Competition among High-Frequency Traders, and Market Quality

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Abstract

We study empirically how competition among high-frequency traders (HFTs) affects their trading behavior and market quality. Our analysis exploits a unique dataset, which allows us to compare environments with and without high-frequency competition, and contains an exogenous event - a tick size reform - which we use to disentangle the effects of the rising share of high-frequency trading in the market from the effects of high-frequency competition. We find that when HFTs compete, their speculative trading increases. As a result, market liquidity deteriorates and short-term volatility rises. Our findings hold for a variety of market quality and high-frequency trading behavior measures.

Keywords: high-frequency trading, competition, high-frequency trading strategies, tick size reform

JEL Classification: G12, G14, G15, G18, G23, D4, D61

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1 Introduction

High-frequency traders (HFTs) are market participants that are characterized by the high speed with which they react to incoming news, the low inventory on their books, and the large number of trades they execute (SEC (2010)). The high-frequency trading industry grew rapidly since its inception in the mid-2000s and today high-frequency trading represents about 50% of trading in US equity markets (down from a 2009 peak, when it topped 60%; see report of the TABB Group, 2017). A distinguishing feature of the high-frequency industry is fierce competition (see, e.g., Wall Street Journal, 2017). While existing empirical research focuses on the general effects of high-frequency trading on market liquidity, price discovery and volatility, the question of how competition among HFTs affects market quality and market dynamics is largely unaddressed.

Recent theoretical models predict that competition among HFTs can harm market liquidity. In Budish et al. (2015) and Menkveld and Zoican (2017) HFTs engage in two types of trading strategies: market-making and speculative. High-frequency market-making provides liquidity and is useful to investors. High-frequency speculative trading entails "sniping"stale quotes of high-frequency market makers, and is detrimental to investors because it increases the cost of liquidity provision. In Budish et al. (2015), any change from a non-competitive high-frequency trading environment to an environment with two or more HFTs harms market liquidity since high-frequency speculative trading increases and liquidity providers incorporate the cost of getting sniped into the bid-ask spread they charge. In Menkveld and Zoican (2017), the higher the number of HFTs in the market, the higher bid-ask spreads.

In this paper, we test these theories and study empirically how competition affects HFTs' trading behavior and market quality. Such tests face several challenges: First, capturing high-frequency trading competition requires having a record of high-frequency trading in all trading venues in which HFTs may trade a particular security. Second, the theories predict that an environment with one HFT (no high-frequency trading competition) generates very different outcomes compared to an environment with two or more HFTs (high-frequency trading competition), necessitating a dataset in which both environments can be observed. Third, data typically confounds two distinct phenomena: more high-frequency trading in the market and the effects of high-frequency trading competition. Previous empirical literature focused on the first phenomenon and found that more high-frequency trading is beneficial for market liquidity (see in particular Hendershott, Jones, and Menkveld (2011) or Menkveld (2013)). Given that theoretical models of high-frequency trading competition suggest that its effects go in the opposite direction, analyzing high-frequency trading competition empirically requires separating the effects of high-frequency trading competition from the effects of rising high-frequency trading. Separating the two effects is also key for deriving policy implications: it may be that regulators should encourage high-frequency trading but not competition among HFTs.

To deal with these challenges, we exploit a unique dataset that captures the trading of internationally well-established large HFTs on the Stockholm Stock Exchange (SSE), the largest Nordic exchange. Our sample consists of NASDAQ/OMXS30 Index stocks and runs from June 2009 through January 2010. The data enable us to track the activity of each individual high-frequency trading firm as we observe unmasked user and trading firm identities of HFTs.[1] Crucially for our analysis of competition, during this period, essentially all trading of listed securities took place on this single exchange. Moreover, we observe environments with one HFT in a stock as well as environments with HFTs competing in a stock. Lastly, our sample contains an exogenous event - a tick size change - which we use to disentangle the effects of the rising share of high-frequency trading in the market from the effects of high-frequency trading competition per se.

We define competition as two or more HFTs trading the security, as in Budish et al. (2015). We map the trading outcomes of each HFT into two broad trading categories - market-marking and speculative - using several measures to perform such classification.

To assess the effects of high-frequency trading competition, we employ two main methodologies. First, we apply a difference-in-differences methodology, in which we use entries and exits of HFTs in specific equities to compare an environment with no high-frequency trading competition to an environment with high-frequency trading competition. We analyze the data at the security-day-trader level and include time and security fixed effects to account for unobserved heterogeneity across time and securities driven by, e.g., stocks' volatility, liquidity, or outstanding volume differences. Our difference-in-differences analysis shows that when HFTs compete,

[1]Our dataset captures high-frequency trading activity coming from dealers' proprietary trading desks as well as from high-frequency trading firms that use direct market access arrangements with registered dealers.

their speculative trading increases relative to their market-making activity and market quality deteriorates, as predicted by the theoretical literature. Specifically, we find that competing HFTs trade on the same side of the market in about 70% of cases when looking at 5-minute intraday periods. Speculative high-frequency trading increases by about 12 percentage points from about 29% to 41% of all high-frequency trading. As a result of more speculative high-frequency trading, market liquidity worsens and intraday volatility increases. In particular, bid-ask spreads increase by 5%, Amihud (2002)'s measures of illiquidity increase by 18%, trade price impact (Kyle's lambda) increases by 23%, and order execution shortfall increases by 4 percentage points. Intraday volatilities increase between 9% and 14%, depending on the length of the intraday interval. By contrast, interday volatility - whether measured from open to close or from close to close prices - does not change significantly. This is intuitive as HFTs usually close their positions at the end of each trading day and should therefore mostly influence intraday measures.

The second methodology we employ is a regression setup of triple differences, which aims at disentangling the effects of the rising share of high-frequency trading in the market from the effects of high-frequency trading competition. We exploit an exogenous event, a tick size harmonization reform by the Federation of European Securities Exchanges (FESE), implemented on October 26th, 2009. The reform decreased tick sizes for most, but not all of the stocks in our sample, effectively splitting the stocks into 3 groups. Group 1 was not affected by the reform because prices of stocks in this group happened to fall within a certain range (e.g., SEK 100 to SEK 150, an equivalent of USD 14.70 to USD 22.05). The other stocks were affected by the reform and experienced a significant decline in tick sizes. Importantly, the relative tick size - the tick size relative to the stock price - declined for some stocks to lower levels than for other stocks. We conjecture that the lower the relative tick size the more likely HFT entry as HFTs weigh benefits and costs of entry and relative tick size is reflective of likely trading costs. To test this conjecture empirically, we use the pre-reform minimum relative tick size to split the affected stock into those whose relative tick sizes are above the pre-reform minimum (Group 2) and those whose relative tick sizes are below the pre-reform minimum (Group 3). Concretely, the minimum relative tick size prior to the reform was about 6 basis points. After the reform, stocks in Group 2 continue to have relative tick sizes above 6 basis points, while stocks in Group 3 have lower relative tick sizes of between 3 and

6 basis points.

We document that Group 1 - unaffected by the tick size change - did not experience any change in high-frequency trading activity. This is one control group. In Groups 2 and 3 - affected by the tick size change - high-frequency trading activity increased.[2] Crucially, we document that while Group 3 experienced HFT entry, there was no change in high-frequency trading competition in Group 2. This is intuitive as HFTs deciding to trade based on relative tick sizes would have already traded stocks with Group 2-like relative tick sizes as they were available in the market prior to the reform.

The tick size reform therefore induces time-series variation in the intensity of high-frequency trading activity whereas relative tick size differences provide cross-sectional variation in high-frequency trading competition, allowing to disentangle the two effects. With regard to the effects of more high-frequency trading per se, we find that market quality is either unaffected or improves. With regard to the effects of high-frequency competition, we find that HFTs use more speculative trading strategies and, as a result, liquidity deteriorates and short-term volatility rises. The results from the triple differences thus confirm that the channel through which high-frequency trading competition adversely affects market quality is through an increase in speculative trading.

We conduct several robustness checks. We show that pre-event stock characteristics do not determine entry, by comparing the pre-competition behavior of a propensity-score-matched sample of the stocks that face competition in the upcoming periods against a propensity-score-matched sample of firms that do not face competition. Furthermore, we report our findings separately for HFT entries and exits, and show that exits have an opposite effect to entries, of similar magnitude. Also, we consider an alternative measure of high-frequency trading competition by exploiting a continuous measure of competition, the Herfindahl-Hirschman Index. Lastly, we provide evidence from an alternative model, a simple panel regression with extensive controls.

Our results have important implications for both regulators and trading venues. The U.S.

[2]Frino et al. (2015), Hagstromer and Norden (2013) or Meling and Odegaard (2017) also document that high-frequency trading activity increases following a decline in a relative tick size. Note that these papers, like ours, investigate both market-making and speculative high-frequency trading. A related strand of literature focuses on market-making HFTs and documents that liquidity-providing HFTs benefit in an environment with larger relative tick sizes (O'Hara et al. (2015)). Yao and Ye (2014) focus on price versus time priority and argue that relatively large tick sizes constrain non-HFTs from providing better prices and allow HFTs to establish time priority over non-HFTs.

Securities and Exchange Commission (SEC) states that high-frequency trading should only be allowed if it benefits long-term investors. Moreover, SEC rules aim at increasing competition among liquidity suppliers. Modern liquidity suppliers are predominantly HFTs. However, our results highlight that competition among HFTs leads to a deterioration of market quality, which originates from an increase in speculative high-frequency trades. Markets should therefore be designed in a way that promotes high-frequency trading but eliminates competition among speculative HFTs.

The paper contributes to the growing empirical literature on high-frequency trading.[3] Two papers most closely related to ours are Boehmer et al. (2018) and Brogaard and Garriott (2018).

Boehmer et al. (2018) use a principal component analysis to determine the correlation between high-frequency trading strategies.[4] They argue that similarity in high-frequency trading strategies is a proxy for the intensity of competition between high-frequency trading firms and conclude that short-term volatility of a stock declines with higher correlation. Like Boehmer et al. (2018), our paper emphasizes the analysis of high-frequency trading strategies. The important difference between their paper and ours is that their analysis of correlations between high-frequency trading strategies cannot disentangle between the effects of the rising share of high-frequency trading in the market from the effects of high-frequency trading competition. This is what our analysis of triple differences allows us to do, and we conclude that more high-frequency trading competition harms market quality.

Brogaard and Garriott (2018) also study high-frequency trading competition and find that high-frequency trading competition improves market quality, a result opposite to ours. An earlier version of this paper precedes Brogaard and Garriott (2018) so we view our paper as contemporaneous. Their paper uses data from the newly established Canadian trading platform Alpha. That dataset has several disadvantages for the analysis of high-frequency trading competition. First, Brogaard and Garriott (2018) do not observe trading identities; instead they assume that trading firms are HFTs if they fulfill certain account characteristics. This makes the number of HFTs in the market - a crucial ingredient to study high-frequency trading competition

[3] Among the theoretical contributions are those of Ait-Sahalia and Saglam (2017), Biais et al. (2015), Bongaerts and Achter (2016), Cespa and Vives (2019), Foucault et al. (2016), Han et al. (2014), Hoffmann (2014), Jovanovic and Menkveld (2016), Li (2014), Pagnotta and Philippon (2018), Rosu (2019), and Vayanos and Wang (2012).

[4] Benos et al. (2017) also examine the extent to which the trading activity of HFTs is correlated and the impact on price efficiency.

according to the theoretical literature - an assumption. Second, high-frequency trading activity in Canadian stocks is split among several trading platforms, with only 7%-18% taking place on the Alpha platform, which provides only a partial record of high-frequency trading in a particular stock and does not allow capturing high-frequency trading competition. Third, throughout their sample period of 2008-2012, Alpha grew rapidly and went through frequent upgrades such as the installation of quicker servers, which affected high-frequency trading activity and can obfuscate the specific effects of competition. By contrast, the dataset and the sample period we use are not affected by these issues. In addition, we exploit an exogenous event to analyze competition-specific effects.[5]

By focusing on how a competitive environment influences HFTs' choice between market-making and speculative trading strategies, our paper relates to a strand of literature which documents HFTs' activities and strategies. Hagstromer and Norden (2013) distinguish between market-making HFTs and opportunistic HFTs, documenting that most high-frequency trading volume is market-making and that the activity of market-making HFTs mitigates intraday price volatility. Even when HFTs follow market-making strategies, however, market liquidity can deteriorate because non-HFTs are crowded out (Yao and Ye (2018)). Foucault et al. (2017) argue that when prices adjust with a lag to new information, this creates arbitrage opportunities and high-frequency arbitrageurs' response to these opportunities impairs liquidity by imposing adverse selection risk on market makers. Other papers analyzing high-frequency trading strategies include, e.g., Baron et al. (2018), Hagstromer et al. (2014), Hirschey (2018), or van Kervel and Menkveld (2018).

By examining the impact of high-frequency trading competition on market quality, our paper is related to a strand of the literature which analyzes the effects of high-frequency trading on markets (e.g., Carrion (2013), Hasbrouck and Saar (2013), Brogaard et al. (2014), Huh (2014), Jarnecic and Snape (2014), or Kirilenko et al. (2017)). Menkveld (2013) examines the trading of one HFT entering the market and finds that market conditions improve. Results from our analysis of triple differences are consistent with this result as we find that more high-frequency

[5]The Alpha exchange itself did not seem to regard high-frequency trading as fully beneficial as it introduced, in 2015, speed bumps to reduce high-frequency trading activity, citing that it aims *"to deliver superior execution quality for natural investors and reduce trading costs"* for *"participants who do not use speed-based trading strategies"* (TMX press release, TMX (2015)). A recent paper by Anderson et al. (2018) shows that the speed bumps on Alpha led to a decline in market share of HFTs and benefitted market quality on the exchange.

trading in the market, if not accompanied by competition, has positive or neutral effects on market quality. Our paper is also related to the literature on algorithmic trading, which is a broader classification than high-frequency trading. Both high-frequency trading and algorithmic trading use algorithms to trade. While algorithmic trading is used to automate, for example, block trades to minimize price impact or for hedging, high-frequency trading involves short-term investments aimed at making profits from buying and (immediately) selling. The literature also investigates the effects of automation on liquidity, informational efficiency and volatility. Contributions include Hendershott et al. (2011), Hendershott and Riordan (2013), and Foucault and Menkveld (2008), and Boehmer et al. (2015).

