Competition between high-frequency traders, and market quality

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Abstract

This is the first empirical evidence on the competition between high-frequency traders (HFTs) and its influence on market quality. We exploit the first entries of international HFTs into the Swedish equity market in 2009 and conduct a difference-in-differences analysis using trade-by-trade data. To further identify the effect, we use the Federation of European Securities Exchanges (FESE) tick size harmonization as an exogenous event that caused HFTs to start trading in stocks. When HFTs compete for trades their liquidity consumption increases. As a result, liquidity deteriorates significantly and short-term volatility rises.

Keywords: competition, high-frequency trading, tick size harmonization, FESE, entry, exit

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

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1 INTRODUCTION

High-frequency traders (HFTs) are market participants that are distinguished 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.[1] By virtue of their substantial share of today's equity markets (ranging from 50% to 85%), HFTs warrant the attention of both academics and practitioners, especially with the recent rise in calls for legislative and regulatory intervention.[2] Existing empirical research focuses on the general effects of high-frequency trading on liquidity, price discovery and volatility. However, to the best of our knowledge, the question of the impact of competition between HFTs on these market quality measures has not been addressed. In fact, competition may alter the effects of high-frequency trading on markets as each HFT's trading strategy is likely to be affected by what other HFTs do. Does competition between HFTs, therefore, ultimately improve market quality and dynamics, and thus benefit investors who use and rely upon financial markets as, for example, the Economist (3/7/12) suggests?

> *Although high-frequency trading techniques are used primarily by professional traders [...] average investors benefit from their use. [...] intense competition between high-frequency traders reduces the transaction costs [...] [and benefits long-term investors].*

Economist Debates: High-frequency trading. Jim Overdahl, Vice-president, Securities and Finance Practice, National Economic Research Associates.

A comprehensive understanding of high-frequency trading competition should aid the efficient functioning of financial markets and enable appropriate regulatory action to be taken. However, empirical work has left this concern over the potential effects of competition between HFTs untouched.

In this paper, we examine the effect of competition between HFTs, so as to assess its impact on market quality, using trade-by-trade data from the Stockholm Stock Exchange (NASDAQ OMXS). Contrary to most related literature, we can observe HFTs' identities and therefore

[1] The SEC (2010) report defines HFTs as market participants that end the day with close to zero inventories, frequently submit and cancel limit orders, use co-location facilities and highly efficient algorithms, and have short holding periods.

[2] Through highly competitive and quick market platforms, the advantages of technologies such as co-location, and/or the use of ultra-quick algorithms, HFTs have influenced financial markets substantially (see, for example Jain (2005)). The TABB Group, a financial market research company, finds the high-frequency trading share to be 73% at US stock exchanges, whereas Brogaard, Hendershott, and Riordan (2012) estimate it to be about 85% (see their Table 1).

distinguish between different high-frequency trading accounts.[3] The first entries of HFTs into the Swedish stock market in 2009 offer a unique chance to investigate the effects of competition, as the high-frequency trading competition varies both among stocks and with time.[4] By conducting a difference-in-differences analysis, we identify the effects on market quality of HFTs facing competition from other HFTs. This difference-in-differences analysis exploits cross-sectional differences between those stocks with one active HFT and those with two or more active HFTs.[5] To establish a causal argument, we use an exogenous event, which is explained in more detail below, that plausibly triggered HFTs to start competing for trades.

Competition between HFTs might have an ambiguous effect on market quality. As HFTs are not regulated, they appear to pursue all profit maximizing short-term investment opportunities. These high-frequency trading opportunities may roughly be divided into liquidity-providing trading strategies and liquidity-consuming trading strategies. On the one hand, competition over truly liquidity-providing trades improves market quality and benefits long-term investors. In order to successfully place orders with a high-frequency market making strategy, for instance, HFTs trade closer to the price midpoint (between bid price and ask price). Spreads decrease and liquidity rises. On the other hand, HFTs do not solely concentrate on liquidity-providing strategies such as market making, but also liquidity-consuming strategies, which worsen market quality. An example of a high-frequency trading strategy with adverse effects on market quality is directional or momentum trading where HFTs buy (sell) during short-term price increases (decreases), chasing the trend. This trend could be triggered by a large trade of a mutual fund, for example, where the fund splits large orders into a series of smaller ones. Subsequently, HFTs try to follow or anticipate this trend (see for instance Hirschey (2013)). Under competition, HFTs pursuing this strategy not only attempt to anticipate trends, but also try to trade ahead of competing HFTs. Thus, price trends are amplified and liquidity deteriorates. To sum up, competition between HFTs

[3]See, for example, Brogaard, Hendershott, and Riordan (2012) or Hasbrouck and Saar (2012), who work with a NASDAQ dataset that flags messages from 26 HFTs, but does not distinguish between individual HFTs. This has been the most comprehensive high-frequency trading database available to researchers for the last few years. Hagstromer and Norden (2013) use the same data as ours but over a later period, and distinguish between groups of HFTs.

[4]All HFTs active in the Swedish equity market at that time were large internationally well-established banks or hedge funds that were also significant players in the American equity market. See Section 3 for a more detailed explanation.

[5]Throughout the rest of the paper, we will use the terminology of entries and exits in the following sense: an entry represents a change from one HFT to two or more HFTs trading in an individual stock, and an exit represents a change from two or more HFTs to one HFT trading in an individual stock.

utilizing liquidity-providing strategies leads to a positive effect on market quality. However, it is possible for the overall effect of competition on market quality to be negative, if the adverse effect from competition between HFTs using liquidity-consuming strategies is sufficiently strong. In this paper, we examine empirically how HFTs are affected by competition and its effect on market quality.

Our findings imply deteriorating market quality for stocks facing competition between HFTs, compared to those in which just one HFT is trading. We find that liquidity, as measured by Amihud (2002)'s measure of illiquidity and price impact factors, decreases significantly. More specifically, sixty-minute liquidity decreases by about 15% and five-minute liquidity by about 9%. Trade price impact increases by about 22%.[6] Furthermore, intraday hourly volatility increases by 20%, five-minute volatility by 9% and maximum intraday volatility by about 14%. Interday volatility, whether measured from opening to closing or from closing to closing prices, however, shows no sign of a significant increase or decrease.

Our empirical analysis suggests that these findings originate from an increase in liquidity consumption by HFTs when they are competing for trades with other HFTs. We find that HFTs in competition trade on the same side of the market in about 70% of cases when looking at five-minute intraday periods, and have a correlation of 0.35 between their inventories. To capture changes in high-frequency liquidity provision through competing HFTs, we examine ratios of liquidity-consuming trades to all high-frequency trades. We document that these ratios double from about 30% to about 60%. Furthermore, we suggest a new measure that captures directional trading, allowing us to investigate changes in momentum trading when HFTs compete. Our findings imply that this trend chasing indeed increases significantly for stocks for which there is competition between HFTs.

While high-frequency trading volume doubles to an average of about 20% in a competitive environment, there is no significant change in the overall volume. This suggests that when a stock becomes subject to competing HFTs, the population of traders trading in it changes. Traders that are likely to be crowded out might be, for instance, non-high-frequency liquidity providers. However, the increase in high-frequency trading volume does not lead to a significant change in overall high-frequency trading profits. Markets also become quicker: median order execution

[6] See Section 3 for a detailed description of our measures. Net buying volume is the turnover of actively purchased shares minus the turnover of actively sold shares.

time, defined as the length of time between an incoming market order or marketable limit order and the standing limit order against which the trade is executed, decreases by about 19%.

Interpreting these results as evidence of the causal effect of competition on market dynamics is only valid if competition can be treated as exogenous to the dependent variables examined. The limitation in our main analysis is that the decision of an HFT to begin trading in an individual stock is a choice, which generates concerns about endogeneity. We address these concerns in several ways. First, we provide evidence 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 will be facing competition in the upcoming periods (the treatment group) against a propensity-score-matched sample of firms that will not be (the control group). Our tests suggest similar estimates to those in the main analysis, both in terms of magnitude and significance. Second, to further test the causal relationship, we exploit a plausibly exogenous event. The Federation of European Securities Exchanges (FESE) tick size harmonization that was implemented on October 26th, 2009 and decreased tick sizes by about 50% for most but not all of the stocks in the sample. Stocks that happen to fall within a certain price range prior the event were not affected and serve as controls. Additionally, the details of the event allow us to untie direct effects caused by this tick size change from competition effects. We conjecture that a HFT is expected to benefit from low relative tick sizes as she can take advantage of more trading opportunities.[7] When relative tick sizes exogenously fall below a certain level, the benefits of entering exceed its costs and additional HFTs start trading. Our findings suggest that the decision to enter at the day of the event was indeed induced by this new relative tick size range, which was not available before. We predict that stocks will face competition between HFTs if pre-event prices fall within a price range that will lead to a relative tick size below a certain threshold after the regime change. Our findings for the direct effect suggest an improvement in market quality that is associated with an increase in high-frequency trading. The effects of competition, however, are the same, in magnitude and significance, as for the entire sample and show deteriorating market quality. Since high-frequency trading activity also increases without competing HFTs, and market quality seems to improve, this suggests that competition between HFTs rather than high-frequency trading volume itself adversely affects market quality. There are

[7]See for example Gai, Yao, and Ye (2013) who find that there is more high-frequency market making with a low tick size.

also no significant pre-event differences in any of the endogenous variables between the treatment and control groups. Overall, all of the tests give us additional confidence that competition causes change in market quality rather than the other way around.

We provide several other pieces of evidence that validate and extend our findings. First, we provide evidence that the pre-treatment parallel trend assumption, which is the key identifying assumption behind a difference-in-differences analysis, is validated.[8] Second, we report all of our findings separately for both entries and exits, and show that exits have an opposite effect to entries, of equal magnitude. Third, we take into account that HFTs might differ in aggressiveness, and control for entries (exits) with an aggressive entrant, but find solely insignificant results. Fourth, to rule out time trends and cross-stock differences, we control for day-fixed effects and stock-fixed effects in all regressions. Finally, we relax our binary definition of competition by exploiting a continuous measure of competition, the Herfindahl-Hirschman Index. The regression results are very similar to our main findings. Overall, our robust results support a causal interpretation that high-frequency trading competition is exogenous to the market quality measures and other endogenous variables affected by competition.

The paper contributes to the rapidly growing empirical literature on high-frequency trading. Jovanovic and Menkveld (2012) show that HFTs react more quickly to new hard information, and are therefore less subject to adverse selection, than other traders. Hasbrouck and Saar (2012) discover an amplified volatility effect due to runs on linked messages in the order book, while Kirilenko, Kyle, and Tuzun (2011) mention that HFTs may have exacerbated the flash crash in May 2010, but did not cause it.[9] Brogaard, Hendershott, and Riordan (2012) find that high-frequency trading improves price discovery and efficiency. Moreover, Hendershott and Riordan (2013) show that algorithmic trading both provides and demands liquidity, and makes prices more efficient. Carrion (2013) documents correlations between HFTs providing (consuming) liquidity and larger (smaller) spreads. There is also an increasing number of papers documenting HFTs' activities. Hirschey (2013) uncovers that HFTs seem to anticipate non-high-frequency trading. Baron, Brogaard, and Kirilenko (2012) find that HFTs earn large and stable profits, while

[8]The above-mentioned propensity score matching is just one such piece of analysis. Figure 3 illustrates that, other than the treatment itself, there is no difference between the short-term volatility in the treated and control groups.

[9]The work of Kirilenko, Kyle, and Tuzun (2011) is unique in the sense that it makes use of the first adequately identified data made available to researchers by the U.S. Commodity Futures Trading Commission.

Clark-Joseph (2013) examines the profitability of HFTs' aggressive orders using the same data. Huh (2013) argues that, in markets where HFTs are liquidity providers and takers, the ability to use machine-readable public information is crucial for HFTs. Hagstromer and Norden (2013) make an attempt to distinguish between liquidity providers (or high-frequency market makers) and liquidity takers (or aggressive HFTs), documenting that most high-frequency trading appears to be market making. Menkveld (2013) provides results of an event study on a market-making HFTs entering a new trading venue. In contrast to our paper, none of these studies consider the effect of competition among HFTs on markets.

Theoretically, competition between HFTs may have an effect on market quality. There is a developing theoretical literature that investigates the benefits or disadvantages of competition between HFTs (or more general short-term investors). Li (2013), based on Chau and Vayanos (2008) who model a monopolistic informed trader, shows that competition increases trading aggressiveness, efficiency and market depth, volume and variance. Li (2013)'s model shows that there is a trade-off in the effect of competition on market depth, but concludes that the market quality improvement outweighs its worsening. However, Li (2013) thinks of HFTs as arbitrageurs and does not consider other high-frequency trading strategies. Similarly, Martinez and Rosu (2013) show that with more HFTs volatility, volume and liquidity increase. In contrast, as suggested by our empirical findings, competition between HFTs may cause a deterioration of market quality. In fact, De Long, Shleifer, Summers, and Waldmann (1990) argue that an increase in the number of speculators who buy assets when prices rise and sell when prices fall may lead to an overreaction of markets. Furthermore, Brunnermeier and Pedersen (2005) show that with competition between strategic traders, prices overshoot and liquidity deteriorates. Last, Vayanos and Wang (2012) model rational hedgers with asymmetric information on expected returns and find that competition may reduce liquidity.

The paper also belongs to the somewhat wider literature of algorithmic trading, which is a broader classification than high-frequency trading.[10] Hendershott, Jones, and Menkveld (2011) investigate the latter using the automation of quotes on the NYSE as an exogenous event, and find it to have a positive effect on liquidity. Foucault and Menkveld (2008) show how investors

[10]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.

benefit from the liquidity supply provided by smart routers in multiple markets. Boehmer, Fong, and Wu (2013) find evidence, by exploiting co-location services across different countries, that algorithmic trading improves liquidity and informational efficiency, but also increases short-term volatility.

Our results have important implications for both regulators and trading venues. The U.S. Securities and Exchange Commission (SEC) states that high-frequency trading should only be allowed if it benefits long-term investors. In fact, the SEC's rules are aimed at increasing competition among liquidity suppliers. However, our results highlight that competition may lead to a deterioration of market quality rather than an improvement. Our findings suggest further that this originates from an increase in liquidity consuming high-frequency trades. It appears, therefore, to be of critical importance to take appropriate regulatory action to ensure that competition between HFTs is indeed competition between liquidity providers.

The rest of the paper proceeds as follows. In Section 2 we develop testable hypotheses to structure our empirical analysis. Section 3 describes our NASDAQ OMXS data as well as our measures of market quality and trading. Section 4 describes the methodology we use to exploit cross-sectional variations between stocks. Section 5 depicts our empirical findings, and we then provide several robustness checks in Section 6. We conclude in Section 7.

2 HYPOTHESIS DEVELOPMENT

This section looks at the arguments on how competition between HFTs might affect liquidity, volatility or the population of traders, and discusses their empirical implications. We develop a theoretical trade-off to structure our empirical analysis by addressing potential channels that could cause market quality to differ between stocks facing competition from HFTs and those without such competition.

With the calls for regulative and legislative interventions, advocates of high-frequency trading like to point to the advantages it brings in terms of market efficiency and liquidity provision. Their main argument is that HFTs are not doing anything particularly differently from the old market makers, but are just better and quicker at it. They are engaged in the same business of making two-sided markets.[11] In contrast, HFTs should exploit both liquidity-providing and

[11] This was, for example, recently debated in The Economist, "Electronic Trading - Dutch Fleet", April 20th, 2013.

liquidity-consuming short-term investment strategies as long as these remain profitable.[12] Without knowing the actual algorithms that are in place, it is hard to argue for one or the other strategy from looking at their trading outcome.[13] There is a second argument suggesting that HFTs follow just one profit-generating strategy as , for instance, the Economist (20/4/2013) suggests: *"[HFTs pursue] lots of different strategies. Some HFTs are momentum traders, riding the wave of a particular trend. Others arbitrage price differences. Others still are market makers providing liquidity to buyers and sellers."*[14] In fact, there is no reason why an HFT should concentrate on one strategy only. In effect, HFTs should exploit all short-term investment strategies that are profitable. Furthermore, there is a finite number of short-term investment strategies that HFTs can exploit. There might be differences in nuances and speed of execution, but HFTs look for the same investment opportunities.[15]

It makes economic sense, therefore, that competition between HFTs implies competition over the same trades. A limited and positively correlated number of profit-generating high-frequency trading strategies can expected to have direct effects on market quality and thus on other investors.[16] These effects are likely to be different under competition between HFTs, depending on their short-term investment strategies.

