Competition between High-Frequency Market Makers, and Market Quality *

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Abstract

High-frequency trading has been the subject of controversial discussions among legislators, regulators and investors alike, leading to calls for legislative and regulative intervention. The first entries of large international high-frequency traders into the Swedish equity market in 2009, using NASDAQ OMXS tick data, offers a unique chance to empirically examine how competition affects market quality. Competition among high-frequency market makers coincides (i) with an increase in intraday volatility of about 25%, but interestingly (ii) with no effect on interday volatility, (iii) with a decrease in order-execution time (length of time between an incoming market order or marketable limit order and the standing limit order against which the trade is executed) by about 20%, and (iv) with an increase in market share for high-frequency traders, but (v) with no significant effect on overall volume. We provide results for both entries and exits, and offer several potential explanations for this first empirical evidence on competition.

Keywords: competition, high-frequency trading, market maker, entry, exit

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

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1 INTRODUCTION

High-frequency traders (HFTs)[1] 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.[2] The sheer size of their share in today's daily volume in the equity markets (about 50% to 85%) demonstrates their importance in academic research and public discussion, in particular with the rise in calls for legislative and regulatory intervention.[3][4] While empirical research has focused on important concerns such as liquidity, price discovery or volatility effects of HFT, a clear identification of HFTs, enabling the study of the impact of high-frequency competition, has not been possible to date due to data limitations. This key concern of the potential effects of competition between HFTs has neither been approached empirically nor compared to existing empirical merits. Competition, however, potentially causes or influences the effects of HFT on markets, considering for instance that HFTs compete for the same trades. Does competition ultimately improve market quality and dynamics, and therefore benefit investors who use and rely upon financial markets? A comprehensive understanding of HFT competition is relevant to the efficient functioning of financial markets and appropriate regulatory action.

In this paper, we examine the effect of competition between HFTs, so as to assess its impact on market quality, using trade ticker-level NASDAQ OMXS data. The first entries of large international HFTs into the Swedish stock market in 2009 offers a unique chance to investigate changing intertemporal competition, as HFT competition varies among stocks and time. In particular, we conduct a difference-in-differences study (see section 3) to exploit the differences between monopolistic and duopolistic HFT within individual stocks in the NASDAQ OMXS 30, which is composed of Sweden's thirty largest companies. All HFTs are large international well-

[1]Henceforth, the abbreviation HFT will be used for "high-frequency trading" and "high-frequency trader", while HFTs will stand for "high-frequency traders".

[2]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.

[3]Through highly competitive and quick market platforms, the advantage of technologies such as co-location, and/or the use of ultra-quick algorithms, HFTs have changed and influenced financial markets substantially (Jain (2005)). The TABB Group, a leading financial market research and advisory company, finds the HFT share to be 73%, whereas Brogaard, Hendershott, and Riordan (2012) estimate it to be about 85% (see Table 1).

[4]These controversial views span topics such as price manipulation, speed of trading, systemic risk due to a high correlation of algorithmic strategies, price discovery and liquidity. The quality of liquidity that HFTs potentially provide is of particular concern, as HFTs have replaced traditional market makers.

established banks or hedge funds that are also significant players in the American equity market. We observe 228 entries and exits, measured by actual trades, for each individual stock and trader.[5] Contrary to previous literature, we can observe trader identities and therefore distinguish between different HFTs.[6] Our findings suggest unequivocally mixed results regarding market quality. First, intraday hourly volatility increases severely by an average of over 25%, five-minute volatility 15% and maximum intraday volatility about 15%. Interday volatility, both measured from opening to closing and closing to closing price, however, shows no sign of a significant increase or decrease. These results hold for both entries and exits, noting that, for the latter, the intraday volatility decreases. Second, order-execution time, defined as the length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed, decreases in its median by about 20%, which is also reflected in a significant reduction of its standard deviation. Finally, even though the HFTs' proportion of total volume increases and decreases significantly after entries and exits respectively, there is, unexpectedly, no significant effect on total volume and the turnover of stocks.

Granting these findings about competition and market quality, there are several plausible interpretations. First, competition increases intraday volatility since HFTs compete for the same trades. We find that HFTs in competition trade on the same side of the market in two-thirds of the cases (Figure 8) and have a correlation of 0.35 between their inventories. Second, HFTs trade more quickly and therefore significantly reduce the time for which limit orders wait to be executed. Third, there is no effect of competition on overall volume. While HFT volume indeed increases, as suggested by theory (Li (2013)), from an average of about 10% to 20%, there is likely to be a crowding out of other investors such as non-high-frequency market makers. Our findings of decreased order-execution time and the increased HFT volume could be related to a crowding out story of slow investors such as traditional market makers. These slower traders that are crowded out are likely to leave the market eventually.[7] Since HFT market making can respond more quickly

[5] Throughout the rest of the paper, when referring to entry or exit, we will use the terminology in the following sense: entry represents the change from HFT monopoly to HFT duopoly within a specific stock, and exit the change from HFT duopoly to HFT monopoly within a specific stock.

[6] 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 and has been the most comprehensive HFT database available to researchers in recent years.

[7] 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.

and potentially follow more sophisticated strategies, non-high-frequency market makers are likely to be less successful in placing their orders. While, in the monopoly case, HFTs can be very selective in the trades undertaken, possibly still leaving some room for slow traders, competition will decrease still further the chance of slow market makers being profitable. This will lead to less trading by these traders in the stock in question. Furthermore, while there are quite large effects on intraday volatility, there does not seem to be any on interday volatility. Both for opening to closing volatility and closing to closing volatility, there is no effect from competition. This is not ultimately surprising, however, considering the zero daily inventories of HFTs and their short investment horizons. Therefore, we can confirm the theory-based empirical prediction of increased volatility within a day, but not interdaily.[8]

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. Therefore, it is crucial to raise the issue of what drives the cross-stock variation in HFTs' market participation. There are several possible reasons why HFTs might enter and exit trading in a particular stock more than once (Table 1) over the sample period. The first could be that HFTs take down their trading algorithms to update them, to fix bugs, or to replace unprofitable codes. HFTs generally do their first trade within the first few minutes of each trading day, but might be absent for days at a time, or stop trading completely. Therefore, the second reason could be that HFTs start or stop participating in a specific stock because of a new trading strategy. Clearly, there are several possible alternatives that show that competition is not necessarily exogenous. It could be that the variables examined, namely volatility, market speed and volume, or some omitted variables in a particular stock, drive competition directly. We address this issue in several ways. To rule out time trends and cross-stock differences, we control for day-fixed effects and stock-fixed effects in all regressions. Controlling for the lags and leads of the variable in question ensures that no increase or decrease in prior or past competition is a driving factor in competition in the present. Also, other controls that might trigger competition are subsequently included in the regressions, but we find that they have no statistically significant effects on changes in the volatility, market speed or volume triggered through HFT competition. The relative evenly

[8]See, for example, Martinez and Rosu (2013) or Li (2013) for theoretical explanations of increased volatility.

distributed entries and exits over the sample period also suggest that there is no particular market reason for the HFTs' entries and exits regarding specific stocks. A placebo regression, where entries and exits are randomly within the sample period finds no effect on any of the variables of interest, giving us additional comfort that the effects of competition on market dynamics are non-spurious. Furthermore, the results do not seem to suffer from a selection issue as entries and exits seem to be fairly well distributed among stocks. The two exceptions do not drive or change any of the results. Excluding Scania AB, which accounts for about 10% for all entries and exits, only improves significance. Dropping Nokia Corporation and Lundin Petroleum AB, which serve exclusively as controls, has no statistically significant effect on the results. Another potential concern could be that the dependent variables of interest are significantly different across stocks before the first trade of the day. This, however, is not the case (Table 3). As there are no differences prior to the first trade, looking at daily measures would only underestimate the effects of competition. A final supporting argument for the validity of our identification is that HFTs cannot observe their opponents' identities.

There are a number of objections and limitations regarding our findings, some of which do curtail the validity of our conclusions. First, we only consider stock trades undertaken on the NASDAQ OMXS, which is the largest trading platform in Sweden and accounts for about 80% of total trading volume. Thus, we may be inaccurately assuming that there are no other active HFTs in the market.[9] Given the advanced access for algorithmic traders, this seems unlikely, but would, if anything, change the interpretation of our results in favor of increased competition. Second, we do not look at the orderbook in our investigation, and cannot draw any conclusions on other market microstructure measures, such as latency, cancelation rate, market depth etc. Even though these measures are important, we are interested in the actual realized market effect, for which the trade ticker database provides an excellent basis. Third, the Swedish stock market is efficient and mature, but by no means as large and liquid as the US market, which raises potential concerns about the importance of our findings. However, the HFTs in our sample are large international HFTs with a big market share in the American market.[10] Additionally, stocks listed

[9]Please see Appendix A for detailed information on this.

[10]HFTs list their activities and sometimes their market shares on their web pages. Due to a confidentiality agreement with NASDAQ OMXS, we unfortunately cannot reveal their names or exact number given that there are less than ten individual HFTs.

on the Swedish stock market and the OMX30 are comparable to liquid US stocks (comfortably comparable to the lower 50th percentile of the S&P 500.), but not to super-liquid stocks, which is where most HFT takes place in the American market. If anything, competition will lead to an underestimation of the effect of competition, as HFT activity increases with increased liquidity.

