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Borsa İstanbul Review

Borsa İstanbul Review 16-4 (2016) 233–248
http://www.elsevier.com/journals/borsa-istanbul-review/2214-8450

Full Length Article

Algorithmic and high-frequency trading in Borsa Istanbul

Oguz Ersan [a,*], Cumhur Ekinci [b]

[a] *Department of International Finance, Yeditepe University, Faculty of Commerce, Inonu Mah. Kayısdagı Cad. 26 Agustos Yerlesimi, Atasehir, 34755, Istanbul, Turkey*

[b] *Department of Management Engineering, Istanbul Technical University (ITU), Faculty of Management, Macka, 34367, Istanbul, Turkey*

Received 2 November 2015; revised 1 August 2016; accepted 5 September 2016
Available online 10 September 2016

Abstract

This paper investigates the levels of algorithmic trading (AT) and high-frequency trading (HFT) in an emerging market, Borsa Istanbul (BIST), utilizing a dataset of 354 trading days between January 2013 and May 2014. We find an upward trend in AT by using common proxies: number of messages per minute and *algo_trad* of Hendershott et al. (2011). Mean *algo_trad* for BIST 100 index constituents varies between −18 and −13 which is parallel to 2003−2005 levels of NASDAQ large cap stocks. Initially, we measure HFT involvement by detecting linked messages as in the way proposed in Hasbrouck and Saar (2013). Next, we propose an extended HFT measure which captures various HFT strategies. This measure attributes approximately 6% of the orders to HFT. HFT involvement is higher in large orders (11.96%), in orders submitted by portfolio/fund management firms (10.40%), after improvement of BIST's order submission platform and tick size reduction for certain stocks.

JEL classification: G10; G12; G14; G23

Keywords: Algorithmic trading; High-frequency trading; Borsa Istanbul; Market microstructure

1. Introduction

Algorithmic trading (AT), which is performed by computer algorithms rather than humans, has been growing extensively with the recent technological developments. High-frequency trading (HFT) is a broad subset of AT. HFT benefits from the technological capability of sending large number of orders in low latencies of milliseconds. Computerized and automated systems are much faster than the possible speed of a human's reaction. This provides HFT algorithms with a significant comparative advantage. Recent observations in order submission patterns show the sharp increase in HFT involvement in financial markets.

Developed markets with qualified technological infrastructures and large participation, experienced HFT earlier and in larger amounts. Introduced in late 1990s, HFT is estimated to reach its peak in 2009. Grant (2010) and Haldane (2010) claim that in that year HFT accounted for 60% of the shares traded and 70% of the turnover in US equity markets while HFT involvement in Europe was around 40%. Brogaard (2010) and Brogaard, Hendershott, and Riordan (2014) study a 120 stock dataset in which NASDAQ identified the trading by 26 high-frequency firms in 2008 and 2009. They report that HFT accounts for 68.5% of dollar volume and it takes part in 74% of trades. Hendershott and Riordan (2013) utilize a similar dataset with identified algorithmic traders. They observe that AT generates 52% of market order volume and 64% of limit order volume in Deutsche Börse. Although it is estimated that HFT involvement in the US equity market has been decreasing after 2009, its share was suggested to be as high as 51% in 2012 (Popper, 2012).

* Corresponding author.
E-mail addresses: oguz.ersan@yeditepe.edu.tr (O. Ersan), ekincicu@itu.edu.tr (C. Ekinci).

Peer review under responsibility of Borsa İstanbul Anonim Şirketi.

http://dx.doi.org/10.1016/j.bir.2016.09.005

Most of the financial markets literature assumes two main motivations for trading: information and liquidity.[1] However, HFT as a new motive for trade initiation actually dominates developed financial markets. Besides it has various consequences on the way we interpret financial environment. On one hand, ideas developed by traditional theories ignoring the existence of HFT may miss part of the truth. For example, Easley, Lopez de Prado, and O'Hara (2011, 2012) suggest that widely used informed trading measure, PIN (probability of informed trading) (Easley, Kiefer, O'Hara, & Paperman, 1996) is no longer capable of detecting informed trading due to large involvement of HFT. Consequently, they develop a new metric named VPIN (volume synchronized PIN) to measure order flow toxicity. Brennan, Huh, and Subrahmanyam (2014) show that explanatory powers of three common risk factors (size, book-to-market ratio and momentum) are significantly distorted by HFT. Chordia, Roll, and Subrahmanyam (2011) suggest that market quality and price efficiency have improved due to increased volume caused by HFT. Chordia, Subrahmanyam, and Tong (2014) further examine various market anomalies. The authors find that their economic and statistical significance have substantially decreased through the recent HFT era. On the other hand, there is a growing interest and questioning about the HFT activity by rule makers. The benefits and drawbacks of HFT are highly debated worldwide (Lewis, 2014).

We believe academic research will be more and more concentrated on HFT in the upcoming years, especially in emerging markets. Measurement of HFT and AT levels is essential in explaining stock price movements and other market characteristics. The relevant literature being very recent and incomplete, this paper is one of the first attempts to deal with this strategic topic.

In the literature, AT is usually linked to the number of total and/or canceled orders. Using 12 days of data for the Xetra system of Deutsche Börse, Prix, Loistl, and Huetl (2007) make a detailed analysis of the orders based on fulfillment. It is shown that 65% of the orders are no-fill deletion orders, i.e., orders that are fully canceled without execution. Moreover, cancellations mostly occur after several specific lifetimes, namely at 1 and 2 s, and after 0.5, 1, 2 and 3 min Hasbrouck and Saar (2009) find that 37% of the limit orders in their NASDAQ dataset are canceled within 2 s. Furthermore, these orders are priced more aggressively than orders with longer lives. On the other hand, they observe that only 6.37% of the total quantity of limit orders is satisfied. These facts are linked to the technological improvements and higher amount of market fragmentation which enhances AT opportunities.

Hendershott, Jones, and Menkveld (2011) use the number of electronic messages per $100 of trading volume as a proxy for AT. Electronic messages include all of the order submissions and cancellations. The proxy is referred as "*algo_trad*". They find that trading volume per electronic message monotonically decreases from $7000 in 2001 to around $1100 by the end of 2005. In a parallel study, Biais and Weill (2009) theoretically show that both number of canceled orders and *algo_trad* are correlated with AT.

In relevant studies, HFT is associated with the speed of order submission, the lifetime of orders and the existence of linked messages in low latencies. Hendershott and Moulton (2011) make a comparative analysis on the periods before and after the activation of NYSE's hybrid market. It is shown that the hybrid market increased automation and reduced execution times from 10 s to less than a second. Riordan and Storkenmaier (2012) examine the effects of a major upgrade in Xetra. The upgraded version of the system reduces the speed of order submission from 50 to 10 ms. Average number of quote changes at the best bid and ask is more than doubled after the upgrade. In addition, the authors propose and use QV ratio which represents the number of quote changes at the best bid or best ask per $10,000 of volume.

Hasbrouck and Saar (2013) (hereafter, HS 2013) propose a proxy for detecting HFT. This proxy is based on strategic runs of messages linked to each other. Specifically, if messages with the same size and in the same direction are observed within 100 ms, they are linked to each other. In this manner, there can be at least two separate orders and three messages (submission of a nonmarketable limit order, its cancellation and its resubmission as a marketable limit order that executes immediately) involved in a run. In order to obtain more confident representatives, the authors select a narrower set of runs with 10 or more messages. Next, they obtain a measure called "*RunsinProcess*" by time weighting the duration of each run in 10-min intervals. Consequently, they detect more than 113 million runs in the dataset that consists of 44 trading days and 350 to 400 NASDAQ stocks. 54%–60% of the cancellations are involved in strategic runs. This measure is shown to be highly correlated with HFT measures based on the trading activity of HFT firms.

Part of the literature uses special datasets which already incorporate information on documented AT or HFT activity of licensed firms.[2] On the other hand, most financial markets do not provide information on whether an order comes from an algorithmic or high-frequency trader. Then, tools for quantifying the levels of AT and HFT in financial markets are needed. Hendershott et al. (2011) AT proxy, *algo_trad* and HS (2013) HFT measure, *RunsInProcess* are among the most widely used of these tools.

HFT in developed markets has been broadly studied. The findings suggest that its share is even larger than 50%. On the other hand, there is not reliable information on the existence and extent of AT and HFT in emerging financial markets. Boehmer, Fong, and Wu (2015), using *algo_trad* (Hendershott et al., 2011), perform the broadest study on AT activity with data from 42 countries including emerging markets. However, they do not state country-specific levels of AT. Haldane (2010)

[1] See for example, broad market microstructure literature initiated by studies such as Kyle (1985), Glosten and Milgrom (1985) and Easley et al. (1996).

[2] See Brogaard et al. (2014), Menkveld (2013), Hagströmer and Norden (2013) and Carrion (2013) among others.

suggests that HFT accounts for only 5–10% of total volume in Asian markets.

This paper conducts analyses on the existence of AT and HFT in an emerging market, Borsa Istanbul (BIST). The main purpose of the study is twofold. First is to provide a strong and widely applicable methodology for detecting and measuring the level of HFT. Considering previously described major role and participation of HFT in financial markets, this should be of large importance. Literature aggregated through relatively short HFT history of up to couple of decades is scarce especially in certain aspects. Detection methodologies of HFT is one of these. Thus, by providing a new methodology, this study enables further research to be performed on HFT and its consequences. Our methodology while initiating from HS (2013) *RunsInProcess* measure, ends up with detecting completely different, more complex and diverse HFT strategies. We expect broad use of our suggested methodology by researchers.

Second purpose of this study is to provide an emerging market evidence on AT and HFT. This is also essential since there does not exist a similar evidence in the literature. Therefore, we expect further studies to link their findings to ours in this respect. In addition to these two main purposes, the study conducts detailed analyses on HFT activity. Specifically, we present evidence on activity among orders with different characteristics (order size, order submitter type), role of system upgrades and rule changes on HFT level (improvement of order submission platform, reduction in tick sizes), activity in the stocks with different characteristics (size, liquidity, volatility).