The rest of the paper proceeds as follows. In Section 2 we describe our NASDAQ OMX data as well as our measures of market quality and trading. In Section 3 we present the methodology. In Section 4 we discuss our findings. We provide several robustness checks in Section 5 and conclude in Section 6.

2 Data and Measurement

In subsection 2.1, we describe the data we use. In subsection 2.2, we discuss the measurement of market quality, volatility and high-frequency trading behavior.

2.1 Data Description

The trading data come from NASDAQ OMX Nordic and incorporate information about all trades executed on the Stockholm Stock Exchange (NASDAQ OMX). We focus on the OMXS30 index, which hosts the thirty biggest public companies in Sweden, because we observe that HFTs trade in liquid stocks and restrict their trading activity to Sweden's major securities during our sample period. For each trade, the dataset contains a rich set of variables. For the purpose of our analysis, we rely on the following variables in particular: exchange membership names, type of access to the exchange (four different speed levels), account information, order size, order placement timestamp, order identity, execution identity, trade size, and trade execution price and trade timestamp. Timestamps are in milliseconds and ranked within each millisecond.

The sample period is from June 2009 through January 2010. The sample period and the data we analyze offer several key advantages for the analysis of competition among HFTs.

First, over our sample period, essentially all continuous trading - which is the one relevant for the analysis of high-frequency trading activity - was taking place on the NASDAQ OMX and was not split among other exchanges in Sweden. This means that we have a comprehensive record of high-frequency trading activity in a particular stock so that we can observe whether or not HFTs are competing in that stock at each point in time.[6]

Second, the dataset allows us to track the activity of individual HFTs. Specifically, we observe unmasked identities for members of the stock exchange, which include all large HFTs. This allows us to directly identify proprietary trading of those HFTs. For non-proprietary trading, we combine, for each trade, account information with the information on the type of connection a trader used to access the exchange to check whether those identities could be assigned to an HFT. We find that non-proprietary trading in our sample does not display any characteristics typical for HFTs. In particular, non-proprietary trader identities using the fast connection to the exchange are characterized by a very low number of trades (often less than 3 per day and security; compared to an average of around 300 trades per day and security for large HFTs). This implies that it is the large HFTs - for which we observed unmasked identities - who are responsible for the high-frequency trading activity in our sample. This finding is not very surprising. For example, Clark-Joseph (2014) documents that also in the U.S. market, the majority of all high-frequency trading is accounted for by the trading volume of the eight largest HFTs accounts.[7]

Third, the Swedish Stock Exchange is an established exchange and the HFTs in our sample are all experienced international HFTs with significant market shares all around the world.[8] Stocks listed on OMXS30 lie in the range of U.S. medium- and large-cap stocks.[9] Our results are therefore

[6]Appendix A provides more institutional details.

[7]We also cross-checked the accuracy of the identities information in the trading data, by matching them to identities used in the proprietary transaction-level data from the Swedish financial supervisory authority (Finansinspektionen), a Swedish equivalent of the U.S. Securities and Exchange Commission, which collects all transactions with financial instruments from financial institutions. Our identities from the trading database match the ones from the financial supervisory authority.

[8]HFTs in our dataset have similar characteristics: On average, each HFT has an about 10% market share (trades and volume), executes around 270 trades per day and stock, and holds near-zero inventories at the end of the trading day.

[9]Table A-1 gives an overview and key statistics for all thirty stocks traded in the OMXS30 (see, e.g., Brogaard et al. (2014) for summary statistics on the US stock market). The number of stock trades per day varies between 1247 and 6103 across all stocks. The average relative time-weighted spread in our sample is between 0.09% and 0.24%.

likely applicable beyond the Swedish market. Indeed, given the high quality of the Swedish data, there are numerous studies by now that analyze trading in the Swedish equity market. For example, Hagstromer and Norden (2013) show that HFTs are important players in the Swedish market. Other empirical studies that use Swedish data include Baron et al. (2018), Brogaard et al. (2015), Hagstromer et al. (2014), and van Kervel and Menkveld (2018).

Fourth, during our sample period of June 2009 through Januaray 2010, those international HFTs just entered the Swedish market, bringing with them time-proven trading strategies from the other markets they operated in. The fact that high-frequency trading in Sweden was in its infancy means that we can observe changes from the non-competitive environment to the competitive environment, and vice versa. This allows us to test the predictions of the theoretical models which suggest that the two environments generate very different outcomes.

We add to the trading database order book information (timestamps, bid and ask prices, bid-ask spreads) on the OMXS30, obtained from Thomson Reuters Tick History. We first match the trades from Thomson Reuters Tick History with the corresponding trades in the trading database, and then complement the trades with the order book information before and after the trade was executed.

Finally, for daily variables that do not need to be computed from the trading data, we rely on Bloomberg.

2.2 Measures

In this subsection, we describe the liquidity measures, volatility measures and high-frequency trading measures we use. All measures are at the stock-day level. Table 1 provides an overview of each measure.[10]

2.2.1 Liquidity Measures

We use several liquidity measures in our analysis, relying on existing measures from the literature and additionally developing new measures, made possible by the granularity of our trading database. We discard trades and orders that are executed off-book, or during call auctions, or within fifteen

[10] In the Appendix, we present a correlation matrix of all measures; see Table A-2.

minutes before or after these auctions.

In terms of existing measures, we compute bid-ask spreads, intraday Amihud (2002) measures of illiquidity, price impact measures (Kyle's lambda), and autocorrelation.

Bid-ask spreads. This is a standard measure of illiquidity. For each stock, we use end of 5-minute spreads, and average those over a day.

Amihud (2002) illiquidity measure. The measure is defined as the ratio of absolute stock return to its volume in units of currency (in this case, Swedish krona or SEK). It is a measure of price impact as it captures the price response associated with one SEK of trading volume. If the price changes quite a bit relative to the volume traded, the stock is illiquid; and vice versa. We compute the illiquidity measures over 5-minute windows, and average them over a day.

Price impact measure (Kyle's lambda). Similarly to the Amihud (2002) measure, this measure aims to capture price impact but unlike Amihud (2002) measure, it is regression-based (see, for example, Stoll (2000)). In particular, daily price impacts are captured by:

$$r_{d,t,j} = IMPACT_{d,j} * NBV_{d,t,j} + \epsilon_{d,t,j}.$$

Here, $r_{d,t,j}$ are the 5-minute returns calculated from the log midpoint prices and $NBV_{d,t,j}$ is the net buy turnover (turnover of active share buys - turnover of active share sells). $IMPACT_{d,j}$ is the price impact parameter and $\epsilon_{d,t,j}$ the error term on day d, for each 5-minute interval t and stock j. To ensure that our daily estimates are comparable, we force all the explanatory power onto the order flow by constraining the estimated intercept parameter to be zero.

Autocorrelation. While not a measure of liquidity, we use autocorrelation to assess market efficiency. Intuitively, the more efficient prices are, the closer they are to a random walk. Deviation from a random walk are indicated by both positive and negative autocorrelation. We measure daily autocorrelations as the absolute first-order return autocorrelation, using the final mid-quote of 5-minute intervals.

The granularity of our trading database allows us to measure liquidity in a new, additional, way.

Order execution shortfall. We compute a measure of marketable orders of non-HFTs that cannot be filled completely, a measure of market depth. When a marketable order hits the market, it is executed against standing limit orders, if there are enough limit orders in the order book. The less liquid the stock, the lower the number of fully executed marketable orders, and vice versa. We therefore compute the ratio of the number of non-high-frequency marketable orders that could not be executed completely to the total number of non-high-frequency marketable orders. We also compute the same ratio based on turnover, rather than the number of orders.

2.2.2 Volatility Measures

We use several variables to assess both intraday and interday price volatility.

Intraday volatility. We define intraday realized volatility as the sum of squared returns based on the final mid-quote of 5 minutes, as well as high-low intervals.

Interday volatility. For interday volatility, the intervals are either open mid-price to close mid-price, or close mid-price from the previous trading day to close mid-price.

2.2.3 High-Frequency Trading Measures

Taking a first look at the trading behavior of HFTs, we find that competing HFTs trade on the same side of the market in about 70% of cases when looking at 5-minute intraday periods. In addition, their inventories are significantly positively correlated when competing for trades. This suggests that HFTs are likely to have correlated trading strategies under competition. Our high-frequency trading measures below formalize this conjecture.

In the models of high-frequency trading competition by Budish et al. (2015) and Zoican and Menkveld (2017), high-frequency trading competition harms market liquidity since HFTs increase their speculative trading. To assess this theoretical prediction, we classify the trades of each HFT into speculative or market-making, using several measures to do so. Our measures fall into two categories.

Price pressure measures. The first category of measures is designed to capture whether a high-frequency trade leans against the price pressure (market-making) or whether it puts a further pressure on the price (speculative). A high-frequency trade is classified as speculative if the stock midpoint price moved upwards (downwards) over the 5 minutes preceding a high-frequency buy (sell) trade, but the midpoint price move reverses over the 5 minutes following that trade. Intuitively, the price reversal indicates that the preceding price move was non-fundamental and therefore suggests that an HFT traded for speculative reasons. We compute the ratio of the number of such speculative high-frequency trades to the total number of high-frequency trades in a particular stock over a day. We also compute the same ratio based on turnover, rather than the number of trades.

Directional trading measures. The second category of measures is designed to capture directional or momentum high-frequency trading (a form of speculative trading). We consider three variants of the directional trade measure, as follows. The first variant is given by:

$$DIRECT1_{d,j} = \frac{1}{T}\sum_{t=1}^{T} r_{d,t,j}\frac{HFTvol_{buy,d,t,j} - HFTvol_{sell,d,t,j}}{turnover_{d,t,j}} \tag{1}$$

with $HFTvol_{buy,d,t,j}$ ($HFTvol_{sell,d,t,j}$) being high-frequency trading turnover from buy (sell) trades on day d, over a 5-minute interval t, in stock j. $r_{d,t,j}$ is the stock's midpoint return over the 5-minute interval and $turnover_{d,t,j}$ is the total stock turnover within this interval.

This measure becomes positive if HFTs buy with an increasing - or sell with a decreasing - stock price, and negative when HFTs trade in the opposite direction to the price movement. A positive $DIRECT1$ measure indicates directional or momentum trading, while a negative measure indicates trading against the trend.[11]

The second variant, $DIRECT2$, replaces the turnover within 5 minutes in the denominator above with the daily average 5-minute turnover, $\frac{1}{T}\sum_{n=1}^{T} turnover_{d,n,j}$. This measure ensures that changes in the directional trading measure are not driven by changes in the turnover within the 5 minutes.

The third variant, $DIRECT3$, replaces the actual midpoint return $r_{d,t,j}$ with an indicator variable, equal to 1 if the return is positive within the 5-minute interval t and equal to -1 when the return is negative. This measure ensures that changes in the directional trading measure are not driven by the midpoint return changes. Note that the interpretation does not change: the measure is positive with directional trading and negative with counter-directional trading.

[11] We share the aim of capturing directional high-frequency trading with the recent papers by Hirschey (2018) and van Kervel and Menkveld (2018) who analyze high-frequency trading around large non-high-frequency trades.

3 Methodology

In subsection 3.1, we discuss our baseline difference-in-differences regression set-up. In subsection 3.2, we discuss the details of the tick size harmonization reform, a plausibly exogenous event, which we exploit to disentangle the effects of the rising share of high-frequency trading in the market from the effects of high-frequency trading competition.

3.1 Baseline Model

We use difference-in-differences tests to exploit daily cross-sectional differences among stocks. Stocks can face repeated competition among HFTs over time, through entries and exits of HFTs. An entry is a change from no high-frequency trading competition to high-frequency trading competition, and an exit is the opposite change. We focus our attention on 228 event windows around changes from no competition to competition, or vice versa.[12] In the baseline model, we use entries and exits jointly (in a robustness check, we also consider entries and exits separately).

The changes from no competition to competition, or vice versa, are the relevant events in the baseline model. For each event window, we assign stocks to be part of the control group if there is one HFT active in them (no competition), and to the treatment group if there are two or more HFTs active in them (competition). This means that we have different control and treatment groups for each event. The advantage of this approach is that multiple treatment and control groups reduce the bias and noise that can be associated with a single comparison (see Bertrand et al. (2004) for details on this approach).

The difference-in-differences test setting is summarized in the following equation:

$$y_{e,j,d} = \alpha + \beta_1 D^{comp}_{e,j,d} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}, \tag{2}$$

with e indexing entry or exit, j being the security and d the time (day). $D^{comp}_{e,j,d}$ is the event dummy set to 1 if there is high-frequency trading competition in security j at time d, and to zero if there

[12] We define these event windows from up to three days before to up to three days after the change. The average length of an event window is 4.3 days. The reason for the differences in length is that there can be a change in the competition status less than three days before or after. We have experimented with different lengths of event windows; our results remained consistently unaltered.

is no high-frequency trading competition. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{e,j,d}$ is the vector of covariates and $u_{e,j,d}$ is the error term. The dependent variable $y_{e,j,d}$ takes the form of market quality and trading measures.