On the one hand, there are liquidity-providing short-term investment strategies that give long-term investors the benefits of reduced spreads and more efficient prices. HFTs competing for these liquidity-providing strategies accept lower profits, which benefits long-term investors. Competition here creates low margins for liquidity providers. Take, for instance, a true market maker, who places passive orders on both sides of the market and does not cancel them when the stock price moves there. To be first in the order book, HFTs offer lower prices. HFTs may also earn a premium by incorporating news more quickly than their competitors, which results in

[12]See Appendix C for a detailed description of high-frequency trading strategies.

[13]Even the fact that a trade is passive (non-marketable limit order) or active (marketable order) could be misleading, for example, anticipating block trades where passive orders on the same side as the block trade will amplify price movements.

[14]The Economist, February 25th, 2012, "High-Frequency Trading: The Fast and the Furious".

[15]The speeds at which trades are executed keep increasing due to investments in trading technology. This makes it more expensive for smaller rivals to compete, leading to markets dominated by a few HFTs. Clark-Joseph (2013) documents that the combined total trading volume of the eight largest HFTs accounts for the majority of all high-frequency trading in the American market. In addition, these eight large traders are very unlikely to be of equal size, which would imply that even fewer HFTs conduct the lion's share of high-frequency trading volume.

[16]We find that, in 70% of cases, HFTs trade on the same side of the market and that their inventories are positively correlated.

a more efficient price.[17] Competition over liquidity-providing strategies should improve market quality.

On the other hand, since high-frequency trading is generally done without the restrictions of regulatory rules, HFTs may also undertake liquidity-consuming short-term investment strategies. One strategy that reduces market quality is the directional or momentum strategy. HFTs chase the price trend attempting to sell (buy) at the peak of the short-term price increase (decrease). This trading strategy, by which HFTs attempt to profit from non-HFTs' future buying and selling pressure, will lead to an amplification of the price movement when there is competition between HFTs. To successfully place orders, HFTs will place more orders on one side of the market, trying to front-run block trading (Hirschey (2013)) and their competing HFTs. There is another plausible argument for competition increasing HFTs' liquidity-consuming trading. Brunnermeier and Pedersen (2005) model financially constrained strategic traders (HFTs) that will eventually need to liquidate their positions. This is observed by other strategic traders (HFTs). Prices overshoot and liquidity deteriorates.[18] Competition over liquidity-consuming high-frequency trading strategies might have a negative effect on market quality.

With HFTs competing for short-term investments, they strive to make their algorithms more sophisticated and quicker in order to stay profitable. This should have direct effects on other non-high-frequency intraday traders, such as the traditional registered and regulated market makers, who simply cannot stay competitive. With increasing high-frequency trading activity, the chances of slower day-traders being profitable decrease further.[19] Markets become quicker and the population of traders changes.

Overall, the effect of competition between HFTs may have two opposing effects: First, competition over liquidity-providing strategies such as market making will improve market quality. Second, competition over liquidity-consuming strategies such as anticipatory trading will worsen market quality. Whether high-frequency trading increases market quality overall remains an empirical question and is the subject of following analysis.

[17] There are other liquidity-providing strategies, which are explained in the appendix.

[18] Figure 1 also shows that some traders are constrained and often seem to trade at their limit.

[19] A famous example is LaBranche Specialist, a long-time specialist on the NYSE that exited the market in 2010 as new rules and technology made profitability difficult. High-frequency market making can respond more quickly and potentially follow more sophisticated strategies. Non-high-frequency market makers are likely to be less successful in placing their orders.

3 DATA

In this section, we start by discussing the data and then move on to market quality and high-frequency trading measures.

3.1 Trading Database

The tick trading data come from NASDAQ OMX Nordic and incorporate all trading information for all trades executed on the Stockholm stock exchange (NASDAQ OMXS). We focus on the OMXS30 index, which hosts the thirty biggest public companies in Sweden, because we observe that HFTs trade solely in liquid stocks, and restrict their trading activity to Sweden's major securities. The sample period is from June to December 2009. Trade timestamps are in milliseconds and ranked within each millisecond. Trades undertaken on the NASDAQ OMXS account for about 80% of total trading volume in all Swedish trading venues, with a seemingly higher share of continuous trading.[20] Daily relative time-weighted spreads are taken from the NASDAQ OMX, and were provided separately. We also rely on COMPUSTAT GLOBAL for daily measures that do not need to be calculated from the trading data.

Table 1 gives an overview, and key statistics, for all thirty stocks traded in the OMXS30. We provide the mean and the standard deviation of daily averages for the number of trades, volume, turnover and relative time-weighted spreads. 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%.[21] Column 3 shows how often a specific stock occurs as a control, column 4 gives the number of changes from a single HFT to two or more HFTs trading in the stock, and column 5 vice versa. Events and controls are fairly well distributed among the securities, with three exceptions. Neither Scania AB, which is overly represented in terms of entries and exits, nor Nokia Corporation nor Lundin Petroleum AB, which do not show any entries or exits, drives our results. The number of unique trading days considered for each stock, before and after entry or exit, is shown in column 6. This is explained in more detail in the later analysis.

[20]The Stockholm Stock Exchange lost, in particular, over-the-counter trades to the competing trading venues of BATS Chi-X Europe, Burgundy and Turquoise. In comparison, the NASDAQ's share of NASDAQ-listed shares in the US was about 30% of trading volume in 2009. Appendix B provides more institutional details.

[21]This lies in the range of American medium-cap and large-cap stocks (Brogaard, Hendershott, and Riordan (2012)).

[Insert Table 1 about here!]

The key distinction of the database that we use is that it allows us to identify proprietary traders that are members of the stock exchange, down to a level showing the channels through which they execute their trades. HFTs will naturally execute their trades by taking advantage of the cheapest and fastest means of access, the algorithmic trading accounts. There are less than ten HFTs in our sample, all with significant trading participation. The HFTs in our sample are large international HFTs with a significant market share in the American market.[22] Due to our confidentiality agreement with NASDAQ OMXS, we cannot release either names or exact numbers of traders. Individual HFTs have about a 10% market share. Other traders that execute trades through algorithmic accounts participate only occasionally and do not satisfy high-frequency trading characteristics (such as low end-of-day inventory or short holding periods).

We cannot release summary statistics for all individual high-frequency trading accounts, but we show statistics for the two most different HFTs in Table 2. Statistics are reported for the daily fraction of high-frequency trading in the entire market, with an average of about 10%, the absolute number of daily high-frequency trades, around 280 per day and stock, the fraction of total daily volume, around 10%, and the fraction of aggressive trades.[23] These two HFTs differ mostly in aggressiveness. While HFT A executed 91% of its trades aggressively, for HFT B the figure is 35%. Aggressiveness, however, does not necessarily stand for differences in investment strategies, but might just reflect differences in execution. Strategies can be exploited by screening the market and jumping actively on opportunities (snake execution strategy) or by passively submitting and cancelling orders. To show this, we provide statistics for the most intuitive of our high-frequency trading measure that divides high-frequency trades into liquidity consuming and liquidity providing trades. We find that HFT A has a liquidity consuming trade ratio of about 60% on average and HFT B of about 54% with no significant difference between them. We will also address potential differences of HFTs in our regression analysis.

[Insert Table 2 about here!]

[22] HFTs list their activities and sometimes their market shares on their web pages.

[23] An aggressive trade is an incoming market order or marketable limit order that is executed against a standing limit order.

We limit our attention to event windows around our 228 entries into and exits from stock trading by (different) HFTs. These event windows are up to six days long, from up to three days before to up to three days after the entry or exit. The average length of an event is 4.3 days. The reason for the differences in lengths is that there might be a change in the competition status less than three days before or after the event.[24] Stocks with competing HFTs within the event window belong to the treatment group and stocks with just one HFT trading to the control group. Note that event windows might overlap, but we do not duplicate observations.

Market quality measures and high-frequency trading measures rely on price midpoints (the price between the bid and the ask price). Since our data do not include orders, we cannot observe the actual midpoint prices. We develop a new technique to approximate them. We evaluate our methodology by comparing the approximated spreads to the actual corresponding spreads. The spreads are nearly perfectly approximated and show a correlation of 0.99. We give a detailed description of this approximation procedure in Appendix A.

3.2 Market Quality and Trading Measures

This subsection presents the liquidity measures, the high-frequency trading measures, and other variables needed to analyze how market quality changes when HFTs compete for the same trades.

3.2.1 High-Frequency Trading Measures

To analyze high-frequency trading activity, we use an intuitive measure of liquidity consumption and propose a new measure of directional momentum trading.

First, the measure of high-frequency liquidity consumption is a simple ratio of the number of high-frequency consuming trades to all high-frequency trades. Alternatively, we look at turnover instead of number of trades. A high-frequency trade is assumed to be consuming liquidity if the stock midpoint price moved upwards (downwards) prior to a high-frequency buy (sell) trade; otherwise, it is assumed to be providing liquidity. We construct our measure for both the one-minute period and the five-minute period prior to each midpoint price change. The intuition behind this measure is that, given a trend, a liquidity provider will execute trades in the opposite direction to the trend. Trading with the trend amplifies it.

[24] The length of the event window is not crucial nor does it affect our results. Six days gives us a reasonable number of events with observations further away from the event to show if the influence through competition is permanent or temporary. For robustness, we also provide evidence for short-term events only in Section 6.

Second, we detect one potential way that high-frequency trading might affect a stock's liquidity. We propose a new measure with which we can potentially capture directional or momentum high-frequency trading. This measure 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 $HFTvol_{buy,d,t,j}$ being high-frequency trading turnover from buy trades and $HFTvol_{sell,d,t,j}$ being high-frequency trading turnover from sell trades on day d, over the five-minute interval t in stock j. $r_{d,t,j}$ is the stock's midpoint return over the five-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.

One concern could be that differences in our measure are not driven by a change in directional high-frequency trading, but by differences in overall turnover within the five minutes. To deal with this concern, we look at the daily average five-minute turnover:

$$DIRECT2_{d,j} = \frac{1}{T}\sum_{t=1}^{T} r_{d,t,j}\frac{HFTvol_{buy,d,t,j} - HFTvol_{sell,d,t,j}}{\frac{1}{T}\sum_{n=1}^{T} turnover_{d,n,j}}. \tag{2}$$

Here, $\sum_{n=1}^{T} turnover_{d,n,j}$ is the average stock turnover per five-minute interval and the other variables are as defined previously.

It could also be that it is not the turnover ratio but the midpoint return that changes while the turnover ratio remains constant. To address this concern, we construct another version of our measure using an indicator function to determine an upward and downward midpoint price movement rather than the actual return. Our measure becomes:

$$DIRECT3_{d,j} = \frac{1}{T}\sum_{t=1}^{T} DIRECTret_{d,t,j}\frac{HFTvol_{buy,d,t,j} - HFTvol_{sell,d,t,j}}{turnover_{d,t,j}} \tag{3}$$

Here, $DIRECTret_{d,t,j}$ is an indicator variable, equal to 1 if the return is positive within the five-minute interval t and -1 when the return is negative. $turnover_{d,t,j}$ is the total stock turnover within this interval. Note that the interpretation does not change; the measure becomes positive with directional trading and negative with counter-directional trading.

We also attempt to calculate trading profits from high-frequency trades. We calculate daily profits by summing up buy turnover and sell turnover. Non-zero end of day inventories are assumed to be leveled at the closing price of the day. However, looking at profits from actual stock trades does not necessarily reflect actual profits. For example, a trader who undertakes index arbitrage will also trade index funds, which are not observed by our data. We will not attempt to draw conclusions about the size of profits due to these limitation, but we will show how this profit measure changes with competition.

3.2.2 Liquidity Measures

We measure liquidity using five-minute and hourly Amihud measures of illiquidity and five-minute price impact factors.

First, we rely on a variation of the well-known Amihud (2002) measure of illiquidity. While the original measure was constructed from daily observations, we focus on five-minute and hourly intervals to capture short-term illiquidities:

$$ILLIQ_{d,j} = \frac{1}{T}\sum_{t=1}^{T}\frac{|r_{d,t,j}|}{turnover_{d,t,j}}. \tag{4}$$

Here, $r_{d,t,j}$ is the stock's midpoint return over the five-minute (hourly) period, and $turnover_{d,t,j}$ is the total stock turnover within this interval, on day d, in each five-minute (hourly) interval t for stock j. The lower the turnover relative to a price change, or the larger the price change relative to turnover, the higher is the illiquidity. Put differently, if buys and sells have relatively little impact on the price, the stock is liquid.

Another way to capture how buying and selling affect prices is with price impact factors. The intuition is similar to that for our first measure of liquidity but this one is regression based.

Daily price impacts are captured by:

$$r_{d,t,j} = IMPACT_{d,j} * NBV_{d,t,j} + \epsilon_{d,t,j}. \tag{5}$$

Here, $r_{d,t,j}$ are the five-minute returns calculated from the log midpoint prices and $NBV_{d,t,j}$ is the net buy turnover (turnover of active share purchases - 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 five-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 α to be zero.

3.2.3 Volatility and Autocorrelation

We also look at five-minute volatility, hourly volatility, maximum intraday volatility, closing-to-opening volatility, closing-to-closing volatility, and autocorrelations. Volatilities are given by:

$$Vola_{d,j} = \sum_{t=1}^{T} (r_{d,t,j})^2 \tag{6}$$

with $r_{d,t,j}$ being the log midpoint return for day d over intraday time interval t for stock j. While short-term volatilities over five and sixty minutes are computed using the above formula, closing-to-closing, opening-to-closing and intraday high-to-low volatilities are simply squared returns. Autocorrelation is calculated by:

$$Autocorr_{d,j} = \sum_{t=1}^{T} \frac{cov(r_{d,t,j}, r_{d,t-1,j})}{var(r_{d,t,j})} \tag{7}$$

where $r_{d,t,j}$ is again the log midpoint return for day d over intraday time interval t for stock j.

3.2.4 Order Execution Time

Order execution time measures the time difference between a limit order entering the order book and being executed. It is an order resting time, in other words the time for which a limit order has to rest in the order book until it is executed against an incoming marketable (limit) order. We look at the median order execution time so as to ensure that the measure is not driven by a few outliers that rest in the orderbook for hours or even sometimes days.

This measure gives an indication of the speed of trading in the market. HFTs tend to submit orders quickly, and might cancel or resubmit orders. A relatively quick median order execution time would also be a rough proxy for HFTs being present (i.e., trading in a stock).

4 METHODOLOGY

We aim to compare measures of market quality such as liquidity or volatilities, and high-frequency trading measures, over two situations: the one where HFTs face competition from other HFTs and the one where they do not. The first entries of large international HFTs into the Swedish equity market offer us a unique chance to empirically examine how competition affects market quality. We use difference-in-differences tests similar to those in Bertrand, Duflo, and Mullainathan (2004) to exploit daily cross-sectional differences among stocks. Stocks can face repeated competition between 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. In this section, we use both entries and exits simultaneously throughout the main analysis. Within each event window, we assign stocks to be part of the control group if there is one HFT active in them, and to the treatment group if there are two or more HFTs active in them. This means that we have different control and treatment groups for each event. The benefit is that multiple treatment and control groups reduce the bias and noise that can be associated with a single comparison.

Under the assumption that treatment is random, or at least not determined by changes in the endogenous variable, this approach permits us to interpret our findings as evidence of the causal effect of competition on market dynamics. We will repeatedly discuss this critical assumption in the following analysis and provide evidence of the causal effect of competition on market quality and high-frequency trading behavior using a plausibly exogenous event in Section 6.

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

$$y_{e,j,d} = \beta_1 d_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}, \tag{8}$$

with e indexing entry or exit , j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading event affected 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 is $y_{e,j,d}$ and takes the form of market quality and trading measures in the analysis. 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. Since, in our analysis, the same stocks do serve as treatment and control stocks within different event windows, differences before an entry or exit are small and turn out not to be significant. Figure 3 illustrates this for both short-term illiquidity on the top graphs and high-frequency consuming turnover ratios on the bottom graphs three days before and three days after the event. We depict entries on the left-hand-side of the graph and exits on the right-hand-side. The small differences between the treatment and control groups in the pre-event periods are not statistically different from each other. We will provide further evidence on this repeatedly in the following analysis.

[Insert Figure 3 about here!]

Table 3 lists descriptive statistics for all stocks and days that serve as the control group and for all stocks and days in the treatment group prior to competition or post competition. Column (1) show statistics for the control group, column (2) gives statistics for the treatment group, and column (3) provides differences between the control and treatment group. We depict the short-term Amihud (2002)'s measure of illiquidity, price impact factor, daily stock turnover, midpoint return auto-correlations and order-execution times. We further provide statistics for hourly volatility, five-minute volatility, max-min volatility, open-to-close volatility and close-to-close volatility. Last, we show statistics of liquidity consuming high-frequency trade ratios and of liquidity consuming high-frequency turnover ratios. Overall, there is no significant difference between the control and treatment groups.