We use high-frequency order and trade data from January 2013 to May 2014 (17 months) obtained from BIST. Time span covers the adoption of improved electronic order submission platform in October, 2013. This enables us to study its possible effects on HFT. We restrict our analysis to 100 stocks listed in BIST 100 index each month. We investigate the order dynamics as well as AT and HFT existence through 85 million orders and 243 million messages.

As the first step, we make an overview of the order submission process presenting the distributions of electronic messages, order sequences and termination ways. We examine in a time series manner, number of total messages submitted, share of cancellation orders, and execution rates, all of which can be considered as signals of AT. We observe an increase in total number of messages through time. Overall execution rate is found to be 66.34% which is much higher than the ones witnessed in developed markets. Unlike most studies, we observe that modifications capture a reasonable share and they are frequently used in BIST. Moreover, number of order sequences with multiple modification messages is considerable and deserves attention.

In order to quantify the level of AT in BIST, we use a common proxy, total messages per minute. Additionally, we examine cancellations and modifications per minute separately. All these proxies exhibit an upward trend through time. Next, we obtain the Hendershott et al. (2011) AT proxy, *algo_trad*, for the stocks on daily basis. We find that *algo_trad* proxy reflects an upward trend between −18 and −13. This is very similar to the 2003–2005 trend for the NYSE large cap stocks as suggested by Hendershott et al. (2011).[3]

Subsequently, we measure HFT with the *RunsInProcess* method suggested by Hasbrouck and Saar (2013). For doing this, first, we obtain runs of linked messages as described in HS (2013). Specifically, we link messages with the same size if a canceled order is followed by another order in the same direction within very low latency. As a result, we obtain 791,000 runs which are very few compared to the original paper.[4] Only around 1.5% of messages are associated with HFT measured in this way.

Upon our preliminary findings on the frequent use of modifications in BIST, we extend the HS (2013) measure by including modification messages and simultaneous orders. In this way, we detect significant HFT activity. Specifically, we obtain 5 million runs with a total of 33.6 million linked messages (13.6% of all messages). Moreover, 36% of these messages are placed in runs with length 10 or more (4.9% of all messages).[5]

In addition, we study "take-profit" strategy that consists of a computer algorithm which sends a new order of the same size in the opposite direction once the first order is executed. Although this type of order combination is used by traders, it is not defined in the trading system of BIST.[6] Thus, detecting take-profit orders makes sense. We find that less than 1% of all messages can be attributed to this strategy, indicating that it is not widespread.

Observing that large orders comprise more messages, we separately examine the orders which have a size of TRY 250,000 or higher. Accordingly, up to one third of the large orders are directly involved in the detected runs. Similarly, we separately examine orders sent by portfolio/fund firms which are professional investors. We find these orders are associated with more HFT activity than orders sent by individual investors.

Although we find that HFT activity in general is higher in the period after the improvement of the order submission platform, the difference is lower than we expected. On the other hand, we provide evidence on the significant positive effect of tick size reduction in 10 stocks on the HFT use. Mean HFT ratio for these stocks increases from 3.49% to 5.22% in the month following the rule change.

We analyze market capitalizations, volatility and liquidity levels of stocks with different HFT levels. Stocks with excessive HFT levels tend to be small, illiquid, least or most volatile stocks. Through portfolios sorted on two market quality measures: liquidity and volatility, we examine cross section of HFT. Interestingly, HFT is relatively higher for both

[3] For a better view of the comparison, see Fig. 1 (ii) on page 8 in Hendershott et al. (2011).

[4] HS (2013) obtain 113 million runs in their analysis of NASDAQ stocks for 44 trading days.

[5] See Section 3 about the use of long runs as more reliable representatives of HFT, originally suggested by HS (2013).

[6] Although take-profit and stop-loss orders have been extensively analyzed in FX markets, evidence in stock markets is missing.

more liquid stocks and more volatile stocks. However, results are not always in economic significance and there does not exist monotonic relationships.

We believe this paper contributes to the literature in several ways. First, we extend the widely used HS (2013) HFT measure to allow for several different ways in which HFT can be performed. Second, we provide evidence on the existence of AT and HFT activities in an emerging market, i.e. BIST. To the best of our knowledge, this is the first paper to conduct analyses on AT and HFT activities in BIST. Third, we obtain solid evidence on more widespread use of HFT through large volume orders and by institutional investors (portfolio/fund management firms). Finally, we present several evidences on order and message traffic in an electronic market, HFT levels among stocks with various characteristics and effects of system upgrade and tick size change on HFT.

The remainder of the paper is organized as follows. Section 2 describes BIST and our data. Section 3 is about the methodology which explains AT proxies and HFT measures that we use as well as provides the details on the performed analyses. Section 4 states the results. Finally, Section 5 summarizes main findings and concludes.

2. Description of BIST and the data

Being one of the ten largest emerging markets in the world, BIST attracts significant foreign investment. By May, 2015, mean daily trading volume was TRY 4.4 billion ($1.63 billion) for the 419 listed stocks in the market. Our study period spans from the beginning of January, 2013 till the end of May, 2014 involving 354 trading days. We narrow our study to the BIST 100 index constituents due to low frequency of trading in most of the remaining stocks. BIST 100 index is formed by the market capitalization based weighted average of 100 largest stocks in the market. We take account of the updates in the list of the stocks included in the index and revise the stocks when needed. BIST 100 constituents account for 90% of the total BIST turnover through our study period.

Further descriptive information on trading rules and mechanisms in BIST would also provide better understanding of AT and HFT involvement in the market. First, it is noteworthy to mention that all publicly held companies' stocks are exclusively traded in BIST, reflecting no market fragmentation. In the opposite case, HFT strategies observed in BIST would most probably be more diverse, resulting in larger amount of HFT (for example HF arbitrage strategies among several markets). Short selling is available for all listed stocks excluding ones in watch list. Stocks in our analyses, restricted to the ones listed in BIST 100 index, can be sold short. In case of gross settlement, investors are obliged to have corresponding amount of cash to buy a stock. Similarly, they have to own the quantity that is demanded to sell. In case of net settlement, trading day difference (net balance) between buy and sell amounts of an investor is credited or debited. Gross settlement rules apply for only few stocks in the market while for the remaining, netting-off facility is used. For only one stock in our analyses, gross settlement exists in two months, which we neglect. Absence of gross settlement is a factor which enhances the use of HFT in Turkish market. This is because, it enables submission of large number of orders without requirement of reserves.

In BIST, trading is continuous from 9:35 to 13:00 and from 14:00 to 17:30. There are three call auction phases. Prices are fixed at 09:30, 13:55 and 17:35 (orders are collected from 09:15 to 09:30, from 13:00 to 13:55 and from 17:30 to 17:35) after which trading continues at closing price until 17:40. For our examined time period of January, 2013 to May, 2014, trading occurs through two sessions (morning and afternoon). Overall trading mechanism is quiet similar though. Both trading sessions initiate with single price call auctions followed by continuous auctions. At the start of our study period, first (second) session's call auction takes place between 09:30 and 9:50 (14:00 and 14:15). Continuous auction for first (second) session is between 09:50 and 12:30 (14:15 and 17:30). Closing call auction takes place between 17:30 and 17:40. Moreover, changes concerning first session trading hours occur on two dates: April 05, 2013 and June 10, 2013. On the first date, period of call auction that initiates the morning session is changed into 09:15 to 09:45. Following continuous auction starts at 09:45. On the second date, length of same call auction is reduced. New call auction is between 09:15 and 09:30 followed by the continuous auction.

Circuit breaker works for the overall market as well as individual stocks with certain conditions.[7] Electronic message types involve entries, modifications, splits and cancellations. During our study period, orders involved four types. *Limit orders* are the ones which include both price and quantity information. Unexecuted part of a limit order remains in passive form until the defined lifetime of the order. *Fill and kill orders* also specify price and quantity information. They differ from limit orders by the fact that unexecuted part is immediately canceled. *Special limit orders* are submitted to trade with all existing orders in the counter-side up to a specified price. Finally, *market orders* involve a specified value to be traded. Unexecuted part is canceled. Order modifications and cancellations are accompanied with varying fee rates mainly based on existence of any improvements. Orders can be canceled by the submitter at any time during the trading sessions. Moreover, large portion of cancellations in our dataset are automatic cancellations after trading hours due to specified validity of orders.

We use two primary data types provided by BIST. First one is the monthly order data with every submitted message and the regarding information such as time stamp in seconds, size, price, message type, submitter type, order ID, stock and trading day. The second one is the monthly trade data which reports all executed orders with the IDs of both sides in addition to details like size, price, time stamp etc. In daily

[7] For the circuit breaker of overall market, physical and extraordinary conditions (i.e., logistic problems and disasters) or technological and system breakdowns are required. For individual stocks, a circuit breaker is applied when threshold values are exceeded (%10 per session prior to the introduction of NASDAQ technology on November 30, 2015 and 20% thereafter).

basis, we combine two datasets for each of the analyzed stocks. Thus, we obtain the numbers and percentages of message types for each stock and trading day. Moreover, linking all the submitted messages of an order as well as the execution notifications together, we reach a sequence of messages for each order. Consequently we have 85 million orders and 243 million messages.

3. Methodology

In this section, we give our methodology to classify orders, detect AT and HFT and perform analyses.

3.1. Number of orders and sequences

Upon identifying the distribution of electronic messages, we obtain the order sequences by combining and matching the order IDs. Furthermore, we categorize each order with respect to its termination. By this way, we calculate the order execution rate (fill ratio) for each stock. Consequently, we focus on the shares of canceled and modified orders.