The key identifying assumption behind a difference-in-differences analysis is that, with the exception of the treatment itself, there is no difference between the treated and control groups that cannot be captured by stock-fixed effects. Put differently, the parallel trend assumption must hold, implying that there is a similar trend in the endogenous variable during the pre-event period for both the treatment and the control group. In our analysis, the same stocks serve as treatment and control stocks within different events. Therefore, differences before an entry or after an exit are small. Figure 1 illustrates this for Amihud's illiquidity measure (top panel), for 5-minute volatility (middle panel), and for high-frequency trading behavior (bottom panel) three days before and three days after an entry.

In addition, Table 1 provides summary statistics for all illiquidity, volatility and high-frequency trading measures we use in the analysis, for both the control group and the treatment group. In the left panel, statistics on the baseline model are reported for the days prior to an HFT entry. The Table documents that differences between the control and treatment group are small, for all measures. See Section 5.1 for a more detailed analysis of these differences, which illustrates that the control group and treatment group pre-treatment are indistinguishable.

3.2 The Tick Size Reform

Our sample period contains an exogenous European-wide event - a tick size reform - which we use to disentangle the effects of the rising share of high-frequency trading in the market from the effects of high-frequency trading competition. While more high-frequency trading benefits market quality, as documented in several empirical studies (e.g., Hendershott, Jones, and Menkveld, 2011 or Menkveld (2013)), high-frequency trading competition can harm market quality, according to the recent theories (Budish et al. (2015) and Menkveld and Zoican (2017)). Disentangling the two effects is important for deriving policy implications: if we confirm empirically that the effects of high-frequency competition go in the opposite direction to the effects of rising high-frequency trading, it follows that regulators may encourage high-frequency trading, but not competition among HFTs.

The tick size reform in 2009 was designed by the Federation of European Securities Exchanges (FESE). The FESE represents 46 exchanges for equities, bonds, derivatives, and commodities. The reform harmonized tick sizes across all major European stock exchanges. The NASDAQ OMX Stockholm introduced the new tick sizes (known as FESE Tick Size Table 2) for its OMXS30 shares as of Monday, October 26, 2009.

Figure 2 summarizes the impact of this reform on the tick sizes in the market. The reform decreased tick sizes for most, but not all, of the stocks in our sample. Whether or not a stock was affected by the reform depends on its price. As nominal stock prices convey no information about the fundamental properties of a stock, such as liquidity or volatility, it is exogenous which stocks were affected by the reform and which were not.[13] [14] Specifically, stocks with the pre-reform tick size of SEK 0.25 saw their tick size decline to SEK 0.10 (the dashed beige line in Figure 2). Stocks with the pre-reform tick size of SEK 0.10 saw their tick size either unchanged (the dash-dotted red line), or decline to SEK 0.05 (the dotted blue line) or even lower to SEK 0.01 SEK (the dashed blue line); the ultimate tick size change depended on the stock's price. Finally, stocks with the pre-reform tick size of SEK 0.02 saw their tick size decline to 0.01 SEK (the solid blue line).[15] [16]

Given the decline in tick sizes following the reform, the relative tick sizes - the tick sizes relative to the stock prices - also declined. The relative tick size changes can be a factor affecting HFT entry as HFTs weigh benefits and costs of entry and relative tick size is reflective of likely trading costs. Importantly, the relative tick size declined for some stocks to lower levels than for other stocks, and the reform reduced the overall minimum relative tick size in the market from 6 to 3 basis points. We can therefore divide the stocks in our sample into three groups, depending on whether or not their relative tick sizes changed, and depending on whether or not the change in the relative tick size is above or below the pre-reform minimum of 6 basis points.

[13]Exceptions are penny stocks, a phenomenon that indicates that the company faces bankruptcy. There are no such stocks in our sample, however.

[14]Note that in principle a stock could experience a decline in the tick size for two reasons: 1) a stock was affected by the reform or 2) a stock's price dropped and fell into a different tick size category. We checked that the second reason never occurred in our sample.

[15]Figure A-1 and Figure A-2 in the Online Appendix provide further details of the tick size changes and the associated bid-ask spreads, for the different tick size tables used on the Stockholm Stock Exchange. Those details are not of key importance to our methodology and are therefore relegated to the Online Appendix.

[16]In US dollar terms, SEK 0.25 corresponds to USD 0.0368; SEK 0.10 to USD 0.0147; SEK 0.05 to USD 0.0074; and SEK 0.01 to USD 0.0015, based on the exchange rate as of the pre-reform trading day of October 23, 2009.

Figure 3 provides the overview of the stocks in the three groups and their relative tick sizes (vertical axis) before and after the reform (horizontal axis). The grey-shaded area in the figure indicates the relative tick size levels that were not available in the market prior to the reform (3 to 6 basis points). Group 1 stocks, represented by the hollow diamonds in Figure 3, are the stocks whose tick size - and therefore relative tick size - was not affected by the reform at all. For the affected stocks, we use the pre-reform minimum relative tick size of 6 basis points to split them into those whose relative tick sizes are above the pre-reform minimum (Group 2, represented by the hollow circles) and those whose relative tick sizes are below the pre-reform minimum (Group 3, represented by the filled circles).

Crucially, we document that while in Group 2 there was no change in high-frequency trading competition, Group 3 experienced HFT entry. This is intuitive as HFTs deciding to trade based on relative tick sizes would have already traded stocks with Group 2-like relative tick sizes as they were available in the market prior to the reform.

Figure 4 documents how the reform affected high-frequency trading activity across the three groups. Group 1 stocks - unaffected by the reform - did not experience any change in high-frequency trading activity (dashed-dotted line). It will thus serve as a control group in our analysis. In Groups 2 (solid line) and 3 (dashed line), high-frequency trading activity increased immediately following the reform. In Group 2, high-frequency trading participation about doubled from before to after the reform, from about 8% to about 16%. In Group 3, high-frequency trading participation about tripled from before to after the reform, from about 8% to about 24% on average.

The tick size reform therefore induced time-series variation in the intensity of high-frequency trading activity whereas relative tick size differences provided cross-sectional variation in high-frequency trading competition. We use an empirical set-up of triple differences to test the effects of high-frequency trading competition, while separating the effects of increased high-frequency trading activity. The set-up is summarized in the following equation:

$$\begin{aligned} y_{j,d} = \alpha + \beta_1(Post_d * Reform_j * Group\,3_j) + \beta_2(Post_d * Reform_j) \\ + p_d + m_j + X_{j,d}\Gamma + u_{j,d}, \end{aligned} \tag{3}$$

with j indexing the security and d being the time (day). $Post_d$ indicates the period after reform and $Reform_j$ indicates whether security j is affected by the tick size reform, i.e. securities belonging to Group 2 or Group 3. $Group\ 3_j$ is also a dummy variable that takes on the value of 1 for securities belonging to Group 3 and 0 otherwise. Therefore, β_1 captures the effect of high-frequency trading competition over and above the general change due to the tick size reform itself. The latter is captured by β_2. Variables p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{j,d}$ is the vector of covariates and $u_{j,d}$ is the error term. The dependent variable is $y_{j,d}$ and takes the form of the same market quality and trading measures as in the test setting above.

Table 1, right panel, provides summary statistics for all liquidity, volatility and high-frequency trading measures we use in the analysis, for Group 1 (unaffected by the reform), and Groups 2 and 3 (affected by the reform but differing in high-frequency trading competition). The table documents that there is no pattern in the pre-event differences, and that differences, if any, are small.

4 Empirical Results

In subsection 4.1, we present results of our baseline difference-in-differences estimations. In subsection 4.2, we present results of the estimation of triple differences, which exploit the tick size reform.

4.1 Baseline Model Results

In our difference-in-differences estimations, we add several controls to account for trader-specific effects and event-type-specific effects that go beyond time and security fixed effects. First, we use a stock-event period dummy to control for whether a specific stock belongs to the treatment group or to the control group during a particular event. Note that this is not collinear with stock fixed effects, because a stock can, for different event periods, be part of the treatment or of the control group. Second, we use an event-type dummy to capture the differences between the effect of entries and of exits. Third, we control for HFT fixed effects to account for heterogeneity among traders. Additionally, we consider past turnover and past bid-ask spreads as controls. All continuous variables are in logs, unless they are simple ratios. Note that standard errors are clustered by stocks as this is the level at which our variable of interest varies.[17]

Tables 2, 3, 4 present results for illiquidity, volatility, and trading behavior, respectively.

In Table 2, our left-hand-side variables are illiquidity measures (bid-ask spread in column 1 and 2, order execution shortfall measures in columns 3 and 4, Amihud (2002) measure of illiquidity in column 5, and price impact measure in column 6), and a market efficiency measure (autocorrelation in column 7). We find a significant increase in all illiquidity measures under competition. For the bid-ask spread, competition increases the spread by about 5% or 1 basis point. The estimated coefficients on competition are very similar with or without control variables (column 1 versus column 2). For the order execution shortfall, competition increases the shortfall based on trades by about 2 percentage points and of the shortfall based on volume by about 4 percentage points, or from about 32% to 36% of all non-high-frequency trading volume. Also for the Amihud (2002) illiquidity measure, we find substantial competition effects: Stocks facing competition among HFTs are 18% more illiquid. For the price impact measure, competition increases price impact by 23%. Lastly, for market efficiency measured as autocorrelation, we do not find statistically significant evidence that competition among HFTs improves market efficiency. Among control variables, only the lagged bid-ask spread and lagged turnover are (mostly) statistically significant, with the expected signs.

In Table 3, our left-hand-side variables are volatility measures. We find that intraday volatilities increase significantly, while interday volatilities are unchanged, under competition among HFTs. This is intuitive as HFTs usually close their positions at the end of each trading day and should therefore, if at all, influence intraday measures. Specifically, 5-minute volatility increases by about 9% under competition (columns 1 and 2, with the latter column adding HFT fixed effect and additional controls such as lagged bid-ask spread and lagged turnover). The maximum squared price range - min-max volatility - during a trading day increases by 14% (column 3). By contrast, interday volatilities, whether measured as close-close volatility (column 4) or as open-close volatility (column 5), show a decline but the coefficients are not statistically significant. As for control variables, turnover and bid-ask spreads are positively associated with volatilities.

[17] Clustering standard errors on relatively few - here 30 - clusters could potentially distort results more than it improves accuracy. We therefore ran several robustness checks with simple robust standard errors, bootstrapped and blocked bootstrapped standard errors and found that our analysis does not suffer from these distortions.

In Table 4, our left-hand-side variables are measures of speculative trading. We find that HFTs do more speculative - and less market-making - trading under competition. This confirms theoretical predictions that the channel through which high-frequency trading competition adversely affects market liquidity and volatility is through an increase in speculative trading. Specifically, the price pressure measure based on volume increases by about 12 percentage points under competition (columns 1 and 2, with latter column adding HFT fixed effect and other additional controls). This amounts to an increase in the average ratio of speculative volume in total from 29% to 41%. Similarly, the price pressure measure based on trades increases by 17 percentage points (column 3). Directional trading measures also increase significantly (columns 4 to 6). Compared to the pre-event averages of these measures, they all more than double when HFTs compete.

Figure 5 summarizes the dynamic impacts of entry (left-hand-side panels) and exit (right-hand-side panels). The estimated regression has the same set-up as the baseline specification but adds dummies for each of the three days before and after the event. The dotted lines represent the 95% confidence interval. The rows show estimates for the Amihud (2002) illiquidity measure (top panel), for the 5-minute volatility measure (middle panel), and for the price pressure measure based on trades (bottom panel). There are three takeaways: First, there is no pre-trend in any of the measures before the event. Second, the event itself has a significant impact, with all measures higher after entry (change from no competition to competition) and before exit (the opposite change). Third, this impact is not temporary but lasts for several days.

4.2 Results of Tick Size Reform

This subsection presents the results of our regression setup of triple differences, which aim at disentangling the effects of the rising share of high-frequency trading in the market from the effects of high-frequency trading competition. As outlined in the methodology section, the effects of competition are captured by the triple interactions term (the effect of the reform on Group 3). The effects of the rising share of high-frequency trading in the market - induced by the tick size reduction - are captured by the interaction term between a post-reform dummy and an indicator of whether a security is predicted to face lower relative tick sizes after the reform (belonging to Group 2 and Group 3).

Table 5 presents the results. With regard to the effects of competition, we find that market quality declines under competition, and the estimates are comparable in both magnitude and statistical significance to those from our baseline regressions. With regard to the effects of tick size reduction and more high-frequency trading, we find that market quality measures are either unaffected or even improve. By highlighting that competition effects may go in the direction opposite to the effects of more high-frequency trading, our findings complement the existing literature that shows that more high-frequency trading may improve market conditions (see, e.g., Menkveld (2013) in the context of one HFT trading in the market). In more detail, Table 5, the top panel shows the results for the illiquidity measures. Concerning the competition effects, we find that order execution shortfall increases by about 5 percentage points (volume) and 8 percentage points (trades), Amihud's measure of illiquidity increases by about 15%, price impact rises by about 21%, while there is no significant decline in autocorrelation. Concerning the effects of more high-frequency trading, illiquidity measures are mostly unaffected, with the exception of the order execution shortfall measure, which decreases by about 6 percentage points and the price impact measure, which falls by about 17%.

Table 5, the middle panel shows the results for volatility measures. With regard to competition effects, we find that 5-minute volatilities increase, by about 15%. The min-max intraday volatility increases as well. As before, we do not find any significant effects of competition on the interday volatility. With regard to the effects of lower tick sizes and more high-frequency trading, intraday volatilities decline significantly while measures of interday volatilities are not affected.

Table 5, bottom panel shows the results for high-frequency trading measures. Concerning the competition effects, price pressure measures based on trades and turnover both increase by about 4 percentage points. Directional trading measures also increase significantly, more than doubling under competition compared to the pre-reform averages. Concerning the effect of more high-frequency trading, speculative trading measures are unaffected.

In sum, our findings indicate that more high-frequency trading may be beneficial for market quality but competition among HFTs is harmful to market quality. These results imply that regulators may encourage high-frequency trading but not competition among HFTs as the latter leads to more speculative trading and less market-making.