[Insert Table 3 about here!]

5 EMPIRICAL RESULTS

The first tests concern stock liquidity. We regress both the short-term Amihud (2002) measure of illiquidity and price impact factors on competition between HFTs. The results are presented in Table 4. In column 1, no additional controls that go beyond the basic difference-in-differences setup are included in the regression. Looking at the effect of competition between HFTs requires us to control for general differences between the treatment and control groups, the event type (entry or exit), and stock- and time-fixed effects. The variation we capture when we additionally control for stock-fixed effects and HFT fixed effect is that of multiple entries or exits of different HFTs. Note that errors are clustered by stocks as this is the level at which our variable of interest varies.[25] Our test suggests a positive and significant increase in illiquidity. In other words, liquidity decreases when HFTs face high-frequency trading competition. In column 2, we additionally control for the HFT-fixed effect, which adds little to R^2 and makes no significant difference on the measure of how competition affects illiquidity. In column 3, we also control for lagged stock turnover, lagged bid-ask spreads and whether an existing HFT faces aggressive or non-aggressive competition.[26] While there is no significant difference between the events, higher turnover is intuitively associated with lower illiquidity, and higher bid-ask spreads with significantly higher illiquidity. The magnitude is not trivial. Stocks facing competition between HFTs are predicted to be 15% less liquid, as measured by hourly intervals, or 9% less if measured by five-minute intervals. Another way to show the liquidity of a stock is to use price impact factors. Column 5 and column 6 show the regression results for net buying volume for five-minute intervals. The estimates show a significant increase of 22% with an R^2 of 87%. Overall, liquidity is negatively affected by HFTs competing for trades. This also holds for all our extensions and robustness checks, as we will show in the later analysis.

[Insert Tables 4 about here!]

In our second series of tests, we look at volatilities and regress them on competition. Table 5 provides the results of the difference-in-differences estimations for various volatilities. In this approach, as mentioned above, variables that control for the level differences are necessary. These are the differences between the treatment and control group, the event type (entry or exit), and stock- and time-fixed effects. In column 1, we run the baseline model without stock-fixed effects for hourly volatility on competition. In columns 2 through 4, we successively add stock-fixed effects, HFT-fixed effects, and turnover and bid-ask spreads for different event types (aggressive or not). The level estimates remain insignificant and volatility increases significantly in stocks

[25] We are aware that clustering standard errors on relatively few, here 30, clusters may distort results more than it improves accuracy. Our analysis, however, does not suffer from these distortions, as we show and discuss in Section 6.

[26] An event is aggressive if the incoming HFT shows aggressiveness above the average of a 65% share of aggressive orders (compared to 35% passive).

facing competing HFTs. The increase in hourly volatility is about 20%. Figure 4 depicts these dynamic impacts of entry and exit (separately) graphically for the three days before and after each event. The graph on the left-hand-side illustrates the regression results for entries, and the graph on the right-hand-side for exits. The dotted lines represent the 95% confidence interval. There is no pre-trend before entry (exit); nor does the effect seem to be temporary. Five-minute volatility, shown in column 5, increases by about 9% and the maximum squared price range during a trading day (column 6) increases by 14%. Note that the data for the latter come from COMPUSTAT Global since these volatilities rely on daily data, suggesting that we are likely to find similar results with data from other sources. The two interday volatilities, squared open-to-close return (column 7) and squared close-to-close return (column 8), show no significant changes. In sum, intraday volatility increases significantly within the HFT's investment horizon; we do not observe any significant change in the interday volatility. This suggests that there are indeed no differences between the treated and untreated observations within investment horizons where HFTs tend not to be active. HFTs usually close their positions at the end of each trading day.

[Insert Table 11 and Figure 4 about here!]

We now turn to the HFT behavior that influences market quality. We find that if HFTs compete for the same trades then, in 70% of the cases, they trade on the same side of the market. In addition, the inventory of different HFTs is significantly positively correlated when stocks face competition between HFTs. This suggests that HFTs indeed trade differently under competition. To test this, we aim to provide evidence on how HFTs react to competition so as to provide reasons why market quality is affected by competing HFTs. First, we test how liquidity consumption of HFTs change. Column 1 through 7 of Table 6 show estimates how competition among HFTs affects high-frequency liquidity consumption. Liquidity consuming trade ratios increase by about 28 percentage points (column 1 through 3). Considering the average being 30% of liquidity consuming trades of total high-frequency trades, this suggest that liquidity consumption ratios double. We depict similar results for high-frequency liquidity consuming turnover (column 4). Column 5 through 7 show regression results for liquidity consuming ratios for high-frequency trades that are assigned to be liquidity consuming based on one minute midpoint price movements prior the trade. Results are similar in both magnitude and significance and imply that relative high-frequency liquidity consumption doubles. Second, columns 8 through 10 show estimates of momentum (directional) trading. Through competition between HFTs, high-frequency momentum trading increases significantly. There is no statistical difference between these two estimates, implying that the actual amount of trading within a five-minute period when HFTs are trading is not driving the results. Our third directional trading measure, which is regressed on competition in column 7, and which captures changes solely in the ratio of directional high-frequency trading turnover to overall turnover, also suggests a significant increase. Finally, our findings suggest that overall high-frequency profit does not change significantly (column 11) with competition among HFTs. This result, however, should be considered with caution as we only observe HFTs' activities on the equity market. We also rebalance end of day inventory, which is not necessarily close to zero, to approximate profits.

Our findings suggest that competition between HFTs affects high-frequency trading behavior and market quality. It is, however, difficult to argue that a trader's endogenous decision to compete is not influenced by any of our measures. For liquidity, for example, it seems possible that HFTs might not prefer lower liquidity. The literature agrees that HFTs prefer liquid to illiquid stocks. The reason for this is intuitive, as HFTs need someone to trade with in order to make a profit. One could argue, however, that HFTs anticipate their influence on liquidity, and therefore the selection of stocks would not be exogenous to liquidity. This anticipation could lead HFTs to trade in stocks to which they would cause the least damage. Our results, therefore, would be a lower bound and our interpretation would hold. For volatility, though, it is fairly difficult to make an argument since we do not know the optimal level that HFTs prefer. We, therefore, exploit a plausibly exogenous event in the next section.

6 ROBUSTNESS

This section presents the results of some important robustness checks. To address concerns about endogeneity, we exploit a plausibly exogenous event, the FESE tick size harmonization. Then, we conduct propensity score matching. This is followed by several other robustness checks: First, we compare how entries and exits affect our measures of liquidity, volatility, and directional trading. Second, we introduce as an alternative measure of competition: the Herfindahl-Hirschman Index. Third, we discuss short-term entries and exits before, finally, providing a discussion of clustered standard errors.

6.1 The FESE Tick Size Harmonization

The problem is that entries and exits to and from trading in individual stocks are endogenous choices made by traders. A trader's decision to trade could depend on many factors, including liquidity and volatility. For example, Goldstein and Kavajecz (2004) find evidence that algorithms trade less often when markets are illiquid and extremely volatile. While the literature agrees that HFTs prefer liquid stocks, the situation is less obvious for volatility. HFTs favor a certain level of volatility, and probably also favor particular levels of other market quality measures. Thus, any of them could cause an entry or exit. From an econometric perspective, this would lead to a biased estimate of the causal effect of a change in high-frequency trading competition on market quality. To approach these endogeneity issues with our baseline difference-in-differences approach above, we exploit the plausibly exogenous FESE tick size harmonization, which triggered a substantial number of HFT entries.

As of Monday, October 26th, 2009, the NASDAQ OMX Stockholm introduced FESE Tick Size Table 2 for its OMXS30 shares.[27] [28] This regime change was part of the implementation of harmonized tick sizes across all major European stock exchanges, and resulted in approximately 50% lower tick sizes on average for the Swedish OMXS30. Prior to the event, 53% of its stocks were traded on the OMXS30 tick size table and 47% on the most liquid shares table, which contains Sweden's blue chip stocks rather than the literally most liquid stocks.

Figure 5 gives an overview of the tick size reduction for the relevant price levels from before to after the event. The graph on the left-hand-side shows the relevant old and new tick size tables for the stocks not traded on the table for the most liquid shares, while the graph on the right-hand-side shows the table for the blue-chip stocks. Nearly all tick size levels were substantially affected by the regime shift, except for those for the stocks traded on the most liquid shares table and with stock prices from 100 SEK to 149.99 SEK. For these shares, about 18% of the entire population, the tick size change had no effect. The reason that these stocks are not affected does not carry

[27]The tick size defines the minimum price movement and hence the minimum difference between bid and ask prices in the order book.

[28]The FESE represents 46 exchanges for equities, bonds, derivatives, and commodities. This tick size harmonization is an agreement drawn up by the Federation of European Exchanges, the London Investment Banking Association and a number of European multilateral trading facilities (MTFs, equivalent to the alternative trading system in the US), in July 2009.

any fundamental information about the stock besides its price. As nominal stock prices usually convey no information about the fundamental value of a stock, such as liquidity or volatility, it is exogenous which stocks are affected and which are not.[29] This reform had a direct effect on the actual bid-ask spread, in which we observe a rapid decrease after the change in the minimum bid-ask spread. Figure 6 exhibits the changes in the bid-ask spreads for the most liquid shares and for the remaining shares listed on the OMXS30. Note that the bid-ask spreads do not change either for the shares that are unaffected by the tick size change.

[Insert Figure 5 and Figure 6 about here!]

This change in the rules is of particular importance to our empirical design. It suggests that we can identify the causal effect of competition between HFTs by comparing stocks that are affected by the tick size change to those that are not using a difference-in-differences approach. To be more precise, we divide all stocks into three portfolios: A, B and C. Portfolio A consists of all shares that are not affected by the tick size harmonization and therefore serve as our control group (about 20% of stocks). The remaining shares are split into two portfolios according to their pre-event price. Portfolio B (about 20% of stocks) contains stocks that, given pre-event stock prices and the new tick sizes, have a higher relative tick size than those stocks in Portfolio C (about 60% of stocks). While the control group has a mean relative tick size of 8 basis points and Portfolio B of about 7 basis points, Portfolio C has an average relative tick size of 3.5 basis points. High-frequency trading becomes more attractive in Portfolio C, and competing HFTs enter into trading. We depict these effects in a stylized way in Figure 7. The relative cutoff point π, below which high-frequency trading competition takes place, can be assumed to be the minimum relative tick size before the event across all stocks. Testing for cross-sectional differences between the control group and Portfolio B allows us to capture the direct effects of this tick size change on market quality. As a second step, testing for differences between the control group (or alternatively Portfolio B) and Portfolio C allows us to identify the effects of competition between HFTs considering the direct effects from the first set of tests. To sum up, given pre-event prices, we can predict which stocks face competition after the introduction of the new tick size regime,

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

and thereby disentangle the direct from the competition effects.

[Insert Figure 7 about here!]

We find that lower relative tick sizes increase high-frequency trading participation. In Figure 8 we show the changes in participation due to the tick size regime shift. While the control group (Portfolio A) shows no increase in high-frequency trading participation, for both the stocks without competing HFTs (Portfolio B) and those with competing HFTs (Portfolio C) there is an increase. High-frequency participation for Portfolio B doubles from about 8% to about 16%, and for Portfolio C it triples from about 8% to about 24% on average. This increase in high-frequency activity for the stocks in Portfolio B is of particular importance, as we will show that market quality tends to improve for those stocks that are only affected by the tick size reduction and not also by competition. This suggests that the decline in market quality does not just reflect a higher share of high-frequency trading, but indeed increased competition. This contributes to a, to date, conflicting literature on how high-frequency trading is affected by tick size. While Gai, Yao, and Ye (2013) find that there is more high-frequency market making with a low tick size, Hagstromer and Norden (2013) find the opposite effect. Since we think of HFTs as traders that exploit multiple investment strategies, we could make arguments for both.

[Insert Figure 8 about here!]

This increase in high-frequency trading activity with lower minimum relative spreads is also the reason why we do not depend on spreads as a liquidity measure throughout our analysis. The existing literature relies on the spread as a measure of liquidity that is affected by high-frequency trading.[30] While we do think that high-frequency trading might lower the bid-ask spread, it is also true that a low minimum bid-ask spread encourages HFTs to trade more. As spreads are correlated with relative tick size (for liquid stocks), it seems to be difficult to identify a causal channel between high-frequency trading competition and spreads.

To confirm that differences in the nominal prices do not reflect any information about the stocks, we provide statistics in Panel B of Table 8. There is no statistically significant difference

[30]See, for example, Hendershott, Jones, and Menkveld (2011) and Menkveld (2013), who show that high-frequency trading activity reduces bid-ask spreads.

between the control and treatment groups for any of the endogenous variables prior to the event. The crucial parallel trend assumption behind our difference-in-differences analysis is also shown to be fulfilled, as there is no difference between the treatment and control group for any variable of interest other than the treatment itself.

Using the tick size regime shift, we attempt to overcome the endogeneity concerns for a subsample of our main dataset. This test is conducted in two steps. First, we test the direct effect of the tick size change on market quality, using the unaffected stocks as the control group (Portfolio A) and the affected, but not treated in the sense of competition, stocks as the treatment group (Portfolio B). Second, we test the impact of competition using the unaffected stocks as the control group and the stocks with competing HFTs as the treatment group. We depicted these results in Panel A (competition effects) and Panel B (direct tick size effects) of Table 9. The difference-in-differences estimation around the tick size regime change takes into account the two weeks before and two weeks after the event. Panel A tests the impact of competition on short-term volatility (column 1), illiquidity (column 2), high-frequency momentum trading (columns 3-5), and price impact factors (column 6 and column 7). The estimates are comparable in both magnitude and statistical significance to our main analysis. Illiquidity decreases by about 18%, and both short-term volatility and directional trading increase significantly. Second, the direct effects of tick size on market quality in Panel B suggest that lower tick size increases market quality. To be more precise, the estimates show signs of improved liquidity, reduced volatility and directional high-frequency trading. However, statistical significance is low or absent. This suggests that a lower tick size might improve market quality and does not deteriorate it. In related literature about tick size effects on market quality, there is no consensus over whether lower tick size improves or worsens market quality (Jones and Lipson (2001) or Goldstein and Kavajecz (2000)). As discussed earlier, all the stocks affected by the tick size change show more high-frequency trading activity. The worry that the effect captured by our tests could be coming from an increase in high-frequency trading activity alone, and not necessarily from competition, is not confirmed. An increase in high-frequency trading activity increases market quality (Portfolio B), while competition between HFTs deteriorates it. Since the results obtained from exploiting this plausibly exogenous event are similar to those of the main analysis, we are confident that our results do indeed, overall, represent the effect of competition between HFTs on market quality.

[Insert Tables 9 about here!]

6.2 Propensity Score Matching

For the main analysis (entire sample), we provide evidence that pre-event stock characteristics do not determine the shock caused by the event. We compare the pre-event behavior of a propensity-score-matched sample of those stocks facing competition in the upcoming period (the treatment group) against a propensity-score-matched sample of those that do not (the control group).

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 group tomorrow given their stock characteristics today.

To calculate the propensity score, we conduct a probit regression at the stock event level, of a dummy variable indicating whether or not a particular stock will face high-frequency trading competition tomorrow, on stock characteristics. Specifically, we control for all market quality and high-frequency trading measures used earlier in this paper, as well as other exogenous variables such as turnover or bid-ask spreads from the pre-event days. There are 125 events (entries) that form the treatment group, and 630 stocks in the control group.[31] From this probit regression, we obtain the propensity scores that we need to retrieve our matched sample. Panel B of Table 7 shows, in the left-hand column, the probit regression on the entire sample and, in the right-hand column, that on the matched sample. The number of stock observations in the control group is reduced to 205 and that in the treatment group to 101 as a result of our matching procedure. All variables become insignificant and capture much less of the variation than prior matching, which indicates that the matching has indeed yielded a sample of more equal pre-event characteristics. Panel C shows the post-match competition effects on the market quality measures. Panel A of

[31]We only show the results for entries, but we obtain similar results for exits. When looking at exits the procedure differs. We need to include only those stock characteristics not related to variables that are affected by high-frequency trading competition prior to the event as stocks are in fact affected at this point. As an alternative, we look at post-exit days and show that stock characteristics, including those affected by competition, do not differ across the treatment and control groups.

Table 7 shows pre-event averages and simple t-test differences between the treatment and control groups prior to the event for both the pre-match and post-match samples. Differences become insignificant throughout after the matching procedure, by design.