There is a developing theoretical literature that argues ambiguously about the benefits or disadvantages of HFT. While empirical work commonly provides evidence to support the view of increased market efficiency, or to show that it is not actually harmful, theoretical work suggests that there might be some other market impacts as well. In today's markets, HFTs both provide and take liquidity. Theoretical models, however, differ in their views. While Jovanovic and Menkveld (2012) and Gerig and Michayluk (2010) think of HFTs as liquidity providers, Martinez and Rosu (2013) and Foucault, Moinas, and Biais (2011) model HFTs as liquidity takers. Cvitanic and Kirilenko (2010) provide loosely related theoretical evidence by showing that markets with HFTs have thinner tails and more mass around the center of the distribution of transaction prices. Finally, Li (2013) emanates from Chau and Vayanos (2008) who model a monopolistic informed trader, and shows that HFT competition increases trading aggressiveness, efficiency and market depth, and contributes substantially to volume and variance. Empirical evidence is also scarce. Jovanovic and Menkveld (2012) show that HFTs react more quickly to new hard information, and are therefore less subject to adverse selection. Hendershott, Jones, and Menkveld (2011) investigate algorithmic trading, a broader classification than HFT, using the automation of quotes on the NYSE as an exogenous event, and find a positive effect on liquidity. Boehmer and Wu (2013) find similar evidence by exploiting co-location services across different countries. Brogaard, Hendershott, and Riordan (2012) and Hendershott and Riordan (2013) find that HFT benefits price discovery and efficiency. There is, however, less consensus about the impact on volatility, as Boehmer and Wu (2013) point out. Hasbrouck and Saar (2012) discover an amplified volatility effect due to runs on linked messages in the orderbook, while Kirilenko, Kyle, and Tuzun (2011) mention that HFTs may have exacerbated the flash crash in May 2010, but did not cause it.[11] Our findings are also closely related to Boehmer and Wu (2013), who document an increased short-term volatility as a result of algorithmic trading. Hirschey (2011) uncovers differences

[11] 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.

among HFTs based on a study of anticipatory trading (NASDAQ equity data). Baron, Brogaard, and Kirilenko (2012) find that HFTs earn large and stable profits, while Clark-Joseph (2012) 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. An attempt to distinguish between liquidity providers (or HFT market makers), and liquidity takers (or aggressive HFTs) is made by Hagstrmer and Norden (2012). While Biais and Woolley (2011) provide a comprehensive overview of the good and bad effects of HFT, the crucial question of how competition among HFTs affects market quality has been left untouched, empirically.

The rest of the paper proceeds as follows. In section 2 we depict strategies and provide descriptive findings on high-frequency market making. Section 3 describes our methodology, used to exploit cross-sectional variations between stocks. Section 4 describes our NASDAQ OMXS data, before we give a comprehensive overview of our findings in section 5. We conclude in section 6.

2 High-Frequency Traders

In this section we present and discuss some statistics on high-frequency market makers.

2.1 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, bringing 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, that 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. The new HFTs, however, are not easily categorized or regulated.

This issue has come to the attention of the Securities Exchange Commission (SEC), which views its mandate as acting on behalf of companies trying to raise capital for long-term projects, and investors with long horizons. Market makers or day traders only have legitimacy if they contribute to long-term investors' interests. 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.

The first HFTs to enter the Swedish market are difficult to categorize in a strict sense. We believe that all have a directional market-making component, but differ in their aggressiveness.

Figure 7 depicts the average intraday inventory over all stocks and days for five minute bins. Inventory is defined as the cumulative turnover divided by total turnover within each five-minute bucket. While the left-hand graph views average inventory over all days and stocks with a monopolistic HFT, the right-hand graph shows inventories under a situation of competition, for both the incumbent and the entrant. Trading takes place from 9am to 5:30pm.

[Insert Figure 7 about here!]

Figure 8 shows the average intraday fractions of trades that were executed on the same side of the market (over all stocks and days), for five-minute and sixty-minute bins under competition. Trades are executed on the same side of the market if, within each bin, both the entrant and the incumbent buy, or both sell. The measure is constructed by assigning the value one if both HFTs trade on the same side of the market, and zero otherwise. The average ratio of trading on the same side of the market as one's competitor is 2/3. The darkly shaded bars are hourly averages.

[Insert Figure 8 about here!]

From the above graphs, we can conclude that, in the pre-closing period, HFTs seem to trade exclusively on the same side of the market. Figure 9 depicts pre-closing trading activity. Pre-closing takes place from 5:20 to 5:30 and determines the closing price by maximizing the tradable volume. Timestamps within the closing period reflect the order time and not the actual transaction time. Average turnover per trade, average total stock turnover and average HFT turnover are shown.

[Insert Figure 9 about here!]

Figure **??** shows the average percentage realized trading cost per share. We calculate the realized cost for each trade as $RealizedCost = 100 * \frac{P_t - M_t}{P_t}$ for marketable buy orders, and $RealizedCost = 100 * \frac{M_t - P_t}{P_t}$ for marketable sell orders, with P_t the transaction price and M_t the prevailing midpoint for 1sec, 2sec, ..., 300sec. The plot shows realized costs for both non-high-frequency trades and high-frequency trades.

[Insert Figure **??** about here!]

3 METHODOLOGY

We aim to compare measures of market quality such as intraday and interday volatility, volume and liquidity under situations of HFT monopoly and HFT duopoly.[12] The first entries of large international HFTs into the Swedish equity market offer us a unique chance to empirically examine how competition affects market qualityby exploiting cross-sectional differences among stocks. Entries into and exits from trading in one specific stock (Table 1) are consistent with the difference-in-differences tests outlined by Bertrand, Duflo, and Mullainathan (2004). This approach permits us to interpret our findings as evidence of the causal effect of competition on market dynamics. Having in mind the limitations outlined earlier, we treat competition as exogenous to the dependent variables examined.

This difference-in-differences test setting allows for multiple time periods and multiple treatment groups, and is summarized in the following equation:

$$y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}, \tag{1}$$

with i indexing entry (the change from HFT monopoly to HFT duopoly or vice versa, or both), s being the security and t the time. d_{is} is an indicator of whether an HFT entry affected security s at time t. p_t are daily time-fixed effects and m_g are security-fixed effects. X_{ist} is the vector of

[12] For a detailed description of our data, see section 4.

covariates and u_{ist} is the error term. The dependent variable is y_{ist}.

In all of the above tests, we rely on the use of entries and exits by HFTs relating to a specific stock, as the measure of competition. We denote entry as the case where there is one additional HFT trading in a specific stock at a specific time (change from monopoly to duopoly) and exit as the case where one HFT trading in a specific stock at a specific time stops trading (a change from duopoly to monopoly). Note that there can be multiple entries and exits over time by the same HFT for the same stock (HFT-fixed effects are included in our analysis). For this changing intertemporal competition across stocks and time, we provide results for both entries and exits, but also entry and exit together. However, these difference-in-differences estimations, with entries and exits summed to a single event (standardized on the entry, i.e. exits were relabeled; one could think of this as reverse entries), do not allow for controls such as lags and leads. If there was an entry into one stock and an exit from another around the same date, it would not be clear to which event we should assign the control group, and would therefore only create spurious effects.

We also use an alternative way of measuring competition, the Herfindahl index, which shows very similar but more significant results (will be available in the online appendix).

4 DATA

The tick trading data comes from NASDAQ OMX Nordic and incorporates 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. As a second data source for our daily measures such as volatility, we rely on COMPUSTAT GLOBAL. As a final source, we use daily relative time-weighted order execution spreads, provided by NASDAQ.

The key distinction of this database 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. Large HFTs will naturally execute their trades taking advantage of the cheapest and fastest means of access, the algorithmic trading accounts. For non-proprietary trading, identities are not precise and might be aggregated. The numbers of identities observed for these traders should therefore be understood as the minimum number of traders; there are about 500 algorithmic trader identities, but the actual number is assumed to be much larger. While the large HFTs, which we label to be high-frequency market makers, are few (less than ten)[13], with all having about a 10% market share both with and without competition, other traders that execute through algorithmic accounts are many and small (the next biggest trader accounts for, at most, 0.5% of trading volume).

We attempt to provide a comprehensive overview of the sample data by showing summary statistics from three different angles: by stock, by HFT, and by treatment/control group.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 an average of 1247 and 6103 across all stocks. The average relative order execution spread in our sample is between 0.09% and 0.24%. Column 3 shows how often a specific stock occurs as a control, column 4 gives the number of changes from HFT monopoly to HFT duopoly, and column 5 the number of changes from HFT duopoly to HFT monopoly. Events and controls are fairly well distributed among the securities, with two exceptions. Excluding Scania AB, which accounts for about 10% of all entries and exits, improves the significance of our results. Dropping Nokia Corporation and Lundin Petroleum AB, which serve exclusively as controls, has no statistically significant effect on the results. The number of unique trading days considered for each stock, before and after entry or exit, is shown in column 6.

[Insert Table 1 about here!]

Table 2 shows summary statistics for the two most different HFTs in the market, HFT A and HFT B. Statistics are reported for the daily fraction of HFT trades in the entire market, the absolute number of daily HFT trades, the fraction of total daily volume, the fraction of daily HFT trades among all algorithmic trades executed, the fraction of aggressive trades (the aggressive side of the trade is an incoming market order or marketable limit order that is executed against

[13] We cannot release either names or numbers due to confidentiality agreements with NASDAQ OMXN. We show, however, summary statistics for the two most different HFTs in Table 2.

a standing limit order), and aggressiveness imbalance, constructed as the difference between aggressive buy transactions and aggressive sell transaction. Descriptive statistics on the timing and impact of the trades are also listed. Statistics are provided for the fraction of HFT trades that involved a price change, HFT buy and sell transactions that involve a price decrease, HFT buy and sell transactions that lead to a price increase, HFT buy and sell trades that are executed before a price increase, and HFT buy and sell trades that are executed before a price decrease (last trade at a specific price level in the orderbook is executed by an HFT). Algorithmic trades are trades that are executed through an algorithmic trading account. This is the cheapest and fastest way to trade on the NASDAQ OMXS. Volume is the number of securities traded. All statistics are based on daily observations for three days prio and three days after the event (for both treatment and control group).