3.2. Algorithmic trading

We employ commonly used proxies to estimate the extent of AT in BIST. These are number of total messages per minute, number of cancellations per minute and the Hendershott et al. (2011) proxy called *algo_trad*. Additionally, we include number of modification messages per minute due to the fact that modifications are frequently used in BIST.

Obtaining total number of messages per minute is straightforward. We divide number of messages on each day and for each of the examined stocks by the length of the daily trading sessions in minutes as below.

$$M^{m}_{i,t} = M^{T}_{i,t} \Big/ D_t \tag{1}$$

where $M^{m}_{i,t}$ and $M^{T}_{i,t}$ are number of messages per minute and number of messages on day t for the stock i, respectively. D_t is the duration of trading day t, in minutes. D_t is equal to 400 (415) until (after) April 05, 2013, on the day the start of morning session is changed. By this way, we obtain the proxy for each stock on daily basis. We reach the numbers of cancellation and modification messages per minute in the same manner.

Hendershott et al. (2011) use number of messages per minute as a proxy for AT. As the next step, they suggest *algo_trad*, as a new proxy for the level of AT. They show that number of messages is correlated with both *algo_trad* and trading volume. Thus, *algo_trad* is normalized by trading volume. As suggested in Hendershott et al. (2011), *algo_trad* is calculated as in Equation (2).

$$algo\_trad_{i,t} = -\frac{V^{T}_{i,t} \Big/ 100}{M^{T}_{i,t}} \tag{2}$$

where, $V^{T}_{i,t}/100$ and $M^{T}_{i,t}$ are trading volume in \$100 and number of messages for stock i on day t, respectively. In order to compare the results with the ones for U.S. market (Hendershott et al., 2011), trading volume is scaled in US dollars. Thus, the proxy represents the level of algorithmic trading considering for different currency (trading volume being converted from Turkish Lira-TRY to US dollar) as well as changes in USD/TRY exchange rate. In each of the calculations, the proxy is a result of current exchange rate.

3.3. High-frequency trading

We primarily use Hasbrouck and Saar (2013) measure called *RunsInProcess* to detect and quantify HFT in BIST. *RunsInProcess* is based on the practice of linking orders which are thought to be submitted by high-frequency traders. For distinguishing these orders, several criteria are used. Two orders are linked if i) the former is canceled and the latter is in the same direction, ii) orders have the same size[8] and iii) the cancellation is followed by an order within a low latency, i.e. 100 ms.

By this way, "runs" of messages are obtained. The shortest run involves four messages: an order entry, its cancellation, second order's entry and its termination. On the other hand, a run might include hundreds of canceled orders which are linked under the described conditions. Panel (a) of Table 1 presents an example of a run formed in this way. The run includes 170 messages lasting 7 min and 7 s. Each of the 85 orders is of the same size and price. Order entries and cancellations are linked within low latencies. HS (2013) narrow cases of HFT to the runs with 10 or more messages. Upon the determination of runs of linked orders and messages, the authors quantify the level of HFT in intervals of 10 min by considering the runs' durations. The duration of a run is simply the time period between the first and last message. Consequently, *RunsInProcess* measure, calculated on a 10-min basis for each stock, is calculated as in Equation (3),

$$RunsInProcess_{i,t} = \sum_{n=1}^{N} D_n / 10 \tag{3}$$

where, $RunsInProcess_{i,t}$ is the HFT measure for stock i and interval t; N is the number of runs which (partially) take place in interval t; D_n is the duration of nth run within interval t. For example, a run that starts exactly at the beginning of interval t and lasts for 15 min adds 1 point to the measure for the interval t and 0.5 point for interval t+1.[9]

[8] In reality, HFT might be performed strategically with varying order sizes. However, detection of these orders seems not possible. Besides, results indicate that HFT is also commonly applied via submission of same sized orders.

[9] In this paper, we quantify HFT activity by obtaining the runs of linked messages. We compare our results on the level of HFT activity with the ones of Hasbrouck and Saar (2013). We perform this through the number of runs, messages and orders. Thus, for the sake of brevity, we do not include our 10-min *RunsInProcess* values.

Table 1a
Examples of HFT Activity in BIST. Panel (a): Example of a run formed in the way described in HS (2013).

Order ID	Time	Message type	Shares	Price
189893	10:54:05	Buy order entry	1086	10.1
189893	10:54:10	Cancellation	1086	10.1
190010	10:54:10	Buy order entry	1086	10.1
190010	10:54:15	Cancellation	1086	10.1
190164	10:54:15	Buy order entry	1086	10.1
190164	10:54:20	Cancellation	1086	10.1
190309	10:54:20	Buy order entry	1086	10.1
190309	10:54:25	Cancellation	1086	10.1
190484	10:54:25	Buy order entry	1086	10.1
190484	10:54:30	Cancellation	1086	10.1
190621	10:54:30	Buy order entry	1086	10.1
190621	10:54:35	Cancellation	1086	10.1
190732	10:54:35	Buy order entry	1086	10.1
190732	10:54:40	Cancellation	1086	10.1
190809	10:54:40	Buy order entry	1086	10.1
190809	10:54:45	Cancellation	1086	10.1
190955	10:54:45	Buy order entry	1086	10.1
190955	10:54:50	Cancellation	1086	10.1

Notes: The run is for the Akfen Holding stock with the ticker symbol "AKFEN" on 31.01.2013. The run comprises 170 messages in 85 consecutive orders, however, only 18 messages are shown in the table. All orders have the same size (1086 shares) and price (TRY 10.1). Each new buy order entry follows the cancellation of the previous one in low latency of lower than 1 s. An additional fact about the example implying that the run is generated via an algorithm is the constant duration of 5 s between each order entry and its cancellation. Altering to four and 6 s as well in the excluded last part, the run stops at 11:01:12 lasting 7 min and 7 s in total.

Table 1b
Examples of HFT Activity in BIST. Panel (b): Example of a run with simultaneous orders formed in the way suggested in this paper.

Order ID	Time	Message type	Shares	Price
164774	10:34:54	Sell order entry	18500	21.30
164775	10:34:54	Buy order entry	18500	20.95
164777	10:34:54	Sell order entry	18500	21.35
164778	10:34:54	Sell order entry	18500	21.25
164774	10:42:00	Modification (S)	18500	21.15
164775	10:42:00	Modification (B)	18500	20.80
164777	10:42:00	Modification (S)	18500	21.20
164774	10:44:53	Modification (S)	18500	21.30
164775	10:44:53	Modification (B)	18500	20.95
164777	10:44:56	Modification (S)	18500	21.35
164774	10:45:53	Modification (S)	18500	21.15
164775	10:45:53	Modification (B)	18500	20.80
164777	10:45:53	Modification (S)	18500	21.20
164774	10:45:54	Modification (S)	18500	21.30
164775	10:47:00	Modification (B)	18500	20.95
164777	10:47:02	Modification (S)	18500	21.35
164778	11:32:13	Modification (S)	18500	21.40
164774	11:32:14	Modification (S)	18500	21.45
164778	11:32:14	Modification (S)	18500	21.25
164774	11:32:15	Modification (S)	18500	21.30
164778	11:39:17	Modification (S)	18500	21.40
164774	11:39:19	Modification (S)	18500	21.45
164774	14:30:43	Modification (S)	18500	21.30
164778	14:31:03	Modification (S)	18500	21.25
164774	14:33:33	Modification (S)	18500	21.15
164775	14:33:33	Modification (B)	18500	20.80
164777	14:33:33	Modification (S)	18500	21.20
164778	14:36:21	Modification (S)	18500	21.10
353871	14:36:21	Buy order entry	18500	20.70
164778	14:40:24	Modification (S)	18500	21.25
353871	14:40:24	Modification (B)	18500	20.85
164774	14:40:26	Modification (S)	18500	21.30
164774	14:40:26	Modification (S)	18500	21.15
164778	14:40:26	Modification (S)	18500	21.10
353871	14:40:28	Modification (B)	18500	20.70
164778	15:03:08	Modification (S)	18500	21.25
353871	15:03:08	Modification (B)	18500	20.85
164774	15:03:10	Modification (S)	18500	21.30
164774	15:03:11	Modification (S)	18500	21.15
164778	15:03:11	Modification (S)	18500	21.10
353871	15:03:13	Modification (B)	18500	20.70
164778	15:03:53	Modification (S)	18500	21.25
353871	15:03:53	Modification (B)	18500	20.85
164774	15:03:55	Modification (S)	18500	21.30

(*continued on next page*)

Table 1b (*continued*)

Notes: The run is for the stock of Türk Halk Bankası with the ticker symbol "HALKB" on 07.05.2013. The table reports the first 44 messages while the run includes 242 electronic messages in total, sent through 7 different orders of same size. Apart from the 3 sell order and 4 buy order entry messages, 1 execution message and 6 cancellations; 227 are modifications. Many of the electronic messages that the orders involve are linked in timing. Consequently, 1 sell order is executed and the remaining 6 orders are canceled. Modifications of buy orders and sell orders are represented by Modification (B) and Modification (S), respectively.

Table 1c
Examples of HFT Activity in BIST. Panel (c): Examples on the "take-profit" strategy.

Order ID	Time	Message type	Shares	Price
54083	09:26:00	Sell order entry	500	6.48
54083	15:38:38	Execution	500	6.48
400433	15:38:39	Buy order entry	500	6.44
400433	15:39:07	Execution	500	6.44
492391	16:52:16	Buy order entry	500	6.42
492391	17:00:27	Execution	500	6.42
506564	17:00:27	Sell order entry	500	6.46
506564	17:28:50	Execution	500	6.46

Notes: Table reports two examples of take-profit strategy from Alarko Holding stock with the ticker symbol "ALARK" on 26.05.2014. The first one starts with a sell order and the second one with a buy order. In low latency of lower than 1 s, a position of the same size on the opposite direction is taken following the execution of first order.