5 Robustness

This section presents the results of several robustness checks. First, we conduct propensity score matching of our baseline model. Second, we compare how HFTs' entries and exits, separately, affect liquidity, volatility, and high-frequency trading behavior. Third, we use the Herfindahl-Hirschman Index as an alternative measure of competition. Last, we discuss a simple panel model approach. Throughout the robustness section, we concentrate on a representative subset of the measures employed in the main analysis for brevity.

5.1 Propensity Score Matching

In this section, we conduct propensity score matching of our baseline model. Our matching procedure relies on a sample of propensity scores that are neither low (less than or equal to 10%) nor high (greater than or equal to 90%). In other words, our matched samples contain more equal stock events, while disregarding events that have a very high likelihood of being treated and events that have a very low likelihood of being treated. In this way, we ensure that our results are not driven by stock events with very different likelihoods of being in the treatment or control group in the upcoming period given their current stock characteristics.

Table 6, the left-hand-side panel, shows pre-event means and simple t-tests of differences between the treatment and control groups prior to the event for both the pre-matched and post-matched samples. Four out of seven means are not different from each other in either the pre- or the post-matched sample. For the remaining three cases, differences in the post-matched sample decrease and are only significant at the 10% level, which is the desired outcome.

To calculate the propensity scores, we run - at the stock event level - a probit regression on stock characteristics. The left-hand-side variable is a dummy variable indicating whether or not a particular stock will face high-frequency trading competition on the next trading day. As controls, we include our market quality and high-frequency trading measures from the pre-event days. There are 125 events (entries) that form the treatment group, and 695 stock-day observation in the control group.[18] From this probit regression, we obtain the propensity scores that we need to

[18]We only show results for entries, but we obtain similar results for exits. Note that when looking at exits, the procedure differs: pre-exit characteristics are likely to be different as the treatment group contains competing HFTs at that point.

retrieve our matched sample.

Table 6, the right-hand-side panel, shows the probit regression on the entire sample (left column) and on the matched sample (right column). The number of stock observations in the control group is reduced to 475 and that in the treatment group to 71 as a result of our matching procedure. Price pressure, which is the only measure statistically significant pre-match, becomes insignificant post-match. Our probit regression also captures less of the variation than prior to matching - the R-squared in the pre-match regression is about 0.27 and in the post-match about 0.19 -, which indicates that the matching has indeed yielded a sample of more equal pre-event characteristics.

Given the matched sample, we repeat our difference-in-differences analysis. Table 7 shows the post-match effects of high-frequency trading competition on market liquidity, volatility and high-frequency trading measures. The magnitudes of the competition coefficient are close to that of the full sample. Specifically, illiquidity increases by 8% when measured by bid-ask spreads (column 1), or by 32% when measured by the price impact factor (columns 2), or by about 3 percentage points when measured by the order execution shortfall (column 3). Intraday volatility increases by about 14% (columns 4), while interday volatility shows no significant increase (column 5). Speculative high-frequency trading goes up by about 15% (column 6) and directional trading increases (column 7). Overall, the propensity score matched regression results are similar to our baseline regression results.

5.2 Entries and Exits Considered Separately

In our main analysis, we used both entries and exits simultaneously, with the relevant event dummy set to 1 if there are two or more HFTs active in a stock (competition) and to zero if there is only one HFT active in a stock (no competition). In this section, we consider entries and exits separately, and re-estimate our baseline model.

The entry dummy is set to 1 if HFT entry leads to a change from no high-frequency trading competition to high-frequency trading competition. The exit dummy is set to 1 if one or more of the competing HFTs stop trading in the stock so that there is only one HFT still active in a stock. This makes entries and exits intuitively comparable. Table 8 presents the results for market quality measures and high-frequency trading measures, for entries (Panel A) and exits (Panel B). Tests suggest that there is a symmetric effect of entries and exists in all specifications: illiquidity, intraday volatility and speculative high-frequency trading increase by about the same magnitude when there is a change from no competition to competition as they *decrease* when there is the opposite change.

5.3 An Alternative Measure of Competition

In our main analysis, we used a discrete measure of competition. In this section, we consider a continuous measure of competition to show that the effects of competition we uncover are robust to the way competition is measured.

To this end, we introduce the Herfindahl-Hirschman Index, calculated as the sum of squares of market shares of all HFTs trading a particular stock on a particular day. The index lies between 0 and 1. When the index is equal to 1, there is no competition; when the index is close to 0, there is perfect competition. An attractive feature of the index is that it gives more weight to traders with larger market shares and can additionally capture the impact of market power on market quality and speculative trading.

We find the effect of competition to be similar to that in our main analysis. Table 9 presents the results. Lower values of the index (more competition, less market power) lead to higher illiquidity (columns 1 to 3), higher intraday volatilities (columns 4), and more speculative trading (columns 5).

5.4 A Panel Regression Approach

In this section, we use a simple panel regression framework as an alternative to our difference-in-differences regression setup and show that our results remain robust.

The model is summarized in the following equation:

$$y_{j,d} = \alpha + \beta_1 D_{j,d}^{comp} + \beta_2 D_{j,d}^{no\ HFT} + X_{j,d}\Gamma + p_d + m_j + u_{j,d}, \tag{4}$$

with j indexing the security and d being the time (day). $D_{j,d}^{comp}$ is a dummy variable that is equal to 1 if stock j faces competing HFTs at day d and $D^{no\,HFT}_{j,d}$ is a dummy variable that is equal to 1 if not a single HFT is trading in stock j at day d, and 0 otherwise. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{e,j,d}$ is the vector of covariates and $u_{e,j,d}$ is the error term. The dependent variable is $y_{j,d}$ and takes the form of the same market quality measures as in the test settings above. Note that the base is the same as in our main analysis, stock-day observation with a single active HFT. That is, β_1 captures the effect of high-frequency trading competition over and above no competition, while β_2 captures the effect of no high-frequency trading in the stock, over and above a single active HFT. This setup allows us to compare the estimates on competition with the estimates obtained in the baseline specifications.

We find the results to be similar to those from our baseline specification as well as to those from our set-up of triple differences, both in magnitude and in statistical significance. Table 10 presents estimates for market quality measures.[19] We again find that high-frequency trading competition leads to an increase in illiquidity (columns 1 to 3), an increase in intraday volatility (columns 4), while having no significant effect on interday volatility (column 5).

6 Conclusion

Recent theoretical models predict that competition among HFTs harms market liquidity. We test these theoretical predictions empirically, analyzing how competition affects HFTs' trading behavior and market quality. Our analysis exploits a unique dataset which allows us to compare environments with and without high-frequency competition, and contains an exogenous event - a tick size reform - which we use to disentangle the effects of the rising share of high-frequency trading in the market from the effects of high-frequency competition per se.

Our difference-in-differences analysis shows that when HFTs compete, their speculative trading increases by about 11 percentage points. As a result of more speculative high-frequency trading, market quality deteriorates, as predicted by the theoretical literature. For example, bid-ask spreads increase by 5%, intraday Amihud (2002)'s measures of illiquidity increase by 18%, and trade price impact (Kyle's lambda) increases by 23%. Our analysis of triple differences, which exploits a tick

[19] Note that in the panel regression setup, the high-frequency trading measures are always zero for observations without any active HFTs. We therefore omit high-frequency trading measures in this setup.

size reform, further documents that when an increase in high-frequency trading is accompanied by high-frequency trading competition, HFTs use more speculative trading strategies and, as a result, liquidity deteriorates and short-term volatility rises.

Our findings highlight that the channel through which high-frequency trading competition adversely affects market quality is through an increase in speculative trading. Markets should therefore be designed in a way that promotes high-frequency trading, but eliminates competition among HFT speculators.

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Figure 1: Summary Statistics around Events

The figures graph simple means of Amihud's illiquidity measure (top panel), 5-minute volatility (middle panel) and high-frequency trading behavior (price pressure measure based on trades, bottom panel) three days before and three days after a change from no competition to competition among HFTs.

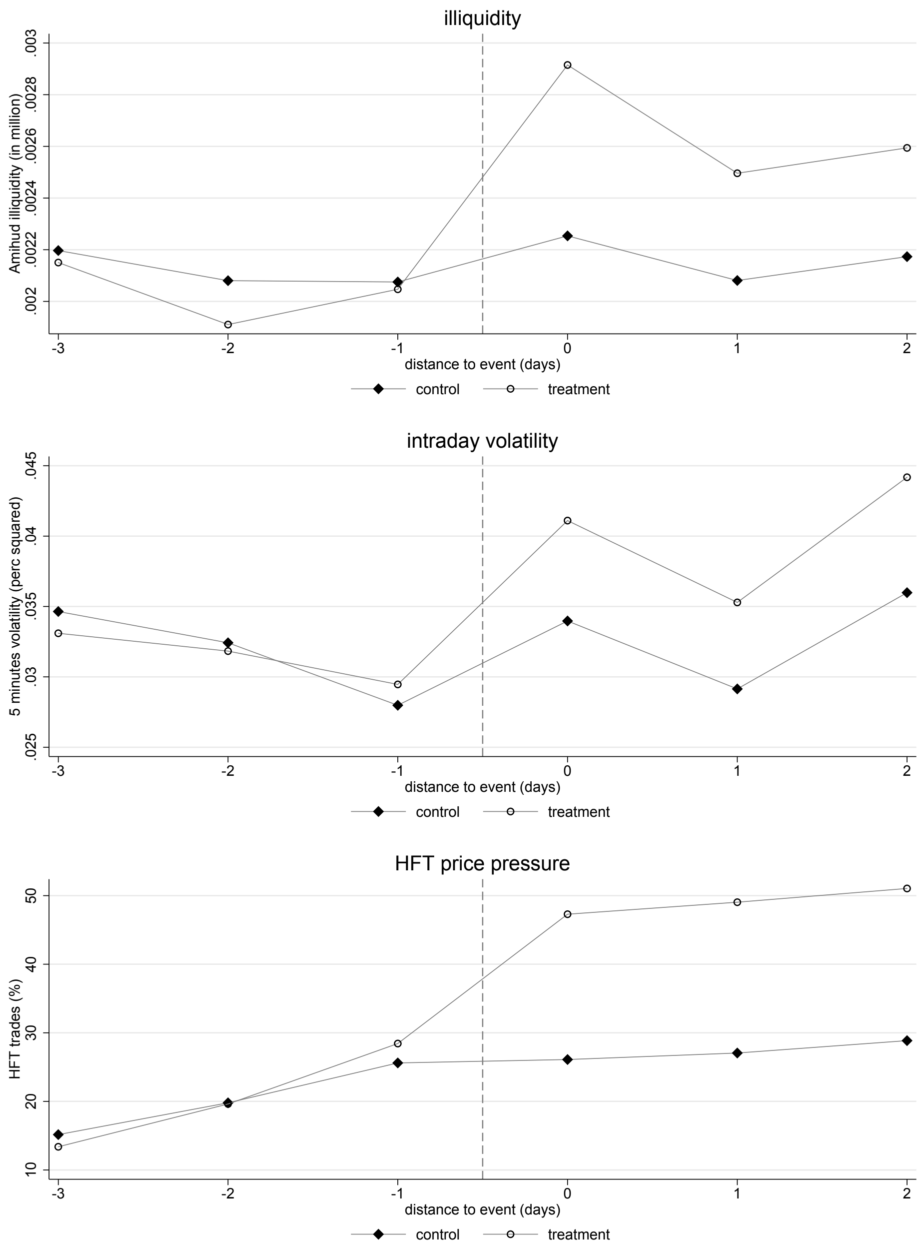

Figure 2: Tick Size Table around the Reform

This figure summarizes the impact of the Federation of European Securities Exchanges (FESE) tick size reform on October 26th, 2009 on the tick sizes in the market, for affected and unaffected stocks. The vertical axis depicts actual tick sizes in place for all relevant price levels.

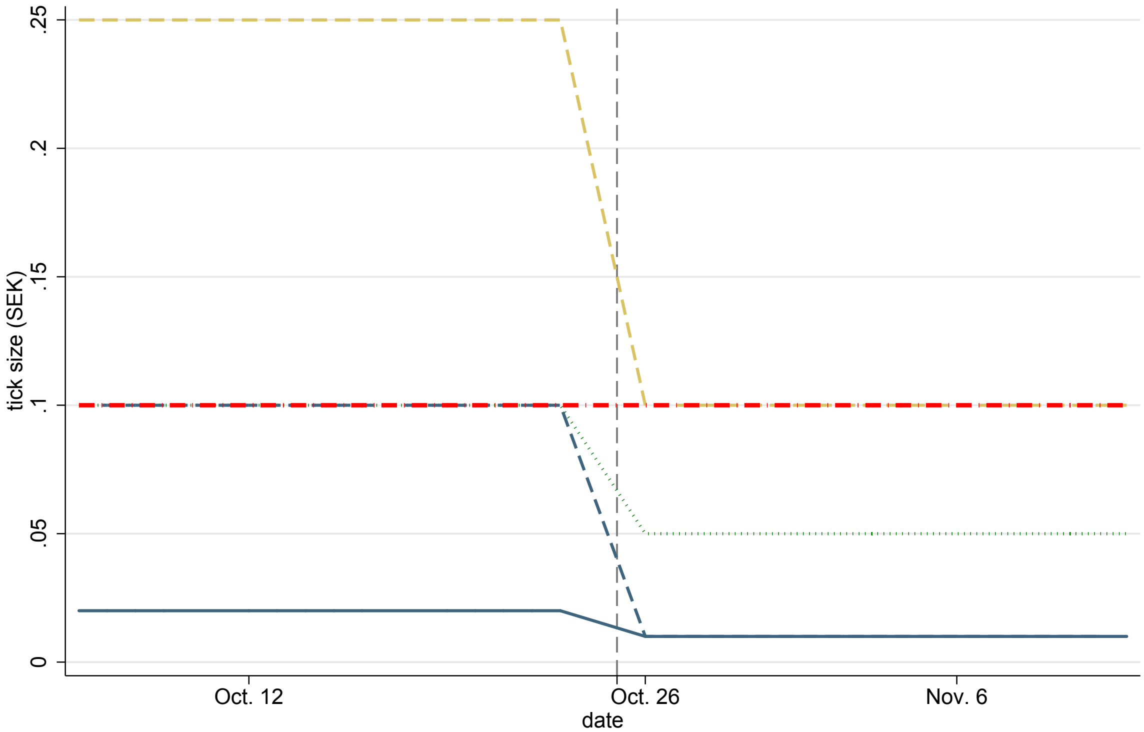

Figure 3: Illustration of the Tick Size Reform

The figure shows relative tick size (tick size to pre-event stock price ratio) for stocks before and after the Federation of European Securities Exchanges (FESE) tick size reform on October 26th, 2009. Stocks are divided into three groups: (i) stocks whose tick size was not affected by the reform (hollow diamonds, Group 1), (ii) stocks whose relative tick sizes are above the pre-reform minimum (hollow circles, Group 2), (iii) stocks whose relative tick sizes are below the pre-reform minimum (filled circles, Group 3). The grey-shaded area in the figure indicates the relative tick size levels that were not available in the market prior to the reform. The horizontal axis represents time, before and after the reform, and the vertical axis gives the relative tick sizes in basis points.

