell side) HFT rates in the number of orders have positive (negative) correlation with returns.

We perform linear regressions in analyzing the impact of HFT on market quality. We apply zero-mean standardization in all the variables included in the regressions. We mainly estimate four models. Initially, we estimate a univariate regression model presented in Equation 4.

$$Quality_{i,t} = \alpha_1 HFTrate_{i,t} + e_{i,t} \tag{4}$$

where $Quality_{i,t}$ is one of liquidity provision, volatility, and excess returns variables for stock *i* on day t. $HFTrate_{i,t}$ is the HFT rate for stock *i* on day t, obtained by the methodology described in Section 3.2.1. Non-zero intercept term does not exist due to the standardization of variables.

Next, we estimate two extended models of Hasbrouck and Saar (2013). Thus, Model 2 incorporates potential effects of stock trading volume on our explained variables. Model 3 further includes two control variables, i.e. market return and absolute value of market return. Latter variable is intended to capture the overall volatility in the market. Two models are given in Equations 5 and 6.

In a final model, we add market capitalization as another control variable. The correlation between trading volume and market capitalization is 23.9% (see Table 2).

$$Quality_{i,t} = \alpha_1 HFTrate_{i,t} + \alpha_2 TradeVol_{i,t} + e_{i,t} \tag{5}$$

$$Quality_{i,t} = \alpha_1 HFTrate_{i,t} + \alpha_2 TradeVol_{i,t} + \alpha_3 R_{M,t} + \alpha_4 |R_{M,t}| + e_{i,t} \tag{6}$$

$$Quality_{i,t} = \alpha_1 HFTrate_{i,t} + \alpha_2 TradeVol_{i,t} + \alpha_3 R_{M,t} + \alpha_4 |R_{M,t}| + \alpha_5 MCAP_{i,t} + e_{i,t} \tag{7}$$

where $TradeVol_{i,t}$ and $MCAP_{i,t}$ are the total trading volume and market capitalization of stock *i* on day t. $R_{M,t}$ and $|R_{M,t}|$ are the market return and absolute value of market return on day t. In order to remedy for heteroscedasticity, serial correlation and spatial correlation problems in the OLS regressions, we report significance based on Driscoll-Kraay extension of Newey-West HAC robust standard errors.

4. Results

Details on the findings of our analyses are presented in the following three sub-sections about liquidity, volatility and returns, respectively. We examine each relationship with four alternative models, presented in Equations 4 to 7. All regressions are repeated with i) HFT rate within total number of orders and ii) HFT rate within total turnover. In all the tables, number and volume based results are reported in the left and right vertical fields, respectively. We estimate the impact of overall HFT involvement on our dependent variables. Next, we inquire the impacts of HFT on the buy side and sell side separately. We perform a more detailed analysis in the liquidity part. Namely, we investigate the effects of buy (sell) side HFT on nonHFT liquidity provision at both buy side and sell side.

4.1. Liquidity

We inquire the impact of HFT existence on the liquidity provision by the nonHFTrs. As described in Section 3.2.2.1., we primarily employ a weighted liquidity provision variable that considers order life-time and volume. Table 3 reports the results from regression estimations. Among the most straightforward and broad facts of the table, we can claim that number of HFT orders is mostly not effective, whereas volume of HFT orders has a significant negative impact on other players' liquidity provision. Given in Panel A, when HFT order volume increases, liquidity provided by other agents diminish, as signaled by negative coefficients significant at 1% in all the four models. For example, Model 4 coefficients indicate that a 1% increase in the volume of HFT orders is estimated to result in a 0.07% reduction in the overall nonHFT liquidity provision. A similar solid impact is not valid for the case of number of HFT orders. HFT coefficient is negative (-0.02%) and significant (at 5% level) in the extended model, Model 4, a finding not supported by the remaining models. Besides, the coefficient (-0.02) is much smaller when compared to HFT order volume coefficient (-0.07).

A potential explanation could be twofold. First, our liquidity provision variable is a weighted variable on order volume. Thus, in case there is an impact of HFT activity on the volume weighted variable, we would expect this to come from HFT volume rather than HFT order number. This is represented by the higher correlation of HFT order volume and liquidity provision variable, given in Table 2. Second, demand and supply of liquidity are better represented by aggregates rather than numbers since numbers are very sensitive to order splits.

Adjusted R-squared values reveal that explained part of nonHFT liquidity provision by HFT rate is substantially low (lower than 1%). However, after controlling for other variables, adjusted R-squared values rise to the range of 21% and 23%.

Among the control variables, volume and market cap are positively and significantly associated with the liquidity variable. On the days when a stock's trading volume is higher when compared to its own daily average, nonHFT liquidity provision is also higher. Specifically, when daily trading volume is doubled, nonHFTrs provide approximately 50% larger liquidity. The strong relationship between trading volume and liquidity provision that is based on order volume is self-explanatory, i.e. days with higher trading volume are most likely to have high order volume as well. Market capitalization as of the last trading day, standardized around the mean at stock level, is a trend variable in that sense. Increased market value of a company result in higher liquidity provision.

Panels B (Buy-Buy) and C (Sell-Sell) of Table 3 report on the impacts of buy and sell side HFT activity on the nonHFT liquidity provision at the same direction, respectively, while panels D (Buy-Sell) and E (Sell-Buy) present results regarding HFT impact on liquidity provision at the opposite direction. The negative impact of HFT on the overall liquidity provision of nonHFTrs is supported by the findings regarding the impacts for the Buy-Buy and Sell-Sell cases. HFT share within buy or sell orders' volume negatively affects nonHFTrs' liquidity provision on the same side.

The effects of buy and sell side HFT on the nonHFT liquidity provision in the opposite direction are documented in Panels D and E of Table 3. As in the case of buy side nonHFT liquidity provision, sell side provision is also negatively affected by buy side HFT. On the other hand, sell side HFT activity has no effect on the nonHFT liquidity provided on the opposite side. This is intuitive considering buyers generally are more aggressive than sellers (Chan, 2005; Ekinci, 2008; and Baruch, 2017).

Negative impact of HFT on nonHFT liquidity provision supports the crowding out effect mentioned in the literature (e.g., Breckenfelder, 2013 and Biais et al., 2015). NonHFTrs are more reluctant to provide liquidity to the market when HFT activity is higher. This may arise from the awareness of nonHFTrs about the competitive advantage of HFTrs, i.e. speed. Although our results are parallel to the literature, the evidence is interesting and novel in the sense the observed negative impact is clear despite a very low HFT share in Borsa Istanbul.