Given this matched sample, we repeat our difference-in-differences analysis; the results are shown in Panel C. Column 1 gives the impact of competition between HFTs on volatility, controlling for the level differences, whether the stock belongs to the treatment or control group, turnover, bid-ask spreads, and time-, HFT-, and stock-fixed effects. The magnitude of the competition coefficient is very close to that of the full sample and increases by about 20%. This is also true for illiquidity, which increases by about 16 (column 2), directional trading that show a significant increase through all three versions of the measure (column 3-5), and finally also for the price impact factor, which increases by about 20%.

[Insert Tables 7 about here!]

Overall, the matching process removed any meaningful differences in stock market quality measures and other stock characteristics in the pre-event period. This gives, not only additional confidence that the parallel trend assumption holds, but also that high-frequency trading competition is exogenous to the market quality measures and other endogenous variables affected by competition.

6.3 Symmetry of Entries and Exits

The effects of entries and exits are estimated simultaneously throughout the main analysis, but here they are addressed separately. Our main results are discussed as events, which can be either entries or exits. As indicated by the non-significant level differences (entry/exit fixed effect), there should be no significant difference between entries and exits. In fact there is none, as we will show. We re-estimate all our main results for entries and exits separately. In our main regression above we combined entries and exit into one variable, and standardized them on entry, thinking of exits as reverse entries. In this section, though, $HFTexit$ is set to 1 if one or more of the competing HFTs stops trading in the stock. This makes entries and exits intuitively comparable; the change due to an entry should be offset by an exit, i.e. the effects are symmetric. Table 10 depicts the results for liquidity and directional trading, for entries (Panel A) and exits (Panel B). The structure and columns of the table are equivalent to the main table described in Section 4. Looking at entries and exits separately does not require us to control for the event type. Our test suggests that there is a symmetric effect throughout. In other words, liquidity increases by about the same magnitude when two or more HFTs are competing for trades as it decreases when there is no high-frequency trading competition. The only measure for which we do not find a symmetric significant effect is the price impact factor based on the number of relative net buying trades. While the price impact factor for net buy volume clearly shows a highly significant increase with entry and a decrease with exit, we find a decrease, but not a significant one, for exits when looking at net buy trades. The magnitude and sign of the estimate, though, point in the correct direction. This measure might be distorted by the unequal sizes of trades. Turning to volatility, entries and exits are symmetric throughout, and the results from our regression are in line with our main empirical findings. Table 11 shows these results. Overall, the symmetric effect of entries and exits throughout our measures, in terms of significance and magnitude, provide additional comfort in our results.

[Insert Table 10 and Table 11 about here!]

6.4 Alternative Measure of Competition

The measure of competition used in the main analysis does not take into account the possibility that one HFT could dominate another trader. A simple dummy that measures competition might be misleadingly interpreted as competition even though the increased HFT participation is mainly coming from the incumbent HFT or entering HFTs. We therefore introduce a continuous measure of competition, the Herfindahl-Hirschman Index. This measure is calculated by summing up all the HFTs' squared shares of total high-frequency trading and is thereby between 0 and 1. With a measure of 1, there is no competition, and with a measure close to zero, there is perfect competition. The estimation results are shown in Table 12. Our findings from the main empirical analysis are confirmed: stocks under more competition have higher short-term volatility, lower liquidity, higher price impact factors, and more momentum trading.

[Insert Table 12 about here!]

6.5 Short-Term Entries and Exits

The main analysis is conducted using observations of the three days before and three days after entry (or exit). There are, however, 75 events (41 entries and 34 exits) that are short-lived. We conduct a robustness check that tests whether short-lived events are different from those that are longer-lived. For short-lived events, we observe only one day of non-changing competition structure around the event. The potential concern here is that the results obtained earlier might be driven by these events. Table 13 shows regression results that are very similar to the overall estimates. The results are slightly smaller in magnitude and significance. This implies that our main results are not just driven by short-term events. This can also be seen in Figure 4, where the effect of competition remains significant after one day and pre-event differences are insignificant.

[Insert Table 13 about here!]

6.6 Standard Errors

We cluster standard errors at the stock level, which is the level at which our variable of interest varies. A concern is that stocks might be serially correlated. This might become a problem as we have only 30 clusters. Standard errors could be severely underestimated as a result. To ensure that this is not actually the case in our research setup, we show a subset of our results both with clustered standard errors on the stock level and without clustered standard errors on the stock level. Table 14 presents these results. Clustering standard errors at the stock level always leads to larger standard errors and thus to a lower significance level. In other words, clustering standard errors at the stock level yields more accurate results.

[Insert Table 14 about here!]

7 CONCLUSION

High-frequency traders (HFTs) play a role of critical importance for the financial markets. HFTs exploit not only liquidity-providing short-term investment strategies (e.g., market making), but also liquidity-consuming short-term investment strategies (e.g., directional trading). When HFTs face competition from other HFTs, liquidity-providing strategies will improve market quality, while liquidity-consuming strategies will naturally worsen market quality. We find that competition among HFTs coincides with a decline in liquidity and an increase in liquidity-consuming high-frequency trades as well as in high-frequency momentum trading. There is also an increase in intraday volatility, but interestingly no effect on interday volatility, which corresponds to HFTs' investment horizons. Furthermore, we find a decrease in order execution time and an increase in the market share of HFTs, although with no effect on overall volume or profit. We exploit the cross-sectional variations in stocks and conduct difference-in-differences tests. Using the FESE tick size harmonization that was implemented on October 26th, 2009, which affected some but not all liquid stocks, we are able to draw causal conclusions. This paper provides results for both entries and exits, both separately and simultaneously. To ensure that entries and exits are not determined by pre-event differences between the endogenous variables, we also conduct propensity score matching.

Through highly competitive and quick market platforms, the advantages of technologies such as co-location, and/or the use of ultra-quick algorithms, HFTs have changed the financial markets substantially, taking up to 85% of today's equity market volume. HFTs tend to end the day with inventories that are close to zero, frequently submit and cancel limit orders, and have short holding periods. These changes have provoked intense discussion among legislators, regulators and investors, leading to controversial views that span topics from price manipulation, speed of trading, and systemic risk due to a high correlation of algorithmic strategies, to price discovery and liquidity. The quality of liquidity that HFTs potentially provide is of particular concern, as HFTs have replaced traditional market makers. Our findings contribute to this discussion, providing new insights into how HFTs affect markets, and suggesting regulatory action that will ensure that competition between HFTs is indeed competition between liquidity providers.

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A MIDPOINT APPROXIMATION

Analyses of short-term stock price behavior have to ensure that results are not determined by market microstructure noise, i.e. the bid-ask bounce. We ensure this by computing our measures based on midpoint prices and not on actual prices. A midpoint price is the price exactly halfway between the bid and ask prices at a certain point in time (here, at five-minute and hourly intraday intervals, for instance). Our data, however, include only actual realized prices and not bid and ask prices. We therefore develop a new methodology for approximating these midpoints, and find that the correlation between our approximated and the actual bid-ask spreads is 0.99. That is, we match the actual bid-ask spread almost perfectly. The midpoint price approximation is:

$$\begin{aligned} Midpoint_t = {} & \frac{P_{active,buy,i} + P_{active,sell,i-1}}{2} * I_{active,buy,P_{active,buy,i} > P_{active,sell,i-1}} \\ & + \frac{P_{active,sell,j} + P_{active,buy,j-1}}{2} * I_{active,sell,P_{active,buy,j-1} > P_{active,sell,j}}, \end{aligned} \tag{9}$$

with i (j) being the last buyer-(seller-)initiated trade in interval t (which could be five minutes long for example) and $i-1$ ($j-1$) being the last seller-(buyer-)initiated trade before this trade. $P_{active,buy}$ ($P_{active,sell}$) is the price from a buyer-(seller-)initiated trade. $I_{active,buy,P_{active,buy,i} > P_{active,sell,i-1}}$ ($I_{active,sell,P_{active,buy,j-1} > P_{active,sell,j}}$) is an indicator function that is one if the last trade in interval t is an active buy (sell) trade and is bigger (smaller) than the last seller-(buyer-)initiated trade.

To evaluate the accuracy of our approximation, we calculate the corresponding approximated spread and compare it to the actual time-weighted relative spreads, which were separately provided by NASDAQ:

$$\begin{aligned} Spread_t = {} & \frac{1}{N} \sum_{i=1}^{N} (P_{active,buy,i} - P_{active,sell,i-1}) * I_{active,buy,P_{active,buy,i} > P_{active,sell,i-1}} \\ & + \frac{1}{M} \sum_{j=1}^{M} (P_{active,sell,j} - P_{active,buy,j-1}) * I_{active,sell,P_{active,buy,j-1} > P_{active,sell,j}} \end{aligned} \tag{10}$$

where i (j) are buyer-(seller-)initiated trades during interval t (five minutes) and $i-1$ ($j-1$) are the previous seller-(buyer-)initiated trades. $P_{active,buy}$ ($P_{active,sell}$) is the price from a buyer-(seller-)initiated trade. $I_{active,buy,P_{active,buy,i} > P_{active,sell,i-1}}$ ($I_{active,sell,P_{active,buy,j-1} > P_{active,sell,j}}$) is an indicator function that is 1 if the trade during interval t is an active buy (sell) trade and is bigger (smaller) than the last seller-(buyer-)initiated trade. N (M) is the total number of buyer-(seller-)initiated trades during these five minutes.

Figure 9 depicts both the approximated and the actual relative bid-ask spread. The approximation works nicely, especially for very liquid stocks. As we focus our analysis on only the most liquid stock, the relatively less liquid (Stock A) and the relatively more liquid (Stock B) stocks in our dataset are both accurately approximated. Overall, for all daily spreads, the correlation between the actual relative spread and our approximated spread is 0.99. Relatively more liquid stocks are even closer than this to a perfect match. Relatively less liquid stocks are somewhat less correlated (a correlation of 0.97 is the lowest we find). Summary statistics showing this are provided in Table 15.

[Insert Figure 9 and Table 15 about here!]

B INSTITUTIONAL AND MARKET BACKGROUND

B.1 Market Share

The NASDAQ OMXS (Stockholm) had about an 80% market share in 2009, with a vast majority of the trading volume in the NASDAQ OMXS 30, which lists Sweden's largest public companies. The closest competitor was BATS Chi-X Europe, with about 10% to 15% of the market share in 2009, followed by Burgundy and Turquoise with less than 5%.

B.2 Trading Hours

The limit order book market is open Monday to Friday from 9am to 5:30pm, CET, except on re days (public holidays). Also, trading closes at 1pm if the following day is a red day. 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.

B.3 Account Types

To access the market, financial intermediaries have four different possibilities: (i) Broker accounts are mostly used by institutional investors or non-automated trading. (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 typically 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.

B.4 Brokers

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

B.5 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, for a one million EUR turnover, a minimum order size of 250,000EUR. As a result, HFTs have no incentive to hide their orders.

C HIGH-FREQUENCY TRADING STRATEGIES

This section gives an overview of high-frequency trading strategies. In the SEC 2010 Concept Release, high-frequency market makers are categorized into four types with four different strategies: passive, arbitrage, structural, and directional market making.

C.1 Market Making

Market makers traditionally provide required amounts of liquidity to the securities market after price pressure or other non-fundamental trading activity has moved the market. Thus, they bring short-term buy- and sell-side imbalances back into equilibrium. In return, these market makers are granted various trade execution advantages. The old structure, in which stock exchanges employed several competing, official market makers, who were required to place orders on both sides of the market and obligated to buy and sell at their displayed bids and offers, has changed dramatically in recent years. Through highly competitive and quick market platforms, the advantage of technologies such as co-location, and/or the use of ultra-quick algorithms, there have emerged new market makers, HFTs, which are making it increasingly difficult for traditional market makers to stay profitable. In 2010, one of the oldest market makers at the NYSE, LaBranche Specialist, exited the market. Market making is a trade-off between offering prices that are keen enough to attract buyers and to attract sellers. Market makers provide liquidity on both sides of the book, and earn the spread.

C.2 Arbitrage

High-frequency arbitrage means profiting from small temporary mispricing. Arbitrageurs mostly trade aggressively (actively) as their opportunities are very short-lived. The mispricing could originate from mispricings between indices or ETFs and their underlying constituents. Arbitrage is mostly not perfect, implying that arbitrageurs often carry risk until their positions are closed.

C.3 Structural

Structural investment strategies take advantage of any structural deficits in the markets or in certain participants.

Layering occurs when a false impression of liquidity is created. Orders may be entered into the order book but canceled as soon as the liquidity is demanded by another trader. Quote stuffing occurs when many orders are put into the order book on one side of the market, suggesting that there is demand. Orders are quickly canceled as soon as the price moves in this direction, and an opposite trading position is assumed.

Quote flooding is a practice whereby a HFT floods the market with quotes to slow down rivals with inferior computer systems.

Firms have actually been sanctioned for spoofing (the above defined practices.).

C.4 Directional

Directional trading strategies involve an attempt to front run or trigger a price movement. This includes anticipatory trading and exploratory trading. These high-frequency directional trading strategies are about taking and unwinding positions so as to profit from anticipated or self-generated price movements.

Table 1: Summary Statistics of Sample Stocks

This table presents summary statistics for the NASDAQ OMXS30 three days prior and after an entry or exit of high-frequency traders. 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. Column three shows how often a specific stock occurs as a control, column four gives the number of changes from no high-frequency trading competition to high-frequency trading competition and column five the changes from high-frequency competition to no high-frequency competition. The number of unique trading days for each stock is shown in column six (Note that a stock may serve as a control for more than one event per day.).

						Trades		Volume (1000)		Turnover (1000SEK)		Bid-Ask Spread	
ISIN Code	Secuity Name	Control	Entry	Exit	No Days	Mean	SD	Mean	SD	Mean	SD	Mean	SD
CH0012221716	ABB Ltd	32	3	2	54	2316	1077	2829	1338	388568	176143	0.173	0.050
FI0009000681	Nokia Corporation	48	0	0	49	1545	570	1205	502	110902	47003	0.112	0.013
GB0009895292	AstraZeneca PLC	29	5	4	55	2455	863	1321	452	418987	143539	0.132	0.058
SE0000101032	Atlas Copco AB A	57	2	1	72	3331	947	5224	1605	488603	150242	0.140	0.054
SE0000103814	Electrolux, AB B	79	1	1	89	3142	1311	2701	1372	439715	223536	0.139	0.051
SE0000106270	Hennes & Mauritz AB, H & M B	57	4	4	82	4236	1677	2060	774	831174	313182	0.093	0.044
SE0000107419	Investor AB B	59	0	1	73	1805	516	1924	702	247540	90601	0.177	0.053
SE0000108227	SKF, AB B	52	2	3	75	2798	1016	3082	1432	350031	168788	0.124	0.036
SE0000108656	Ericsson, Telefonab. L M B	62	5	5	79	5986	2019	17108	8753	1197412	617496	0.109	0.034
SE0000112724	Svenska Cellulosa AB SCA B	55	1	2	72	2266	818	2154	862	208511	84315	0.118	0.037
SE0000113250	Skanska AB B	57	2	3	83	2109	811	1965	914	213179	99676	0.139	0.045
SE0000115446	Volvo, AB B	21	2	3	37	4171	943	6984	2183	472870	149712	0.103	0.049
SE0000122467	Atlas Copco AB B	49	2	5	75	1250	460	1163	510	97269	43480	0.186	0.064
SE0000148884	Skandinaviska Enskilda Banken A	57	4	4	77	4651	1679	11070	4734	513746	211720	0.169	0.094
SE0000163594	Securitas AB B	64	4	4	79	1659	782	1940	1063	131865	73863	0.156	0.050
SE0000171100	SSAB AB A	56	2	3	79	2746	917	2820	1049	306488	109205	0.198	0.069
SE0000193120	Svenska Handelsbanken A	46	5	5	77	2255	963	1786	641	338677	117238	0.189	0.101
SE0000202624	Getinge AB B	60	2	3	70	1535	518	887	473	113873	58061	0.169	0.060
SE0000242455	Swedbank AB A	41	5	5	71	5454	2076	11386	5355	765288	376062	0.226	0.140
SE0000255648	ASSA ABLOY AB B	53	3	4	76	2270	897	2070	1009	249035	120835	0.130	0.043
SE0000308280	SCANIA AB B	8	14	13	74	1351	636	906	387	82726	35999	0.239	0.096
SE0000310336	Swedish Match AB	32	9	8	66	1446	499	1012	386	148239	55642	0.143	0.050
SE0000314312	Tele2 AB ser. B	54	2	2	72	2216	854	2001	1111	198433	107238	0.131	0.016
SE0000412371	Modern Times Group MTG AB B	67	5	4	83	1485	537	355	154	110940	47783	0.182	0.049
SE0000427361	Nordea Bank AB	47	7	6	74	3577	1389	9194	3447	672128	260518	0.145	0.036
SE0000667891	Sandvik AB	50	6	5	71	3406	955	5497	1768	431676	138283	0.133	0.054
SE0000667925	TeliaSonera AB	33	5	4	58	2688	1390	9271	5183	440023	259887	0.167	0.075
SE0000695876	Alfa Laval AB	35	7	7	67	2215	674	2225	962	193898	79892	0.114	0.035
SE0000825820	Lundin Petroleum AB	74	0	0	83	1790	515	1436	481	86773	28329	0.174	0.038
SE0000869646	Boliden AB	60	1	0	73	4241	1485	5188	2019	423193	167698	0.156	0.071
	Total/Mean	1494	128	100	2145	2749	1648	3922	4722	357223	324766	0.153	0.070

Table 2: Summary Statistics of High-Frequency Traders

This table shows summary statistics for the two most different high-frequency traders in the market, high-frequency trader A and high-frequency trader B. Statistics are reported for the daily fraction of high-frequency trades in the entire market, the absolute number of daily high-frequency trades, the closing inventory of a high-frequency trader, the fraction of active trades, and the fraction of high-frequency liquidity consuming trades. Closing inventory is the fraction of end of day stock holding over absolute high-frequency trading over the day. The active side of the trade is an incoming market order or marketable limit order that is executed against a standing limit order. A high-frequency liquidity consuming trade is a stock buy after an increase in the stock price or a stock sell after an decline in the stock price.