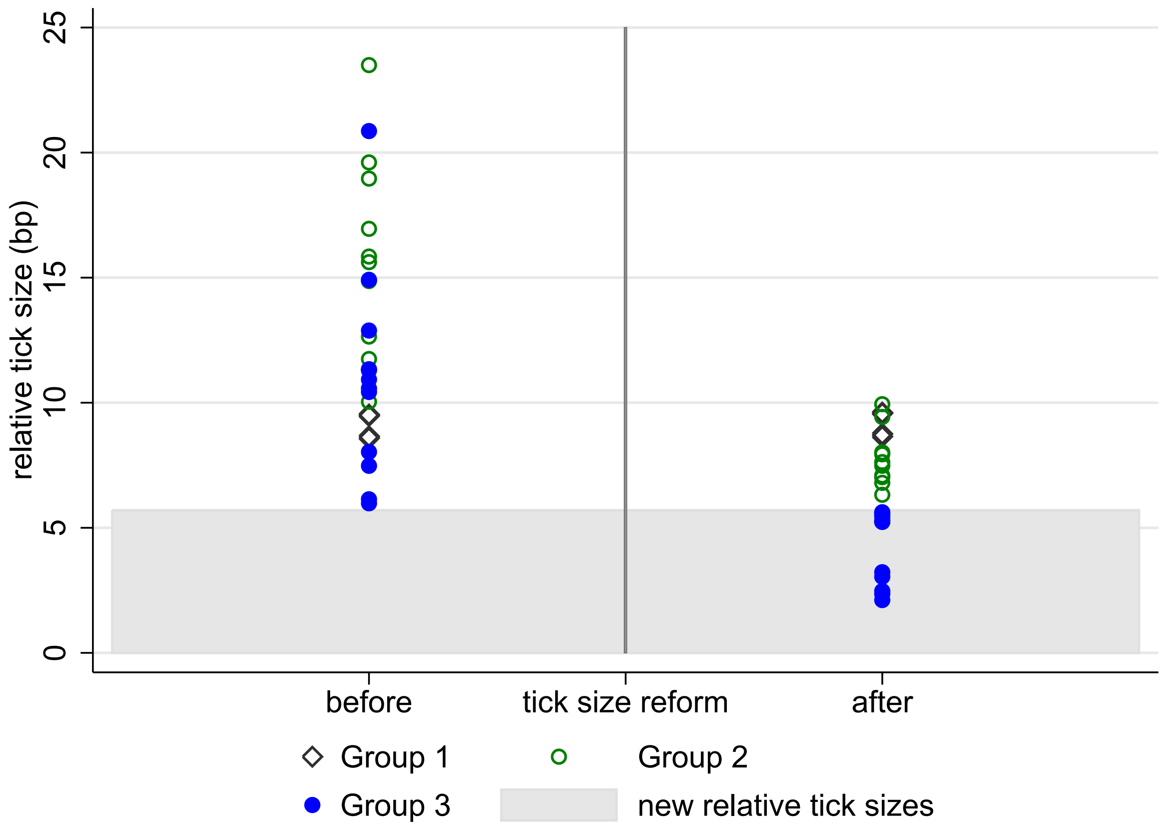

Figure 4: High-Frequency Trading Activity around the Reform

This figure documents how the Federation of European Securities Exchanges (FESE) tick size reform on October 26th, 2009 affected high-frequency trading activity as a % of all trades across three groups of stocks: (i) stocks whose tick size was not affected by the reform (dashed-dotted line, Group 1), (ii) stocks whose relative tick sizes are above the pre-reform minimum (solid line, Group 2), (iii) stocks whose relative tick sizes are below the pre-reform minimum (dashed line, Group 3).

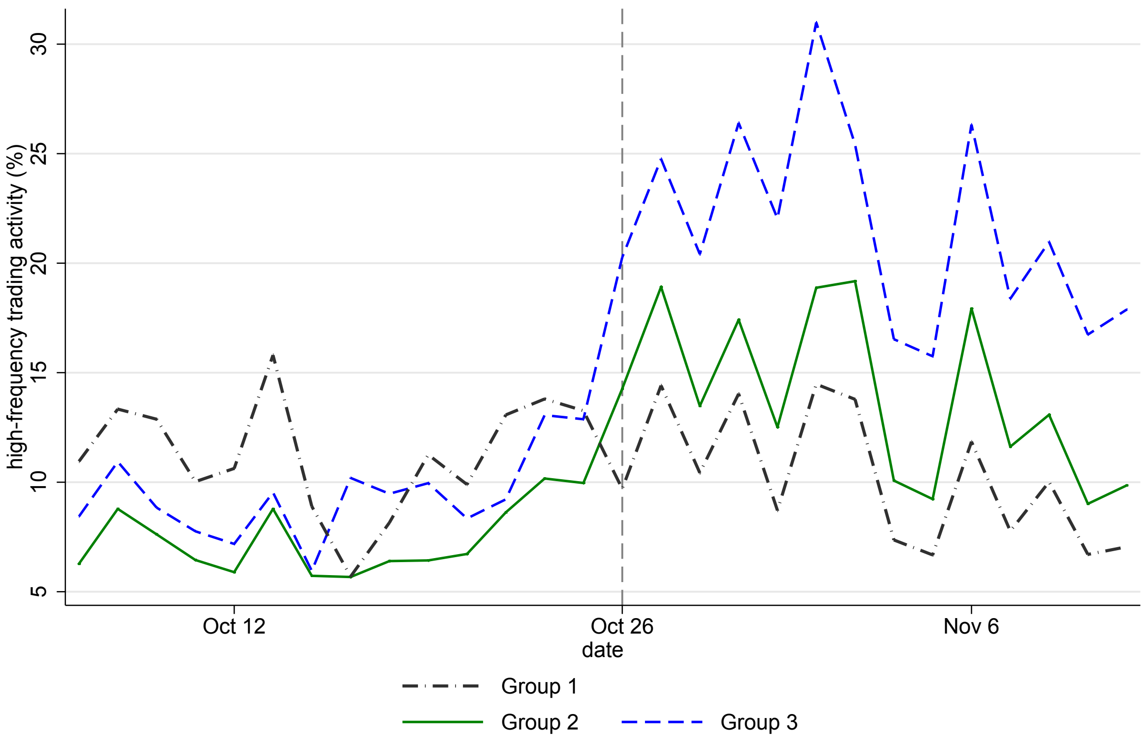

Figure 5: Dynamic Impact of Entry and Exit

This figure shows point estimates for three days before and three days after the event from the difference-in-differences estimation of entry (left-hand-side panels) and exit (right-hand-side panels). The plotted coefficients come from the following regression: $y_{j,d} = \alpha + \beta_1 dist^{-3}_{j,d} + \beta_2 dist^{-2}_{j,d} + \cdots + \beta_3 dist^{2}_{j,d} + X_{j,d}\Gamma + p_d + m_j + u_{j,d}$, which allows for multiple time periods and multiple treatment groups, with j indexing the security and d the time (day). $dist{-}3_{j,d}$, for example, is an indicator of security j that belongs to the treatment group at time d three days before entry (exit). p_d are daily time fixed effects and m_j are security fixed effects. $X_{j,d}$ is the vector of covariates and $u_{j,d}$ is the error term. The dependent variables is $y_{j,d}$. The rows show estimates for the Amihud (2002) illiquidity measure (top panels), for the 5-minute volatility measure (middle panels), and for the price pressure measure based on trades (bottom panels). The dotted lines represent the 95% confidence interval.

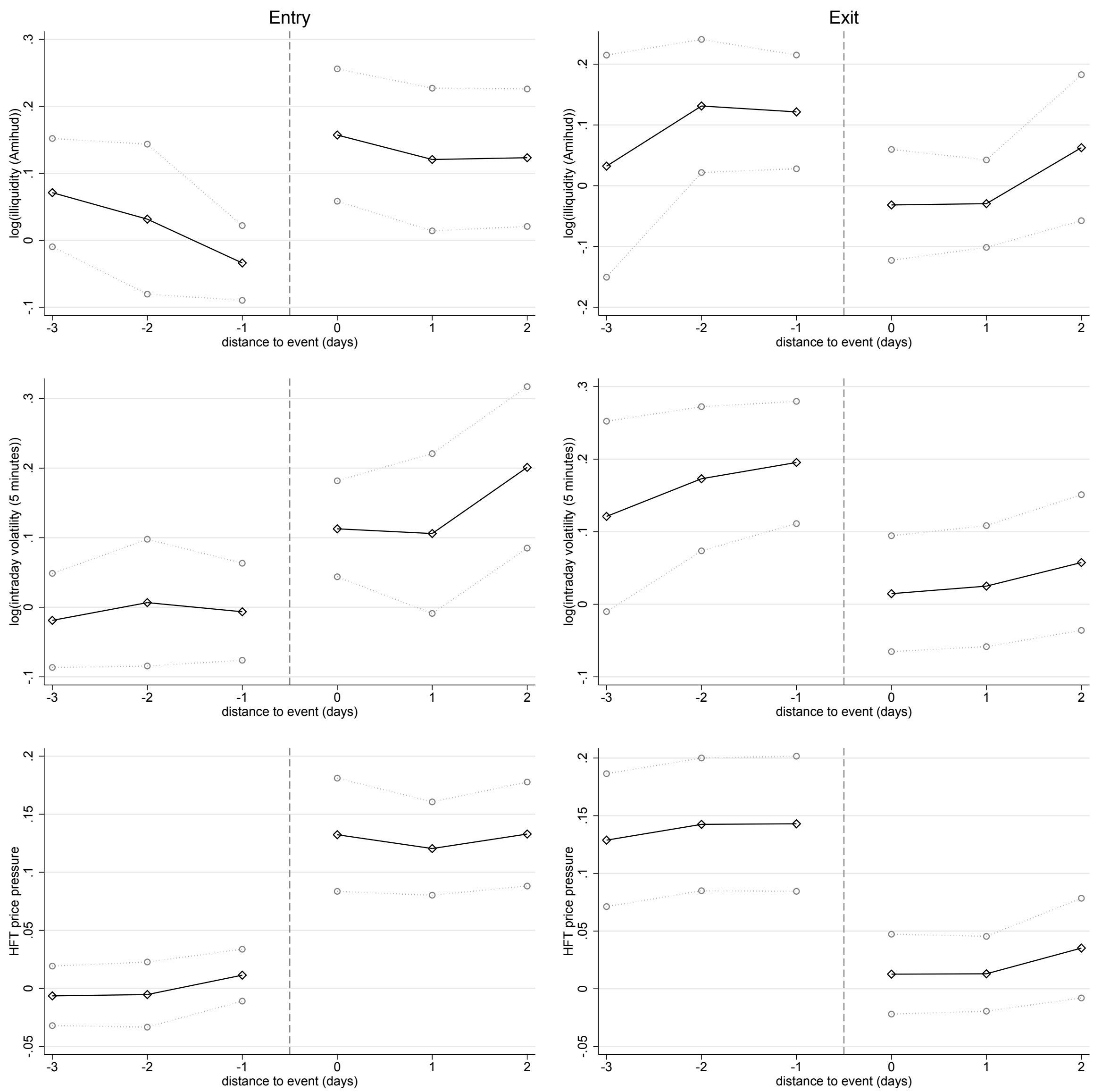

Table 1: Summary Statistics

This table provides summary statistics for all illiquidity (Panel A), volatility (Panel B) and high-frequency trading measures (Panel C) used in the analysis. Illiquidity measures are: bid-ask spreads, order execution shortfalls (based on trades and volume), Amihud's measure of illiquidity, price impact as measured by Kyle's lambda, and autocorrelation (measure of price efficiency). Volatility measures contain: intraday volatilities (5-minute and min-max) and interday volatilities (close-close and open-close). High-frequency trading measures are: price pressure measures (based on trades and volume) and three directional trading measures. In the left panel, statistics on the baseline model are reported for the days prior to an HFT entry, for both the control groups and the treatment group. In the left panel, summary statistics on Group 1 (unaffected by the reform), Groups 2 and 3 (affected by the reform but differing in high-frequency trading competition) affected and unaffected by the Federation of European Securities Exchanges (FESE) tick size reform on October 26th, 2009, are shown for the day prior to the reform.