As alternatives to the primary nonHFT liquidity provision variable, we employ number and volume of nonHFT orders not cancelled and not executed. Table 4 replicates the results by using these two variables. Left and right vertical parts report on the number based and volume based variables for nonHFT liquidity provision. Overall HFT rate has a significantly negative impact on the nonHFT liquidity provision, when measured by number of orders and also volume of orders. When both Number and Volume columns in Table 4 are compared to Number column in Table 3, results such as negative coefficients for HFT rate and asymmetric impacts on buy and sell sides are rather confirmed. However the significance of negative HFT coefficients in Table 4 is relatively higher. [12]

4.2. Volatility

Table 5 presents the regression results on the impact of HFT on volatility in the prices of 30 blue chip stocks of our analysis. In general, we do not observe a significant HFT effect on volatility. Given in Panel A of Table 5, the coefficient of HFT variable, that is the overall HFT share within the number of orders, is negative (-0.03) and slightly significant at 10% level (t-value=1.65) in the univariate model. Similar results hold in Panel B that represents the impact of buy side HFT on volatility. However, this weak relationship found in Model 1 is supported by none of the extended models. After incorporating relevant control variables, adjusted R-squared values reach to 35% whereas estimating stock price

[12] Both panels (Number and Volume) of Table 4 are replicates of the left Panel of Table 3 (Number) since all use HFT rate within number of orders.

volatility solely by HFT rate yields adjusted R-squared values of less than 1%. Thus, we conclude that, controlling for the variables of interest, overall HFT rate does not have an observable impact on volatility.

We can ground this fact with two arguments. First, although daily variations in the HFT share is relatively high (see Table 1 for the distribution of HFT variables), overall HFT involvement in the market is substantially low - daily average HFT rate is 3.21% (2%) within number (volume) of orders. Thus, HFT activity currently being far from dominating the market in vast majority of day-stock pairs, is not strong enough to have a significant effect on volatility. Second, HFT may have both deteriorating and improving effect on volatility that partially offset each other. Both arguments find preliminary evidence in Ersan and Ekinci (2016), studying 120 large- and mid-cap stocks listed in the same stock exchange, BIST, with a 2013-2014 dataset. They report relatively higher HFT levels in the higher volatility stocks' portfolios. On the other hand, for the stocks with highest HFT rates, volatility is either low or high when compared to the rest of the stocks (see Table 10 and Figure 4 in the referred study).

Presented by Panel C of Table 5, we observe a positive impact of HFT share within the sell side order volume on volatility. The coefficient of sell side HFT rate is 0.03, significant at 5% and 10% levels in Model 3 and Model 4, respectively. In other words, after controlling for the effects of stock volume, market return, market volatility and company market capitalization, a 1% rise in the HFT share on the sell side at a given stock would result in a 0.03% increase in volatility of that stock's price. Observing significant coefficients for sell side HFT and no significant coefficients for buy side or overall HFT, we conclude that HFTrs contribute to price fluctuation when they are on sell side.

Absolute value of market return, representing market volatility has a positive and significant effect on stock level volatility. On days with higher volatility in the overall market, examined stocks' prices also experience higher volatility. Moreover, volatility is significantly lower on days with high market return. This supports the argument that volatility and uncertainty are higher through periods of downturns and bad conditions. While our trend variable (market cap) has not impact on volatility, there exists a positive relationship between stock volume and volatility. On a day when a company's stock is traded with larger volume, the stock price is more volatile.

4.3. Returns

In this section, we examine the role of HFT in returns. Panels B and C of Table 6 together imply that there is a positive relationship between HFT and excess returns. More specifically, when the share of HFTrs on the buy side is large, excess returns are high. On the contrary, on days with large HFT share on sell side, excess returns are low.

Stocks yield lower (and potentially negative) excess returns on the days when HFTrs sell more. This relationship is robust to number of HFT orders and volume of HFT orders. An increase either in the number or volume of orders submitted by HFTrs makes prices move in the direction of HFTrs positions. For example, Model 4 suggests that a 1% rise in the buy side HFT share in the number (volume) of orders causes excess returns to grow by 0.07% (0.04%). Based on the same model, excess returns diminish by 0.05% when the sell side HFT rate increases by 1%. The coefficients of HFT rate are significant at 1%. This finding supports the earlier evidence on the existence of HFT profits (see Brogaard, 2010 among others) and the relationship between HFT and asset returns (Brogaard et al., 2014; and Hirshey, 2017). Our finding is important as it concerns an emerging market with very low HFT activity.

As Panels B and C suggest, since an HFT impact on the excess returns is mainly based on whether HFTrs are on the buy side or sell side, the effect of the overall HFT activity on the excess returns is ambiguous. Reflected by Panel A, we observe positive and negative coefficients in different models and with the use of number and volume specifications. However, our primary focus is on HFT activity on two directions in analyzing excess returns.

Market return as the main explanatory factor in individual stock returns has large and significant coefficient in our models. This is obvious considering that CAPM betas are positive for most blue chip stocks. Stock traded volume positively affects excess returns. This is probably due to the increasing path of BIST 30 index throughout the study period. High volume days are associated with excess positive returns.

On the other hand, a stock's market cap as of last trading day has a negative impact on returns exhibiting contrarian effects rather than momentum. Our market cap variable stands for a lagged stock performance since it is standardized around the mean for each stock. Therefore, negative coefficient of the market cap variable points out to a mean reversion effect in the prices. A higher market cap value that is usually caused by an outperformance in preceding day(s) results in a consequent underperformance. While market cap coefficients are all negative, they are also significant at 1% level. Finally, market wide volatility has slightly negative impact on returns. The coefficients of market wide volatility are negative and significant at 10% level or not significant at all.

5. Conclusion

Thanks to technological developments, the last decade of major financial markets is characterized by ultra-fast speed of order submission, i.e. a continuous travel from milliseconds to nanoseconds. The activity of HFTrs, usually defined as low latency profit-motivated traders, constitutes a substantial share in the overall order flow and trading in financial markets.

The large HFT involvement is accompanied with extensive research studying the impacts of HFT on financial markets. While there exists a large body of literature providing empirical evidence for the positive effects of HFT on markets, many other studies argue against HFT. Major issues include deterioration in market quality and potential costs incurred by the rest of participants, e.g. positive HFT profits and the crowding out of nonHFTrs.