In this paper, we initially calculate the original *RunsInProcess* measure described above with one exception. Due to the fact that the data provided by BIST does not show time stamps in milliseconds, we alter the time limit of 100 ms with 1 s. Altered duration of 1 s is still clearly lower than a possible human response enabling us to detect HFT orders.

The scope of the original *RunsInProcess* measure is narrow capturing a HFT strategy that uses consecutive orders with cancellation. In our preliminary analyses on the BIST order data, we discover several other applications of HFT. Thus, as the next step, we suggest an extended version of the measure called *RunsInExtended* which captures a wider relation among orders and messages. Specifically, in addition to consecutive orders, simultaneous orders are widely used in HFT. This is mainly due to modification messages. Panel (b) of Table 1 gives an example of a run with several orders submitted, modified and canceled together. 7 orders result in 242 messages, 227 of which are modifications. Consequently, all orders except one are canceled.

In the extended version, we link two orders with the same size if they have messages submitted within 1 s. To obtain runs of linked orders for a stock on a given day, we group orders with the same size. We only select order entries, modifications and cancellations within the trading sessions while we leave out execution messages and automatic cancellations that take place after the trading sessions. Next, we link the messages arriving within 1 s. As in the original *RunsInProcess* measure, there is always the probability of classification errors in attributing linked messages to HFT in our extended measure. However, restricting runs to the ones with at least 10 messages should substantially increase the reliability of the measure.

In our next analysis, we focus on a specific trading strategy called "take-profit". It is applied via two consecutive orders in opposite directions. When the first order is filled, another order with the same size and in the opposite direction is submitted to the system with a price that seeks generating profit. If the first order is a buy (sell), following sell (buy) order entry is submitted at a higher (lower) price. Thus, the main purpose of the strategy is to earn the profit between the prices of targeted transactions. Many order submission interfaces involve take-profit as an easy-to-use preference. Second order is submitted automatically when the first is filled. With this characteristic, it is a straightforward HFT strategy in which the second order is submitted in a low latency without the inclusion of an additional human intervention.

In order to obtain take-profit runs, we link the orders with the same size if execution of the first one is followed by the entry of the second within 1 s. In addition, we require a run starting with a buy (sell) to be followed by a sell (buy) order of higher (lower) price. Consecutively, take-profit strategy runs mostly involve sequence of the type: a buy (sell) entry, its execution, a sell (buy) entry and its execution (or cancellation).[10]

3.4. Analyses on HFT

We perform various analyses on HFT. These include comparative examination of HFT levels in different order types. Moreover, we investigate potential effects of system upgrades and rule changes on HFT extent. Finally, we overview cross section of HFT among stocks with different characteristics and draw conclusions.

Initially we perform two comparative analyses with respect to order size and order submitter type (individual investor or portfolio/fund). In fact, we expect to see more HFT activity in large orders. This implies more messages per orders for large sized orders. We define large orders as the ones with a turnover of TRY 250,000 or more.[11] Similarly, we expect professional investors (i.e., portfolio management or fund management firms) to be involved in HFT activity more than individual investors. The employed data enables this comparison since it includes "order submitter type" information. Specifically, orders are from one of three types: regular customers (müşteri), portfolio firms (portföy) and fund management firms (fon). First type, "regular customers", includes individual investors as well as firms and corporations. Second type involves brokerage firms. Finally, fund management firms also include mutual funds. Order submitter type is detected by BIST at the time of order submission via the observation of stated account owners. Brokerage firms may submit orders for their own account and for their customers' accounts. This information on order submitter type is stored by BIST in the dataset we use. Comparing first type with other two is not identical to the comparison of individual and institutional investors in the market. However, it is obviously a reasonable representative. Individual investors can perform HFT activity through both their facilities and brokerage firms with existing technological facilities.

Next, we examine the effect of a major improvement in the electronic order submission platform of BIST on October 4, 2013. We expect to see higher HFT activity in the second part of our dataset due to the adopted improvement. Rule changes regarding the overall trading mechanism can influence the HFT level. Therefore, we search for such changes through the notifications on BIST website. One significant change is about the reduction of tick sizes to TRY 0.01 for ten large cap stocks. New tick sizes are applied from January 2, 2014. Considering the fact that smaller tick sizes may increase trading efficiency, this change stands as a potential factor in HFT level. O'Hara, Saar, and Zhong (2015) show that HF traders are the only ones who increase their share in trading activity when tick size is smaller. This is explained by more aggressive use of the market with larger number of submitted orders. We examine HFT levels in two months surrounding tick size reduction both for stocks with and without the change. We test for the significance of differences in means via one sided paired t-test with the alternative hypothesis of larger HFT activity in latter month.

Finally, we examine cross section of HFT with market quality measures. Specifically, liquidity and volatility levels are two main representatives of market quality. High liquidity and low volatility are preferred in any financial market. Literature suggests contradicting ideas about the role of HFT in financial markets. Thus, observing the extent of HFT among stocks with different characteristics is essential. It is noteworthy to mention that the main goal of this paper is twofold: to improve and develop measurement methodologies for AT and HFT and to provide an emerging market evidence on AT and HFT extent. However, our further analyses described in

[10] Stop-loss strategy is analogous to take-profit strategy, however, it is hard to detect with the currently available data.

[11] USD/TRY exchange rate is 1.78 at the beginning of our study period and 2.09 at the end. Increasing the lower limit to TRY 500,000 for the large orders does not distort the results. However, pool of large orders decreases substantially.

Table 2
Numbers of messages.

	Message type	No. of messages	% (in all)	% (B/S side)
Buy	Order entry (O)	45,202,813	18.63	36.91
	Order modification (M)	5,713,895	2.36	4.67
	Order split (S)	118,511	0.05	0.10
	Execution (E)	56,184,397	23.16	45.88
	Execution (merged)	32,050,827		
	Cancellation within the session (C)	7,445,646	3.07	6.08
	Automatic cancellation at the end of 1st session (AC1)	1,747,299	0.72	1.43
	Automatic cancellation at the end of 2nd session (AC2)	6,039,666	2.49	4.93
	Subtotal	122,452,227	50.47	100
Sell	Order entry (O)	39,826,195	16.41	33.14
	Order modification (M)	7,888,641	3.25	6.56
	Order split (S)	241,176	0.10	0.20
	Execution (E)	56,184,397	23.16	46.75
	Execution (merged)	25,347,113		
	Cancellation within the session (C)	5,608,901	2.31	4.67
	Automatic cancellation at the end of 1st session (AC1)	1,921,627	0.79	1.60
	Automatic cancellation at the end of 2nd session (AC2)	8,503,269	3.50	7.08
	Subtotal	120,174,206	49.53	100.00
	Total	242,626,433	100.00	

Notes: Numbers of occurrence for different message types and their percentages in the dataset are reported. Last two columns present percentage shares within all messages and within only buy or sell side, respectively. The message types include order entries, modification requests, order splits, executions and cancellations. While order entries, modifications, splits and cancellations are withdrawn from the 'BIST order data', executions are listed in the separate 'BIST trade data'. 'Executions (merged)' refers to the executions after consecutively listed partial executions are merged into one for each order. They are not included in calculation of subtotals in order to prevent double counting. Cancellations are categorized into three: the ones requested by traders during session hours and automatic cancellations at the end of the first and second sessions due to predefined lifetimes of the orders. Letter representations of different message types are given in brackets.

this subsection would also reveal several outcomes regarding potential factors in HFT level and consequences of HFT.

As a measure of liquidity, we use daily turnover in TRY for each stock. We calculate volatility measure on daily basis by $(max. - min.)/(max. + min.)/2$ where max. and min. represent highest and lowest prices of a stock within a given trading day. After calculating liquidity and volatility variables on daily basis, we obtain the monthly variables by simply taking the average of daily values in each month.

In addition to liquidity and volatility, we analyze the HFT level with respect to market capitalization (market cap). Market cap values are reported by the end of each month. In order to obtain better representatives, we use the average of two consecutive values for each month. Specifically, for month t, we use $(M_{t-1} + M_t)/2$, where M_t is the market cap of a stock by the end of month t. We obtain the data on liquidity, volatility and market cap from Thomson Reuters Eikon.

In a preliminary step, we examine HFT levels for a total of 120 stocks which take place in BIST 100 index in all or certain part of studied months. Sorting by HFT levels, we attempt to draw conclusions on the characteristics of stocks with excess HFT levels. In the next step, we originate 25 (5 × 5) portfolios on two market quality measures: volatility and liquidity. For each of the 17 months, we update the portfolios based on monthly liquidity and volatility values and updated list of 100 stocks listed in BIST 100 index. We report consequent HFT levels for the portfolios by taking the averages of 17 months. By this way, we seek for any potential systematic changes in HFT level with respect to market quality measures. Differences in HFT levels between highest and lowest volatility (liquidity) portfolios are reported. We test for the significance of differences in means via one sided paired t-test with the alternative hypothesis of higher HFT activity in most liquid and most volatile portfolios.[12,13]

4. Results

This section includes the results about number of orders and sequences as well as the levels of AT and HFT in Borsa Istanbul.

4.1. Number of orders and sequences

In this subsection, we provide an overview of the order dynamics in BIST. In other words, we explore various characteristics about orders such as their numbers, sequence and way of termination. We compare these figures to the ones observed in developed financial markets with high AT and HFT involvement.

Table 2 presents the numbers and percentages of different message types in our dataset.[14] There exist 243 million messages listed in the order and trade dataset we examine for the time period January 2013 – May 2014. The messages are of four types: order entries, modifications, cancellations and executions. Cancellations can be performed via separate messages from the order owners. In addition, they can occur after the end of both sessions. These are automatic cancellations of the system to terminate orders with lifetimes of one or two sessions. While most of the messages consist of new buy/sell request or execution notifications, cancellation and modification messages are also numerous.