		baseline				***tick size reform***					
		treatment		control		Group 1		Group 2		Group 3	
	units	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
PANEL A: *ILLIQUIDITY MEASURES*											
bid-ask spread		0.120	0.068	0.160	0.067	0.125	0.012	0.193	0.059	0.207	0.054
exec shortfall (trades)	ratio [0,1]	0.498	0.150	0.421	0.193	0.525	0.047	0.340	0.207	0.296	0.201
exec shortfall (volume)	ratio [0,1]	0.318	0.084	0.301	0.105	0.351	0.130	0.268	0.085	0.247	0.083
illiquidity (Amihud)	million SEK	0.002	0.006	0.002	0.009	0.003	0.004	0.004	0.009	0.004	0.006
price impact (Kyle's Λ)	million SEK	11.744	21.153	10.724	22.349	6.373	3.049	14.768	37.264	7.963	7.889
price efficiency (autocorr)		-0.045	0.136	-0.066	0.134	-0.053	0.130	-0.082	0.129	-0.104	0.135
PANEL B: *VOLATILITY MEASURES*											
intraday vola (5-min)	perc squared	0.030	0.025	0.033	0.025	0.029	0.015	0.039	0.023	0.031	0.023
intraday vola (min-max)	perc squared	7.856	9.934	10.108	72.257	8.042	8.421	18.344	142.838	7.923	11.977
interday vola (close-close)	perc squared	3.889	6.462	3.383	7.004	3.394	4.823	3.779	5.879	2.441	4.984
interday vola (open-close)	perc squared	3.088	51.420	1.145	30.086	2.802	5.253	2.799	3.815	1.764	2.523
PANEL C: *HIGH-FREQUENCY TRADING MEASURES*											
price pressure (volume)	ratio [0,1]	0.287	0.277	0.242	0.250	0.170	0.213	0.082	0.186	0.180	0.282
price pressure (trades)	ratio [0,1]	0.276	0.230	0.252	0.254	0.207	0.248	0.086	0.192	0.161	0.240
directional trading 1	ratio	0.423	1.026	0.959	1.182	0.945	0.801	1.140	1.268	0.308	0.818
directional trading 2	ratio	0.445	1.361	1.212	1.736	1.016	1.069	1.513	1.873	0.472	1.557
directional trading 3	ratio	2.762	6.987	5.835	7.644	6.164	5.887	7.028	8.685	2.358	7.163

Table 2: Competition among High-Frequency Traders: Effects on Illiquidity

This table displays the estimates of the baseline difference-in-differences test setting summarized in the following equation: $y_{e,j,d} = \alpha + \beta_1 D^{comp}_{e,j,d} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$ with e indexing entry or exit, j being the security and d the time (day). $D^{comp}_{e,j,d}$ is the event dummy set to 1 if there is high-frequency trading competition in security j at time d, and to zero if there is no high-frequency trading competition. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{e,j,d}$ is the vector of covariates and $u_{e,j,d}$ is the error term. The dependent variable $y_{e,j,d}$ takes the form of illiquidity measures (bid-ask spread in columns 1 and 2, order execution shortfall measures in columns 3 and 4, Amihud (2002) measure of illiquidity in column 5, and price impact measure in column 6), and a market efficiency measure (autocorrelation in column 7). Additional controls to account for trader-specific effects and event-type-specific effects that go beyond time and security fixed effects are: (i) a stock-event period dummy to control for whether a specific stock belongs to the treatment group or to the control group during a particular event, (ii) an event-type dummy to capture the differences between the effect of entries and of exits, (iii) HFT fixed effects, (iv) past turnover, and (v) past bid-ask spreads. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	bid-ask spread	bid-ask spread	exec shortfall (trades)	exec shortfall (volume)	illiquidity (Amihud)	price impact (Kyle's lambda)	price efficiency (autocorr)
HFT competition (event * treatment)	**0.056****	**0.051*****	**0.016****	**0.042****	**0.182****	**0.233*****	**-0.134**
	(0.027)	(0.013)	(0.008)	(0.018)	(0.088)	(0.061)	(0.161)
event period dummy	0.002	-0.007	-0.014	-0.002	-0.025	0.052	-0.003
	(0.033)	(0.012)	(0.006)	(0.019)	(0.077)	(0.066)	(0.123)
entry vs exit dummy	-0.036	-0.017	-0.002	-0.011	0.001	-0.010	-0.161
	(0.021)	(0.011)	(0.008)	(0.010)	(0.050)	(0.053)	(0.101)
lagged log turnover		-0.052***	0.028***	-0.033***	-0.447***	-0.173***	-0.043
		(0.009)	(0.005)	(0.011)	(0.064)	(0.032)	(0.051)
lagged log bid-ask spread		0.771***	-0.082***	-0.306***	0.238	-0.063	0.062
		(0.040)	(0.010)	(0.033)	(0.156)	(0.050)	(0.136)
Observations	2,175	2,175	2,175	2,175	2,175	2,175	2,175
R-squared	0.8429	0.9473	0.3236	0.7794	0.6162	0.8488	0.0749
-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Competition among High-Frequency Traders: Effects on Volatility

This table displays the estimates of the baseline difference-in-differences test setting summarized in the following equation: $y_{e,j,d} = \alpha + \beta_1 D^{comp}_{e,j,d} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$ with e indexing entry or exit, j being the security and d the time (day). $D^{comp}_{e,j,d}$ is the event dummy set to 1 if there is high-frequency trading competition in security j at time d, and to zero if there is no high-frequency trading competition. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{e,j,d}$ is the vector of covariates and $u_{e,j,d}$ is the error term. The dependent variable $y_{e,j,d}$ takes the form of interday volatility measures (5-minute volatility in columns 1 and 2, and min-max volatility in column 3) and intraday volatility measures (close-close volatility in column 4 and open-close volatility in column 5). Additional controls to account for trader-specific effects and event-type-specific effects that go beyond time and security fixed effects are: (i) a stock-event period dummy to control for whether a specific stock belongs to the treatment group or to the control group during a particular event, (ii) an event-type dummy to capture the differences between the effect of entries and of exits, (iii) HFT fixed effects, (iv) past turnover, and (v) past bid-ask spreads. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
	intraday vola (5-min)	intraday vola (5-min)	intraday vola (min-max)	interday vola (close-close)	interday vola (open-close)
HFT competition (event * treatment)	**0.092****	**0.096****	**0.141****	**-0.060**	**-0.145**
	(0.044)	(0.043)	(0.053)	(0.125)	(0.209)
event period dummy	0.039	0.037	0.091	0.379*	0.173
	(0.036)	(0.036)	(0.073)	(0.211)	(0.188)
entry vs exit dummy	-0.020	-0.007	-0.018	-0.021	-0.147
	(0.034)	(0.034)	(0.076)	(0.124)	(0.150)
lagged log turnover		0.200***	0.340***	0.166	0.390***
		(0.026)	(0.043)	(0.116)	(0.121)
lagged log bid-ask spread		0.335***	0.336***	0.199	0.802***
		(0.041)	(0.094)	(0.192)	(0.214)
Observations	2,175	2,175	2,175	2,175	2,175
R-squared	0.7247	0.7423	0.5331	0.2723	0.2526
-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES
HFT FE	NO	YES	YES	YES	YES
-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Competition among High-Frequency Traders: Effects of Speculative Trading

This table displays the estimates of the baseline difference-in-differences test setting summarized in the following equation: $y_{e,j,d} = \alpha + \beta_1 D^{comp}_{e,j,d} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$ with e indexing entry or exit, j being the security and d the time (day). $D^{comp}_{e,j,d}$ is the event dummy set to 1 if there is high-frequency trading competition in security j at time d, and to zero if there is no high-frequency trading competition. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{e,j,d}$ is the vector of covariates and $u_{e,j,d}$ is the error term. The dependent variable $y_{e,j,d}$ takes the form of speculative trading measures (price pressure measure based on volume (column 1 and column 2) and trades (column 3)), and directional trading measures (column 4 to column 6). Additional controls to account for trader-specific effects and event-type-specific effects that go beyond time and security fixed effects are: (i) a stock-event period dummy to control for whether a specific stock belongs to the treatment group or to the control group during a particular event, (ii) an event-type dummy to capture the differences between the effect of entries and of exits, (iii) HFT fixed effects, (iv) past turnover, and (v) past bid-ask spreads. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
	price pressure (volume)	price pressure (volume)	price pressure (trades)	directional trading 1	directional trading 2	directional trading 3
HFT competition (event * treatment)	**0.118*** **	**0.117*** **	**0.173** **	**0.392*** **	**0.403** **	**2.321** **
	(0.020)	(0.021)	(0.063)	(0.139)	(0.179)	(0.857)
event period dummy	0.010	0.010	0.068**	-0.018	0.063	0.288
	(0.013)	(0.013)	(0.030)	(0.098)	(0.141)	(0.605)
entry vs exit dummy	0.009	0.008	0.009	-0.013	-0.159	-0.574
	(0.009)	(0.009)	(0.022)	(0.096)	(0.156)	(0.683)
lagged log turnover		-0.000	-0.004	-0.207***	-0.296***	-1.359***
		(0.008)	(0.016)	(0.061)	(0.100)	(0.363)
lagged log bid-ask spread		-0.020	-0.011	-0.575***	-0.570**	-3.482***
		(0.030)	(0.072)	(0.140)	(0.208)	(1.001)
Observations	2,175	2,175	2,175	2,175	2,175	2,175
R-squared	0.5755	0.5765	0.5445	0.5379	0.4198	0.3982
-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES
HFT FE	NO	YES	YES	YES	YES	YES
-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Competition among HFTs and the Tick Size Reform

This table presents the results of the regression set-up of triple differences around the Federation of Federation of European Securities Exchanges (FESE) tick size on reform on October 26th, 2009. This set-up tests the effects of high-frequency trading competition while separating the effects of increased high-frequency trading activity. The model is summarized in the following equation: $y_{j,d} = \alpha + \beta_1(Post_d * Reform_j * Group\ 3_j) + \beta_2(Post_d * Reform_j) + p_d + m_j + X_{j,d}\Gamma + u_{j,d}$, with j indexing the security and d being the time (day). $Post_d$ indicates the period after the reform and $Reform_j$ indicates whether security j is affected by the tick size reform, i.e. whether it belongs to Group 2 or Group 3. $Group\ 3_j$ is also a dummy variable that is 1 for securities belonging to Group 3 and 0 otherwise. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{j,d}$ is the vector of covariates and $u_{j,d}$ is the error term. In Panel A, the dependent variable $y_{j,d}$ takes the form of illiquidity measures (bid-ask spread in column 1, order execution shortfall measure in columns 2, Amihud (2002) measure of illiquidity in column 3, and price impact measure in column 4), and a market efficiency measure (autocorrelation in column 5). In Panel B, the dependent variable $y_{j,d}$ takes the form of intraday volatility measures (5-minute volatility in column 2, and min-max volatility in column 3) and interday volatility measures (close-close volatility in column 4 and open-close volatility in column 5). In Panel C, the dependent variable $y_{j,d}$ takes the form of speculative trading measures (price pressure measure based on volume in column 1 and trades in column 2), and directional trading measures in column 3 to column 5. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
PANEL A: *ILLIQUIDITY MEASURES*	exec shortfall (trades)	exec shortfall (volume)	illiquidity (Amihud)	price impact (Kyle's lambda)	price efficiency (autocorr)
HFT competition (post * reform * Group 3)	**0.080*****	**0.051*****	**0.148***	**0.208****	**-0.100**
	(0.013)	(0.015)	(0.077)	(0.100)	(0.197)
tick size reform (post * reform)	**-0.059*****	**0.022**	**-0.150**	**-0.170****	**-0.072**
	(0.014)	(0.023)	(0.095)	(0.082)	(0.227)
lagged log turnover	-0.019***	-0.001	-0.870***	-0.293***	0.149
	(0.006)	(0.009)	(0.057)	(0.028)	(0.108)
R-squared	0.8751	0.3355	0.6509	0.6378	0.0838
PANEL B: *VOLATILITY MEASURES*		intraday vola (5-min)	intraday vola (min-max)	interday vola (close-close)	interday vola (open-close)
HFT competition (post * reform * Group 3)		**0.146****	**0.359*****	**0.122**	**0.015**
		(0.060)	(0.126)	(0.252)	(0.230)
tick size reform (post * reform)		**-0.224*****	**-0.340*****	**-0.037**	**-0.664**
		(0.062)	(0.129)	(0.399)	(0.416)
lagged log turnover		-0.008	0.071**	-0.062	0.310*
		(0.019)	(0.034)	(0.188)	(0.161)
R-squared		0.5867	0.5036	0.2880	0.2595

- continued on next page

Table 5 - continued from previous page

__PANEL C:__ HIGH-FREQUENCY TRADING MEASURES

	price pressure (volume)	price pressure (trades)	directional trading 1	directional trading 2	directional trading 3
HFT competition (post * reform * Group 3)	**0.042*** **	**0.041***	**0.250****	**0.420****	**1.968****
	(0.014)	(0.024)	(0.117)	(0.194)	(0.928)
tick size reform (post * reform)	**0.022**	**0.043**	**-0.059**	**-0.232**	**-1.698**
	(0.019)	(0.037)	(0.155)	(0.231)	(1.138)
lagged log turnover	0.019***	0.029***	-0.684***	-1.105***	-5.190***
	(0.004)	(0.009)	(0.072)	(0.122)	(0.535)
R-squared	0.5091	0.4882	0.5841	0.4758	0.4460
-	-	-	-	-	-
Observations	950	950	950	950	950
Time FE	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Robustness: Propensity Score Matching Diagnostics

This table provides statistics for pre-matched and post-matched propensity score samples. The left-hand-side panel shows pre-event means and t-tests of differences between the treatment and control groups prior to high-frequency trading competition for both the pre-matched and post-matched samples. The right-hand-side panel depicts the probit regression employed to calculate the propensity scores at the stock-event level. The dependent variable is a dummy variable indicating whether or not a particular stock will face high-frequency trading competition the day after. As controls, market quality and high-frequency trading measures from the pre-event days are included. The propensity score matched sample is that with propensity scores between 0.1 and 0.9.