Regarding the ongoing debates on HFT impacts, so far, to our knowledge, one question has not been well explored. Are the suggested negative externalities of HFT special to the developed markets dominated by HFT or are they also present in an emerging market with very low HFT share? We inquire answers to this question examining thirty blue chip stocks listed in Borsa Istanbul (BIST) for the period between Dec 2015 and Mar 2017.

We show that there exist negative impacts of HFT despite its small part in the market. First, liquidity provided by nonHFTrs is significantly lower with HFT. This is robust to buy and sell side HFT. The finding supports the concerns regarding the crowding out effect of HFT. Our analysis of the relationship between HFT participation and stock returns implies that HFT generates positive profits. Finally, overall HFT rate does not have a pronounced impact on stock price volatility. However, volatility is found to be increasing with sell side HFT.

This paper shows that HFT may have substantial effects even in a market with very low HFT involvement. This finding suggests that regulatory and restrictive actions on HFT resulting in reduced HFT share do not necessarily provide full protection for financial markets. Moreover, the observed negative impacts of HFT in an emerging market should be handled with great care by the regulators and policy makers.

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Table 1.a. Stock-based Summary Statistics

Notes: Table reports stock-based desciptive statistics. Data covers the time span of Dec. 2015 and Mar. 2017, in 339 trading days for each of the 30 blue chip stocks listed in BIST 30 index of Borsa Istanbul. 'nb' and 'vol' stand for number and volume based calculations, respectively. Order_nb and Order_vol are the daily number and volume of orders. HFT_nb (HFT_vol) is the HFT rate within number (volume) of orders. Liq.Prov.Duration is our main nonHFT liquidity provision variable constructed based on order size and lifetime. While we calculate HFT and liqudity provision variables overally, for the buy side and sell side separately, we only report statistics on the overall calculation for the sake of brevity. Volatility is the daily price volatility variable of price range. Excess return is the stock return over market return. Volume is daily stock trading volume. MCAP is the market capitalization as of previous day. HFT, volatility, and return variables are presented in percentage values; liquidity provision, volume and MCAP variables are given in million TL. All variables are calculated as described in Section 3.2. Last line states the statistics for the overall trading in all 30 stocks.

	Order_nb			Order_vol			HFT_nb			HFT_vol			Liq.Prov.Duration			Volatility			Excess Return			Volume			MCAP		
Ticker	min	md	max	min	md	max	min	md	max	min	md	max	min	md	max	min	md	max	min	md	max	min	md	max	min	md	max
AKBNK	2351	10279	39333	80.7	568.1	2845.0	0.0	2.3	23.1	0.0	1.4	16.3	16.7	39.7	142.3	0.5	2.1	8.7	-2.5	0.0	2.8	2.6	23.8	145.7	25800.0	31560.0	37040.0
ARCLK	656	5859	20841	7.4	86.2	636.5	0.0	4.9	32.4	0.0	2.8	13.9	2.4	6.5	232.1	0.7	2.2	7.6	-6.8	0.0	6.7	0.1	1.2	6.7	9257.5	13595.7	16082.3
BIMAS	707	4583	15145	16.7	158.7	1112.5	0.0	4.0	39.3	0.0	2.3	31.8	4.5	14.2	210.8	0.5	2.0	7.3	-6.3	-0.1	6.0	0.0	0.7	4.8	14251.0	16166.7	19157.2
DOHOL	920	2780	26225	14.3	73.8	475.9	0.0	0.2	27.6	0.0	0.1	10.3	8.2	21.1	65.2	1.2	3.6	18.2	-7.5	-0.2	16.0	0.9	14.4	201.0	1203.8	1674.8	2486.1
EKGYO	1424	5932	28580	52.3	272.0	1301.1	0.0	0.9	33.3	0.0	0.4	8.7	16.6	37.2	99.4	0.6	2.2	14.2	-5.5	0.0	3.8	2.1	29.3	195.6	8930.0	11020.0	12236.0
ENKAI	763	3214	10010	7.0	58.9	646.0	0.0	2.6	21.1	0.0	1.7	13.6	2.0	5.9	49.4	0.7	2.2	11.8	-5.4	0.0	6.8	0.4	3.4	60.8	16000.0	19080.0	26292.0
EREGL	1381	5993	13350	26.0	219.6	822.4	0.0	1.8	30.0	0.0	1.7	16.5	7.8	18.7	72.0	0.9	2.8	11.0	-5.0	0.1	6.3	1.3	16.7	54.6	10115.0	15295.0	21735.0
FROTO	576	4177	14547	4.1	45.2	211.2	0.0	4.0	22.4	0.0	2.6	14.3	1.9	4.2	69.0	0.6	2.2	10.4	-5.6	-0.1	3.6	0.0	0.4	1.9	9748.3	11566.0	14099.6
GARAN	5254	18550	54987	293.7	2070.7	5676.3	0.0	1.0	15.5	0.0	0.7	8.0	56.6	138.3	306.8	0.5	1.9	11.7	-3.3	0.0	2.4	10.7	99.2	299.8	28686.0	32298.0	38094.0
HALKB	1896	13437	89575	84.5	774.8	4999.2	0.0	1.6	24.8	0.0	1.0	9.3	17.5	56.0	419.8	0.5	2.0	11.3	-13.2	-0.1	5.9	3.1	28.2	175.1	9362.5	11900.0	15125.0
ISCTR	1789	9650	46576	43.5	469.2	1113.5	0.0	1.5	20.6	0.0	1.4	10.6	18.3	46.0	109.9	0.4	2.0	10.0	-2.0	0.0	3.0	1.6	32.2	85.4	18944.9	21599.9	30374.8
KCHOL	753	7581	21455	9.9	174.1	726.8	0.0	4.9	34.3	0.0	2.9	28.1	2.6	12.5	263.8	0.5	2.1	11.6	-2.5	0.0	3.5	0.2	3.5	18.0	27159.5	33321.7	40067.2
KOZAL	1351	7141	44369	6.7	43.7	611.8	0.0	3.3	23.8	0.0	2.7	42.3	1.5	4.6	147.7	0.9	4.0	30.5	-12.9	0.0	21.6	0.1	0.7	11.1	1399.9	2469.0	3358.1
KRDMD	1627	4965	51894	55.7	187.0	680.9	0.0	0.3	4.4	0.0	0.4	11.2	17.0	39.7	78.9	0.8	2.7	15.0	-5.2	-0.2	8.2	3.4	33.5	136.7	749.0	975.3	1256.2
MGROS	368	2374	14622	2.6	25.1	270.3	0.0	2.3	24.7	0.0	1.3	15.4	1.0	3.1	194.2	0.6	2.1	11.3	-3.6	-0.1	4.4	0.0	0.4	3.7	2595.7	3115.5	3959.4
OTKAR	1102	3408	20538	12.4	44.6	356.9	0.0	1.4	18.0	0.0	0.6	13.5	1.7	6.3	58.4	0.7	2.2	9.5	-6.4	-0.2	7.6	0.0	0.1	1.3	1983.6	2491.2	3566.4
PETKM	1319	5314	13315	20.9	160.0	816.0	0.0	1.2	43.5	0.0	1.1	28.4	7.0	18.9	113.0	0.7	2.4	7.0	-4.0	-0.2	5.4	1.4	13.4	95.3	4370.0	6075.0	7920.0
PGSUS	1051	4445	26616	5.2	54.6	729.4	0.0	0.5	5.4	0.0	0.3	4.5	2.2	6.4	36.0	0.4	2.0	11.4	-5.7	-0.3	9.5	0.1	1.3	18.8	1135.2	1516.7	1871.6
SAHOL	1120	6460	17496	21.8	195.9	1218.1	0.0	3.2	22.8	0.0	1.9	23.6	6.4	14.4	213.7	0.5	2.0	9.5	-4.0	0.0	2.6	0.5	5.7	63.8	15466.3	18873.7	21383.4
SISE	580	3277	10538	7.1	61.0	277.2	0.0	1.7	35.1	0.0	1.3	42.5	2.0	4.7	27.7	0.8	2.4	8.3	-3.7	-0.1	4.0	0.5	4.8	22.3	5073.0	6859.0	8630.5
TAVHL	1005	7230	34759	7.8	102.2	794.3	0.0	3.6	19.7	0.0	2.2	8.2	2.5	9.2	253.9	0.6	2.4	17.4	-10.3	-0.3	6.2	0.1	2.1	12.4	3832.6	5452.9	7643.4