Table 3 summarizes the order termination types and their shares. Consequent execution rate is found to be 66.34% (65.4% full execution, 0.9% partial execution). This is much higher compared to around 21% in a similar Deutsche Börse analysis (Prix et al., 2007) although with an older dataset. 29%

[12] We check for the normality of sample distributions by the use of Shapiro–Wilk normality test. We cannot reject the null hypothesis of normal distribution for the vast majority of portfolios. We also apply the normality test for monthly HFT ratios of stocks with tick size reduction, again not rejecting null hypothesis of normal distribution.

[13] We thank the anonymous referee for contributory comments on consideration for rule changes and inclusion of analyses on HFT with respect to market quality measures.

[14] In Tables 2–5 which provide descriptive information on orders and messages we state numbers as well as percentage shares. We report percentage shares in total messages (or orders) for an overview of distributions. In addition, we present shares in buy and sell sides separately, following Fong and Liu (2010), which compares between two sides of trades.

Table 3
Order termination.

	Termination type		No. of orders	% (in all)	% (B/S side)
Buy	Full execution		31,248,295	36.60	69.01
	Partial execution		438,206	0.51	0.97
	Cancellation	Within the sessions	5,430,036	6.36	11.99
		Automatic: end of 1st session	1,742,400	2.04	3.85
		Automatic: end of 2nd session	6,039,666	7.07	13.34
	Unidentified		384,463	0.45	0.85
		Subtotal	45,283,066	53.03	100.00
Sell	Full execution		24,590,985	28.80	61.32
	Partial execution		369,924	0.43	0.92
	Cancellation	Within the sessions	4,126,582	4.83	10.29
		Automatic: end of 1st session	1,914,904	2.24	4.77
		Automatic: end of 2nd session	8,503,269	9.96	21.20
	Unidentified		597,931	0.70	1.49
		Subtotal	40,103,595	46.97	100.00
		Total	85,386,661	100.00	

Notes: The table reports termination ways of 85 million orders for the BIST100 index stocks between January 2013 and May 2014. Last two columns present percentage shares within all orders and within only buy or sell side, respectively. Canceled orders are grouped analogously to Table 2.

of buy orders and 36% of sell orders are canceled, larger part being automatic end of session cancellations. The proportion of canceled orders is around 70% in Prix et al. (2007) and even higher (90%—92%) in 2007—2008 NASDAQ analyses of HS (2013). Anyway, the share of canceled orders in our dataset is still high. Almost one third of the orders are canceled.

Table 4
Order sequences.

	Order sequence	Number of orders	% (in all)	% (B/S side)
Buy	O − E	28,798,378	33.73	64.44
	O − C	4,888,360	5.72	10.94
	O − AC1	1,432,911	1.68	3.21
	O − AC2	5,435,415	6.37	12.16
	O − M − E	2,653,931	3.11	5.94
	O − M − C	377,877	0.44	0.85
	O − M − AC1	276,420	0.32	0.62
	O − M − AC2	521,106	0.61	1.17
	O − C − E	309,241	0.36	0.69
		44,693,639	52.34	100.00
Sell	O − E	20,807,622	24.37	53.24
	O − C	3,694,176	4.33	9.45
	O − AC1	1,674,463	1.96	4.28
	O − AC2	7,636,310	8.94	19.54
	O − M − E	3,839,496	4.50	9.82
	O − M − C	294,072	0.34	0.75
	O − M − AC1	185,982	0.22	0.48
	O − M − AC2	710,551	0.83	1.82
	O − C − E	238,595	0.28	0.61
		39,081,267	45.77	100.00
	Other	1,611,755	1.89	
Total		85,386,661	100.00	

Notes: The table reports numbers and percentages of sequences in 85 million orders. Last two columns present percentage shares within all orders and within only buy or sell side, respectively. O represents order entries; C represents cancellations within session hours; AC1 and AC2 show automatic cancellations after 1st and 2nd sessions, respectively; M stands for modifications and E for executions. Most frequent types of order sequences in the dataset are reported. There exist thousands of different sequences with different combinations of messages. First, we group similar types together. Second, we only report sequences with larger than 0.1% share in the dataset. Consequently, reported sequences in the table sum up to 98.20% of all order sequences. In grouping different sequences together, we combine multiple M's, E's, C's into one. For example, the sequence O − M − E includes less frequent sequences of such as "O − M − M − M − E" or "O − M − E − E − …".

Examination of order sequence types and their relative shares provides additional information on order dynamics. Table 4 summarizes main sequence types, their numbers and percentages for the buy and sell sides. Multiple occurrence of modification messages are represented as one. We followed the same approach for the execution and cancellation messages. This enables us to include thousands of different sequences with low occurrence rates in our analysis. Various repetitions of messages may represent different motives and intentions. For example, one modification message in an order sequence more probably signal the intention to modify the previously sent price detail while 50 modifications in the same order may reflect a possible strategy including AT or HFT. However, we leave this analysis for the further part of the section.

The table shows that the order—execution (O—E) sequence (i.e. an order entry followed by an execution message without any modification or cancellation request) constitutes 58.1% (33.73% on buy side and 24.37% on sell side) of all the sequences. Remaining portion of the sequences either involves

Table 5
Order modifications.

	Modification(s) in an order					
	1	2	3	4—10	10+	Total
Buy orders	3,003,115	601,911	169,432	136,609	15,335	3,926,402
% (in all)	33.42	6.70	1.89	1.52	0.17	43.70
% (B/S side)	76.49	15.33	4.32	3.48	0.39	100.00
Sell orders	3,733,150	865,581	257,672	184,150	18,028	5,058,581
% (in all)	41.55	9.63	2.87	2.05	0.20	56.30
% (B/S side)	73.80	17.10	5.10	3.64	0.36	100.00
Total	6,736,265	1,467,492	427,104	320,759	33,363	8,984,983
% (in all)	74.97	16.33	4.75	3.57	0.37	100.00

Notes: The table reports numbers and percentages of orders with various modification repetitions. Within buy (sell) orders, percentage shares in all orders and in all buy (sell) orders with modifications are given in consecutive rows.

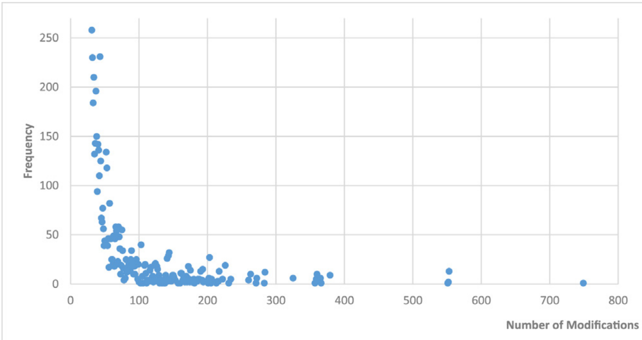

Fig. 1. Number of modifications in an order. The figure represents the orders with more than 30 modifications. An order includes at most 751 modification messages in the dataset.

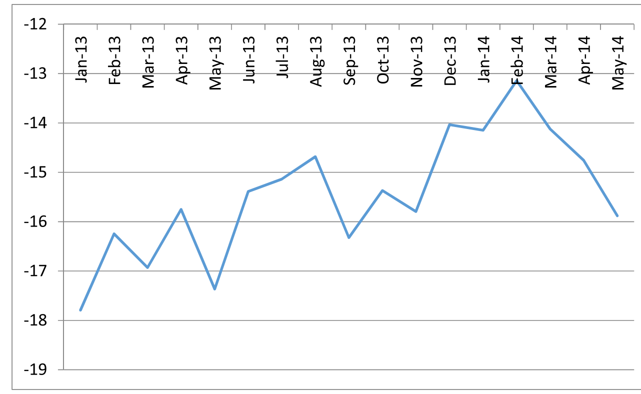

Fig. 3. *Algo_trad*. The proxy of Hendershott et al. (2011) is the negative of dollar volume (in $100) per electronic message. The higher the ratio the higher the AT activity.

one or multiple modification requests; one or more cancellation messages; or both.

The most frequent five sequences constitute around 95% of the overall dataset. These are orders submitted and executed (O–E), orders canceled in and out of the session hours (O–C) and orders executed after modification(s) (O–M–…). Table 4 also reflects that modification and cancellation messages do not frequently involve within same orders. Specifically, order sequences having both of the message types account for roughly 3% of the orders. This is important since two message types may act as the tools for AT and HFT.

Table 5 presents the number of modifications in the orders which had at least one modification message. Most commonly, orders are modified once (74.97%) or twice (16.33%). It is also interesting to see that sell orders are modified more than buy orders (56.3% vs 43.7%). Fig. 1 further investigates the orders which involve more than 30 modification messages. We observe that some orders are modified many times (>500 times). In addition, existence of more than one order with the same large number of modifications implies the existence of computer algorithms sending predefined numbers of messages to the trading system. For example, there are 13 orders which involve 553 modification messages each.

4.2. Algorithmic trading

Revealed by the order sequences and message distributions, we observe traits of AT in BIST. In order to quantify the level of AT in the market, we use widely known AT proxy, *algo_trad*, developed by Hendershott et al. (2011) as well as number of messages (also cancellations and modifications) per minute.