		pre-match			*post-match*			*probit regression*		
		treatment	control	t-test	treatment	control	t-test		pre-match	post-match
bid-ask spread	mean	0.126	0.142	0.016**	0.122	0.139	0.017*	*log bid-ask spread*	0.645	-1.185
	sd	0.075	0.062		0.056	0.063			(0.930)	(1.486)
exec shortfall (volume)	mean	0.322	0.312	-0.01	0.329	0.313	-0.016	*exec shortfall (volume)*	-0.350	-2.902
	sd	0.085	0.104		0.086	0.106			(1.436)	(2.329)
price impact (Kyle's λ)	mean	10.486	11.362	0.876	12.048	12.167	0.118	*log price impact (Kyle's λ)*	0.058	0.274
	sd	16.993	23.37		20.939	25.147			(0.251)	(0.320)
intraday vola (5-min)	mean	0.029	0.030	0.001	0.029	0.029	0.000	*log intraday vola (5-min)*	0.013	0.300
	sd	0.025	0.024		0.028	0.024			(0.493)	(0.462)
interday vola (close-close)	mean	3.931	3.546	-0.385	4.319	3.808	-0.512	*log close-close vola*	0.063	0.013
	sd	6.191	7.309		7.139	8.239			(0.094)	(0.113)
price pressure (volume)	mean	0.293	0.251	-0.042**	0.303	0.275	-0.029*	*price pressure (volume)*	**1.525***	1.281
	sd	0.205	0.216		0.243	0.253			(0.779)	(1.237)
directional trading 1	mean	0.337	0.843	0.506***	0.537	0.773	0.236*	*directional trading 1*	-0.400	-0.415
	sd	1.096	1.082		1.142	0.992			(0.260)	(0.330)
								constant	0.335	6.516
									(6.257)	(7.386)
# entries									125	71
Observations									695	475

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Robustness: Propensity Score Matching Estimations

Given the matched sample from Table 6, this table repeats the baseline difference-in-differences analysis. The model set-up is: $y_{e,j,d} = \alpha + \beta_1 D^{comp}_{e,j,d} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, with e indexing entry, j being the security and d the time (day). $D^{comp}_{e,j,d}$ is the event dummy set to 1 if there is high-frequency trading competition in security j at time d, and to zero if there is no high-frequency trading competition. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{e,j,d}$ is the vector of covariates and $u_{e,j,d}$ is the error term. The dependent variable $y_{e,j,d}$ takes the form of market illiquidity (bid-ask spreads in column 1, price impact factor in column 2, and order execution shortfall measure in column 3), volatility (intraday volatility in column 4, and interday volatility in column 5) and speculative high-frequency trading measures (price pressure measure in column 6, and directional trading measure in column 7). Additional controls to account for trader-specific effects and event-type-specific effects that go beyond time and security fixed effects are: (i) a stock-event period dummy to control for whether a specific stock belongs to the treatment group or to the control group during a particular event, (ii) an event-type dummy to capture the differences between the effect of entries and of exits, (iii) HFT fixed effects, (iv) past turnover, and (v) past bid-ask spreads. The propensity score matched sample is that of propensity scores between 0.1 and 0.9. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	bid-ask spread	price impact (Kyle's lambda)	exec shortfall (volume)	intraday vola (5-min)	interday vola (close-close)	price pressure (volume)	directional trading 1
HFT competition (event * treatment)	**0.079*** **	**0.325** **	**0.028* **	**0.140** **	**0.010**	**0.156** **	**0.319** **
	(0.021)	(0.137)	(0.016)	(0.059)	(0.224)	(0.071)	(0.145)
event period dummy	-0.018	0.099	-0.025*	0.008	0.402	0.045	-0.107
	(0.012)	(0.061)	(0.012)	(0.043)	(0.238)	(0.028)	(0.086)
entry vs exit dummy	-0.023	-0.082	0.008	0.018	-0.047	0.002	0.083
	(0.014)	(0.057)	(0.009)	(0.045)	(0.171)	(0.032)	(0.087)
lagged log turnover	0.030***	-0.161***	-0.000	0.248***	0.172	0.002	-0.206***
	(0.010)	(0.044)	(0.007)	(0.030)	(0.169)	(0.015)	(0.056)
lagged log bid-ask spread	0.805***	0.002	-0.099***	0.349***	-0.083	-0.045	-0.552***
	(0.030)	(0.076)	(0.013)	(0.052)	(0.224)	(0.069)	(0.099)
Observations	1,346	1,346	1,346	1,346	1,346	1,346	1,346
R-squared	0.9428	0.8607	0.3193	0.7542	0.3038	0.5690	0.5502
-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES
HFT FE	YES	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Robustness: Competition Effects of HFT Entry and Exit separately

This table provides results for HFT entries (Panel A) and exits (Panel B), and displays estimated coefficients of the following regression: $y_{e,j,d} = \alpha + \beta_1 D^{comp}_{e,j,d} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, with e indexing entry or exit, j being the security and d the time (day). $D^{comp}_{e,j,d}$ is the event dummy set to 1 if there is high-frequency trading competition in security j at time d, and to zero if there is no high-frequency trading competition. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{e,j,d}$ is the vector of covariates and $u_{e,j,d}$ is the error term. The dependent variable $y_{e,j,d}$ takes the form of market illiquidity (bid-ask spreads in column 1, price impact factor in column 2, and order execution shortfall measure in column 3), volatility (intraday volatility in column 4, and interday volatility in column 5) and speculative high-frequency trading measures (price pressure measure in column 6, and directional trading measure in column 7). Additional controls to account for trader-specific effects and event-type-specific effects that go beyond time and security fixed effects are: (i) a stock-event period dummy to control for whether a specific stock belongs to the treatment group or to the control group during a particular event, (ii) an event-type dummy to capture the differences between the effect of entries and of exits, (iii) HFT fixed effects, (iv) past turnover, and (v) past bid-ask spreads. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PANEL A: *ENTRY*	bid-ask spread	price impact (Kyle's lambda)	exec shortfall (volume)	intraday vola (5-min)	interday vola (close-close)	price pressure (volume)	directional trading 1
HFT competition (event * treatment)	**0.055*****	**0.249****	**0.044****	**0.097****	**-0.122**	**0.187*****	**0.411*****
	(0.017)	(0.115)	(0.016)	(0.046)	(0.147)	(0.058)	(0.136)
event period dummy	-0.012	-0.001	-0.009	0.001	0.321	0.055*	-0.035
	(0.011)	(0.047)	(0.020)	(0.034)	(0.207)	(0.031)	(0.088)
entry vs exit dummy	0.025	0.121*	0.017	0.077	0.154	-0.019	0.069
	(0.021)	(0.068)	(0.020)	(0.048)	(0.216)	(0.033)	(0.106)
lagged log turnover	0.026***	-0.172***	-0.044***	0.204***	0.165	-0.011	-0.221***
	(0.009)	(0.043)	(0.011)	(0.025)	(0.128)	(0.016)	(0.064)
lagged log bid-ask spread	0.821***	-0.087	-0.311***	0.312***	0.046	-0.014	-0.585***
	(0.030)	(0.068)	(0.036)	(0.042)	(0.188)	(0.070)	(0.144)
R-squared	0.9452	0.8490	0.7858	0.7395	0.2853	0.5372	0.5295
Observations	1,942	1,942	1,942	1,942	1,942	1,942	1,942
PANEL B: *EXIT*							
HFT competition (event * treatment)	**-0.056*****	**-0.230***	**-0.039****	**-0.094***	**0.133**	**-0.152****	**-0.283***
	(0.016)	(0.125)	(0.019)	(0.049)	(0.157)	(0.062)	(0.149)
event period dummy	0.014	0.228	0.024	0.094*	0.124	0.225***	0.312*
	(0.016)	(0.147)	(0.030)	(0.054)	(0.160)	(0.075)	(0.176)
entry vs exit dummy	0.006	0.216***	0.032	0.094*	0.494**	-0.045	0.141
	(0.021)	(0.074)	(0.023)	(0.056)	(0.235)	(0.054)	(0.140)
lagged log turnover	0.024**	-0.180***	-0.038***	0.195***	0.236*	0.006	-0.184**
	(0.010)	(0.043)	(0.011)	(0.027)	(0.124)	(0.018)	(0.074)
lagged log bid-ask spread	0.787***	-0.060	-0.281***	0.284***	0.201	0.002	-0.466***
	(0.033)	(0.059)	(0.033)	(0.045)	(0.205)	(0.080)	(0.135)
R-squared	0.9421	0.8502	0.7618	0.7425	0.2651	0.5273	0.5637
Observations	1,730	1,730	1,730	1,730	1,730	1,730	1,730
-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES
HFT FE	YES	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Robustness: Herfindahl-Hirschman Index

This table displays results for an alternative measure of competition, the Herfindahl-Hirschman Index and shows estimated coefficients of the following regression: $y_{e,j,d} = \alpha + \beta_1 HHI_{j,d} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, with e indexing entry or exit, j being the security and d the time (day). $HHI_{j,d}$ is the Herfindahl-Hirschman Index of competition among high-frequency traders for entry and security j at time d. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{e,j,d}$ is the vector of covariates and $u_{e,j,d}$ is the error term. The dependent variable $y_{e,j,d}$ takes the form of market illiquidity (bid-ask spreads in column 1, price impact factor in column 2, and order execution shortfall measure in column 3), volatility (intraday volatility in column 4, and interday volatility in column 5) and speculative high-frequency trading measures (price pressure measure in column 6, and directional trading measure in column 7). Additional controls to account for trader-specific effects and event-type-specific effects that go beyond time and security fixed effects are: (i) a stock-event period dummy to control for whether a specific stock belongs to the treatment group or to the control group during a particular event, (ii) an event-type dummy to capture the differences between the effect of entries and of exits, (iii) HFT fixed effects, (iv) past turnover, and (v) past bid-ask spreads. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	bid-ask spread	price impact (Kyle's lambda)	exec shortfall (volume)	intraday vola (5-min)	interday vola (close-close)	price pressure (volume)	directional trading 1
Herfindahl	**-0.088****	**-0.485*****	**-0.059****	**-0.242****	**0.427**	**-0.285*****	**-0.930*****
	(0.038)	(0.150)	(0.028)	(0.106)	(0.489)	(0.029)	(0.270)
event period dummy	-0.007	0.022	-0.004	0.012	0.350**	0.005	-0.022
	(0.011)	(0.049)	(0.008)	(0.033)	(0.164)	(0.008)	(0.070)
lagged log turnover	0.026***	-0.174***	-0.044***	0.203***	0.163	-0.004	-0.222***
	(0.008)	(0.032)	(0.006)	(0.025)	(0.123)	(0.005)	(0.053)
lagged log bid-ask spread	0.820***	-0.090	-0.311***	0.311***	0.051	-0.025***	-0.592***
	(0.019)	(0.056)	(0.012)	(0.042)	(0.211)	(0.010)	(0.088)
Observations	1,942	1,942	1,942	1,942	1,942	1,942	1,942
R-squared	0.9449	0.8485	0.7847	0.7393	0.2853	0.5701	0.5295
-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES
HFT FE	YES	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Table 10: Robustness: Panel Regression

The model is summarized in the following equation: $y_{j,d} = \alpha + \beta_1 D^{comp}_{j,d} + \beta_2 D^{no\ HFT}_{,j,d} + X_{j,d}\Gamma + p_d + m_j + u_{j,d}$, with j indexing the security and d being the time (day). $D^{comp}_{j,d}$ is a dummy variable that is equal to 1 if stock j faces competing HFTs at day d and $D^{no\ HFT}_{,j,d}$ is a dummy variable that is equal to 1 if not a single HFT is trading in stock j at day d, and 0 otherwise. p_d are daily time-fixed effects and m_j are security-fixed effects. $X_{e,j,d}$ is the vector of covariates and $u_{e,j,d}$ is the error term. The base remains the same as in the baseline analysis, stock-day observation with a single active HFT. The dependent variable $y_{e,j,d}$ takes the form of market illiquidity (bid-ask spreads in column 1, price impact factor in column 2, and order execution shortfall measure in column 3), and volatility (intraday volatility in column 4, and interday volatility in column 5). Additional controls to account for trader-specific effects and event-type-specific effects that go beyond time and security fixed effects are: (i) a stock-event period dummy to control for whether a specific stock belongs to the treatment group or to the control group during a particular event, (ii) an event-type dummy to capture the differences between the effect of entries and of exits, (iii) HFT fixed effects, (iv) past turnover, and (v) past bid-ask spreads. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
	bid-ask spread	price impact (Kyle's lambda)	exec shortfall (volume)	intraday vola (5-min)	interday vola (close-close)
dummy for two or more HFTs	**0.031****	**0.139****	**0.021****	**0.097****	**-0.066**
	(0.015)	(0.063)	(0.011)	(0.042)	(0.215)
dummy for no HFT	-0.011	-0.047	-0.022	-0.268*	-0.459
	(0.023)	(0.101)	(0.016)	(0.155)	(0.553)
lagged log turnover	0.003	0.049	-0.011**	0.025	-0.347***
	(0.008)	(0.036)	(0.005)	(0.028)	(0.124)
lagged log bid-ask spread	0.231***	-0.013	-0.026	-0.002	0.208
	(0.081)	(0.099)	(0.023)	(0.099)	(0.419)
Observations	3,840	3,840	3,840	3,840	3,840
R-squared	0.9772	0.8854	0.5279	0.8076	0.4355
-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES
HFT FE	YES	YES	YES	YES	YES
-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES

*** p<0.01, ** p<0.05, * p<0.1

Online Appendix

Competition among High-Frequency Traders, and Market Quality

A Institutional and Market Background

This section provides institutional details about the Stockholm Stock Exchange for the sample period from June 2009 to December 2010.