	High-Frequency Trader A			High-Frequency Trader B		
	Mean	Median	SD	Mean	Median	SD
HFT Trades / Total Trades	0.1017	0.0841	0.0648	0.0964	0.0807	0.0705
HFT Trades (per Day)	270	190	254	271	198	225
Closing Inventory (Daily fraction)	-0.0001	0.0000	0.0993	0.0031	0.0000	0.1161
Active Trades (fraction)	0.8974	0.9854	0.2602	0.3456	0.2676	0.2155
Liquidity Consuming Trades / All Trades	0.5979	0.5802	0.1288	0.5358	0.5375	0.1039

Table 3: Summary Statistics of the Control and Treatment Group

This table lists descriptive statistics for all stocks that serve as the control group and for all stocks in the treatment group up to three days prior entry or three days post exit. We provide means and t-statistics for both the treatment and the control group and their differences for a short-term versions of Amihud (2002)s measure of illiquidity, price impact factor, daily stock turnover, midpoint return auto-correlations and order-execution times. Order-execution time is the median time of how long an order is resting in the orderbook before it gets executed. We further provide statistics for hourly volatility computed from hourly intraday returns, five-minute volatility based on five-minute intraday returns, max-min volatility computed as the squared change from the maximum price within a day to the minimum price, open-to-close volatility shows the squared change from the opening price to the closing price of the day and close-to-close volatility calculated from the squared change from the previous day's closing price to today's closing price. Last, we show means and t-statistics for ratios of liquidity consuming high-frequency trades and ratios of liquidity consuming high-frequency turnover. A trade is assumed to be liquidity consuming if a buy trade follows a price (midpoint) increase five minutes prior to the trade or if a sell trade follows a price decline.

	(1)	(2)	(3)
VARIABLES	Control	Pre-Event Treatment	Difference
$Illiquidity\ (60\ min) * 1000k$	0.018***	0.017***	-0.001
	(37.97)	(14.27)	(-0.60)
$Illiquidity\ (5\ min) * 1000k$	0.058***	0.055***	-0.003
	(36.83)	(16.35)	(-0.73)
$Price\ Impact * 1000$	0.098***	0.113***	0.015
	(17.56)	(9.66)	(1.14)
$Turnover\ (in\ million\ SEK)$	31.850***	37.412***	5.562
	(7.47)	(5.50)	(1.31)
$Autocorrelation$	-0.016***	-0.015**	0.001
	(-4.67)	(-2.01)	(0.16)
$Order - Execution\ Time\ (in\ sec)$	70.514***	57.181***	-13.334
	(9.83)	(6.37)	(-1.29)
$Volatility\ (60\ min)$	0.023***	0.021***	-0.002
	(35.93)	(9.60)	(-0.89)
$Volatility\ (5\ min)$	0.045***	0.045***	0.000
	(48.90)	(7.86)	(0.08)
$Volatility\ (Min - Max)$	0.075***	0.067***	-0.008
	(14.35)	(10.14)	(-1.46)
$Volatility\ (Closing - Closing)$	0.032***	0.039***	0.007
	(11.46)	(8.14)	(1.61)
$Volatility\ (Opening - Closing)$	0.025***	0.029***	0.003
	(10.55)	(6.72)	(0.83)
$Liquidity\ Consuming\ Trades$	0.268***	0.321***	0.053
	(12.64)	(8.25)	(1.40)
$Liquidity\ Consuming\ Turnover$	0.269***	0.323***	0.054
	(11.99)	(8.02)	(1.38)
Observations	1,310	447	

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Liquidity Effects of Competition between High-Frequency Traders

This table displays estimated coefficients of the following regression: $y_{e,s,d} = \beta_1 d_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading entry affected 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 variables is $y_{e,j,d}$ and takes the form of a short-term versions of Amihud (2002)s measure of illiquidity (column 1-4), price impact factors (column 5 and column 6), daily stock turnover (column 7), five minute midpoint return auto-correlations (column 8) and order-execution times (column 9). Order-execution time is the median time of how long an order is resting in the orderbook before it gets executed. Additional controls, besides the level variables (treatment fixed effect and entry fixed effects for the type of event, entry or exit), are daily time fixed effects, stock fixed effect, lagged turnover, lagged bid-ask spreads and a dummy variable that indicates whether a relatively more aggressive trader enters. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	ILLIQ	ILLIQ	ILLIQ	ILLIQ (5 min)	Price Impact	Price Impact	Turnover	Autocorr	Order-Execution Time
$Competition_{i,t}$	**0.112*****	**0.168****	**0.148****	**0.089****	**0.237*****	**0.217*****	**-0.029**	**0.026**	**-0.189****
	(0.039)	(0.080)	(0.057)	(0.034)	(0.073)	(0.061)	(0.047)	(0.097)	(0.073)
$Treatment\ FE_{i,t}$	-0.027	-0.016	-0.004	-0.017	0.020	0.024	0.017	-0.063	-0.002
	(0.049)	(0.048)	(0.040)	(0.034)	(0.047)	(0.045)	(0.044)	(0.099)	(0.049)
$Entry\ FE_{i,t}$	0.036	0.038	0.026	0.031	0.018	-0.020	-0.032	0.030	-0.084*
	(0.046)	(0.044)	(0.040)	(0.029)	(0.050)	(0.043)	(0.041)	(0.080)	(0.048)
$Aggressive\ Event\ FE_{i,t}$			-0.003	0.034		0.095	-0.003	-0.147	0.038
			(0.048)	(0.037)		(0.057)	(0.064)	(0.107)	(0.062)
$Log(Turnover_{i,t-1})$			-0.673***	-0.771***		-0.497***		0.163**	-0.618***
			(0.035)	(0.026)		(0.033)		(0.063)	(0.031)
$Log(Bid - Ask\ Spread_{i,t-1})$			0.146**	-0.057		-0.186***	-0.054	0.025	1.232***
			(0.062)	(0.040)		(0.044)	(0.076)	(0.137)	(0.101)
Observations	2,165	2,165	2,165	1,999	2,169	2,169	2,175	2,175	2,175
R-squared	0.7210	0.7212	0.7815	0.8788	0.8513	0.8723	0.8346	0.0747	0.8154
-	-	-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	YES	YES	YES	NO	YES	YES	YES	YES
-	-	-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES	YES	YES

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

Table 5: Volatility Effects of Competition between High-Frequency Traders

This table displays estimated coefficients of the following regression: $y_{e,s,d} = \beta_1 d_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading entry affected 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 variables is $y_{e,j,d}$ and takes the form of hourly log volatility computed from hourly intraday returns (column 1-3), five-minute log volatility based on five-minute intraday returns (column 4), max-min log volatility computed as the squared change from the maximum price within a day to the minimum price (column 5 and column 6), open-to-close log volatility shows the squared change from the opening price to the closing price of the day (column 7) and close-to-close log volatility calculated from the squared change from the previous day's closing price to today's closing price (column 8). Additional controls, besides the level variables (treatment fixed effect and entry fixed effects for the type of event, entry or exit), are daily time fixed effects, stock fixed effect, lagged turnover, lagged bid-ask spreads and a dummy variable that indicates whether a relatively more aggressive trader enters. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Vola (hourly)	Vola (hourly)	Vola (hourly)	Vola (5 min)	Vola (min-max)	Vola (min-max)	Vola (close-close)	Vola (open-close)
$Competition_{i,t}$	**0.156****	**0.191****	**0.199****	**0.094****	**0.127****	**0.141****	**-0.062**	**-0.008**
	(0.071)	(0.078)	(0.075)	(0.037)	(0.058)	(0.060)	(0.124)	(0.176)
$Treatment\ FE_{i,t}$	-0.010	-0.003	0.001	0.041	0.055	0.059	0.362	0.122
	(0.082)	(0.082)	(0.073)	(0.038)	(0.054)	(0.072)	(0.215)	(0.184)
$Entry\ FE_{i,t}$	0.015	0.016	0.029	-0.003	-0.038	-0.021	-0.048	-0.175*
	(0.078)	(0.078)	(0.071)	(0.028)	(0.039)	(0.067)	(0.124)	(0.096)
$Aggressive\ Event\ FE_{i,t}$			-0.089	0.003		0.009	0.172	-0.023
			(0.086)	(0.044)		(0.073)	(0.186)	(0.198)
$Log(Turnover_{i,t-1})$			0.270***	0.205***		0.290***	0.148	0.338***
			(0.055)	(0.030)		(0.043)	(0.122)	(0.119)
$Log(Bid - Ask\ Spread_{i,t-1})$			0.227**	0.585***		0.284***	0.171	0.623***
			(0.092)	(0.049)		(0.093)	(0.201)	(0.152)
Observations	2,175	2,175	2,175	2,175	2,125	2,125	2,069	2,103
R-squared	0.4927	0.4928	0.5041	0.7395	0.5348	0.5512	0.2820	0.2732
-	-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	YES	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES	YES

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

Table 6: Effects of Competition between HFTs on High-Frequency Trading Strategies

This table displays estimated coefficients of the following regression: $y_{e,s,d} = \beta_1 d_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading entry affected 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 variables is $y_{e,j,d}$ and takes the form of ratios of liquidity consuming high-frequency trades (column 1-3) and ratios of liquidity consuming high-frequency turnover (column 4). A trade is assumed to be liquidity consuming if a buy trade follows a price (midpoint) increase five minutes prior to the trade or if a sell trade follows a price decline. Column 5-7 show changes in liquidity consumption based on one minute pre-trade midpoint changes. The left hand side variable takes also the form of three measures of directional (momentum) high-frequency trading (column 8-10) and of profit in column 11. Additional controls, besides the level variables (indicator for the treated security, indicator for the type of event, entry or exit, and daily time fixed effects), are stock fixed effect, volume, bid-ask spreads and an indicator variable whether a relatively more aggressive trader enters or exits. Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	LC Trade Ratio (5min)	LC Trade Ratio (5min)	LC Trade Ratio (5min)	LC Turnover Ratio (5min)	LC Trade Ratio (1min)	LC Trade Ratio (1min)	LC Turnover Ratio (1min)	DIRECT1	DIRECT2	DIRECT3	Profit in 1000SEK
$Competition_{i,t}$	**0.186*****	**0.275*****	**0.276*****	**0.301*****	**0.249*****	**0.251*****	**0.341*****	**0.337*****	**0.449****	**3.044****	244.208
	(0.027)	(0.048)	(0.049)	(0.052)	(0.057)	(0.058)	(0.058)	(0.116)	(0.193)	(1.106)	(281.630)
$Treatment\ FE_{i,t}$	0.025	0.041	0.040	0.053*	0.055	0.054	0.037	-0.020	0.076	0.390	349.375
	(0.032)	(0.030)	(0.030)	(0.030)	(0.036)	(0.035)	(0.034)	(0.073)	(0.140)	(0.674)	(220.981)
$Entry\ FE_{i,t}$	0.015	0.017	0.014	0.008	0.045	0.042	0.028	-0.008	-0.175	-0.803	48.287
	(0.028)	(0.028)	(0.028)	(0.027)	(0.032)	(0.031)	(0.029)	(0.076)	(0.160)	(0.839)	(190.897)
$Aggressive\ Event\ FE_{i,t}$			-0.061	-0.055		-0.077*	-0.054	0.036	0.098	0.201	-465.723
			(0.040)	(0.038)		(0.044)	(0.039)	(0.090)	(0.119)	(0.670)	(291.859)
$Log(Turnover_{i,t-1})$			-0.013	-0.010		-0.004	-0.010	-0.383***	-0.646***	-3.727***	274.019
			(0.017)	(0.016)		(0.018)	(0.018)	(0.071)	(0.139)	(0.584)	(222.843)
$Log(Spread_{i,t-1})$			-0.040	-0.037		-0.058	-0.054	-0.333**	-0.289	-3.167**	-219.899
			(0.078)	(0.078)		(0.090)	(0.085)	(0.149)	(0.239)	(1.341)	(339.050)
Observations	2,175	2,175	2,175	2,175	2,175	2,175	2,175	2,175	2,175	2,175	2,175
R-squared	0.5947	0.6012	0.6021	0.6093	0.5975	0.5987	0.6052	0.4526	0.3618	0.3679	0.1321
-	-	-	-	-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

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

Table 7: Propensity Score Matching Diagnostics

This table provides evidence that we can treat competition as exogenous to the dependent variables. The sample consists of the most liquid stocks. Stocks facing competition from other HFTs form the treatment group and stocks not facing this competition make up the control group. This table shows results for the 125 entries. Panel A presents pairwise comparisons of the variables that might trigger entry for the control, treatment and their differences. The time is for each event the cross-section of the pre-event day. The Pre-Match columns show the entire sample and the Post-Match columns the after match sample. Panel B shows parameter estimates from the probit model used to estimate the propensity scores for the treatment and control group. The dependent variable is one if the stock faces competition between HFTs in the following period and zero if not. All covariates included in the probit regression are pre-competition realizations. The Pre-Match column shows the parameter estimates of the probit estimated on the entire sample prior to matching. The Post-Match column contains the parameter estimates of the reduced sample after matching. From estimated propensity scores of the whole sample, we keep the event if the score is above 10% or below 90%. Panel C gives results of the effect of competition between HFTs on market quality with the matched sample entries.