Fig. 2 reflects the trend of various types of messages, i.e. total messages, cancellations and modifications. As the time period of the study is seventeen months, we do not observe dramatic changes. However, each of the three panels in the figure exhibits upward trend. The figure shows that on average total number of messages per minute vary between 1363 and 2,094, cancellations per minute vary between 195 and 250 and modifications per minute vary between 77 and 125. This level of activity is much more intense than the one in the examined period of 2001–2005 in Hendershott et al. (2011) NYSE study. Specifically, for the largest cap quintile, their study

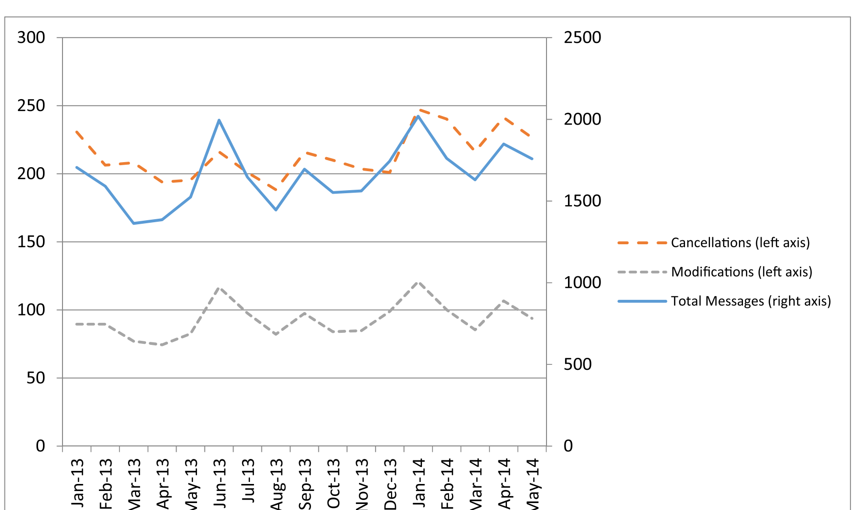

Fig. 2. Number of messages per minute.

reports totally 40 messages per minute in 2001 and around 250 messages by the end of 2005.

Normalizing for the trading volume, *algo_trad* enables comparisons among different markets and through time. Fig. 3 provides mean *algo_trad* from Jan 2013 to May 2014 for the 100 stocks included in our analysis. The proxy varies between −18 and −13, again with an upward trend. Hendershott et al. (2011) report that *algo_trad* starts from −70 at the beginning of 2001 and reaches almost −10 by the end of 2005 for the NYSE largest cap quintile. Referring to the study of Hendershott et al. (2011), AT level on BIST is similar to the ones observed in 2003–2005 on the NYSE.

These findings suggest that although BIST has a large number of messages, it carries out a much lower AT activity compared to NYSE. Measured by *algo_trad*, the recent level of AT in BIST is similar to the 2003–2005 levels in NYSE.

Both the concept of AT and its commonly used proxies (number of messages and *algo_trad*) give insight on the order submission dynamics and motivations behind orders. However, the concept is extremely wide and captures numerous strategies including HFT. In order to reveal specific types of AT, we move on to its subset, HFT, which is performed in various ways some of which can be more easily detected and quantified.

4.3. High-frequency trading

Table 6 reports HFT runs detected by *RunsInProcess* as suggested in HS (2013) and in its extended form suggested in our paper. *RunsInProcess*, capturing consecutive orders linked with a cancellation message, finds 790,994 runs with a total of 3,758,643 messages. Majority of the runs (around % 80) include three or four messages. Similarly, almost 90% of the involved messages are placed in the runs of length up to ten. HS (2013) report that runs of length ten or more, as reliable representatives of HFT, comprise 67% of all messages in the runs. This rate is as low as 10.66% in our study which disables the restriction to longer runs. Consequently, number of detected runs is limited and the vast majority is of length up to ten.

On the other hand, our extended measure incorporates several different features. First, it captures 5 million runs with a total of more than 33 million messages. Considering that we work with 243 million messages, 13.6% are associated with HFT. Compared to the original, extended version involves more strategies of low latency trading. Especially with the inclusion of simultaneous orders and modification messages, the number of detected HFT runs increases sharply. Secondly, 36% of the detected messages are placed in the runs of length ten or more. Narrowing down the number of runs to longer ones is even more essential for the use of the extended measure because the likelihood of classification errors is higher when extending the possible combinations of messages. However, runs with ten or more messages are unlikely to be sourced by errors. Using the extended measure with only longer runs, we both quantify a broad HFT activity and sustain the reliability of the measure.

Last row of Table 6 provides information on the use of take-profit strategy in BIST. It is reflected that the strategy is not widespread. We detect 343,000 runs with a total of approximately 1.5 million messages (less than 1% of total messages).

The last two columns of Table 6 show that execution rates decrease systematically with the length of runs. This is intuitive since longer runs are more reliable representatives of HFT. Especially with the original *RunsInProcess* measure, execution rate decreases from 80% in runs of length up to four to around 14% in runs with longer than 100 messages. Reported in Section 4.1, mean execution rate for the examined orders is 66.34%, which is much higher compared to the rates in developed markets with intense HFT activity.

4.4. Analyses on HFT

Table 7 reports the numbers and percentages of HFT orders with respect to three specifications: order size, order submitter

Table 6
RunsInProcess (original and extended) and take-profit runs.

	Length of runs	Runs (#)	Runs (%)	Messages (#)	Messages (%)	Total exec. (#)	Exec. rate (%)
RunsInProcess	3–4	628,033	79.40	2,510,107	66.78	507,704	80.84
	5–9	143,629	18.16	847,610	22.55	94,940	66.10
	10–19	14,446	1.83	178,250	4.74	6561	45.42
	20–99	4629	0.59	154,964	4.12	858	18.54
	100 +	257	0.03	67,762	1.80	35	13.62
	All	790,994	100	3,758,643	100	610,098	77.13
RunsInExtended	3–4	2,738,199	54.40	10,881,860	32.39	1,702,627	62.18
	5–9	1,679,822	33.38	10,708,163	31.87	895,704	53.32
	10–19	469,817	9.33	5,862,285	17.45	219,905	46.81
	20–99	138,799	2.76	4,457,165	13.27	61,243	44.12
	100 +	6374	0.13	1,691,362	5.03	2729	42.81
	All	5,033,011	100	33,600,835	100	2,882,208	57.27
Take-profit	All	343,349	100	1,525,682	100	195,247	56.75

Notes: The table provides information on the runs detected by *RunsInProcess* measure, both in the way described in HS (2013) and in our extended form. Specifically, numbers and percentages of runs (as well as included messages) are reported based on the length of runs. Last two columns include total execution numbers and execution rates for each length group. The last row gives the same figures for take-profit strategy.

Table 7
Numbers and percentages of HFT orders.

Panel (a)	Large (>TRY 250,000)		Small (<TRY 250,000)	
	#	%	#	%
All	2,525,141	100	82,861,520	100
RunsInProcess	103,214	4.09	1,687,960	2.04
RunsInExtended	872,487	34.55	14,253,027	17.20
RunsInExtended_10	302,023	11.96	4,695,890	5.67
Take-profit	11,024	0.44	684,808	0.83
Panel (b)	**Portfolio/Fund**		**Individual investor**	
	#	%	#	%
All	2,056,512	100	83,330,149	100
RunsInProcess	96,000	4.67	1,695,174	2,03
RunsInExtended	563,427	27.40	14,562,087	17.48
RunsInExtended_10	213,859	10.40	4,784,054	5.74
Take-profit	10,130	0.49	685,702	0.82
Panel (c)	**Before 2014-10-04**		**After 2014-10-04**	
	#	%	#	%
All	44,271,299	100	41,115,362	100
RunsInProcess	848,870	1.92	942,304	2.29
RunsInExtended	7,535,462	17.02	7,590,052	18.46
RunsInExtended_10	2,386,726	5.39	2,611,187	6.35
Take-profit	368,063	0.83	297,513	0.72

Notes: The comparative results are based on three categories (order size, order submitter type and position to the structural change) and four structural methods (*RunsInProcess*, *RunsInExtended*, *RunsInExtended_10* and take-profit). *RunsInProcess* represents the HFT runs suggested in HS (2013). *RunsInExtended* is the extended measure proposed in our study. *RunsInExtended_10* involves the runs with at least 10 messages. Take-profit represents the take-profit strategy orders. Panel (a) provides information based on order size. On the left (right) hand side, numbers and proportions of HFT orders which are larger (smaller) than TRY 250,000 are reported. Percentages are obtained by dividing number of HFT based large (small) orders by the total number of large (small) orders. Panel (b) reports the numbers and shares of HFT orders based on the order submitter type as classified in BIST order and trade data. On the left (right) hand side, there are HFT orders submitted by portfolios and funds (individual investors). Panel (c) specifies information on HFT activity before and after October 4, 2013, which is the day on which improved electronic order submission platform is adopted by BIST. In all the panels, percentages represent proportions of HFT orders within the specified subgroups.

type and position in time. Panel (a) of the table reflects the level of HFT activity for small and large orders. While the vast majority of orders (82.86 million) have volume smaller than TRY 250,000, number of large orders is 2.53 million which is large enough to infer conclusions. We observe that HFT activity in general is much higher for large orders. This is in line with our expectations as large orders have higher significance and handled more strategically. The percentage of HFT orders obtained through HS (2013) runs is almost double in large sized orders (2.04% vs 4.09%). This finding holds for *RunsInExtended* (17.2% vs 34.55%) and *RunsInExtended_10* (5.67% vs 11.96%) measures too.

Higher rate of HFT activity in large orders can be inquired with respect to other aspects. For example, why are not large HFT orders strategically split into smaller orders? First, only 6.08% of overall HFT activity (i.e., for *RunsInExtended_10*, as also inferred from Table 7) is performed through large orders, while the remaining majority is within small orders. Thus, we can assume that HFT is already being performed through split orders. Since we do not have data on which small orders are split orders, direct inference cannot be obtained. Similarly, certain part of large orders might be already split orders representing an even wider demand. We consider orders of TRY 250.000 and higher as relatively large orders in our dataset. However, financial institutions are expected to trade with much larger amounts. Second, splitting large orders into smaller ones may have additional costs in terms of HFT algorithms' efficiency. Therefore, it should be applied only when expected gain is large enough. One purpose in splitting these orders could be to strategically hide them. In Turkish market, this may not be as important as in developed markets through our examination period with low HFT activity. In developed markets HFT firms apply various strategies, many are based on detecting and acting upon other HF traders' actions. Similarly, significant effort is put in hiding HFT strategies, for which splitting orders is one way. In this study we find that HFT is in its first steps in BIST. This fact most probably plays a role in the existence of large HFT orders. Final potential explanation on large HFT orders concerns their broader market impact. The underlying purpose in submitting some of these orders might be manipulating observed liquidity, quotes and spreads and by this way affecting rest of the market. As a result, we expect increased part of the HFT activity to be performed through small sized orders in the future mainly due to more complicated, competitive and broader HFT use. Significant part of small HFT orders is from individual investors and firms without the technological tools for HFT. This is another factor in relatively lower rate of HFT activity among small orders.