A.A Market Share

Over the sample period, essentially all continuous trading - which is the one relevant for the analysis of high-frequency trading activity - was taking place on the NASDAQ OMXS. This is one of the key advantages of our dataset for the analysis of competition as it means we have a comprehensive record of high-frequency trading in a particular security.

Historically, the Stockholm Stock Exchange held all trading in Sweden. By 2009, alternative trading venues BATS Chi-X Europe, Burgundy and Turquoise held a small share of over-the-counter trading. Today, their shares are significantly higher and trading is no longer concentrated on one exchange only.

A.B Trading Hours

The limit order book market is open Monday to Friday from 9am to 5:30pm, CET, except on public holidays. Also, trading closes at 1pm if the following day is a public holiday. Both opening and closing prices are set by call auctions. The priority rank of an order during the trading day is price, time and visibility.

A.C Account Types

To access the market, financial intermediaries have four different possibilities: (i) Broker accounts are mostly used by institutional investors or non-automated trader. (ii) An order routing account allows customers of the exchange member intermediary to route their orders directly to the market. This is mostly used by direct banks such as internet banks. (iii) A programmed account is used to execute orders through an algorithm such as a big sequential sell or buy order. (iv) Finally, there is the algorithmic trading account, which is the quickest and the cheapest in terms of transaction costs and thus a natural choice for HFTs.

A.D Brokers

There are about one hundred financial firms (members) registered at the NASDAQ OMXS.

A.E Hidden Orders

An important detail about the NASDAQ OMXS is that members cannot place small hidden orders. The rule for being able to hide orders depends on the average daily turnover of a specific stock, but such orders must be at least 50,000EUR. This figure, however, increases with turnover and reaches, for example, a minimum order size of 250,000EUR for a one million EUR turnover. As a result, HFTs have no incentive to hide their orders.

B Additional Tables and Figures

Figure A-1 of the Online Appendix provides further details of the tick size changes. Prior to the tick size reform, stocks on the Stockholm Stock Exchange were exposed to two different tick size tables, Tick Size Table 1 (53% of the stocks) and Tick Size Table 2 (47% of the stocks). The two different tick size tables were a historical relict and do not reflect any differences in stocks' liquidity or volatility today. (Historically, stocks traded on the tick size table 1 where younger corporations, while stocks traded on the tick size table 2 were blue chip stocks.)

The graph on the left-hand-side shows the relevant old and new tick size tables for the Tick Size Table 1 stocks, while the graph on the right-hand-side shows the table for the Tick Size Table 2 stocks. Nearly all stocks were substantially affected by the reform, except those stocks that traded on the Tick Size Table 2 and that had stock prices from SEK 100 SEK to SEK 149.99 (level 3 in the right-hand-side graph of Figure A-1). Note that Figure 2 in the main text combines the two graphs, and depicts the stocks unaffected by the reform using the red dashed line.

Figure A-1: Tick Size Tables

This figure depicts tick sizes around the FESE tick size reform on October 26th, 2009 for all relevant price levels and their corresponding Tick Size Tables on the OMXS30. The graph on the left-hand-side shows the relevant old and new tick size tables for the Tick Size Table 1 stocks, while the graph on the right-hand-side shows the table for the Tick Size Table 2 stocks. The vertical axis depicts the tick sizes for all relevant price levels.

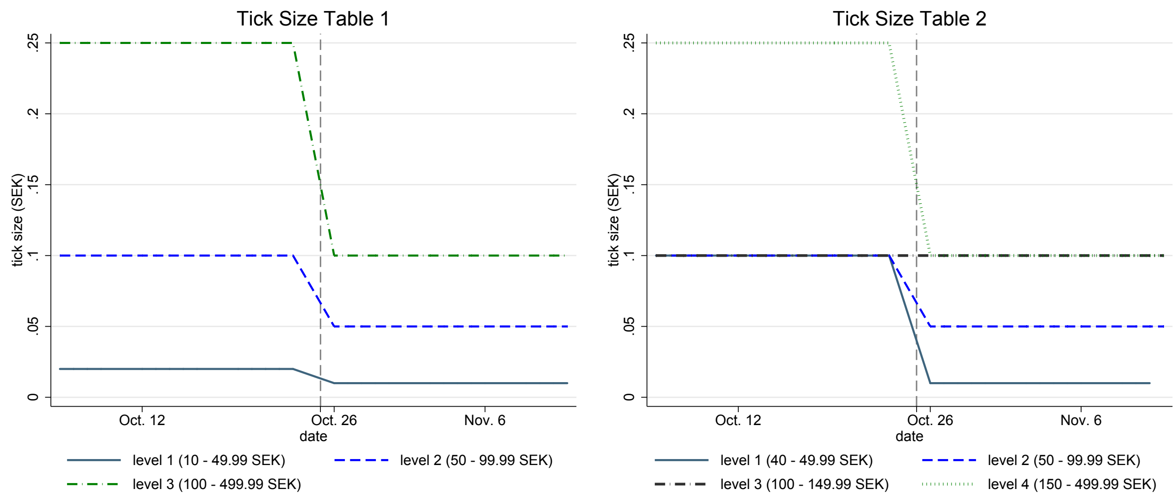

Figure A-2: Bid-Ask Spreads

This figure depicts the relative bid-ask spreads around the FESE tick size reform on October 26th, 2009 for all relevant price levels and their corresponding Tick Size Tables on the OMXS30. The graph on the left-hand-side shows the relative bid-ask spreads for the Tick Size Table 1 stocks, while the graph on the right-hand-side shows the relative bid-ask spreads for the Tick Size Table 2 stocks. The vertical axis depicts the relative bid-ask spreads for all relevant price levels.

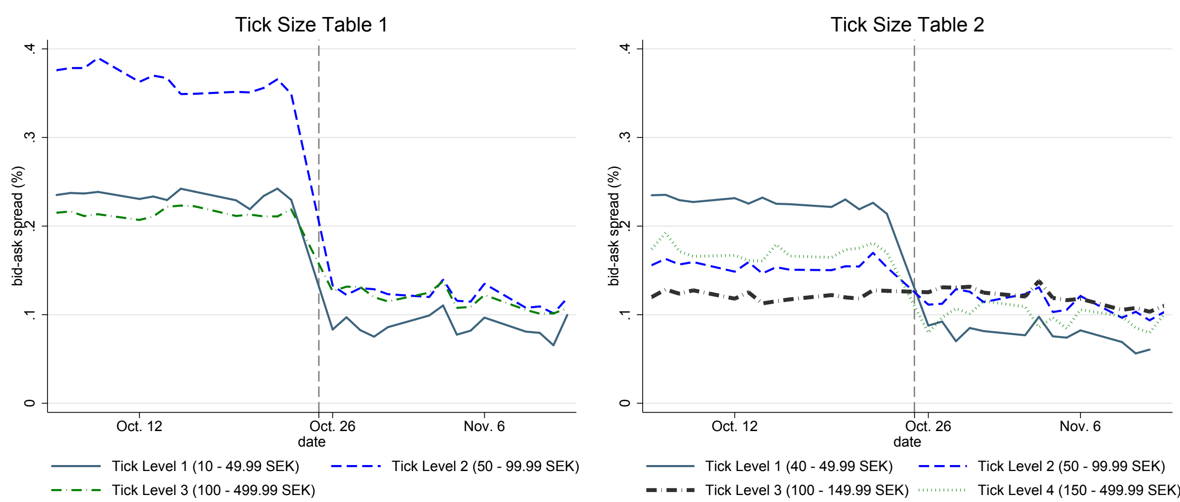

Table A-1: Summary Statistics of Sample Stocks

This table presents summary statistics for the NASDAQ OMXS30 during the sample period June 2009 through January 2010. It lists the ISIN code, the company's name, number of daily trades, daily volume (in 1000 units), daily turnover (in 1000 SEK) and the relative time-weighted bid-ask spread.

		Trades		Volume (1000)		Turnover (1000SEK)		Bid-Ask Spread	
ISIN Code	Secuity Name	Mean	SD	Mean	SD	Mean	SD	Mean	SD
CH0012221716	ABB Ltd	2316	1077	2829	1338	388568	176143	0.173	0.050
FI0009000681	Nokia Corporation	1545	570	1205	502	110902	47003	0.112	0.013
GB0009895292	AstraZeneca PLC	2455	863	1321	452	418987	143539	0.132	0.058
SE0000101032	Atlas Copco AB A	3331	947	5224	1605	488603	150242	0.140	0.054
SE0000103814	Electrolux, AB B	3142	1311	2701	1372	439715	223536	0.139	0.051
SE0000106270	Hennes & Mauritz AB, H & M B	4236	1677	2060	774	831174	313182	0.093	0.044
SE0000107419	Investor AB B	1805	516	1924	702	247540	90601	0.177	0.053
SE0000108227	SKF, AB B	2798	1016	3082	1432	350031	168788	0.124	0.036
SE0000108656	Ericsson, Telefonab. L M B	5986	2019	17108	8753	1197412	617496	0.109	0.034
SE0000112724	Svenska Cellulosa AB SCA B	2266	818	2154	862	208511	84315	0.118	0.037
SE0000113250	Skanska AB B	2109	811	1965	914	213179	99676	0.139	0.045
SE0000115446	Volvo, AB B	4171	943	6984	2183	472870	149712	0.103	0.049
SE0000122467	Atlas Copco AB B	1250	460	1163	510	97269	43480	0.186	0.064
SE0000148884	Skandinaviska Enskilda Banken A	4651	1679	11070	4734	513746	211720	0.169	0.094
SE0000163594	Securitas AB B	1659	782	1940	1063	131865	73863	0.156	0.050
SE0000171100	SSAB AB A	2746	917	2820	1049	306488	109205	0.198	0.069
SE0000193120	Svenska Handelsbanken A	2255	963	1786	641	338677	117238	0.189	0.101
SE0000202624	Getinge AB B	1535	518	887	473	113873	58061	0.169	0.060
SE0000242455	Swedbank AB A	5454	2076	11386	5355	765288	376062	0.226	0.140
SE0000255648	ASSA ABLOY AB B	2270	897	2070	1009	249035	120835	0.130	0.043
SE0000308280	SCANIA AB B	1351	636	906	387	82726	35999	0.239	0.096
SE0000310336	Swedish Match AB	1446	499	1012	386	148239	55642	0.143	0.050
SE0000314312	Tele2 AB ser. B	2216	854	2001	1111	198433	107238	0.131	0.016
SE0000412371	Modern Times Group MTG AB B	1485	537	355	154	110940	47783	0.182	0.049
SE0000427361	Nordea Bank AB	3577	1389	9194	3447	672128	260518	0.145	0.036
SE0000667891	Sandvik AB	3406	955	5497	1768	431676	138283	0.133	0.054
SE0000667925	TeliaSonera AB	2688	1390	9271	5183	440023	259887	0.167	0.075
SE0000695876	Alfa Laval AB	2215	674	2225	962	193898	79892	0.114	0.035
SE0000825820	Lundin Petroleum AB	1790	515	1436	481	86773	28329	0.174	0.038
SE0000869646	Boliden AB	4241	1485	5188	2019	423193	167698	0.156	0.071
	Mean	2749	1648	3922	4722	357223	324766	0.153	0.070

Table A-2: Correlation Matrix

This table provides correlations between all illiquidity, volatility and high-frequency trading measures we use in the analysis. Illiquidity measures are: bid-ask spreads, order execution shortfalls (based on trades and volume), Amihud's measure of illiquidity, price impact as measured by Kyle's lambda, and autocorrelation (measure of price efficiency). Volatility measures contain: intraday volatilities (5-minutes and min-max) and interday volatilities (close-close and open-close). High-frequency trading measures are: price pressure measures (based on trades and volume) and three directional trading measures.

	bid-ask spread	exec shortfall (trades)	exec shortfall (volume)	illiquidity (Amihud)	price impact (Kyle's lambda)	price efficiency (autocorr)	intraday vola (5-min)	intraday vola (min-max)	interday vola (close-close)	interday vola (open-close)	price pressure (volume)	price pressure (trades)	directional trading 1	directional trading 2
bid-ask spread	1													
exec shortfall (trades)	-0.70 *	1												
exec shortfall (volume)	-0.43 *	0.46 *	1											
illiquidity (Amihud)	0.17 *	-0.09 *	-0.03	1										
price impact (Kyle's λ)	0.07 *	-0.14 *	-0.08 *	0.17 *	1									
price efficiency (autocorr)	-0.14 *	0.14 *	0.11 *	0.00	0.05	1								
intraday vola (5-min)	0.32 *	-0.14 *	0.08 *	0.02	0.03	0.05	1							
intraday vola (min-max)	0.02	0.00	0.00	-0.02	-0.01	0.01	0.12 *	1						
interday vola (close-close)	-0.02	-0.02	0.01	-0.01	-0.01	0.02	0.18 *	0.06 *	1					
interday vola (open-close)	-0.02	0.03	0.05	-0.01	0.11 *	0.03	0.04	0.03	0.00	1				
price pressure (volume)	-0.30 *	0.35 *	0.20 *	-0.06	-0.04	0.04	-0.01	-0.03	-0.05	0.02	1			
price pressure (trades)	-0.33 *	0.38 *	0.23 *	-0.08 *	-0.04	0.05	-0.02	-0.03	-0.05	0.05	0.87 *	1		
directional trading 1	-0.03	0.13 *	0.03	0.19 *	0.25 *	-0.04	0.12 *	-0.01	-0.05	0.02	-0.05	0.04	1	
directional trading 2	-0.03	0.05	-0.04	0.19 *	0.26 *	-0.06 *	0.05	-0.01	-0.06 *	0.02	-0.07 *	-0.02	0.82 *	1
directional trading 3	-0.06 *	0.07 *	-0.04	0.19 *	0.25 *	-0.03	-0.03	0.00	-0.07 *	0.02	-0.05	0.00	0.81 *	0.87 *

* $p<0.05$