TCELL	1416	6608	19503	21.3	168.8	501.3	0.0	3.9	26.8	0.0	2.4	23.8	5.5	14.3	148.6	0.5	1.9	15.9	-3.9	-0.1	3.6	0.4	4.3	14.4	19558.0	23100.0	27390.0
THYAO	5325	17165	66839	149.3	1074.1	2977.0	0.0	0.4	7.3	0.0	0.5	4.5	45.5	97.7	208.9	0.7	2.1	16.7	-6.0	-0.3	4.4	6.3	62.0	197.7	6389.4	7893.6	10984.8
TKFEN	1197	4581	34564	10.3	96.0	879.7	0.0	2.3	24.3	0.0	1.3	15.9	2.6	8.7	76.6	0.7	2.6	16.8	-7.1	-0.1	17.4	0.4	4.8	48.2	1306.1	2564.1	3392.9
TOASO	629	5044	13184	7.1	72.1	303.8	0.0	4.6	23.5	0.0	2.9	10.8	1.8	5.1	192.5	0.7	2.3	7.8	-5.2	0.1	5.1	0.1	0.8	4.5	8965.0	11380.0	14070.0
TTKOM	642	4184	11487	5.9	80.8	249.7	0.0	3.4	14.3	0.0	1.9	20.3	2.0	6.4	48.4	0.5	2.1	8.7	-5.8	-0.1	3.5	0.2	3.6	14.3	17465.0	20195.0	24500.0
TUPRS	1375	8156	32309	21.2	326.3	3116.5	0.0	3.2	35.7	0.0	1.9	30.0	7.6	27.2	1048.3	0.5	1.8	8.6	-5.9	0.0	4.5	0.1	1.4	7.4	14123.6	17692.1	22838.2
ULKER	365	4801	61260	3.4	67.6	1586.0	0.0	4.9	43.9	0.0	3.0	36.1	1.5	5.1	1214.0	0.6	2.4	14.3	-7.6	-0.1	5.5	0.0	1.0	20.1	5249.7	6566.4	7640.3
VAKBN	2344	9151	28755	57.7	388.4	1079.4	0.0	1.4	24.0	0.0	1.0	9.9	15.2	34.2	119.6	0.7	2.3	14.8	-5.1	0.0	5.1	3.3	28.7	79.8	9000.0	11050.0	14025.0
YKBNK	1520	7427	23638	31.1	282.1	962.2	0.0	1.2	11.8	0.0	0.9	6.8	11.0	31.5	107.0	0.3	2.2	11.2	-4.4	0.0	8.7	1.3	24.3	113.2	13302.0	15997.1	18866.2
Market	67599	215884	556563	1475.9	8986.8	20259.7	0.0	2.7	10.1	0.0	1.9	4.8	396.0	829.0	2264.7	1.1	2.5	9.1	-0.7	0.0	1.1	60.7	486.1	1158.1	11119.4	12737.3	15055.2

Table 1.b. Summary Statistics Marketwide

Notes: Table presents descriptive statistics on the variables utilized in the regression analyses. Data covers the time span of Dec. 2015 and Mar. 2017, including 10170 observations in 339 trading days for 30 blue chip stocks listed in BIST 30 index of Borsa Istanbul. 'nb' and 'vol' stand for number and volume based calculations, respectively. HFT_nb (HFT_vol) is the HFT rate within number (volume) of orders. Liq.Prov.Duration is our main nonHFT liquidity provision variable constructed based on order size and lifetime. Respectively, Liq.Prov.nb and Liq.Prov.vol are the alternative nonHFT liquidity provision variables based on number and volume of nonHFT orders not cancelled or traded. HFT and liqudity provision variables are calculated overally, for the buy side and sell side separately, represented by 'All', 'Buy' and 'Sell' extensions. For example, HFT_nb_Buy is the HFT rate in the number of buy orders. Volatility is the daily price volatility variable of price range. Return is the percentage change in stock price. Market return is the return on the BIST 100 index. Abs(Market return) is the absolute value of market return. Excess return is stock return over market return. Volume is daily stock trading volume. MCAP is the market capitalization as of previous day. HFT, volatility, and all return variables are presented in percentage values; liquidity provision, volume and MCAP variables are given in million TL. All variables are calculated as described in Section 3.2.