Panel (b) that gives comparative results based on order submitter types yields very similar results with Panel (a) on order size. Again, results based on three measures reflect that HFT is much more common among portfolio/fund management firms. For example, *RunsInProcess* (respectively *RunsInExtended* and *RunsInExtended_10*) measures 4.67% (resp. 27.40% and 10.40%) of HFT activity for portfolio/fund investors whereas 2.03% (resp. 17.48% and 5.74%) for individual investors.

Despite the clear results mentioned above, figures about take-profit strategy shown in the last rows of Panel (a) and Panel (b) reveal the opposite. The proportion of HFT orders for large (small) orders is 0.44% (0.83%) and for orders submitted by portfolio/fund (individual) investors is 0.49% (0.82%). By contrast to the overall HFT activity, it is performed less through large orders and by portfolio/fund firms. We attribute this result to the fact that the strategy does not require an advanced technology and is easily applicable by individual and small investors as well.

Figures about HFT involvement before and after October 4, 2013 are given in Panel (c). Except for the take-profit strategy, HFT activity is relatively higher in the second part of the data (e.g. 1.92% vs 2.29% for *RunsInProcess*, 17.02% vs 18.46% for *RunsInExtended* and 5.39% vs 6.35% for *RunsInExtended_10*). Although there is a slight increase in the figures for the period after Oct 4, 2013, the difference is small for inferring a robust conclusion.

Another point in time which may have a differential effect on HFT level is January 2, 2014. Starting from this day, tick

Table 8
Effect of tick size reduction.

	December, 2013	January, 2014	Difference
Stocks with tick size reduction	3.49	5.22	1.73**
Remaining stocks	3.76	3.98	0.22

Notes: HFT ratio is calculated by dividing number of HFT messages by total number of messages for each stock in a given month. HFT messages are obtained via the *RunsinExtended_10* measure. All values are in percentages. Last column reports the differences between mean HFT ratios of two consecutive months. Significance is from one sided paired t-test with the alternative hypothesis of larger mean HFT ratio for January, 2014. (**) represents significance at 5% level.

size for ten heavily traded stocks is reduced to TRY 0.01. We perform a comparative analysis on the HFT levels between the preceding and following months (December, 2013 and January, 2014). Table 8 presents HFT levels surrounding tick size reduction day. For ten stocks with tick size reduction, percentage of messages attributed to HFT increases by 1.5 times from 3.49% to 5.22%. The difference is significant at almost 1% level ($p = 0.013$). On the other hand, remaining stocks experience a slight increase in HFT activity which implies that there is not a market wide large difference in HFT levels between the two months. Our finding is in line with O'Hara et al. (2015) who find that HF traders significantly increase their market share with small relative tick sizes due to more aggressive and frequent participation.

In our next analyses, we examine HFT level in stocks with different characteristics. Specifically, we inquire whether stocks with excess HFT activity have common features such as small or big size, low or high liquidity and volatility. By this way, we can infer directions on the relation between HFT and market quality as well. In the closely related study, Hasbrouck and Saar (2013) also examine volatility and liquidity as representatives of market quality. Table 9 reports descriptive statistics on the variables for BIST 100 index stocks through 17 months. We observe that maximum HFT ratio is as high as 26% although mean ratio is 4.54%. This reflects that for certain stocks and time periods, there may exist excessive HFT activity.

Table 9
Descriptive statistics.

	Mean	Median	Stdev	Min.	Max.	No. of obs.
HFT (%)	4.54	3.69	2.92	0.85	26.47	1700
MCap (millions of TRY)	4587.51	1332.94	7398.44	51.52	41,160.00	1700
Liquidity (millions of TRY)	26.83	6.55	64.64	0.20	667.95	1700
Volatility (%)	3.19	2.96	1.13	0.76	9.08	1700

Notes: HFT ratio is calculated by dividing number of HFT messages by total number of messages for each stock and month. HFT messages are obtained via the *RunsinExtended_10* measure. MCap is the average of two consecutive market capitalization values (by the end of previous month and current month) for a stock. Liquidity is daily turnover. Volatility is calculated in daily basis by $(max. - \min.)/(max. + min.)/2$ which is followed by simply taking the average of daily observations on each month. HFT and volatility values are reported in percentages while MCap and liquidity are in millions of TRY.

Table 10
Cross section of HFT with market quality measures.

		Volatility					
		Low	2	3	4	High	High − low
Liquidity	Low	4.37	4.32	4.25	4.02	5.73	1.36***
	2	4.73	4.27	3.79	4.78	5.21	0.48
	3	4.08	3.49	4.62	4.25	4.33	0.25
	4	4.25	4.25	4.39	4.82	4.90	0.65*
	High	4.53	5.14	5.09	4.27	5.52	0.99**
	High − Low	0.18	0.82**	0.84**	0.25	−0.21	

Notes: Mean HFT ratios are reported for 25 portfolios originated by volatility and liquidity. HFT ratio is calculated by dividing number of HFT messages by total number of messages for each stock and month. HFT messages are obtained via the *RunsinExtended_10* measure. Reported HFT ratios are the averages of monthly HFT ratios of included stocks in each portfolio. Portfolios are revised each month with the changing volatility and liquidity values. Liquidity is daily turnover. Volatility is calculated in daily basis by $(max. - \min.)/(max. + min.)/2$ which is followed by simply taking the average of daily observations on each month. Last column (row) reports the differences between highest and lowest volatility (liquidity) portfolios. Significances are from one sided paired t-test with the alternative hypothesis of larger mean HFT ratio for highest volatility (liquidity) portfolios. (***), (**) and (*) represent significance at 1%, 5% and 10% levels, respectively.

We examine cross section of HFT with two market quality measures: volatility and liquidity. 25 portfolios based on two variables exhibit varying HFT activities. Table 10 reports mean monthly HFT ratios for the portfolios. Comparing HFT activity in least and most volatile portfolios of stocks (high−low), we see that HFT activity is systematically larger for most volatile stocks. Positive difference is significant at 1% and 5% levels for only the lowest and highest liquidity portfolios, respectively. In addition, moving towards more volatile portfolios of stocks in general, we do not observe persistently increased HFT level. Besides, lowest HFT activity is usually observed in portfolios in the middle. Similarly, we observe larger HFT activity for most liquid portfolios when compared to least liquid portfolios. The differences are significant at 5% level for two of the five portfolios sorted by volatility. Again, there does not exist a steady increase when we move towards more liquid stocks.

These results on HFT levels among stocks with different liquidity and volatility imply contradictory and weak relationships. HFT is relatively higher for the stocks with higher liquidity which is one market quality indicator. On the other hand, HFT activity is not large, but instead relatively small for stocks with low volatility which is the second indicator of a qualitative market. Again, both results are not persistent for all portfolios and there does not exist monotonic increase when we move from low to high liquidity (volatility) portfolios. We link the absence of strong relationships to the fact that HFT is not a dominant and broadly practiced figure in Turkish stock market through the examined time period. Examination of the relationships, market wide causes and consequences of HFT activity in financial market with larger amount of HFT activity would be contributory in this sense. One way to draw further inferences in this study is to focus on stock characteristics with excessive HFT activity.