The only blatant difference is in aggressiveness. While HFT A executed 91% of its trades aggressively, for HFT B the figue is just 35%. Statistics on the actual trades show that there is only a minor difference in how often a trade initiates a price change. HFT A, the more aggressive trader, initiates a price change in 10% of its trades, while HFT B initiates a price change in about 20% of the cases, both with a fairly large standard deviation. We do believe that aggressiveness is not as informative as the literature seems to imply. Aggressiveness, often associated as an identifying characteristic of HFT, is rather misleading as it might simply reflect different ways of executing trades with a similar strategy.[14] HFTs with a high level of aggressiveness might be following a "snake strategy", which means that the algorithm places quickly marketable orders when any anomalies, such as deviations from trends, are observed. In contrast, low aggressiveness might appear when a trader follows a strategy in which it follows the market, in placing and canceling orders; it will appear less aggressive as the executed trades are limit orders. Table 2 shows detailed characteristics for the two most different HFTs in terms of aggressiveness in the sample, HFT A and B.

Trade timestamps and message timestamps are in milliseconds and ranked within each millisecond.

[14] The aggressive side of the trade is an incoming market order or marketable limit order that is executed against a standing limit order.

[Insert Table 2 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. Panel A shows statistics for entries (the change from HFT monopoly to HFT duopoly) and Panel B for exits (the change from HFT duopoly to HFT monopoly). Order-execution time is the amount of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed. The hourly and five-minute volatilities are calculated from hourly and five-minute intraday returns (given in squared percentages). Max-Min, Open-Close and Close-Close volatilities are calculated as squared percentages, that is, the percentage difference squared. Max-Min is the squared difference between the maximum price in a day and the minimum price. Open-Close is the squared difference between the opening price and the closing price on a given day. Close-Close is the inter-day volatility and is calculated as the squared difference between the previous day's closing price and today's closing price. Further, the table shows the number of securities traded (volume), the absolute number of daily HFT trades, the fraction of daily HFT trades out of all algorithmic trades executed, and the daily relative time-weighted spread. There is no significant difference between the control and treatment groups, which should not come as a surprise given that the same stocks serve as observations in both the control and the treatment group in relation to different stocks and different days. We isolate quite visible effects on order-execution time and volatility after entry or exit in descriptive statistics the regressions.

[Insert Table 3 about here!]

5 EMPIRICAL RESULTS

Table 4 displays the estimated coefficients from our entry difference-in-differences tests of hourly volatility computed from hourly intraday returns (column 1-4), five-minute volatility based on five-minute intraday returns (column 5), Max-Min (column 6), Open-Close volatility (column 7) and Close-Close volatility (column 8). Besides the level variables (indicator for the treated security and time-fixed effects), we use stock-fixed effect, volume, order execution time and lagged variables as additional controls. Standard errors are clustered at the stock level and reported in parentheses. Our findings suggest unequivocally ambiguous results on market quality. Intraday hourly volatility increases severely by an average of over 20% and five-minute volatility by an average of nearly 20%. Interdaily (both Open-Close and Close-Close), however, shows no sign of any increase or decrease. These results hold for both entries and exits, noting that, for the latter, the intraday volatility decreases (Table 5). We also provide results considering both entries and exits as one event (one can think of exits as reverse entries) in Table 6.

[Insert Tables 4, 5, 6 about here!]

Table 7 displays the estimated coefficients from our entry difference-in-differences tests of order execution time (columns 1-4) and the order-execution time's daily standard deviation (column 5). Besides the level variables (indicator for the treated security and time-fixed effects), we use stock-fixed effect, volume, volatility (computed as intraday volatility of hourly returns) and lagged variables as controls. Standard errors are clustered at the stock level and reported in parentheses. The order-execution time decreases on average by about 20%, which is also reflected in a significant reduction in its standard deviation. Surprisingly, there is no significant positive effect for exits (Table 8), only a marginally significant increase in its standard deviation. Table 9 combines entries and exits and shows marginally significant estimates.

[Insert Tables 7, 8, 9 about here!]

Table 10 displays the estimated coefficients from our entry difference-in-differences tests of volume, measured as the number of securities traded (column 1-4), and the fraction of daily HFT volume (column 5). Besides the level variables (indicator for the treated security and time-fixed effects), we use the stock-fixed effect, order execution time, volatility (computed as intraday volatility of hourly returns) and lagged variables as controls. Standard errors are clustered at the stock level and reported in parentheses. Even though the HFTs' proportion of total volume increases or decreases significantly after entries or exits respectively, there is, unexpectedly, no effect on total volume. We treat this as an indication that there is a crowding-out effect, as we outlined earlier in the paper.

[Insert Tables 10, 11, 12 about here!]

6 CONCLUSION

High-frequency traders (HFTs) play a role of critical importance for the financial markets. We find that competition among HFTs coincides with a stark increase in intraday volatility, but interestingly has no effect on interday volatility. We also find a decrease in order-execution time (the difference between an incoming market order or marketable limit order and the standing limit order against which the trade is executed) and an increase in the market share of HFTs, although with no effect on overall volume. We make an attempt to draw causal conclusions by exploiting the cross-sectional variations in stocks and conducting difference-in-differences tests. This paper provides results for both entries and exits (understood as (daily) changes from monopoly to duopoly and vice versa), and offers several explanations in favor of our findings. To briefly sum up the discussion, HFT competition has a stark impact on short-term volatility, as HFTs compete for the same prices. Their investment horizon, however, is short and therefore there is no effect on long-term volatility. There is a decrease in order-execution time, which reflects that HFT market making responds more quickly and potentially follows a more sophisticated strategy, thereby increasing market quality. The decrease in order-execution time, increase in the HFT market ratio, and the seemingly steady volume suggest a crowding out of slower investors, potentially other market makers, which become unsuccessful in placing their orders.

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 and influenced 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 intensive discussion by 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 and give new insights into how HFTs affect markets.

Calls for more regulatory action in the HFT industry may merit a new perspective given these new findings about the effects of competition between HFTs.

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A INSTITUIONAL AND MARKET BACKGROUND

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

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

To access the market, financial intermediaries have four different possibilities. (i) A broker account, which is mostly used by institutional investors or non-automated trading. (ii) An order routing account that allows customers of the exchange member intermediary to rout 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 algorithmic trading account which is the quickest and the cheapest in terms of transaction costs and thus a natural choice for high-frequency traders.

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

An important detail about 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 must be at least 50,000EUR. This, however, increases with turnover and reaches for example for one million euro a minimum order size of 250,000EUR. As a result, HFTs have no incentive to hide their orders.

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 a high-frequency market maker. 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 high-frequency trading (HFT) monopoly to HFT duopoly and column five the changes from HFT duopoly to HFT monopoly. 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 HFT trades in the entire market, the absolute number of daily HFT trades, the fraction of total daily volume, the fraction of daily HFT trades among all algorithmic trades executed, the fraction of aggressive trades (the aggressive side of the trade is an incoming market order or marketable limit order that is executed against a standing limit order), and aggressiveness imbalance, constructed as the difference between aggressive buy transactions and aggressive sell transaction. Descriptive statistics on the timing and impact of the trades are also listed. Statistics are provided for the fraction of HFT trades that involve a price change, HFT buy and sell transactions that involve a price decrease, HFT by and sell transactions that lead to a price increase, HFT buy and sell trades that are executed before a price increase, and HFT buy and sell trades that are executed before a price decrease (last trade on a specific price level in the orderbook is executed by an HFT). Algorithmic trades are trades that are executed through an algorithmic trading account. This is the cheapest and fastest way to trade on the NASDAQ OMX. Volume is the number of securities traded. All statistics are based on daily observations for three days prior and after the event (for both treatment and control group).

	High-Frequency Trader A			High-Frequency Trader B		
	Mean	Median	SD	Mean	Median	SD
HFT Trades / Total Trades	0.1001	0.0832	0.0639	0.0956	0.0757	0.0749
HFT Trades (per Day and Stock)	279	193	258	266	190	229
HFT Volume / Total Volume	0.1033	0.0829	0.0729	0.0549	0.0379	0.0494
Closing Inventory (fraction)	0.0019	0.0000	0.0910	0.0024	0.0000	0.1090
HFT Trades / Algorithmic Trades	0.3020	0.2799	0.1528	0.2592	0.2349	0.1575
Aggressive Trades (fraction)	0.9106	0.9836	0.2345	0.3459	0.2672	0.2123
Aggressiveness Imbalance	-0.0271	-0.0243	0.1538	-0.0036	0.0000	0.1295
Trades Initiate a Price Changes (fraction)	0.0956	0.0710	0.0815	0.2169	0.2018	0.1687
Buy Trades Initiate a Price Decrease (fraction)	0.0117	0.0085	0.0139	0.0625	0.0455	0.0846
Sell Trades Initiate a Price Decrease (fraction)	0.0337	0.0226	0.0350	0.0427	0.0308	0.0379
Sell Trades Initiate a Price Increase (fraction)	0.0127	0.0096	0.0143	0.0697	0.0485	0.0897
Buy Trades Initiate a Price Increase (fraction)	0.0305	0.0201	0.0320	0.0380	0.0291	0.0343
Buy Trades Before a Price Decrease (fraction)	0.0402	0.0361	0.0267	0.0471	0.0394	0.0320
Sell Trades Before a Price Decrease (fraction)	0.0634	0.0584	0.0365	0.0558	0.0510	0.0336
Sell Trades Before a Price Increase (fraction)	0.0450	0.0403	0.0300	0.0506	0.0432	0.0351
Buy Trades Before a Price Increase (fraction)	0.0631	0.0588	0.0353	0.0525	0.0460	0.0330

Table 3: Summary Statistics of the Control and Treatment Group

This table lists descriptive statistics for all stocks and days that serve as the control group and for all stocks an days in the treatment group. Panel A shows statistics for entries (the change from HFT monopoly to HFT duopoly) and Panel B for exits (the change from HFT duopoly to HFT monopoly). Order-execution time is the amount of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which that the trade is executed. The hourly and five-minute volatilities are calculated from hourly and five-minute intraday returns. The Max-Min, Open-Close and Close-Close volatilities are calculated as the sum of squared percentage changes. Max-Min is the squared change between the maximum price within a day and the minimum price. Open-Close shows the squared change between the opening price and the closing price of the day. Close-Close is the inter-day volatility and calculated from the squared change between the previous day's closing price and today's closing price. Further, the table shows the number of securities traded (volume), the absolute number of daily HFT trades, the fraction of daily HFT trades out of algorithmic trades executed, and the daily relative time-weighted bid-ask spread. Algorithmic trades are trades that are executed through an algorithmic trading account. This is the cheapest and fastest way to trade on the NASDAQ OMX. All statistics are based on daily observations.