	Mean	Sd.	Min.	1%	5%	25%	Median	75%	95%	99%	Max.
HFT_nb_All	3.21	3.52	0	0	0.16	0.96	2.27	4.2	9.36	17.7	43.93
HFT_nb_Buy	3	3.94	0	0	0.05	0.69	1.88	3.92	9.04	20.75	58.49
HFT_nb_Sell	3.19	3.98	0	0	0.07	0.76	2.03	4.22	9.57	20.51	49.37
HFT_vol_All	2	2.18	0	0	0.08	0.65	1.47	2.69	5.46	9.28	42.52
HFT_vol_Buy	1.96	2.6	0	0	0.01	0.41	1.24	2.6	6.1	11.98	54.31
HFT_vol_Sell	1.97	2.48	0	0	0.02	0.44	1.28	2.67	5.98	10.92	54.24
Liq.Prov.Duration_All	27.98	38.26	0.95	2.19	3.12	6.3	14.57	35.27	106.39	167.08	1214.03
Liq.Prov.Duration_Buy	11.96	19.89	0.26	0.66	1.1	2.33	5.83	14.95	42.39	79.81	1030.3
Liq.Prov.Duration_Sell	16.02	24.49	0.53	1.12	1.75	3.68	8.01	19.62	58.81	96.55	1210.75
Liq.Prov.nb_All	976.8	772.45	138	246	331	529	788	1162	2357.1	3738.72	27877
Liq.Prov.nb_Buy	422.5	480.87	36	82	123	212	323	510	1047.55	1721.65	26788
Liq.Prov.nb_Sell	554.3	413.12	61	122.69	176	297	440	664	1358.2	2301.86	3666
Liq.Prov.vol_All	43.04	58.82	1.31	3.33	5.74	12.08	27.32	51.63	145.03	232.56	2699.06

Liq.Prov.vol_Buy	20.25	37.65	0.26	1.11	2.2	5.24	11.82	23.75	66.32	127.98	2659.25
Liq.Prov.vol_Sell	22.79	34.65	0.7	1.65	2.88	6.26	13.47	26.72	75.77	133.24	1468.5
Volatility	2.65	1.66	0.3	0.77	1.05	1.64	2.26	3.15	5.44	8.99	30.46
Return	0.08	2.03	-19.95	-5.31	-2.89	-1.01	0	1.15	3.19	5.47	20
Market Return	0.06	1.27	-7.08	-3.36	-1.76	-0.62	0.05	0.8	2.25	3.4	4.15
Abs(Market Return)	0.93	0.87	0	0.01	0.05	0.32	0.73	1.23	2.57	4.11	7.08
Excess Return	0.03	1.61	-13.25	-3.77	-2.14	-0.82	-0.07	0.76	2.48	4.61	21.57
Volume	16.52	26.28	0.02	0.08	0.27	1.21	4.67	22.46	69.36	127.37	299.8
MCAP	12893.46	9429.72	749.02	889.46	1351.47	5010.56	11460.36	18751.31	32437.36	36708	40067.19

Table 2. Correlation Matrix

Notes: Table reports Pearson's correlation coefficients in percentages. Data covers the time span of Dec. 2015 and Mar. 2017, including 10170 observations in 339 trading days for 30 blue chip stocks listed in BIST 30 index of Borsa Istanbul. 'nb' and 'vol' stand for number and volume based calculations, respectively. HFT_nb (HFT_vol) is the HFT rate within number (volume) of orders. Liq.Prov.Duration is our main nonHFT liquidity provision variable constructed based on order size and lifetime. Respectively, Liq.Prov.nb and Liq.Prov.vol are the alternative nonHFT liquidity provision variables based on number and volume of nonHFT orders not cancelled or traded. HFT and liqudity provision variables are calculated overally, for the buy side and sell side separately, represented by

	HFT_nb_All	FT_nb_Buy	FT_nb_Sell	HFT_vol_All	FT_vol_Buy	FT_vol_Sell	uration_All	ration_Buy	ration_Sell	Prov.nb_All	ov.nb_Buy	ov.nb_Sell	rov.vol_All	ov.vol_Buy	ov.vol_Sell	Volatility	Return	ket Return	ket Return)	ess Return	Volume	MCAP
HFT_nb_All	100																					
HFT_nb_Buy	81.39***	100																				
HFT_nb_Sell	78.98***	31.03***	100																			
HFT_vol_All	80.99***	64.5***	66.35***	100																		
HFT_vol_Buy	66.53***	81.88***	25.83***	79.29***	100																	
HFT_vol_Sell	65.2***	24.28***	83.41***	79.54***	29.04***	100																
Liq.Prov.Duration_All	-16.78***	-13.37***	-14.62***	-19.75***	-15.61***	-16.3***	100															
Liq.Prov.Duration_Buy	-13.12***	-10.29***	-11.51***	-15.92***	-13.77***	-11.62***	82.74***	100														
Liq.Prov.Duration_Sell	-15.55***	-12.53***	-13.48***	-17.92***	-13.2***	-16.03***	89***	48.03***	100													
Liq.Prov.nb_All	-23.52***	-19.7***	-19.45***	-20.41***	-17.6***	-17***	61.26***	48.63***	56.18***	100												
Liq.Prov.nb_Buy	-16.42***	-13.33***	-13.68***	-14.04***	-12.29***	-11.45***	43.3***	38.77***	36.15***	88.47***	100											
Liq.Prov.nb_Sell	-24.87***	-21.32***	-20.45***	-21.81***	-18.61***	-18.46***	64.14***	45.81***	62.97***	84***	49.02***	100										
Liq.Prov.vol_All	-9.19***	-7.01***	-8.1***	-14.65***	-11.01***	-11.53***	93.19***	84.01***	77.34***	51.25***	37.37***	52.34***	100									
Liq.Prov.vol_Buy	-6.73***	-5.05***	-5.83***	-10.54***	-9.34***	-6.62***	71.57***	93.53***	35.82***	36.98***	31.43***	32.55***	83.02***	100								
Liq.Prov.vol_Sell	-8.28***	-6.42***	-7.41***	-13.42***	-8.55***	-12.38***	80.46***	41***	92.37***	46.83***	29.28***	53.49***	79.57***	32.29***	100							
Volatility	-4***	-3.83***	-1.83***	-0.8	-1.66***	0.41	1	2.07***	-0.12	8.43***	8.51***	5.85***	2.06***	2.39***	0.9	100						
Return	-0.41	5.53***	-6.79***	-4.06***	-0.42	-6.49***	-2.51***	5.34***	-8.25***	-3.75***	7.12***	-15.29***	-1.7***	5.3***	-8.64***	-0.55	100					
Market***	-1.83***	0.79	-4.22***	-4.42***	-4.68***	-2.97***	-1.1	2.03***	-3.37***	1.05	6.43***	-5.52***	-1.25	0.76	-2.96***	-15.61***	61.3***	100				
Abs(Market***	-0.98	0.46	-1.39	0.25	1.17	0	4.82***	6.93***	1.89***	0.93	4.03***	-2.96***	7.05***	7.9***	3.38***	30.99***	-2.53***	-4.09***	100			
Excess***	0.93	6.38***	-5.25***	-1.63***	3.18***	-5.86***	-2.3***	5.15***	-7.78***	-5.57***	3.91***	-14.97***	-1.16	6.1***	-8.59***	11.67***	77.99***	-1.64***	0.03	100		
Volume	-23.73***	-18.89***	-21.27***	-23.05***	-18.9***	-20.48***	72.37***	62.02***	62.68***	63.41***	47.63***	63.11***	59.5***	45.75***	51.3***	15.24***	0.53	-0.39	8.38***	0.98	100	
MCAP	20.28***	18.39***	17.04***	14.45***	12.05***	12.94***	29.09***	27.3***	23.27***	4.62***	6.92***	0.59	32.45***	26.1***	26.74***	-19.06***	-1.23	-0.66	-1.38	-1.03	23.88***	100