Panel A: Pairwise Comparisons

	Pre-Match			Post-Match		
	Control	Treatment	Difference	Control	Treatment	Difference
$Log(Bid - Ask\ Spread_{i,t})$	-2.035***	-2.202***	-0.167	-2.231***	-2.217***	0.015
	(-53.74)	(-20.40)	(-1.59)	(-32.95)	(-23.17)	(0.17)
$Log(Turnover_{i,t})$	3.121***	3.136***	0.015	3.315***	3.207***	-0.108
	(21.36)	(15.04)	(0.08)	(18.39)	(17.26)	(-0.85)
$Log(HourlyVola_{i,t})$	-11.090***	-11.190***	-0.100	-11.134***	-11.195***	-0.060
	(-155.57)	(-71.91)	(-0.67)	(-108.58)	(-82.63)	(-0.43)
$Log(ILLIQ_{i,t})$	-22.872***	-23.023***	-0.151	-23.129***	-23.088***	0.041
	(-154.44)	(-94.35)	(-0.70)	(-124.31)	(-110.27)	(0.28)
$DIRECT1_{i,t}$	0.229**	0.022	-0.207	0.122	0.059	-0.063
	(2.39)	(0.23)	(-1.62)	(1.32)	(0.67)	(-0.63)
$DIRECT2_{i,t}$	0.231**	-0.027	-0.258*	0.084	0.026	-0.058
	(2.06)	(-0.29)	(-1.81)	(1.12)	(0.32)	(-0.60)
$DIRECT3_{i,t}$	0.456*	0.076	-0.380	0.227	0.167	-0.061
	(2.01)	(0.50)	(-1.39)	(1.21)	(1.10)	(-0.27)
$Log(IMPACT_{i,t})$	-12.267***	-12.264***	0.003	-12.338***	-12.306***	0.032
	(-57.42)	(-47.63)	(0.02)	(-36.20)	(-43.98)	(0.24)
Observations	734	125	859	209	100	309

Panel B: Probit Regression Result

	Pre-Match	Post-Match
$Log(HourlyVola_{i,t})$	0.077	0.054
	(0.31)	(0.27)
$Log(ILLIQ_{i,t})$	-0.758*	-0.336
	(-1.90)	(-0.86)

– **continued on next page**

Table 7 – continued from previous page

$DIRECT1_{i,t}$	0.254	0.201
	(0.37)	(0.31)
$DIRECT2_{i,t}$	-0.370	-0.374
	(-0.62)	(-0.67)
$DIRECT3_{i,t}$	0.074	0.086
	(0.46)	(0.56)
$Log(IMPACT_{i,t})$	-0.094	0.254
	(-0.26)	(0.88)
$Log(Turnover_{i,t})$	-0.312	-0.351
	(-0.46)	(-0.71)
$Log(Bid-Ask\ Spread_{i,t})$	0.924	-0.419
	(0.81)	(-0.80)
$Intercept$	-18.697***	-4.248
	(-2.65)	(-0.60)
Time FE	YES	YES
Stock FE	NO	NO
Control	630	205
Treatment	125	101
Observations	755	306
Pseudo R^2	0.35	0.12

Panel C: Post-Match Competition Effects (Entry)

	(1)	(2)	(3)	(4)	(5)	(6)
	Hourly Vola	ILLIQ	DIRECT1	DIRECT2	DIRECT3	IMPACT nb
$Competition_{i,t}$	0.196**	0.162**	0.364***	0.370**	2.130**	0.203***
	(0.085)	(0.074)	(0.122)	(0.159)	(0.958)	(0.060)
$level : Treatment_{i,t}$	-0.078	-0.038	-0.030	-0.040	0.013	0.004
	(0.072)	(0.053)	(0.057)	(0.085)	(0.519)	(0.042)
$Log(Turnover_{i,t})$	0.706***	-0.581***	-0.304***	-0.504***	-3.284***	-0.188***
	(0.082)	(0.050)	(0.065)	(0.092)	(0.640)	(0.065)
$Log(Bid-Ask\ Spread_{i,t})$	0.816***	0.360***	-0.287	-0.218	-3.200**	0.097
	(0.177)	(0.106)	(0.185)	(0.274)	(1.535)	(0.099)
Observations	779	778	779	779	779	775
R-squared	0.5813	0.8104	0.5710	0.5268	0.5368	0.8228
-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES
HFT FE	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES

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

Table 8: Summary Statistics: Tick Size Regime Change

This table depicts summary statistics and differences tests for before and after the event period as well as before differences between the treatment and control group. Panel A shows statistics for two weeks prior and two weeks after the event. We give statistics for bid-ask spreads, high-frequency volume, number of daily trades, stock turnover and order-execution time. In Panel B, we show statistics and their differences for both the control and treatment group prior the event. We depict means and t-statistics for bid-ask spreads, stock turnover, volatility, the measure of illiquidity, price impact factors and three directional (momentum) high-frequency trading measures.

PANEL A: PRE AND POST EVENT

	Before New Regime				After New Regime			
	Obs	Mean	Median	SD	Obs	Mean	Median	SD
$Bid-Ask\ Spread_{i,t}$	389	0.201	0.195	0.058	356	0.109	0.104	0.029
$HFTVolume_{i,t}(\%)$	389	0.098	0.078	0.074	356	0.195	0.174	0.105
$Trades_{i,t}(\#)$	389	2521	2177	1501	356	3467	3120	1963
$Turnover_{i,t}$	389	37.820	28.727	38.708	356	38.538	30.126	34.277
$Volume_{i,t}(in1000)$	389	4686	2473	5627	356	4606	2605	5190
$Order-Execution\ Time_{i,t}$	389	99.645	78.998	84.677	356	33.690	25.002	24.176

PANEL B: PRE EVENT DIFFERENCES

	Control	Treatment	Difference
$Bid-Ask\ Spread_{i,t}$	0.200***	0.206***	0.007
	(12.32)	(10.10)	(0.26)
$Turnover_{i,t}$	24.882***	45.278***	20.396*
	(4.54)	(4.84)	(1.93)
$HourlyVola_{i,t}$	0.327***	0.335***	0.008
	(7.85)	(4.35)	(0.09)
$ILLIQ_{i,t}$	0.000**	0.000***	-0.000
	(3.32)	(3.51)	(-1.21)
$DIRECT1_{i,t}$	0.248**	0.256*	0.008
	(2.64)	(2.27)	(0.06)
$DIRECT2_{i,t}$	0.262**	0.224*	-0.038
	(2.61)	(1.97)	(-0.26)
$DIRECT3_{i,t}$	0.491**	0.363	-0.129
	(2.49)	(1.54)	(-0.43)
$IMPACT_{i,t}$	0.152	0.062*	-0.090
	(1.40)	(2.24)	(-0.82)
Observations	153	236	389

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

Table 9: Competition Between HFTs and the Tick Size Effect

This table provides separate results for both high-frequency traders entries (Panel A) and for high-frequency trading tick size effects (Panel B), and displays estimated coefficients of the following regression: $y_{e,s,d} = \beta_1 d_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading entry affected 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 variables is $y_{e,j,d}$ and takes the form of short-term volatility (column 1), a short-term version of Amihud (2002)s measure of illiquidity (column 2), three measures of directional (momentum) trading (column 3-5), and price impact factors (column 6 and column 7) . Additional controls, besides the level variables (treatment fixed effect and entry fixed effects for the type of event, entry or exit), are daily time fixed effects, stock fixed effect, turnover, bid-ask spreads and a dummy variable that indicates whether a relatively more aggressive trader enters. Robust standard errors are reported in parentheses.

	(1) Hourly Vola	(2) ILLIQ	(3) DIRECT1	(4) DIRECT2	(5) DIRECT3	(6) IMPACT nbv	(7) IMPACT nb
PANEL A: COMPETITION EFFECTS							
$Competition_{i,t}$	0.274**	0.182**	0.568***	0.573***	0.804**	0.001	0.150**
	(0.136)	(0.082)	(0.205)	(0.209)	(0.376)	(0.086)	(0.070)
$Log(Turnover_{i,t})$	0.637***	-0.601***	-0.123	-0.080	-0.399*	-0.424***	-0.097*
	(0.095)	(0.058)	(0.083)	(0.117)	(0.212)	(0.060)	(0.050)
$Log(Bid-Ask\ Spread_{i,t})$	0.498***	0.316***	0.067	0.228	-0.194	-0.101	0.168**
	(0.145)	(0.104)	(0.191)	(0.209)	(0.454)	(0.105)	(0.082)
Observations	745	739	744	744	744	745	745
R-squared	0.5732	0.8052	0.1711	0.1705	0.1584	0.8728	0.7283
PANEL B: TICK SIZE EFFECTS							
$TickSizeEffect_{i,t}$	-0.028	-0.080	-0.456**	-0.370*	-0.344	0.067	-0.080
	(0.127)	(0.080)	(0.179)	(0.198)	(0.403)	(0.081)	(0.064)
$Log(Turnover_{i,t})$	0.695***	-0.671***	-0.335***	-0.287**	-0.417	-0.519***	-0.182***
	(0.146)	(0.071)	(0.121)	(0.146)	(0.284)	(0.075)	(0.047)
Observations	524	524	499	499	499	522	524
R-squared	0.5080	0.7128	0.3068	0.2924	0.3096	0.5000	0.5113
-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	NO	NO	NO	NO	NO	NO
-	-	-	-	-	-	-	-
Cluster Stock	NO	NO	NO	NO	NO	NO	NO

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

Table 10: Competition Effects of HFT Entry and Exit: Liquidity

This table provides separate results for both high-frequency traders entries (Panel A) and exits (Panel B), and displays estimated coefficients of the following regression: $y_{e,s,d} = \beta_1 d_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading entry affected 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 variables is $y_{e,j,d}$ and takes the form of a short-term version of Amihud (2002)s measure of illiquidity (column 1-4), three variations of our measures of directional (momentum) high-frequency trading (column 5-7), an midpoint autocorrelation measure (column 8) and price impact factors (column 9-10). Additional controls, besides the level variables (treatment fixed effect and entry fixed effects for the type of event, entry or exit), are daily time fixed effects, stock fixed effect, turnover, bid-ask spreads and a dummy variable that indicates whether a relatively more aggressive trader enters. Standard errors are clustered at the stock level and reported in parentheses.

	(1) ILLIQ	(2) ILLIQ	(3) ILLIQ	(4) ILLIQ 5 min	(5) DIRECT1	(6) DIRECT2	(7) DIRECT3	(8) Autocorr	(9) IMPACT nbv	(10) IMPACT nb
PANEL A: ENTRY										
HFT Entry	0.137***	0.202**	0.167**	0.099***	0.367***	0.476**	3.170***	-0.012	0.233***	0.152**
	(0.045)	(0.089)	(0.063)	(0.035)	(0.114)	(0.182)	(1.029)	(0.108)	(0.063)	(0.062)
Treatment Dummy	-0.038	-0.027	-0.033	-0.028	-0.044	0.005	0.243	0.026	-0.022	-0.029
	(0.044)	(0.045)	(0.035)	(0.030)	(0.071)	(0.110)	(0.425)	(0.081)	(0.044)	(0.035)
Active Trader's Entry or Exit			0.031	0.046	0.066	0.040	-0.171	-0.209*	0.117*	0.101*
			(0.053)	(0.037)	(0.097)	(0.133)	(0.677)	(0.120)	(0.064)	(0.051)
Log Turnover(t)			-0.649***	-0.765***	-0.395***	-0.668***	-3.823***	0.195***	-0.496***	-0.142***
			(0.037)	(0.027)	(0.075)	(0.136)	(0.434)	(0.071)	(0.035)	(0.027)
Log(Bid-Ask Spread)			0.241***	0.080*	-0.317**	-0.286	-3.121***	0.093	-0.105**	0.125***
			(0.071)	(0.041)	(0.143)	(0.219)	(0.831)	(0.147)	(0.050)	(0.042)
Observations	1,932	1,932	1,932	1,783	1,942	1,942	1,942	1,942	1,936	1,937
R-squared	0.7206	0.7209	0.7824	0.8762	0.4578	0.3691	0.3756	0.0814	0.8711	0.7581
PANEL B: EXIT										
HFT Exit	-0.170**	-0.230**	-0.164**	-0.105**	-0.293**	-0.384*	-2.682**	-0.099	-0.210***	-0.110
	(0.066)	(0.096)	(0.069)	(0.043)	(0.121)	(0.192)	(1.063)	(0.133)	(0.074)	(0.070)
treatment_control_exit_day3	0.137**	0.208**	0.186**	0.179***	0.347**	0.361	2.625**	-0.006	0.221***	0.081
	(0.058)	(0.095)	(0.071)	(0.047)	(0.156)	(0.236)	(1.113)	(0.128)	(0.077)	(0.065)
Active Trader's Entry or Exit			0.015	0.045	-0.010	0.007	0.199	-0.131	0.222***	0.141***
			(0.061)	(0.037)	(0.119)	(0.147)	(0.849)	(0.130)	(0.065)	(0.049)
Log Turnover(t)			-0.665***	-0.686***	-0.414***	-0.736***	-4.107***	0.135*	-0.525***	-0.155***
			(0.033)	(0.028)	(0.080)	(0.150)	(0.529)	(0.074)	(0.041)	(0.032)
Log(Bid-Ask Spread)			0.240***	0.192***	-0.185	-0.158	-1.681**	-0.083	-0.075	0.148***
			(0.071)	(0.053)	(0.154)	(0.262)	(0.809)	(0.153)	(0.059)	(0.050)
Observations	1,727	1,727	1,727	1,620	1,730	1,730	1,730	1,730	1,724	1,724
R-squared	0.7259	0.7263	0.7881	0.8671	0.4765	0.3863	0.3966	0.0800	0.8799	0.7617
-	-	-	-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

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

Table 11: Competition Effects of HFT Entry and Exit: Intra- and Inter-Day Volatilities

This table provides separate results for both high-frequency traders entries (Panel A) and exits (Panel B), and displays estimated coefficients of the following regression: $y_{e,s,d} = \beta_1 d_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading entry affected 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 variables is $y_{e,j,d}$ and takes the form of hourly log volatility computed from hourly intraday returns (column 1-4), five-minute log volatility based on five-minute intraday returns (column 5), max-min log volatility computed as the squared change from the maximum price within a day to the minimum price (column 6), open-to-close log volatility shows the squared change from the opening price to the closing price of the day (column 7) and close-to-close log volatility calculated from the squared change from the previous day's closing price to today's closing price (column 8). Additional controls, besides the level variables (treatment fixed effect and entry fixed effects for the type of event, entry or exit), are daily time fixed effects, stock fixed effect, turnover, bid-ask spreads and a dummy variable that indicates whether a relatively more aggressive trader enters. Standard errors are clustered at the stock level and reported in parentheses.

	(1) Hourly Vola	(2) Hourly Vola	(3) Hourly Vola	(4) Hourly Vola	(5) 5 Min Vola	(6) Max-Min Vola	(7) Open-Close Vola	(8) Close-Close Vola
PANEL A: ENTRY								
HFT Entry	0.240***	0.183**	0.225***	0.225***	0.085*	0.138**	0.019	-0.077
	(0.088)	(0.075)	(0.081)	(0.084)	(0.048)	(0.067)	(0.219)	(0.159)
Treatment Dummy	-0.047	-0.063	-0.056	-0.045	0.013	0.044	0.113	0.321
	(0.076)	(0.070)	(0.076)	(0.069)	(0.039)	(0.054)	(0.166)	(0.208)
Active Trader's Entry or Exit				-0.067	-0.009	0.006	0.018	0.208
				(0.091)	(0.049)	(0.064)	(0.203)	(0.222)
Log Turnover(t)				0.643***	0.396***	0.795***	1.031***	1.134***
				(0.057)	(0.024)	(0.049)	(0.127)	(0.132)
Log(Bid-Ask Spread)				0.395***	0.834***	0.378***	0.671***	-0.012
				(0.087)	(0.046)	(0.074)	(0.222)	(0.183)
Observations	1,942	1,942	1,942	1,942	1,942	1,892	1,886	1,841
R-squared	0.2901	0.4899	0.4900	0.5474	0.7075	0.6330	0.3099	0.3347
PANEL B: EXIT								
HFT Exit	-0.291***	-0.191**	-0.253***	-0.278***	-0.124***	-0.164**	0.035	0.048
	(0.102)	(0.092)	(0.092)	(0.093)	(0.048)	(0.074)	(0.232)	(0.177)
treatment_control_exit_day3	0.273***	0.195**	0.269***	0.309***	0.162***	0.219***	-0.034	0.188
	(0.096)	(0.088)	(0.092)	(0.093)	(0.055)	(0.073)	(0.234)	(0.181)
Active Trader's Entry or Exit				-0.075	-0.020	0.015	-0.083	0.481**
				(0.104)	(0.057)	(0.066)	(0.226)	(0.232)
Log Turnover(t)				0.621***	0.386***	0.779***	1.152***	1.187***
				(0.062)	(0.027)	(0.052)	(0.134)	(0.124)
Log(Bid-Ask Spread)				0.361***	0.850***	0.305***	0.723***	0.117
				(0.096)	(0.050)	(0.085)	(0.256)	(0.226)
Observations	1,730	1,730	1,730	1,730	1,730	1,681	1,672	1,639
R-squared	0.2780	0.4812	0.4816	0.5349	0.7021	0.6351	0.3126	0.3154
-	-	-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Stock FE	NO	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	NO	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES	YES

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

Table 12: 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: $y_{e,s,d} = \beta_1 HHI_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $HHI_{e,j}$ is the Herfindahl-Hirschman Index of competition between 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 variables is $y_{e,j,d}$ and takes the form of short-term volatility (column 1-2), of a short-term version of Amihud (2002)s measure of illiquidity (column 3), three variations of our measures of directional (momentum) high-frequency trading (column 4-6), and price impact factors (column 7). Additional controls, besides the level variables (treatment fixed effect and entry fixed effects for the type of event, entry or exit), are daily time fixed effects, stock fixed effect, turnover, bid-ask spreads and a dummy variable that indicates whether a relatively more aggressive trader enters. Standard errors are clustered at the stock level and reported in parentheses.