Panel A: Entry	Control Group				Treatment Group Before Entry			
	Obs	Mean	Median	SD	Obs	Mean	Median	SD
Order-Execution Time (sec)	1408	73.401	57.259	60.555	251	60.549	53.000	58.165
5min Vola	1408	0.050	0.042	0.033	251	0.042	0.031	0.033
60min Vola	1408	0.389	0.224	0.521	249	0.281	0.196	0.311
Max-Min Change Squared	1358	7.302	5.206	7.208	251	7.017	4.751	6.558
Open-Close Change Squared	1408	2.614	0.941	4.780	251	3.245	1.118	4.887
Close-Close Change Squared	1359	3.479	1.254	7.204	251	3.946	1.756	6.209
Volume (in 1000)	1408	3821	2182	4344	251	4395	2046	6262
HFT Volume (%)	1408	0.100	0.082	0.069	251	0.085	0.061	0.072
Trades (#)	1408	2635	2264	1488	251	3104	2625	2041
Algorithmic Trades (#)	1408	813	698	475	251	1021	866	639
HFT of Algorithmic (%)	1408	0.323	0.302	0.162	251	0.327	0.312	0.137
Bid-Ask Spread (SEK)	1408	0.161	0.143	0.066	251	0.127	0.101	0.074

Panel B: Exit	Control Group				Treatment Group After Exit			
	Obs	Mean	Median	SD	Obs	Mean	Median	SD
Order-Execution Time (sec)	1274	65.778	52.254	54.409	187	52.104	42.000	57.016
5min Vola	1274	0.049	0.043	0.032	187	0.037	0.029	0.031
60min Vola	1264	0.376	0.224	0.479	186	0.296	0.185	0.310
Max-Min Change Squared	1225	7.552	5.285	7.084	187	6.220	3.974	6.194
Open-Close Change Squared	1274	2.682	1.003	4.451	187	2.760	0.813	4.518
Close-Close Change Squared	1225	3.306	1.208	5.675	187	3.884	1.625	6.679
Volume (in 1000)	1274	3856	2209	4561	187	4669	2185	5789
HFT Volume (%)	1274	0.104	0.084	0.073	187	0.090	0.067	0.068
Trades (#)	1274	2694	2309	1499	187	3301	2766	2151
Algorithmic Trades (#)	1274	858	748	465	187	1119	929	763
HFT of Algorithmic (%)	1274	0.325	0.310	0.152	187	0.351	0.337	0.137
Bid-Ask Spread (SEK)	1274	0.153	0.140	0.063	187	0.109	0.096	0.059

Table 4: Competition Effects of HFT Entry: Intra- and Inter-Day Volatilities

This table displays estimated coefficients of the following regression: $y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}$, which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly), s being the security and t the time. d_{is} is an indicator if an HFT entry affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is 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 (indicator for the treated security and time fixed effects), are stock fixed effect, volume, median order-execution time (length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed). Standard errors are clustered at the stock level and reported in parentheses.

VARIABLES	(1) Hourly Vola	(2) Hourly Vola	(3) Hourly Vola	(4) Hourly Vola	(5) 5 Minutes Vola	(6) Max-Min Vola	(7) Intraday Vola	(8) Daily Vola
HFT Entry	0.289***	0.290***	0.280***	0.267**	0.150***	0.151**	0.088	-0.123
	(0.090)	(0.089)	(0.086)	(0.104)	(0.053)	(0.073)	(0.216)	(0.150)
Treatment Dummy	-0.091	-0.095	-0.087	-0.091	0.004	0.046	0.251	0.405*
	(0.078)	(0.075)	(0.073)	(0.081)	(0.033)	(0.063)	(0.169)	(0.224)
Log Turnover(t)		0.641***	0.547***	0.546***	0.254***	0.770***	1.215***	1.177***
		(0.075)	(0.090)	(0.090)	(0.052)	(0.059)	(0.112)	(0.164)
Log Order-Execution Time(t)			-0.145**	-0.146**	0.087**	-0.082*	0.053	-0.099
			(0.060)	(0.059)	(0.036)	(0.045)	(0.118)	(0.124)
Observations	1,882	1,882	1,882	1,882	1,905	1,855	1,834	1,804
R-squared	0.3971	0.4316	0.4343	0.4343	0.7515	0.6319	0.3443	0.3448
-	-	-	-	-	-	-	-	-
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	NO	NO	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

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

Table 5: Competition Effects of HFT Exit: Intra- and Inter-Day Volatilities

This table displays estimated coefficients of the following regression: $y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}$, which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly), s being the security and t the time. d_{is} is an indicator if an HFT entry affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is 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 (indicator for the treated security and time fixed effects), are stock fixed effect, volume, median order-execution time (length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed). Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Hourly Vola	Hourly Vola	Hourly Vola	Hourly Vola	5 Minutes Vola	Max-Min Vola	Intraday Vola	Daily Vola
HFT Exit	-0.239**	-0.273**	-0.269**	-0.254**	-0.149**	-0.139**	-0.091	-0.002
	(0.114)	(0.104)	(0.103)	(0.112)	(0.070)	(0.059)	(0.242)	(0.170)
Treatment Dummy	0.298***	0.300***	0.276***	0.270***	0.124	0.156**	-0.042	0.294*
	(0.102)	(0.092)	(0.089)	(0.092)	(0.077)	(0.073)	(0.207)	(0.171)
Log Turnover(t)		0.577***	0.473***	0.475***	0.227***	0.743***	1.230***	1.211***
		(0.070)	(0.090)	(0.090)	(0.054)	(0.052)	(0.115)	(0.155)
Log Order-Execution Time(t)			-0.166**	-0.164**	0.062	-0.092*	-0.011	-0.114
			(0.062)	(0.062)	(0.038)	(0.045)	(0.106)	(0.122)
Observations	1,630	1,630	1,630	1,630	1,650	1,601	1,596	1,562
R-squared	0.4049	0.4337	0.4372	0.4372	0.7647	0.6398	0.3354	0.3243
-	-	-	-	-	-	-	-	-
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	NO	NO	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Competition Effects of HFT Entry and Exit: Intra- and Inter-Day Volatilities

This table displays estimated coefficients of the following regression: $y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}$, which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly), s being the security and t the time. d_{is} is an indicator if an HFT entry affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is 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 (indicator for the treated security and time fixed effects), are stock fixed effect, volume, median order-execution time (length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed). Standard errors are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Hourly Vola	Hourly Vola	Hourly Vola	Hourly Vola	5 Minutes Vola	Max-Min Vola	Open-Close Vola	Close-Close Vola
HFT Entry or Exit x Date (Dummy)	0.246***	0.256***	0.250***	0.275***	0.142**	0.149**	0.095	-0.030
	(0.082)	(0.075)	(0.073)	(0.091)	(0.053)	(0.060)	(0.204)	(0.130)
Treatment (Dummy)	-0.111	-0.144**	-0.140**	-0.134*	0.016	0.043	0.200	0.373
	(0.082)	(0.069)	(0.067)	(0.070)	(0.034)	(0.063)	(0.176)	(0.227)
Entry or Exit	0.148*	0.160**	0.147*	0.150*	-0.018	-0.023	-0.248***	0.006
	(0.082)	(0.076)	(0.075)	(0.075)	(0.034)	(0.064)	(0.082)	(0.137)
Log Turnover(t)		0.621***	0.544***	0.544***	0.247***	0.771***	1.260***	1.201***
		(0.068)	(0.085)	(0.085)	(0.052)	(0.055)	(0.104)	(0.160)
Log Order-Execution Time(t)			-0.124**	-0.122**	0.094**	-0.068	0.095	-0.030
			(0.058)	(0.057)	(0.038)	(0.044)	(0.096)	(0.119)
Passive Traders ($\triangleright$ 50%)				-0.036	-0.106*	-0.111	-0.209	-0.206
				(0.083)	(0.059)	(0.079)	(0.220)	(0.189)
Observations	2,119	2,119	2,119	2,119	2,145	2,095	2,064	2,039
R-squared	0.3988	0.4314	0.4334	0.4335	0.7555	0.6304	0.3330	0.3255
-	-	-	-	-	-	-	-	-
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
HFT FE	NO	NO	NO	YES	YES	YES	YES	YES
-	-	-	-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Competition Effects of HFT Entry: Order-execution Time

This table displays estimated coefficients of the following regression: $y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}$, which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly), s being the security and t the time. d_{is} is an indicator if an HFT entry affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is log order-execution time measured by the median length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed (column 1-4) and the log order-execution time daily standard deviation (column 5). 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 are clustered at the stock level and reported in parentheses.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Order-Execution Time	Order-Execution Time	Order-Execution Time	Order-Execution Time	Order-Execution Time (SD)
HFT Entry	-0.128**	-0.124***	-0.102**	-0.188***	-0.075
	(0.049)	(0.042)	(0.041)	(0.056)	(0.048)
Treatment Dummy	0.082	0.087	0.084	0.047	0.043
	(0.061)	(0.056)	(0.055)	(0.061)	(0.032)
Log Turnover(t)		-0.677***	-0.642***	-0.643***	-0.161***
		(0.041)	(0.042)	(0.042)	(0.026)
Log Volatility(t)			-0.049***	-0.049***	0.040***
			(0.010)	(0.009)	(0.010)
Observations	1,905	1,905	1,882	1,882	1,882
R-squared	0.5938	0.6939	0.6956	0.6968	0.3637
-	-	-	-	-	-
Stock FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
HFT FE	NO	NO	NO	YES	YES
-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Competition Effects of HFT Exit: Order-execution Time

This table displays estimated coefficients of the following regression: $y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}$, which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly), s being the security and t the time. d_{is} is an indicator if an HFT entry affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is log order-execution time measured by the median length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed (column 1-4) and the log order-execution time daily standard deviation (column 5). 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 are clustered at the stock level and reported in parentheses.