Table 3. Regression Results about HFT Impact on Liquidity

Notes: Table presents regression results on the impacts of HFT on nonHFT liquidity provision. Data covers the time span of Dec. 2015 and Mar. 2017, including 10170 observations in 339 trading days for 30 blue chip stocks listed in BIST 30 index of Borsa Istanbul. Left and right vertical sides stand for the regressions using the HFT rate within number and volume of orders, respectively. nonHFT liquidity provision variable is Liq.Prov.Duration, constructed based on order size and lifetime. Regressions are repeated for the impacts of overall HFT on overall nonHFT liquidity provision as well as for the buy and sell side HFT on each of the buy and sell side provision. Panel A is for the overall HFT - overall provision case. Panels B and C are for the Buy - Buy and Sell - Sell cases, respectively. Panel D (E) stands for the buy (sell) side HFT - sell (buy) side provision case. Each analysis is performed by 4 models presented in Equations 4 to 7 in Section 4. Volume is daily stock trading volume. Rm, market return is the return on the BIST 100 index. Abs(Rm) is the absolute value of market return. MCAP is the market capitalization as of previous day. All variables are calculated as described in Section 3.2. Variables are standardized around the means at the stock level. Adjusted R-squared values are given in last columns in each panel. t-values are given in even numbered lines that follow the lines reporting variable coeffcients. We report significance based on Driscoll-Kraay extension of Newey-West HAC robust standard errors.(*), (**) and (***) represent significance at 10%, 5% and 1% levels, respectively.

	HFT	Volume	Rm	abs(Rm)	MCAP	R2	HFT	Volume	Rm	abs(Rm)	MCAP	R2
(A) ALL-ALL	-0.02					0	-0.09***					0.01
	-1.45						-5.29					
	0	0.46***				0.21	-0.05***	0.45***				0.21
	0.01	21.97					-3.14	21.74				
	0	0.46***	0	-0.03		0.21	-0.05***	0.46***	-0.01	-0.03		0.21
	-0.05	22.26	-0.24	-1.4			-3.2	21.99	-0.38	-1.35		
	-0.02**	0.48***	0	-0.03	0.11***	0.22	-0.07***	0.47***	0	-0.02	0.11***	0.23
	-2.1	22.94	0.04	-1.25	6.88		-4.65	22.71	-0.13	-1.15	7.76	
(B) BUY-BUY	0					0	-0.07***					0
	-0.41						-6.32					

	0	0.41***				0.17	-0.04***	0.41***				0.17
	0.36	19.04					-4.15	18.94				
	0	0.41***	0.09***	-0.02		0.18	-0.03***	0.41***	0.09***	-0.02		0.18
	0.17	19.69	6.87	-0.99			-3.94	19.62	6.62	-0.96		
	-0.01	0.42***	0.1***	-0.01	0.07***	0.18	-0.04***	0.42***	0.1***	-0.01	0.07***	0.18
	-1.14	20.22	7.53	-0.81	4.9		-5.11	20.22	7.3	-0.74	5.37	
(C) SELL-SELL	0					0	-0.05***					0
	0.1						-3.57					
	0.01	0.37***				0.13	-0.03*	0.37***				0.14
	1.23	17.12					-1.87	16.95				
	0.01	0.38***	-0.07***	-0.05***		0.14	-0.03**	0.38***	-0.08***	-0.05**		0.14
	0.83	17.95	-4.73	-2.6			-2.15	17.75	-4.76	-2.55		
	-0.01	0.39***	-0.07***	-0.05**	0.12***	0.16	-0.05***	0.39***	-0.07***	-0.05**	0.12***	0.16
	-0.95	18.05	-4.74	-2.55	6.76		-3.52	17.88	-4.76	-2.46	7.31	
(D) BUY-SELL	-0.02**					0	-0.04***					0
	-2.51						-3.68					
	-0.02*	0.37***				0.13	-0.02	0.37***				0.13
	-1.71	17.2					-1.42	17.11				
	-0.01	0.38***	-0.07***	-0.05***		0.14	-0.02*	0.38***	-0.08***	-0.05**		0.14
	-1.63	18.04	-4.69	-2.58			-1.75	17.98	-4.79	-2.56		
	-0.03***	0.39***	-0.07***	-0.05**	0.12***	0.16	-0.04***	0.39***	-0.07***	-0.05**	0.12***	0.16
	-4.15	18.1	-4.64	-2.52	7.29		-3.53	18.06	-4.82	-2.49	7.15	
(E) SELL-BUY	0					0	-0.01					0
	0.13						-0.29					
	0.02	0.41***				0.17	0.02	0.41***				0.17
	1.06	18.98					1.39	18.86				
	0.02	0.41***	0.1***	-0.02		0.18	0.03*	0.42***	0.1***	-0.02		0.18