VARIABLES	(1) Hourly Vola	(2) Hourly Vola	(3) ILLIQ	(4) DIRECT1	(5) DIRECT2	(6) DIRECT3	(7) IMPACT nb
$Competition_{i,t}\ (Herfindahl)$	-0.329**	-0.296**	-0.196*	-0.736***	-0.895***	-6.322***	-0.323**
	(0.159)	(0.148)	(0.108)	(0.224)	(0.316)	(1.895)	(0.157)
$Aggressive\ Event_{i,t}$		-0.089	0.001	0.019	0.037	-0.095	0.077
		(0.084)	(0.047)	(0.088)	(0.114)	(0.638)	(0.052)
$Log(Turnover_{i,t})$		0.625***	-0.661***	-0.385***	-0.645***	-3.731***	-0.149***
		(0.053)	(0.036)	(0.071)	(0.140)	(0.598)	(0.037)
$Log(Bid - Ask\ Spread_{i,t})$		0.373***	0.240***	-0.334**	-0.273	-3.108**	0.141**
		(0.082)	(0.070)	(0.147)	(0.235)	(1.324)	(0.052)
Observations	2,175	2,175	2,165	2,175	2,175	2,175	2,169
R-squared	0.4920	0.5461	0.7826	0.4525	0.3604	0.3665	0.7549
-	-	-	-	-	-	-	-
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 13: Robustness: Short-Lived Entries and Exits

This depicts results for entries and exits that are short-lived (one day) and displays estimated coefficients of the following regression: $y_{e,s,d} = \beta_1 d_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading entry affected 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 variables is $y_{e,j,d}$ and takes the form of short-term volatility (column 1-2), of a short-term version of Amihud (2002)s measure of illiquidity (column 3), and three variations of our measures of directional (momentum) high-frequency trading (column 4-6). Additional controls, besides the level variables (treatment fixed effect and entry fixed effects for the type of event, entry or exit), are daily time fixed effects, stock fixed effect, turnover, bid-ask spreads and a dummy variable that indicates whether a relatively more aggressive trader enters. Standard errors are clustered at the stock level and reported in parentheses.

VARIABLES	(1) Hourly Vola	(2) Hourly Vola	(3) ILLIQ	(4) DIRECT1	(5) DIRECT2	(6) DIRECT3
$Competition_{i,t}$	0.192*	0.208*	0.162**	0.336**	0.393*	2.819**
	(0.095)	(0.104)	(0.065)	(0.129)	(0.195)	(1.175)
$level : Treatment_{i,t}$	-0.001	-0.019	-0.072	-0.015	-0.003	0.743**
	(0.094)	(0.082)	(0.052)	(0.059)	(0.095)	(0.347)
$level : Event\ Type_{i,t}$	0.070	0.092	0.070	-0.018	-0.025	-0.677
	(0.080)	(0.066)	(0.049)	(0.056)	(0.079)	(0.557)
$Aggressive\ Event_{i,t}$		-0.071	0.015	0.010	-0.040	-0.677
		(0.102)	(0.071)	(0.117)	(0.160)	(1.042)
$Log(Turnover_{i,t})$		0.620***	-0.667***	-0.374***	-0.612***	-3.732***
		(0.069)	(0.040)	(0.071)	(0.128)	(0.573)
$Log(Bid - Ask\ Spread_{i,t})$		0.362***	0.252***	-0.238	-0.131	-2.159
		(0.093)	(0.059)	(0.150)	(0.247)	(1.309)
Observations	1,715	1,715	1,710	1,715	1,715	1,715
R-squared	0.4875	0.5406	0.7904	0.4585	0.3548	0.3633
-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES
HFT FE	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES

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

Table 14: Robustness: Clustered versus Robust Standard Errors

This table shows results why clustered standard errors are larger and therefore provide more robust results. We depict estimated coefficients of the following regression: $y_{e,s,d} = \beta_1 d_{e,j} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d}$, which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading entry affected 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 variables is $y_{e,j,d}$ and takes the form of short-term volatility (column 1 and column 2), one of our measures of directional (momentum) high-frequency trading (column 3 and column 4). Additional controls, besides the level variables (indicator for the treated security and daily time fixed effects), are stock fixed effect, volume, volatility (computed as intraday volatility of hourly returns). Standard errors alter between clustered standard errors at the stock level and robust standard errors (in parentheses).

VARIABLES	(1) Hourly Vola	(2) Hourly Vola	(3) DIRECT1	(4) DIRECT1	(5) IMPACT nb	(6) IMPACT nb
$Competition_{i,t}$	0.194**	0.194**	0.337***	0.337***	0.135***	0.135**
	(0.083)	(0.084)	(0.087)	(0.116)	(0.045)	(0.059)
$level : Treatment_{i,t}$	-0.006	-0.006	-0.020	-0.020	0.027	0.027
	(0.062)	(0.067)	(0.065)	(0.073)	(0.034)	(0.036)
$level : Event\ Type_{i,t}$	0.056	0.056	-0.008	-0.008	-0.038	-0.038
	(0.058)	(0.064)	(0.061)	(0.076)	(0.031)	(0.029)
$Aggressive\ Event_{i,t}$	-0.108	-0.108	0.036	0.036	0.090**	0.090*
	(0.076)	(0.082)	(0.080)	(0.090)	(0.042)	(0.046)
$Log(Turnover_{i,t})$	0.627***	0.627***	-0.383***	-0.383***	-0.149***	-0.149***
	(0.041)	(0.063)	(0.043)	(0.071)	(0.022)	(0.027)
$Log(Bid - Ask\ Spread_{i,t})$	0.380***	0.380***	-0.333***	-0.333**	0.140***	0.140***
	(0.074)	(0.088)	(0.078)	(0.149)	(0.040)	(0.040)
Observations	2,175	2,175	2,175	2,175	2,169	2,169
R-squared	0.5469	0.5469	0.4526	0.4526	0.7550	0.7550
-	-	-	-	-	-	-
Time FE	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES
HFT FE	YES	YES	YES	YES	YES	YES
-	-	-	-	-	-	-
Cluster Stock	NO	YES	NO	YES	NO	YES

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

Table 15: Summary Statistics of Midpoint and Spread Approximation

This table shows summary statistics comparing the approximated bid-ask spread to the actual bid-ask spread.

	Obs	Mean	Median	SD	Correlation
Panel A: All Stock					
Bid-Ask Spread (%)	3870	0.182	0.155	0.094	
Bid-Ask Spread Approximation(%)	3870	0.184	0.156	0.095	0.9899
Panel B: More Liquid Stock					
Bid-Ask Spread (%)	129	0.200	0.161	0.123	
Bid-Ask Spread Approximation(%)	129	0.197	0.147	0.123	0.9961
Panel C: Less Liquid Stock					
Bid-Ask Spread (%)	129	0.264	0.309	0.104	
Bid-Ask Spread Approximation(%)	129	0.270	0.318	0.111	0.9675

Figure 1: Stylized Motivating Example: Inventory

This figure shows a motivating example of an entering high-frequency trader. It presents high-frequency trading inventory over a period of 20 days in 2009 for a single stock. Each vertical line represents the beginning of a new trading day. The gray area is one entry event that enters the analysis. While the lighter gray area are trading days of the incumbent alone, the darker gray area are days when there are competing HFTs trading in the stock.

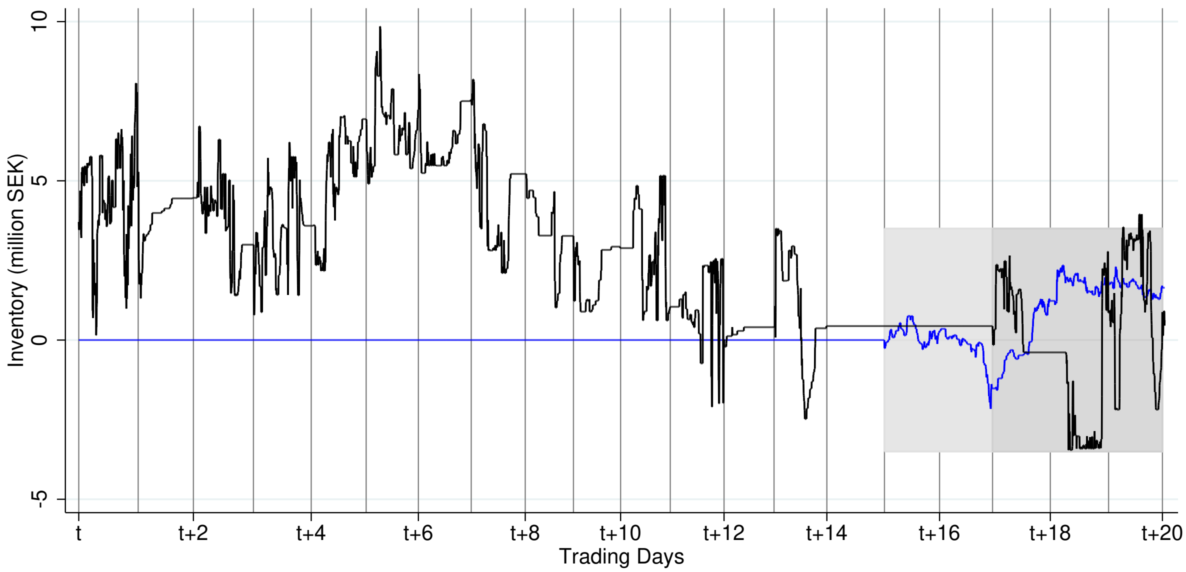

Figure 2: Summary Statistics of High-Frequency Trading Participation

This figure shows graphically average deviations from average trading participations of individual stocks for both the control and the treatment group. Average trading participation under no competition is about 10%. The left-hand-side of the graph shows average effects of entries and the right-hand-side average effects of exits three days prior and three days after the event.

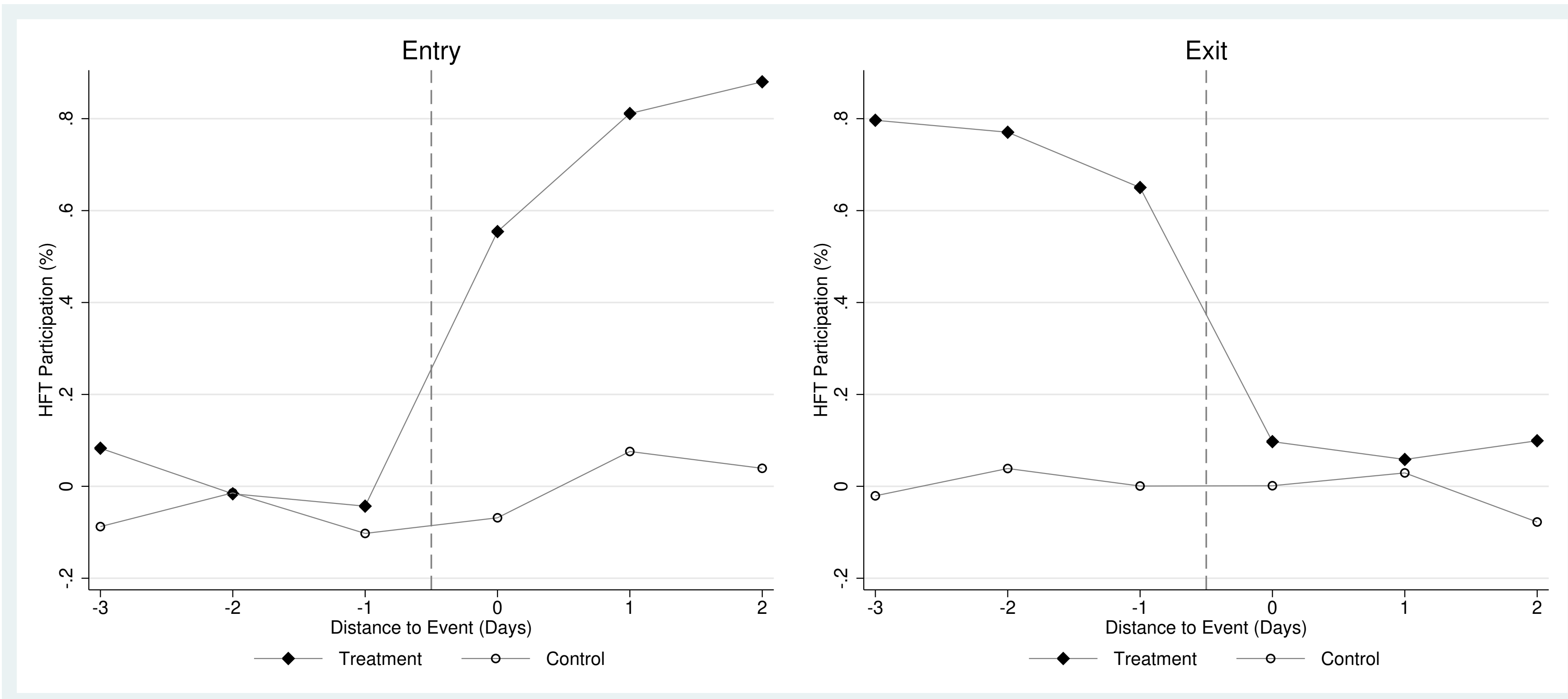

Figure 3: Summary Statistics of Illiquidity and Liquidity Consuming Turnover Ratios

This figure illustrates the effect of competition between high-frequency traders with simple means three days prior and three days post the event. The left-hand graphs show entries and the right-hand graphs exits. The graph on the top shows means around the event a short-term version of Amihud (2002)s measure of illiquidity. The bottom graph depicts averages for high-frequency consuming turnover ratios. A trade is assumed to be liquidity consuming if a buy trade follows a price (midpoint) increase five minutes prior to the trade or if a sell trade follows a price decline.

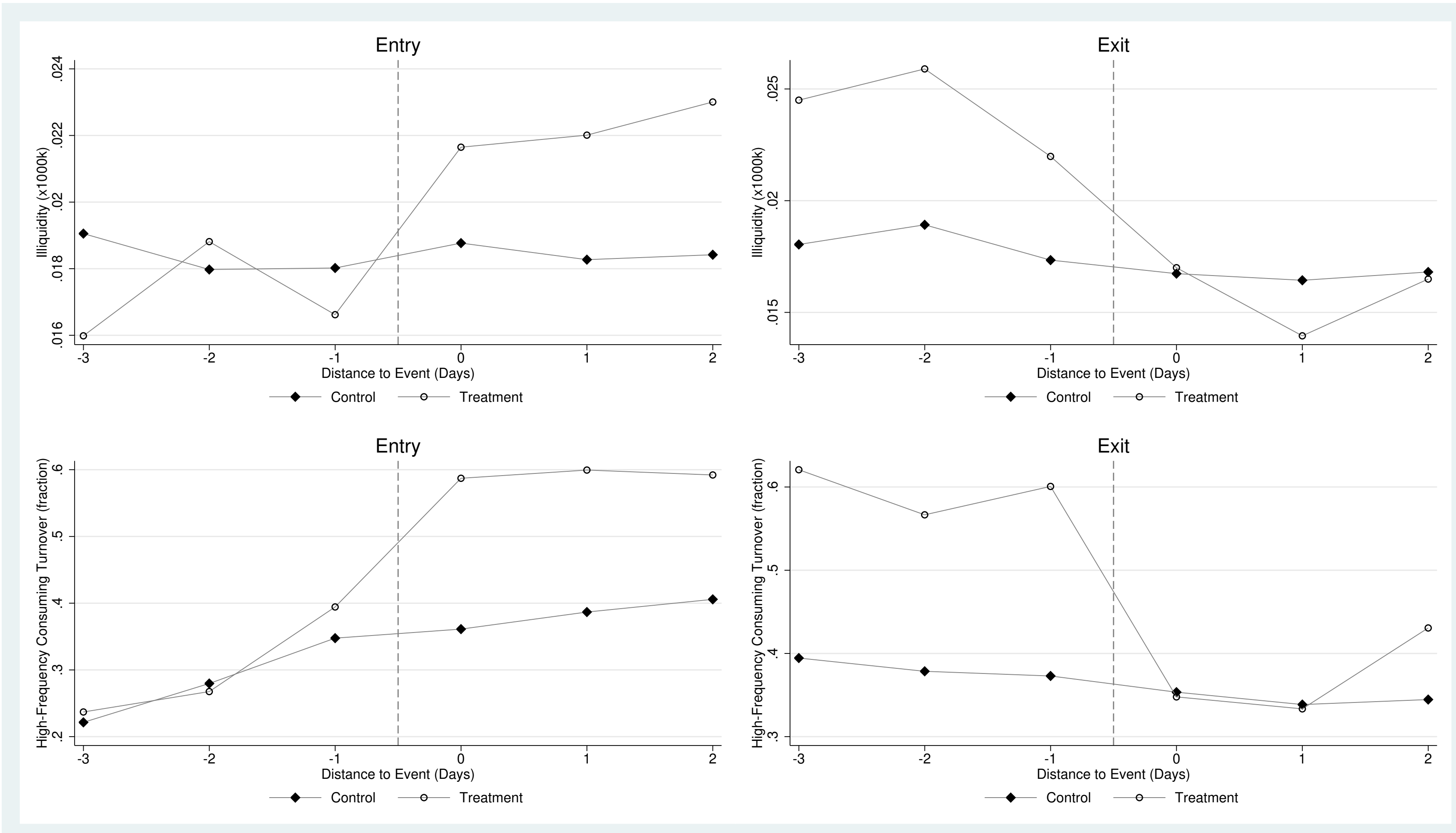

Figure 4: Dynamic Impact of Entry and Exit on Volatility

This figure shows point estimates for three days before and three days after the event from the difference-in-differences estimation. The plotted coefficients originate from following regression:

$$y_{e,j,d} = \beta_1 d_{e,j}^{-3} + \beta_2 d_{e,j}^{-2} + \cdots + \beta_3 d_{e,j}^{3} + X_{e,j,d}\Gamma + p_d + m_j + u_{e,j,d},$$

which allows for multiple time periods and multiple treatment groups. With e indexing entry or exit of additional high-frequency traders, j being the security and d the time (day). $d_{e,j}$ is an indicator of whether a high-frequency trading entry affected 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 variables is $y_{e,j,d}$ and takes the form of short-term volatility. On the left, we show the volatility increase after entry and on the right we show the volatility decrease after exit.