VARIABLES	(1) Order-Execution Time	(2) Order-Execution Time	(3) Order-Execution Time	(4) Order-Execution Time	(5) Order-Execution Time (SD)
HFT Exit	0.022	0.062	0.040	0.202***	0.060
	(0.048)	(0.043)	(0.043)	(0.054)	(0.040)
Treatment Dummy	-0.185**	-0.196**	-0.174**	-0.395***	-0.068**
	(0.088)	(0.074)	(0.075)	(0.082)	(0.030)
Log Turnover(t)		-0.668***	-0.634***	-0.635***	-0.158***
		(0.047)	(0.047)	(0.046)	(0.026)
Log Volatility(t)			-0.050***	-0.049***	0.018*
			(0.011)	(0.011)	(0.009)
Observations	1,650	1,650	1,630	1,630	1,630
R-squared	0.5830	0.6826	0.6844	0.6891	0.4727
-	-	-	-	-	-
Stock FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
HFT FE	NO	NO	NO	YES	YES
-	-	-	-	-	-
Cluster Stock	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Competition Effects of HFT Entry and Exit: Order-execution Time

This table displays estimated coefficients of the following regression: $y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}$, which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly), s being the security and t the time. d_{is} is an indicator if an HFT entry affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is log order-execution time measured by the median length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed (column 1-4) and the log order-execution time daily standard deviation (column 5). 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 are clustered at the stock level and reported in parentheses.

VARIABLES	(1) Order-Execution Time	(2) Order-Execution Time	(3) Order-Execution Time	(4) Order-Execution Time
HFT Entry or Exit x Date (Dummy)	-0.098*	-0.102**	-0.085*	-0.200**
	(0.049)	(0.043)	(0.043)	(0.076)
Treatment (Dummy)	0.041	0.086	0.083	-0.008
	(0.066)	(0.060)	(0.060)	(0.061)
Entry or Exit	-0.126*	-0.155***	-0.153***	-0.116**
	(0.065)	(0.054)	(0.053)	(0.052)
Log Turnover(t)		-0.675***	-0.643***	-0.609***
		(0.041)	(0.042)	(0.048)
Log Volatility(t)			-0.042***	-0.028**
			(0.010)	(0.011)
Passive Traders ($\triangleright$ 50%)				0.232**
				(0.106)
Observations	2,145	2,145	2,119	2,119
R-squared	0.5835	0.6815	0.6825	0.7269
-	-	-	-	-
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
HFT FE	NO	NO	NO	YES
-	-	-	-	-
Cluster Stock	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Competition Effects of HFT Entry: Trading Volume

This table displays estimated coefficients of the following regression: $y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}$, which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly), s being the security and t the time. d_{is} is an indicator if an HFT entry affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is log volume measured as daily turnover (column 1-4) and the fraction of daily HFT volume (column 5). Additional controls, besides the level variables (indicator for the treated security and time fixed effects), are stock fixed effect, order-execution time (length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed) volatility (computed as intraday volatility of hourly returns). Standard errors are clustered at the stock level and reported in parentheses.

VARIABLES	(1) Daily Volume	(2) Daily Volume	(3) Daily Volume	(4) Daily HFT Volume
HFT Entry	-0.005	-0.040	-0.012	0.078***
	(0.034)	(0.029)	(0.034)	(0.011)
Treatment Dummy	0.007	0.028	0.012	0.002
	(0.038)	(0.034)	(0.033)	(0.006)
Log Order-Execution Time(t)		-0.319***	-0.321***	-0.026***
		(0.031)	(0.032)	(0.004)
Log Volatility(t)		0.061***	0.061***	-0.004***
		(0.012)	(0.012)	(0.001)
Observations	1,905	1,882	1,882	1,882
R-squared	0.8420	0.8803	0.8805	0.6438
-	-	-	-	-
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
HFT FE	NO	NO	YES	YES
-	-	-	-	-
Cluster Stock	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Competition Effects of HFT Exit: Trading Volume

This table displays estimated coefficients of the following regression: $y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}$, which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly), s being the security and t the time. d_{is} is an indicator if an HFT entry affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is log volume measured as daily turnover (column 1-4) and the fraction of daily HFT volume (column 5). Additional controls, besides the level variables (indicator for the treated security and time fixed effects), are stock fixed effect, order-execution time (length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed) volatility (computed as intraday volatility of hourly returns). Standard errors are clustered at the stock level and reported in parentheses.

VARIABLES	(1) Daily Volume	(2) Daily Volume	(3) Daily Volume	(4) Daily HFT Volume
HFT Exit	0.068*	0.069**	0.033	-0.078***
	(0.038)	(0.032)	(0.045)	(0.012)
Treatment Dummy	-0.012	-0.067	-0.053	0.081***
	(0.052)	(0.040)	(0.043)	(0.015)
Log Order-Execution Time(t)		-0.319***	-0.324***	-0.025***
		(0.038)	(0.039)	(0.004)
Log Volatility(t)		0.056***	0.056***	-0.004**
		(0.013)	(0.013)	(0.001)
Observations	1,650	1,630	1,630	1,630
R-squared	0.8455	0.8810	0.8815	0.6567
-	-	-	-	-
Stock FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
HFT FE	NO	NO	YES	YES
-	-	-	-	-
Cluster Stock	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Competition Effects of HFT Entry and Exit: Trading Volume

This table displays estimated coefficients of the following regression: $y_{ist} = \beta_1 d_{is} + X_{ist}\Gamma + p_t + m_s + u_{ist}$, which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly), s being the security and t the time. d_{is} is an indicator if an HFT entry affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is log volume measured as daily turnover (column 1-4) and the fraction of daily HFT volume (column 5). Additional controls, besides the level variables (indicator for the treated security and time fixed effects), are stock fixed effect, order-execution time (length of time (in seconds) between an incoming market order or marketable limit order and the standing limit order against which the trade is executed) volatility (computed as intraday volatility of hourly returns). Standard errors are clustered at the stock level and reported in parentheses.

VARIABLES	(1) Daily Volume	(2) Daily Volume	(3) Daily HFT Volume
HFT Entry or Exit x Date (Dummy)	-0.023	-0.020	0.077***
	(0.034)	(0.038)	(0.011)
Treatment (Dummy)	0.059	0.048	0.000
	(0.043)	(0.037)	(0.005)
Entry or Exit	-0.029	-0.063**	-0.001
	(0.036)	(0.027)	(0.005)
Log Order-Execution Time(t)		-0.305***	-0.027***
		(0.031)	(0.004)
Log Volatility(t)		0.063***	-0.005***
		(0.012)	(0.001)
Passive Traders ($\triangleright$ 50%)			-0.043***
			(0.014)
Observations	2,145	2,119	2,119
R-squared	0.8442	0.8796	0.6470
-	-	-	-
Stock FE	YES	YES	YES
Time FE	YES	YES	YES
HFT FE	NO	YES	YES
-	-	-	-
Cluster Stock	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Stylized Motivating Example: Participation

This figure presents a motivating example how entry (the change from monopoly to duopoly) of a high-frequency market maker typically affects trading participation within an average stock. It shows the incumbent high-frequency trader (HFT) and the entering HFT. Daily ratios of both HFTs' trading participation and total stock turnover are plotted.