1.35	19.67	7.08	-0.97			1.65	19.53	7.09	-1.01		
0.01	0.42***	0.1***	-0.01	0.06***	0.18	0.02	0.42***	0.1***	-0.01	0.06***	0.18
0.69	20.26	7.63	-0.81	4.67		1.16	20.11	7.66	-0.84	4.62	

Table 4. Regression Results about HFT Impact on Liquidity (Alternative Definition)

Notes: Table presents regression results on the impacts of HFT on nonHFT liquidity provision via alternative liquidity provision variables. Data covers the time span of Dec. 2015 and Mar. 2017, including 10170 observations in 339 trading days for 30 blue chip stocks listed in BIST 30 index of Borsa Istanbul. Left vertical side stands for the regressions using the HFT rate within number of orders; and nonHFT liquidity provision based on number of nonHFT orders not cancelled or executed. Right vertical side is for the regressions using the HFT rate within volume of orders; and nonHFT liquidity provision based on volume of nonHFT orders not cancelled or executed. Regressions are repeated for the impacts of overall HFT on overall nonHFT liquidity provision as well as for the buy and sell side HFT on each of the buy and sell side provision. Panel A is for the overall HFT - overall provision case. Panels B and C are for the Buy - Buy and Sell - Sell cases, respectively. Panel D (E) stands for the buy (sell) side HFT - sell (buy) side provision case. Each analysis is performed by 4 models presented in Equations 4 to 7 in Section 4. Volume is daily stock trading volume. Rm, market return is the return on the BIST 100 index. Abs(Rm) is the absolute value of market return. MCAP is the market capitalization as of previous day. All variables are calculated as described in Section 3.2. Variables are standardized around the means at the stock level. Adjusted R-squared values are given in last columns in each panel. t-values are given in even numbered lines that follow the lines reporting variable coeffcients. We report significance based on Driscoll-Kraay extension of Newey-West HAC robust standard errors.(*), (**) and (***) represent significance at 10%, 5% and 1% levels, respectively.

	HFT	Volume	Rm	abs(Rm)	MCAP	R2	HFT	Volume	Rm	abs(Rm)	MCAP	R2
(A) ALL-ALL	-0.07***					0	-0.07***					0.01
	-3.81						-4.68					
	-0.05***	0.49***				0.25	-0.04**	0.45***				0.21
	-3.17	26.1					-2.57	21.77				
	-0.05***	0.51***	0.04**	-0.09***		0.26	-0.03**	0.45***	0.02	-0.01		0.21
	-3.29	27.25	2.05	-3.43			-2.51	21.99	0.8	-0.6		
	-0.03*	0.5***	0.04*	-0.09***	-0.11***	0.27	-0.06***	0.47***	0.02	0	0.14***	0.22
	-1.87	26.39	1.71	-3.52	-4.64		-4.51	22.85	1.18	-0.21	10.19	
(B) BUY-BUY	-0.04**					0	-0.06***					0
	-2.55						-5.5					

	-0.03**	0.44***				0.19	-0.03***	0.39***				0.15
	-2.25	23.44					-3.48	18.63				
	-0.04**	0.43***	0.18***	0.02		0.23	-0.03***	0.39***	0.1***	0		0.16
	-2.57	24.69	6.56	0.53			-3.17	19.17	6.17	-0.21		
	-0.02	0.42***	0.18***	0.01	-0.11***	0.24	-0.04***	0.4***	0.11***	0	0.1***	0.17
	-1.24	24.86	6.09	0.29	-5.36		-4.63	19.97	6.91	0.16	7.53	
(C) SELL-SELL	-0.02					0	-0.04***					0
	-1						-2.95					
	0	0.38***				0.14	-0.02	0.35***				0.12
	-0.15	20.17					-1.33	16.71				
	-0.01	0.4***	-0.1***	-0.14***		0.17	-0.02	0.35***	-0.07***	-0.03*		0.13
	-0.73	22.1	-5.67	-6.86			-1.57	17.48	-4.34	-1.84		
	0	0.39***	-0.1***	-0.15***	-0.07***	0.17	-0.04***	0.37***	-0.06***	-0.02	0.13***	0.14
	0.17	20.99	-5.7	-6.78	-2.83		-3.17	17.67	-4.23	-1.55	8.71	
(D) BUY-SELL	-0.08***					0.01	-0.03**					0
	-5.24						-2.36					
	-0.07***	0.37***				0.15	0	0.35***				0.12
	-5.33	20.16					-0.31	16.77				
	-0.07***	0.4***	-0.09***	-0.14***		0.17	-0.01	0.35***	-0.07***	-0.03*		0.13
	-5.2	22.08	-5.45	-6.77			-0.56	17.59	-4.33	-1.86		
	-0.06***	0.39***	-0.1***	-0.15***	-0.06**	0.18	-0.02**	0.37***	-0.06***	-0.02	0.13***	0.14
	-4.79	20.9	-5.51	-6.72	-2.42		-2.5	17.77	-4.25	-1.58	8.48	
(E) SELL-BUY	-0.03*					0	0					0
	-1.78						0.17					
	-0.01	0.44***				0.19	0.03**	0.39***				0.15
	-0.93	23.46					2.27	18.75				
	0	0.43***	0.18***	0.02		0.23	0.03***	0.39***	0.11***	0		0.16

	-0.16	24.65	6.52	0.54			2.64	19.27	6.57	-0.24		
	0.02	0.42***	0.18***	0.01	-0.11***	0.24	0.02*	0.4***	0.11***	0	0.09***	0.17
	1.55	24.92	6.13	0.29	-5.78		1.8	20	7.21	0.1	6.62	

Table 5. Regression Results about HFT Impact on Volatility

Notes: Table presents regression results on the impacts of HFT on stock price volatility. Data covers the time span of Dec. 2015 and Mar. 2017, including 10170 observations in 339 trading days for 30 blue chip stocks listed in BIST 30 index of Borsa Istanbul. Left and right vertical sides stand for the regressions using the HFT rate within number and volume of orders, respectively. Volatility is the daily price volatility variable of price range. Regressions are repeated for the impacts of overall HFT, buy-side HFT and sell-side HFT on volatility, separately. Panel A is for overall HFT. Panels B and C are for the buy side and sell side HFT impacts on volatility, respectively. Each analysis is performed by 4 models presented in Equations 4 to 7 in Section 4. Volume is daily stock trading volume. Rm, market return is the return on the BIST 100 index. Abs(Rm) is the absolute value of market return. MCAP is the market capitalization as of previous day. All variables are calculated as described in Section 3.2. Variables are standardized around the means at the stock level. Adjusted R-squared values are given in last columns in each panel. t-values are given in even numbered lines that follow the lines reporting variable coeffcients. We report significance based on Driscoll-Kraay extension of Newey-West HAC robust standard errors.(*), (**) and (***) represent significance at 10%, 5% and 1% levels, respectively.