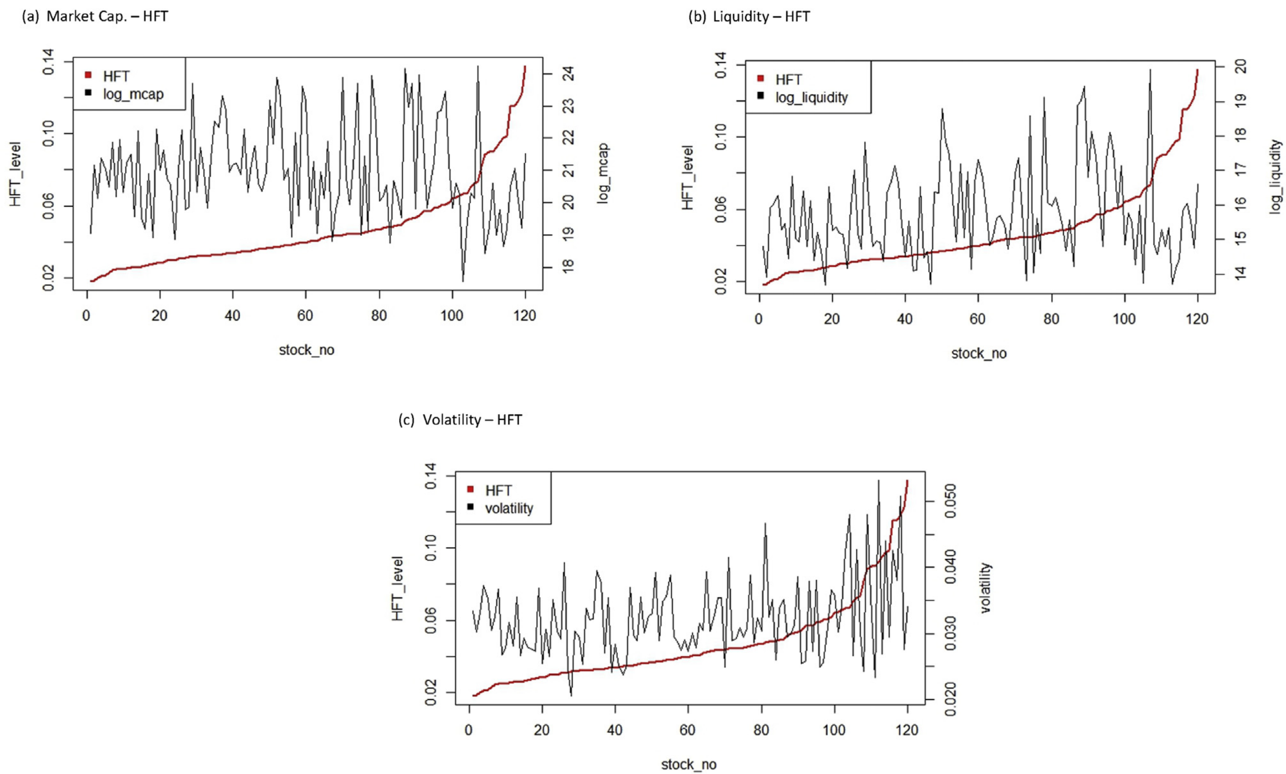

Fig. 4. Characteristics of stocks with different HFT Levels. In each panel, mean values for HFT level, market cap, liquidity and volatility are calculated for each stock via the use of monthly values. Logarithms of MCap and liquidity are used in order to scale for large differences among stocks. There exist 120 different stocks in the analyses due to replacements in BIST 100 constituents. Panels (a) to (c) examine MCap, liquidity and volatility of stocks which are sorted by their HFT activity, respectively. Moving right on the x-axis, we find stocks with larger HFT activity. While HFT levels are shown on the left y-axis and represented by red line, stock characteristics in each panel are on the right y-axis and drawn by black lines.

Fig. 4 reflects the characteristics of stocks with different HFT levels. HFT levels for 120 stocks are drawn by red lines in plots (a) to (c). We observe that red line mostly resembles a linear line implying a uniform distribution between the approximate range of 2% and 7%. On the other hand, there exist several stocks (highest HFT decile) with excess HFT levels (varying from mean of 8%–14%) which can be seen on the right hand side of the plots. Initiating from the fact that these stocks exhibit substantial HFT activity, we focus on each plot in order to analyze stock characteristics.

Plot (a) of Fig. 4 illustrates the market capitalization of stocks sorted by HFT activity. Interestingly, almost all of the stocks with excess HFT activity are small company stocks. Identical pattern is observed in Plot (b) which shows how liquid are the stocks with different HFT levels. Stocks with distinctive HFT activity are relatively illiquid ones with one or two exceptions. Plot (c) on volatility and HFT relation reflects another intriguing pattern for stocks with large HFT activity. Most of these stocks are either quite volatile or among the ones with lowest volatility. In overall, we observe that stocks with excess HFT activity tend to have four characteristics: small size, low liquidity and substantially low or high volatility.

While we observe that stocks with excess HFT activity are relatively less liquid stocks (plot (b) of Fig. 4), Table 10 suggests that HFT activity tend to increase with liquidity in general. It is noteworthy to mention that suggested pattern in Fig. 4 is only valid for stocks with excess HFT activity. On the other hand, for the remaining majority of stocks, there is a slight upward trend in liquidity when we move towards stocks with higher HFT activity. Similarly, we observe exceptions in two portfolios with lowest liquidity.

5. Summary and conclusions

Often combined with complex strategies, algorithmic trading (AT) and high-frequency trading (HFT) practices can challenge traditional financial theories that try to explain investor behavior. Hence, inquiring about the details of these practices is necessary for drawing inference about markets. Although AT and HFT activities have gained ground substantially all over the world in the last decade, studies about their existence and their impacts have not followed especially in less developed markets. Moreover, in the literature, very few studies exist to develop a methodology to calculate their extent. Motivated by these facts, we investigate the AT and HFT involvement in the orders and electronic messages submitted in Borsa Istanbul (BIST). Being one of the main emerging markets in the world, BIST draws significant international attention and has a large potential to grow concerning AT and HFT.

Our study, examining 100 stocks listed in BIST 100 index, covers the time span of 354 trading days from Jan. 2013 to May 2014. We analyze the traffic on 85 million orders and 243 million messages with three respects: message types, order sequences and order termination ways. 58.19% of order sequences are composed of only an entry and execution while the remaining part contains at least one modification and/or cancellation messages. Orders with large number of modifications tend to involve same number of modifications. Thus, we infer the involvement of computer algorithms submitting predetermined number of modification messages. The execution rate (66.34%) is significantly higher than in developed markets.

To quantify the level of AT in BIST, we employ widely used AT proxies, i.e. number of messages and Hendershott et al. (2011) *algo_trad* proxy. Additionally, we examine the number of modifications and cancellations per minute. Our analysis shows that all have upward trend indicating larger AT involvement through time. *Algo_trad* for the examined stocks varies between −18 and −13 which is equivalent to the 2003–2005 levels for the NYSE largest cap quintile as mentioned by Hendershott et al. (2011).

Next, we focus on measuring HFT. Initially, we employ the most popular HFT measure, HS (2013) *RunsInProcess* which originates runs by linking same sized messages within low latencies. However, covered link among messages is narrow. This is because, only consecutive orders linked with a cancellation message are considered as a HFT tool. 3.75 million messages detected via this methodology constitutes only 1.5% of all messages. Moreover, only 0.15% of all messages are placed in runs with at least 10 messages as reliable HFT representatives.

We propose a new methodology extending the ways in which possible links among messages can occur. We consider the case in which multiple orders are used simultaneously rather than consecutively. We link orders with same size if they have messages arriving in low latencies. By this way, HFT activity revealed by frequent modifications or submission/cancellation of multiple orders in low latencies is captured as well. Our proposed formation of runs (*RunsInExtended*) detects significant number of linked orders and messages. Specifically, 33 million messages (13.6% of all messages) are placed in detected runs. In addition, 36% of linked messages (4.9% of all messages) are placed in long runs of 10 and more messages enabling the use of long runs as more reliable HFT measure (we call this *RunsInExtended_10*). A run with 10 or more messages is much less likely to be the result of classification errors.

Analyses on HFT suggest various other facts. First, HFT activity is almost double for large orders and for orders posted by portfolio/fund firms. Around 12% of the large orders and 10% of the orders submitted by institutional investors are attributable to HFT. Existence of very similar comparative results for each measurement way in this study provides evidence on robustness and applicability. Hasbrouck and Saar (2013) show that correlations between *RunsInProcess* and HFT firms' trading activity is as high as 80% which is a strong evidence in validating this measure. We observe identical patterns in *RunsInProcess* and *RunsInExtended* through our comparative analyses, e.g., large vs small orders, individual vs institutional orders. This is an indicator of *RunsInExtended* providing reasonable estimates on HFT activity.

A second line of analyses inquire the effects of a system upgrade and a rule change. HFT activity in BIST stays relatively stable through our study period. However, we observe a modest increase after the adoption of the improved order submission platform in Oct 4, 2013. Moreover, we detect a significant positive effect of tick size reduction in ten stocks on HFT activity. In the month following the change, mean HFT ratio increases to 1.5 fold.

Third, we investigate any potential relationship between market quality measures and HFT level. We observe that HFT is relatively higher for more liquid stocks but also for more volatile stocks. However, overall results are not strong and consistent. This may result from the fact that HFT extent in BIST through the examined period is narrow disabling formation of systematic relationships with other market variables. Focusing on the stocks with excess HFT activity reflects that these stocks are small, illiquid and least or most volatile ones among all.

While HF traders seek profits from low latency trades, long term investors usually trade for other sources of utility. These arise from purposes such as investing and borrowing, hedging, exchanging assets. It can be reasonably argued that, the primary goal of financial markets is to serve for these investors who play critical role in long term price discovery. Therefore, it is essential to assess our findings with respect to how market participants will be affected. HF traders have the comparative advantage of speed. In the first place, stating that only 6% of all orders can be attributed to HFT, we suggest that other investors and traders have larger chances to obtain trading profits when compared to developed markets. For example, most of the arbitrage opportunities are consumed within milliseconds in markets with broad HFT activity. Similarly, traders in BIST can invest on an arriving news usually without losing their lines to fast HF traders.

There exists another important inference that the market participants draw from our findings on Turkish stock market. This regards the reliability of traditional financial theories. In two recent studies, Brennan et al. (2014) and Chordia et al. (2014) argue that explanatory powers of common risk factors, i.e., size, book-to-market ratio and momentum, are heavily distorted by large HFT inclusion. While investors in markets with large HFT activity may have difficulty in following investment strategies based on these theories, investors in BIST can still rely on explanatory powers of mentioned factors in forming their portfolios. Finally, investors should consider for substantially larger probability of facing a HF trader in certain types of orders and stocks. Specifically, large orders and institutional orders, small and illiquid stocks as well as stocks with very low or high volatility or with small tick sizes convey larger HFT activity in BIST.

This paper contributes to the literature by providing evidences on the existence and extent of AT and HFT in an emerging market, BIST. We apply proxies of AT and measures of HFT. We propose a broader HFT measure that detects HFT to a much larger extent compared to HS (2013) *RunsInProcess* measure. We find that

HFT involvement in BIST is not negligible and deserves attention. We show that large orders and orders submitted by professional investors exhibit more involvement in HFT.

Acknowledgment

We appreciate the valuable contributions of Aslı Alıcı. We are grateful for the support of Ömer Gökay and Faculty of Commerce at Yeditepe University. We appreciate significant contributions of an anonymous referee. We thank 2nd BIFEC participants for their comments. We are thankful to Borsa Istanbul and Istanbul Technical University (ITU) Finance Lab for providing the data. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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