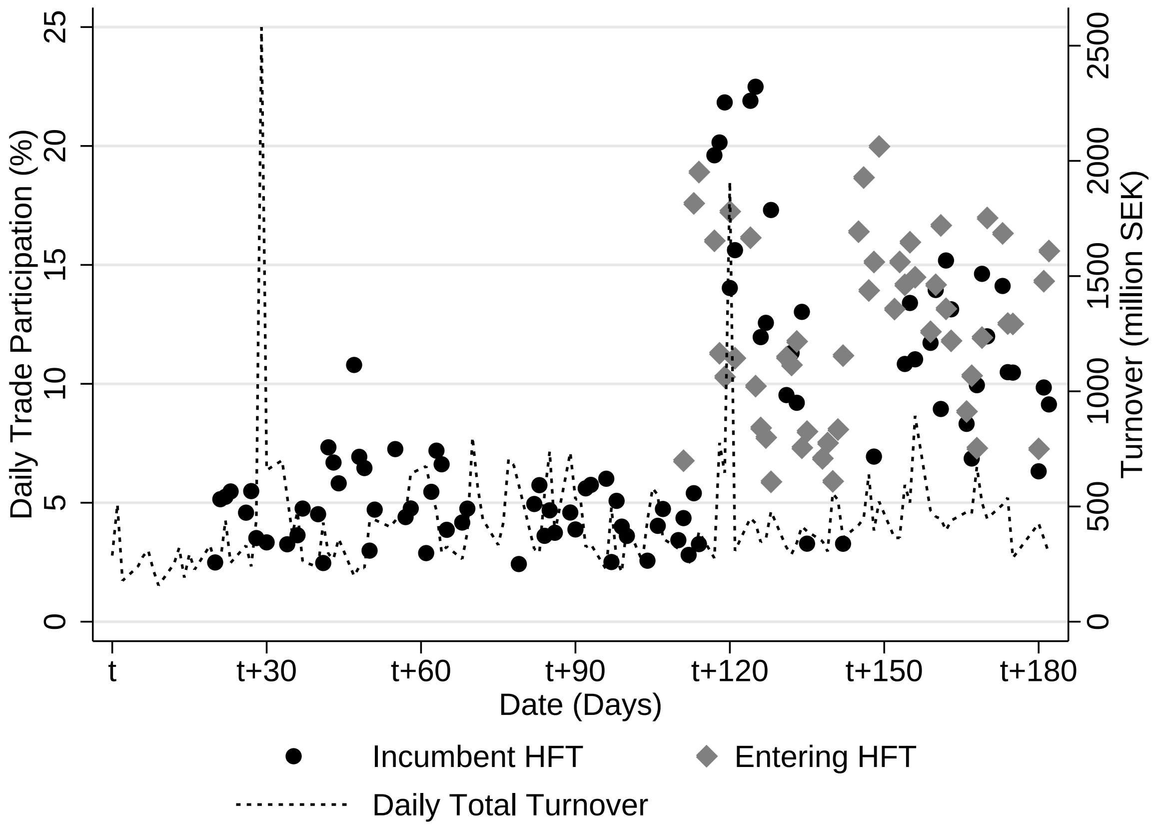

Figure 2: Stylized Motivating Example: Inventory

This figure shows a motivating example of an entering high-frequency market maker. It present high-frequency trading inventory over a period of 20 days. 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 facing competition.

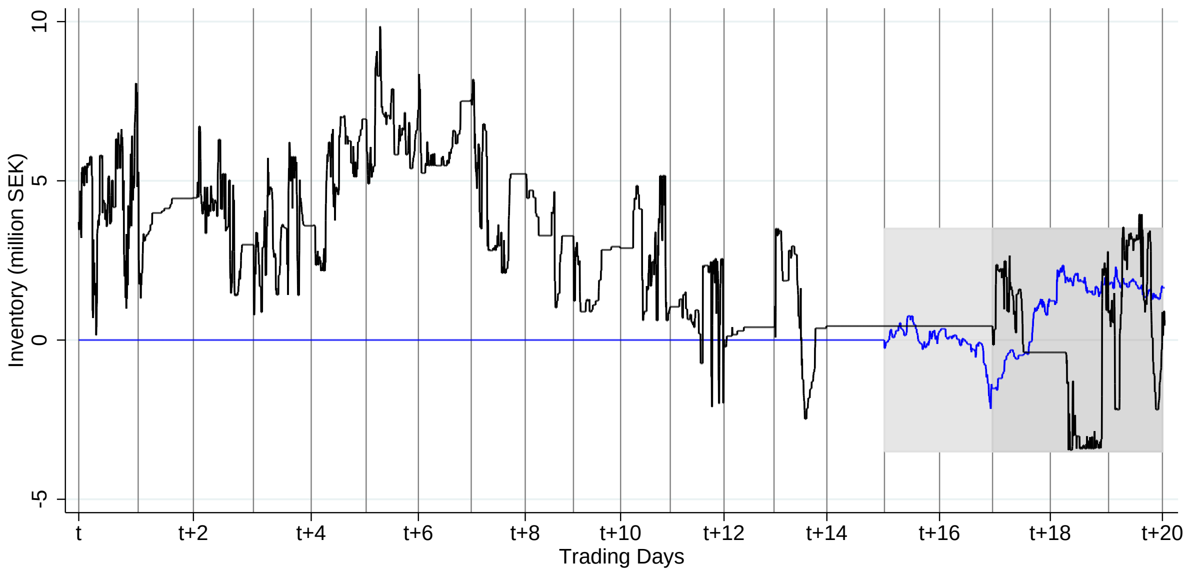

Figure 3: Entries and Exits over Time

All entries and exits that occur during the transition period from a single high-frequency market maker to competition are pictured in this figure. Each tick on the y-axis is one of the 30 individual stocks.

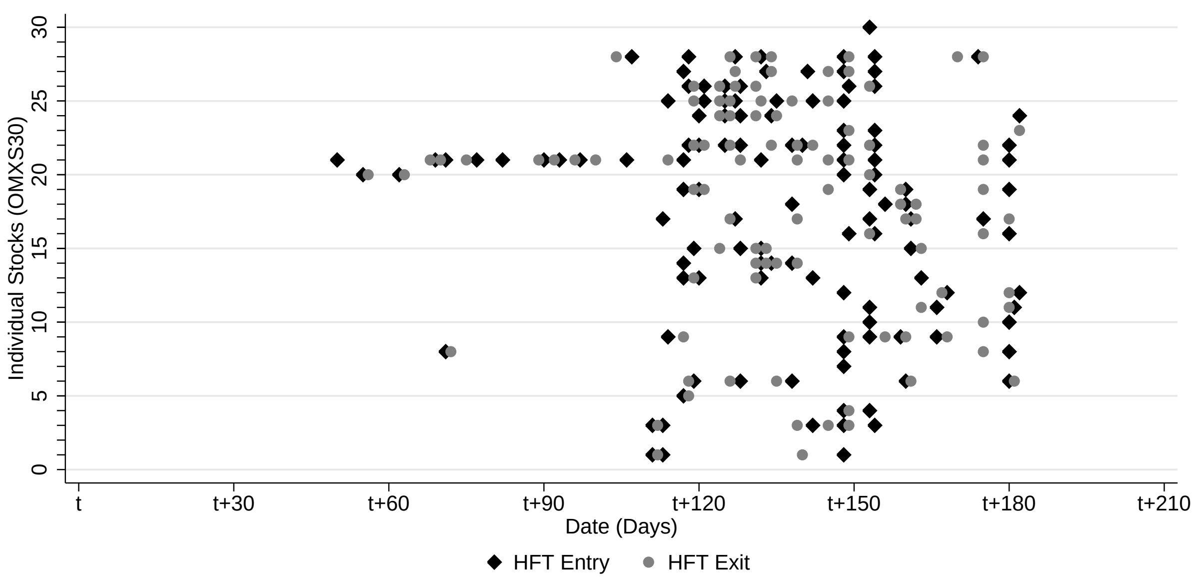

Figure 4: Summary Statistics of High-Frequency Trading Participation

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.

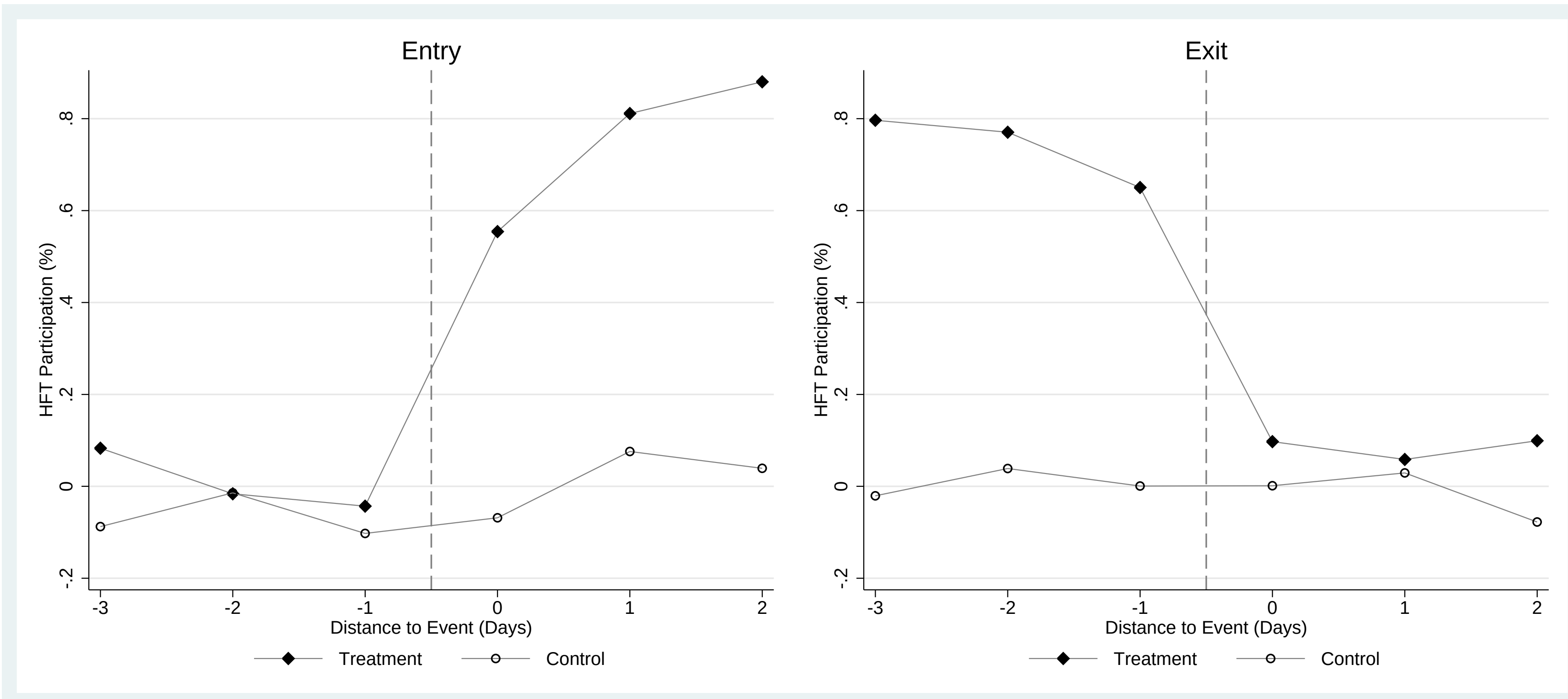

Figure 5: Summary Statistics of Short-Term Volatility

This figure illustrates average deviations from average short-term volatilities (60 minute volatilities) of individual stocks for both the control and the treatment group. 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.