	HFT	Volume	Rm	abs(Rm)	MCAP	R2	HFT	Volume	Rm	abs(Rm)	MCAP	R2
(A) ALL-ALL	-0.03*					0	-0.01					0
	-1.65						-0.4					
	-0.01	0.49***				0.24	0.03	0.49***				0.24
	-0.63	13.98					1.31	13.73				
	-0.01	0.44***	-0.17***	0.29***		0.35	0.02	0.44***	-0.17***	0.29***		0.35
	-0.68	20.44	-5.97	9.4			1.33	20.28	-6.02	9.46		
	-0.01	0.44***	-0.17***	0.29***	0.01	0.35	0.02	0.44***	-0.17***	0.29***	0	0.35
	-0.82	20.58	-5.97	9.42	0.6		1.22	20.42	-6.02	9.48	0.25	
(B) BUY-BUY	-0.03*					0	-0.02					0
	-1.89						-0.93					

	-0.02	0.49***				0.24	0.01	0.49***				0.24
	-1.42	14.05					0.75	13.85				
	-0.01	0.44***	-0.17***	0.29***		0.35	0	0.44***	-0.17***	0.29***		0.35
	-1.26	20.47	-5.93	9.42			0.2	20.34	-6	9.44		
	-0.01	0.44***	-0.17***	0.29***	0.01	0.35	0	0.44***	-0.17***	0.29***	0.01	0.35
	-1.43	20.6	-5.93	9.44	0.64		0.12	20.47	-6	9.46	0.47	
(C) SELL-SELL	-0.01					0	0					0
	-0.31						0.12					
	0.01	0.49***				0.24	0.04	0.49***				0.24
	0.64	13.99					1.63	13.84				
	0.01	0.44***	-0.17***	0.29***		0.35	0.03**	0.44***	-0.17***	0.29***		0.35
	0.79	20.47	-5.99	9.44			2.01	20.36	-6.02	9.49		
	0.01	0.44***	-0.17***	0.29***	0.01	0.35	0.03*	0.44***	-0.17***	0.29***	0	0.35
	0.66	20.58	-6	9.45	0.38		1.88	20.49	-6.02	9.5	0.21	

Table 6. Regression Results about HFT Impact on Returns

Notes: Table presents regression results on the impacts of HFT on excess stock returns. Data covers the time span of Dec. 2015 and Mar. 2017, including 10170 observations in 339 trading days for 30 blue chip stocks listed in BIST 30 index of Borsa Istanbul. Left and right vertical sides stand for the regressions using the HFT rate within number and volume of orders, respectively. Excess return is the stock return over market return. Regressions are repeated for the impacts of overall HFT, buy-side HFT and sell-side HFT on returns, separately. Panel A is for overall HFT. Panels B and C are for the buy side and sell side HFT impacts on returns, respectively. Each analysis is performed by 4 models presented in Equations 4 to 7 in Section 4. Volume is daily stock trading volume. Rm, market return is the return on the BIST 100 index. Abs(Rm) is the absolute value of market return. MCAP is the market capitalization as of previous day. All variables are calculated as described in Section 3.2. Variables are standardized around the means at the stock level. Adjusted R-squared values are given in last columns in each panel. t-values are given in even numbered lines that follow the lines reporting variable coeffcients. We report significance based on Driscoll-Kraay extension of Newey-West HAC robust standard errors.(*), (**) and (***) represent significance at 10%, 5% and 1% levels, respectively.

	Number						Volume					
	HFT	Volume	Rm	abs(Rm)	MCAP	R2	HFT	Volume	Rm	abs(Rm)	MCAP	R2
(A) ALL-ALL	-0.01					0	-0.06***					0
	-0.65						-3.17					
	-0.01	0.08*				0.01	-0.05**	0.07*				0.01
	-0.45	1.91					-2.54	1.79				
	0	0.07***	0.65***	-0.01		0.43	-0.01*	0.07***	0.65***	-0.01		0.43
	0.77	3.49	98.21	-1.31			-1.85	3.4	100.09	-1.32		
	0.01**	0.06***	0.65***	-0.01*	-0.05***	0.43	0	0.06***	0.65***	-0.01*	-0.05***	0.43
	2.09	3.18	95.3	-1.67	-6.94		-0.63	3.14	97	-1.69	-6.49	

(B) BUY-BUY	0.07***					0.01	0					0
	4.27						0					
	0.07***	0.08**				0.01	0.01	0.08*				0.01
	4.37	1.97					0.3	1.9				
	0.06***	0.07***	0.65***	-0.01		0.43	0.03***	0.07***	0.65***	-0.01		0.43
	6.24	3.56	92.72	-1.26			3.98	3.59	97.33	-1.36		
	0.07***	0.06***	0.64***	-0.01*	-0.06***	0.43	0.04***	0.07***	0.65***	-0.01*	-0.05***	0.43
	6.27	3.19	90.07	-1.72	-7.87		4.37	3.27	94.6	-1.79	-7.33	
(C) SELL-SELL	-0.09***					0.01	-0.09***					0.01
	-5.27						-5.24					
	-0.09***	0.07*				0.01	-0.08***	0.07*				0.01
	-5.02	1.84					-4.59	1.77				
	-0.06***	0.07***	0.65***	-0.01		0.43	-0.06***	0.07***	0.65***	-0.01		0.43
	-7.3	3.41	97	-1.55			-6.88	3.31	96.81	-1.33		
	-0.05***	0.06***	0.64***	-0.01*	-0.04***	0.43	-0.05***	0.06***	0.64***	-0.01	-0.04***	0.43
	-6.32	3.17	94.58	-1.81	-4.95		-6.2	3.07	94.37	-1.63	-5.39	