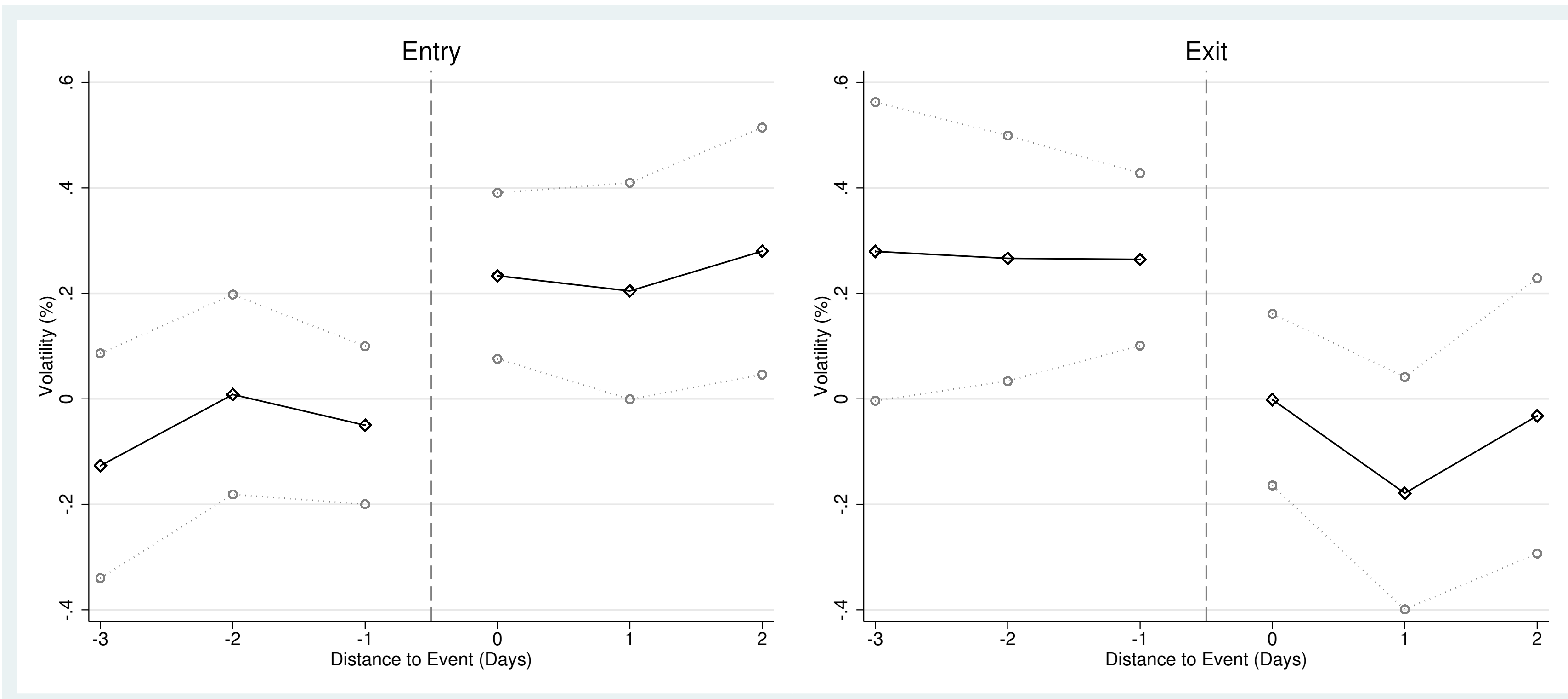

Figure 5: FESE Tick Size Harmonization

This figure gives an overview of the FESE tick size harmonization October 26th, 2009 for the OMXS30 for all relevant price levels. Swedens most liquid stocks are traded on two different tick size regimes prior the harmonization. The graph on the right-hand side shows the levels for Swedens blue-chip companies, the Most Liquid Shares, and the left-hand graph for the remaining liquid stocks. The vertical axis depicts actual tick sizes in place for all relevant price levels.

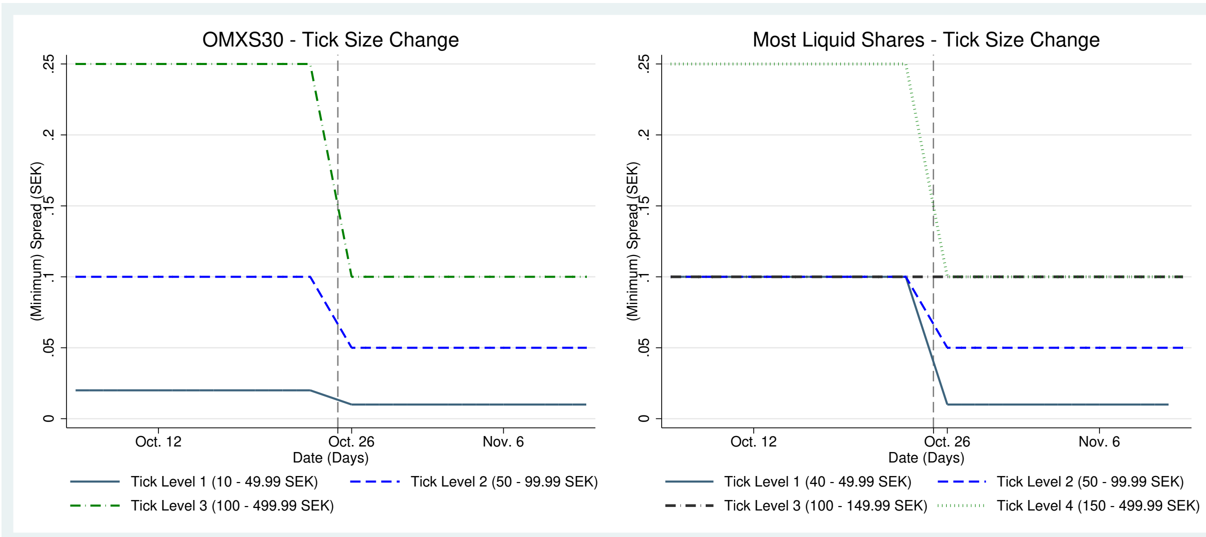

Figure 6: Actual Bid-Ask Spreads

This figure depicts the actual relative bid-ask spreads around the FESE tick size harmonization October 26th, 2009 for the OMXS30 for all relevant price levels. Swedens most liquid stocks are traded on two different tick size regimes prior the harmonization. The graph on the right-hand side shows the relative bid-ask spreads for Swedens blue-chip companies, the Most Liquid Shares, and the left-hand graph for the remaining liquid stocks. The vertical axis depicts actual relative bid-ask spreads for all relevant price levels.

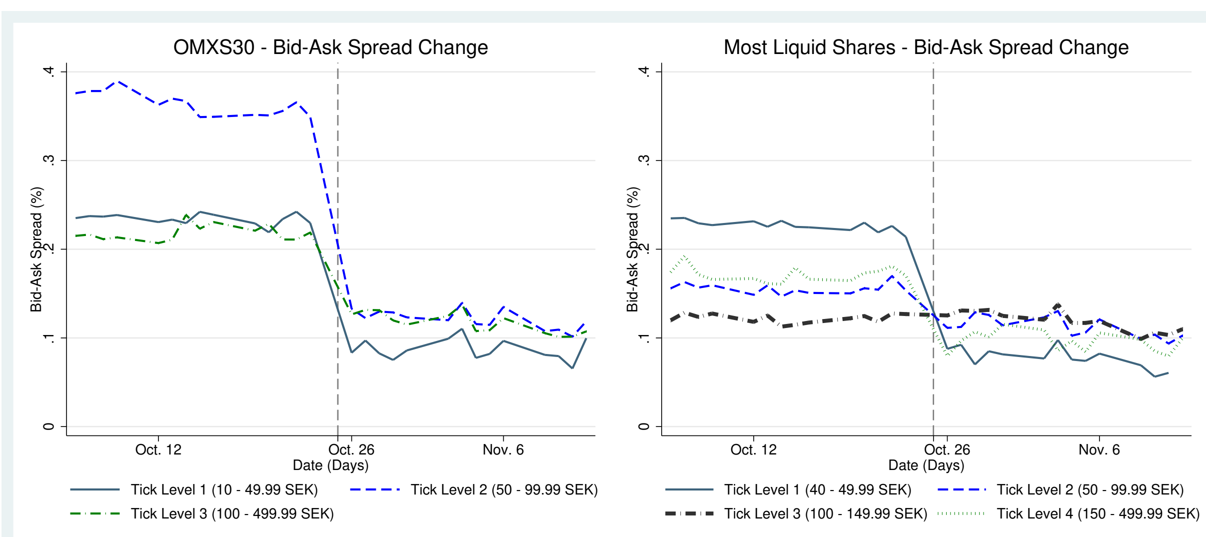

Figure 7: Stylized Illustration of the Tick Size Regime Change

This figure presents how the FESE tick size harmonization October 26th, 2009 impacted stocks. The left-hand side shows relative tick size (tick size / pre-event stock price) for all stocks prior the event and the right-hand side post event. Stocks falling below the threshold π (assumed to be the lowest relative tick size before the event) are predicted to face competing high-frequency traders. Stocks are split into three portfolios according to pre-event prices. Portfolio A are stocks with prices from 100SEK to 149.99SEK (blue-chip companies) and are not affected by the tick size change. Portfolio B contains stocks that have relative higher predicted relative tick sizes than those stocks in Portfolio C. HFTs trading Portfolio C face competition after the event.

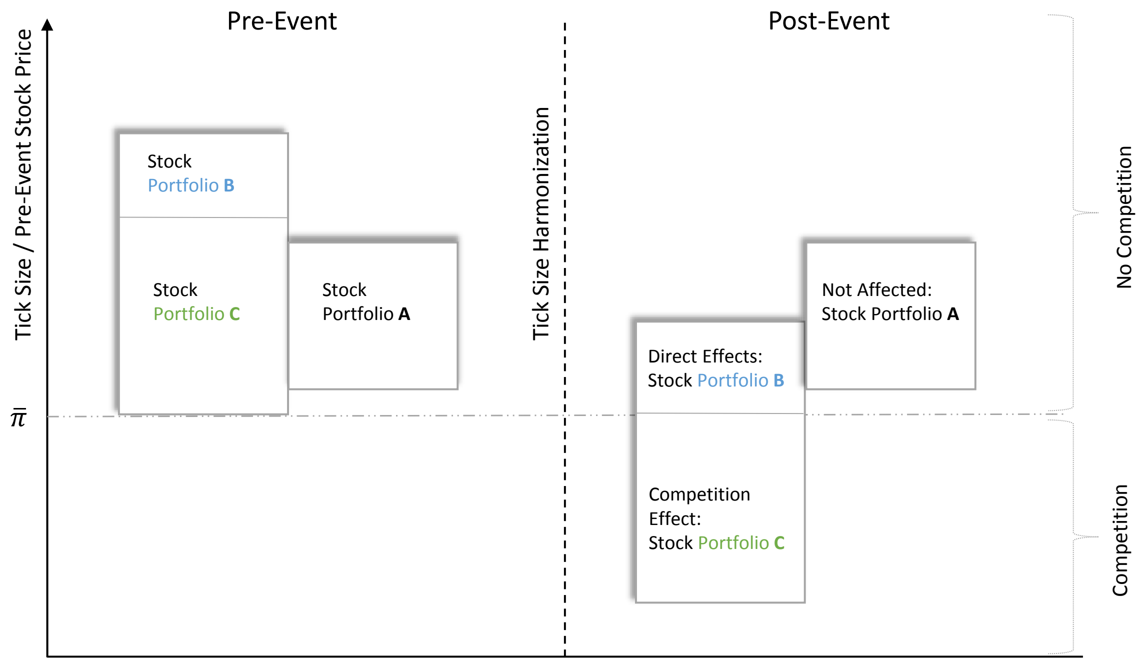

Figure 8: High-Frequency Trading Participation

This figure presents how high-frequency traders react on the FESE tick size harmonization October 26th, 2009 for the OMXS30 for three different groups of stocks. The control groups are those stocks that traded within a price range of 100SEK to 149.99SEK prior to the event were therefore not affected by the tick size regime change. The tick size effect (direct effect) is captured by those stocks without competing HFTs before and after the event. Finally, the figure shows how high-frequency trading participation changes for stocks that face competing HFTs after the event. The vertical axis depicts high-frequency trade participation, which measures how often a high-frequency trader participates in trading relative to all trades.

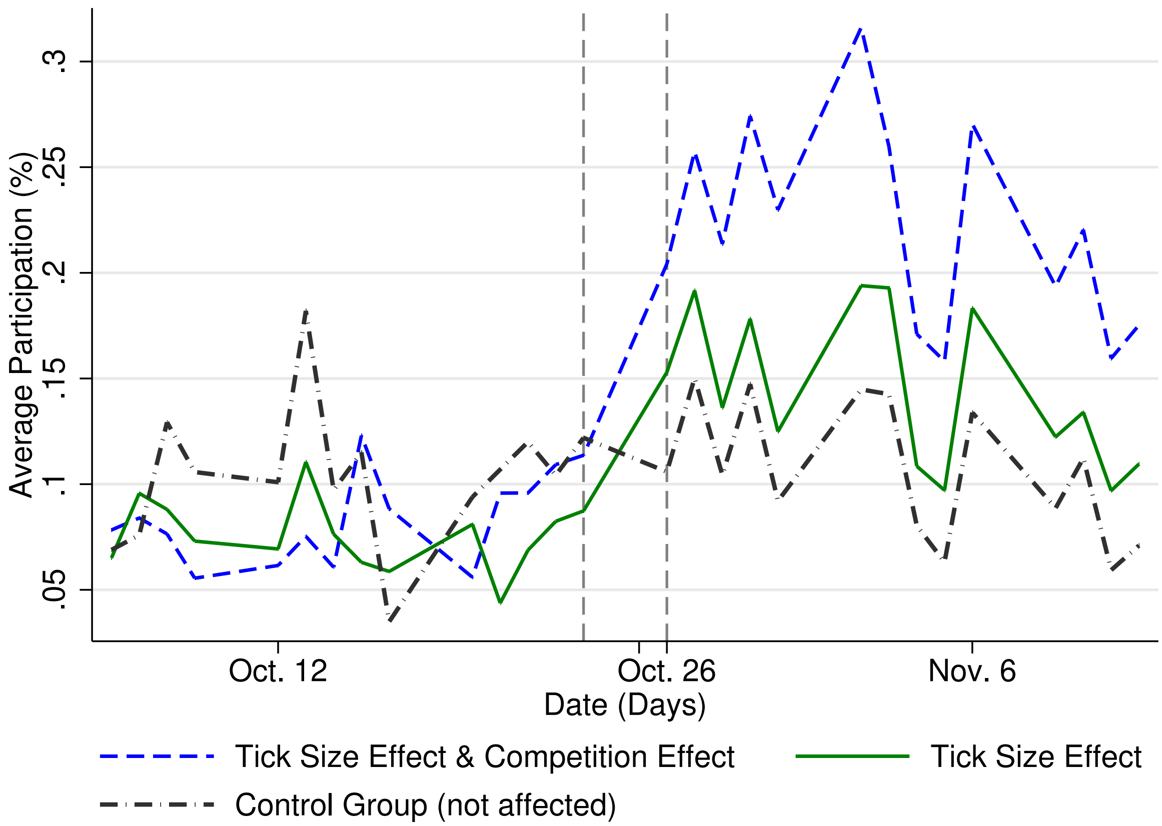

Figure 9: Midpoint and Spread Approximation

This figure pictures how our spread approximation and therefore our midpoint approximation performs against the actual benchmark. The graph shows for a random time sample for both a less liquid stock (Stock A) and a more liquid stock (Stock B), how close the actual spread and our approximation is. The vertical axis depicts relative bid-ask spreads.