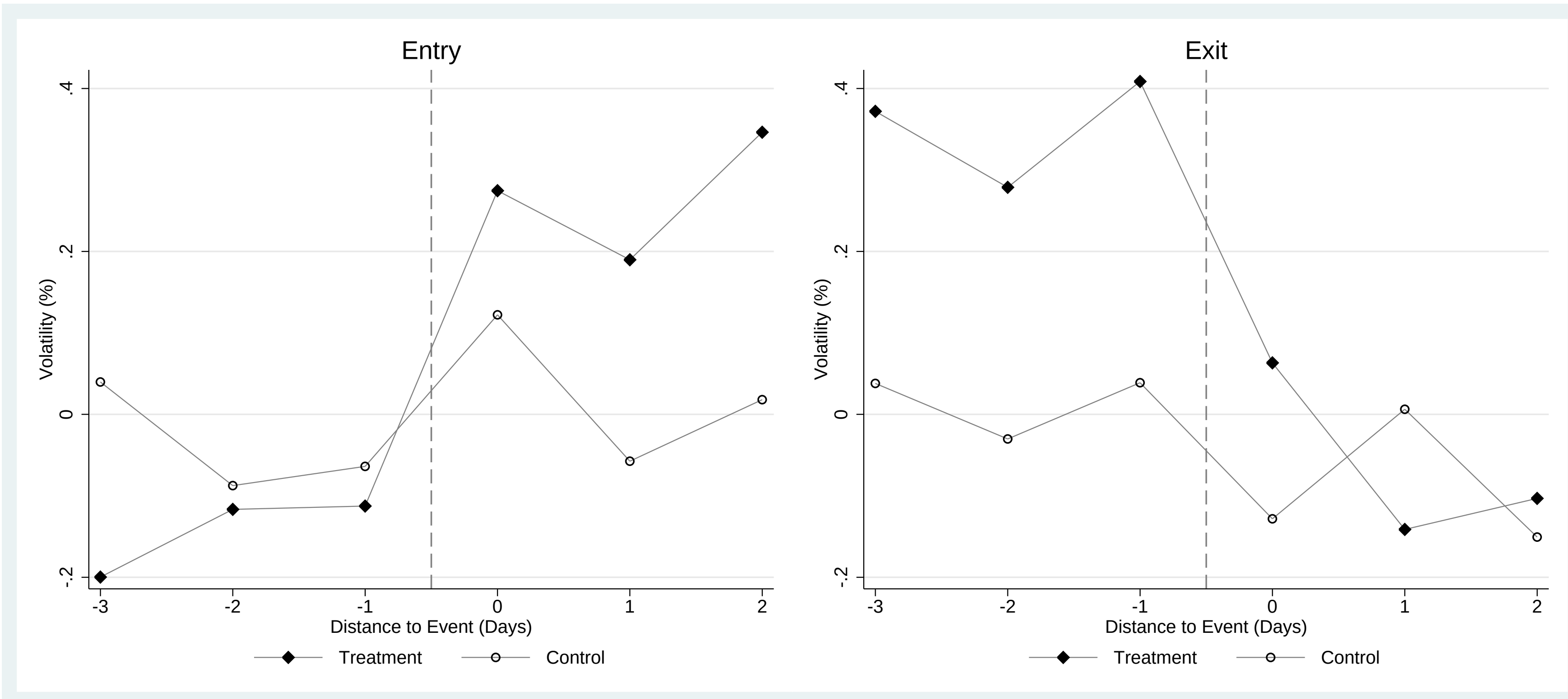

Figure 6: Summary Statistics of Order-Execution Time

This figure illustrates average deviations from average median order-execution time of individual stocks for both the control and the treatment group. Averages are not only related to averages within each stock, but also to differences caused by aggressiveness (high-frequency traders are split in two groups, aggressive (aggressive trades ¿=50%) and passive (passive trades¡50%)) and have an immediate effect on order-execution time as shown in the regressions. 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.

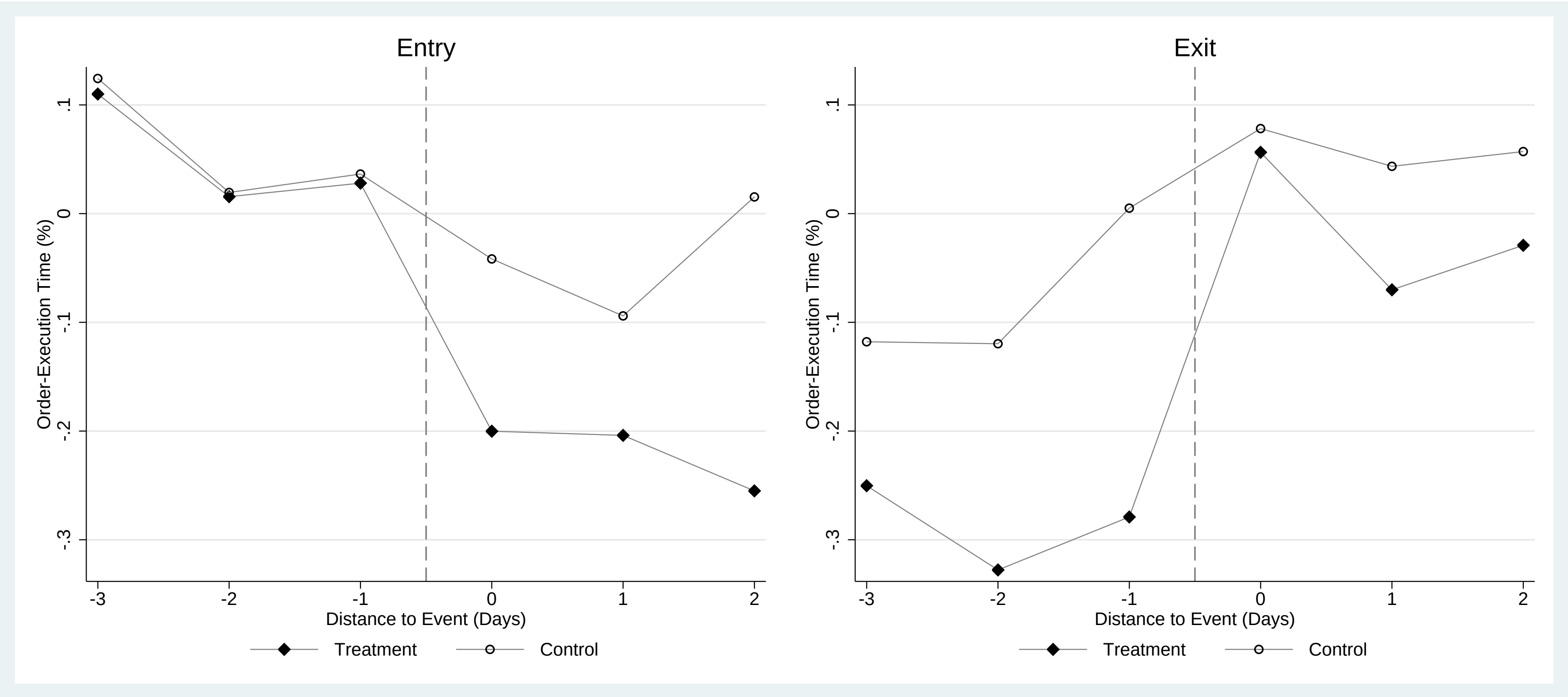

Figure 7: Intraday Average Inventory of High-Frequency Traders

This figure pictures the average intraday inventory over all stocks and days for five minute bins. Inventory is defined as the cumulative turnover divided by total turnover within each five minute bucket. While the left graph views average inventory over all days and stocks with a monopolistic high-frequency trader, the right hand graph shows inventories under competition for both the incumbent and entrant. Trading takes place from 9am to 5:30pm.

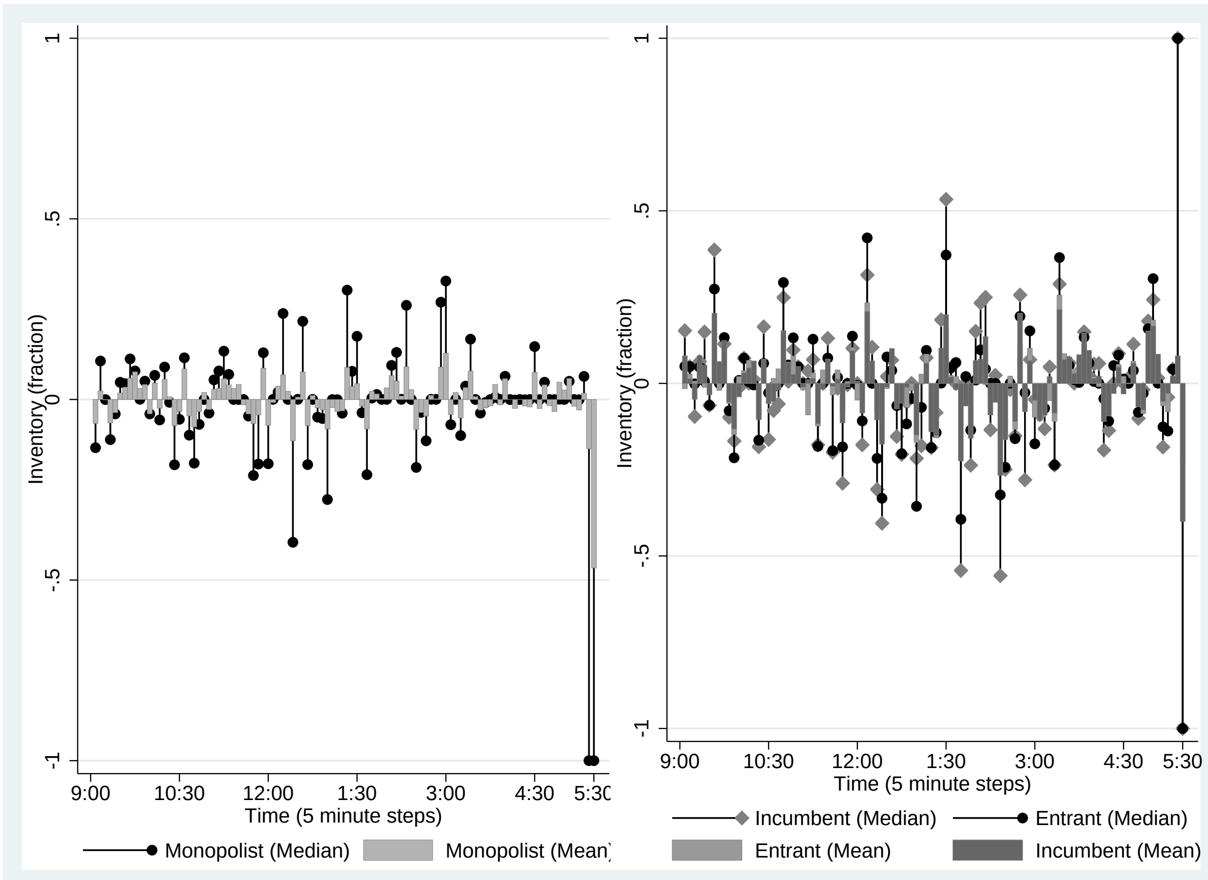

Figure 8: Competition over the Same Trades

This figure images the average intraday fraction of trades that were executed on the same side of the market (over all stocks and days) for five minute and sixty minute bins under competition. Trades are executed on the same side of the market if within each bin both the entrant and the incumbent buy or sell. The measure is constructed by assigning one if both high-frequency traders trade on the same side of the market and zero if not. The average ratio of trading on the same side of the market as their competitor is 2/3. The dark shaded bars are hourly averages. The market is open from 9am to 5:30pm.

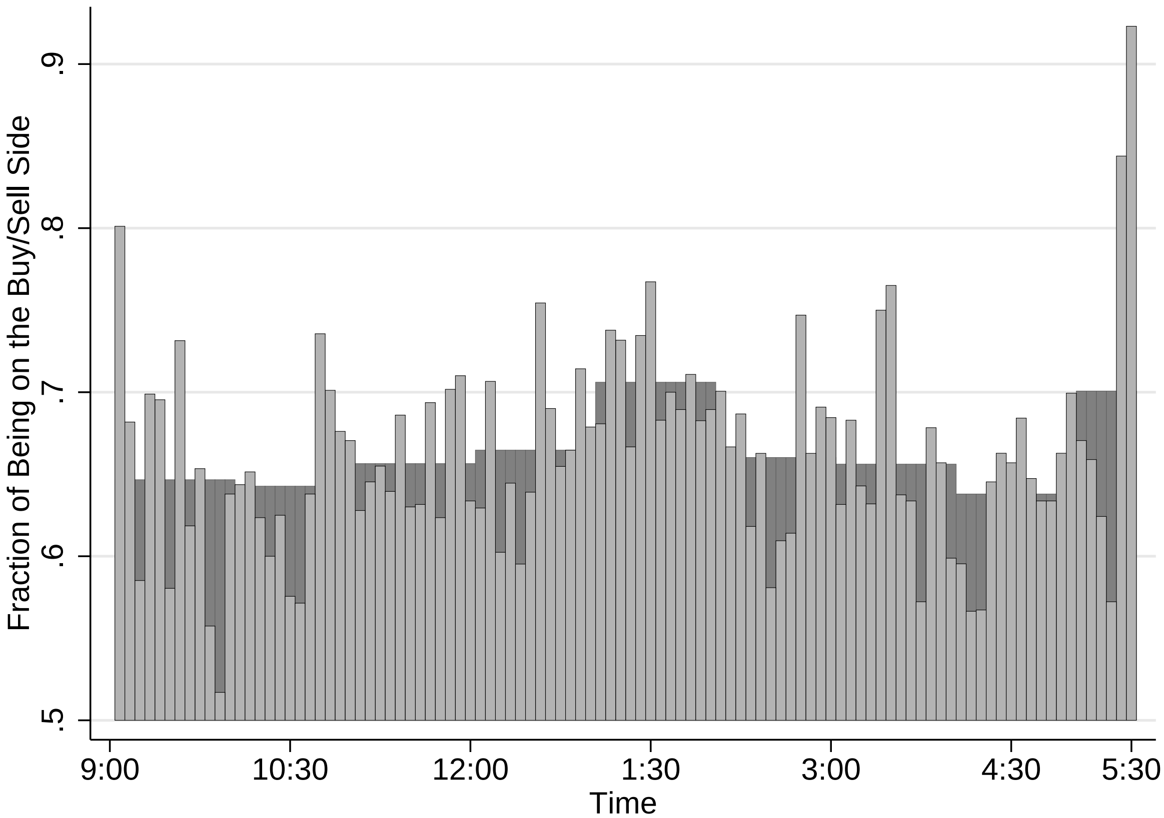

Figure 9: Pre-Closing Trading

This figure pictures pre-closing trading activities. Pre-closing takes place from 5:20 to 5:30 and determines the closing price by maximizing tradable volume. Timestamps within the closing period reflect the order time and not the actual transaction time. Average turnover per trade, average total stock turnover and average high-frequency trading turnover are printed.

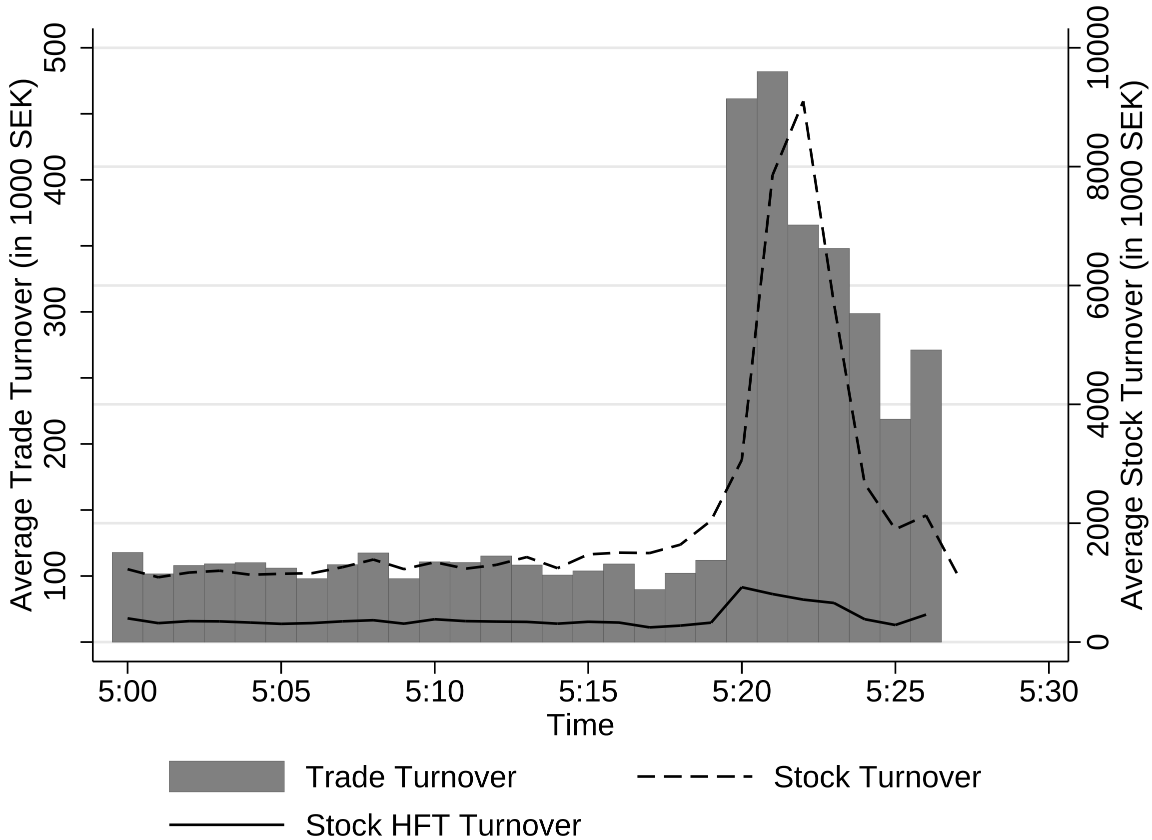

Figure 10: Dynamic Impact of Entry and Exit on Volatility

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

$$y_{ist} = \beta_1 d_{is}^{-5} + \beta_2 d_{is}^{-4} + \cdots + \beta_{10} d_{is}^{5} + X_{ist}\Gamma + p_t + m_s + u_{ist},$$

which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly and vice versa), s being the security and t the time. d_{is}^{j} is an indicator for the distance, j, if an HFT entry or exit affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is hourly volatility computed from hourly intraday returns. On the left, we show the volatility increase after entry and on the right we show the volatility decrease after exit.

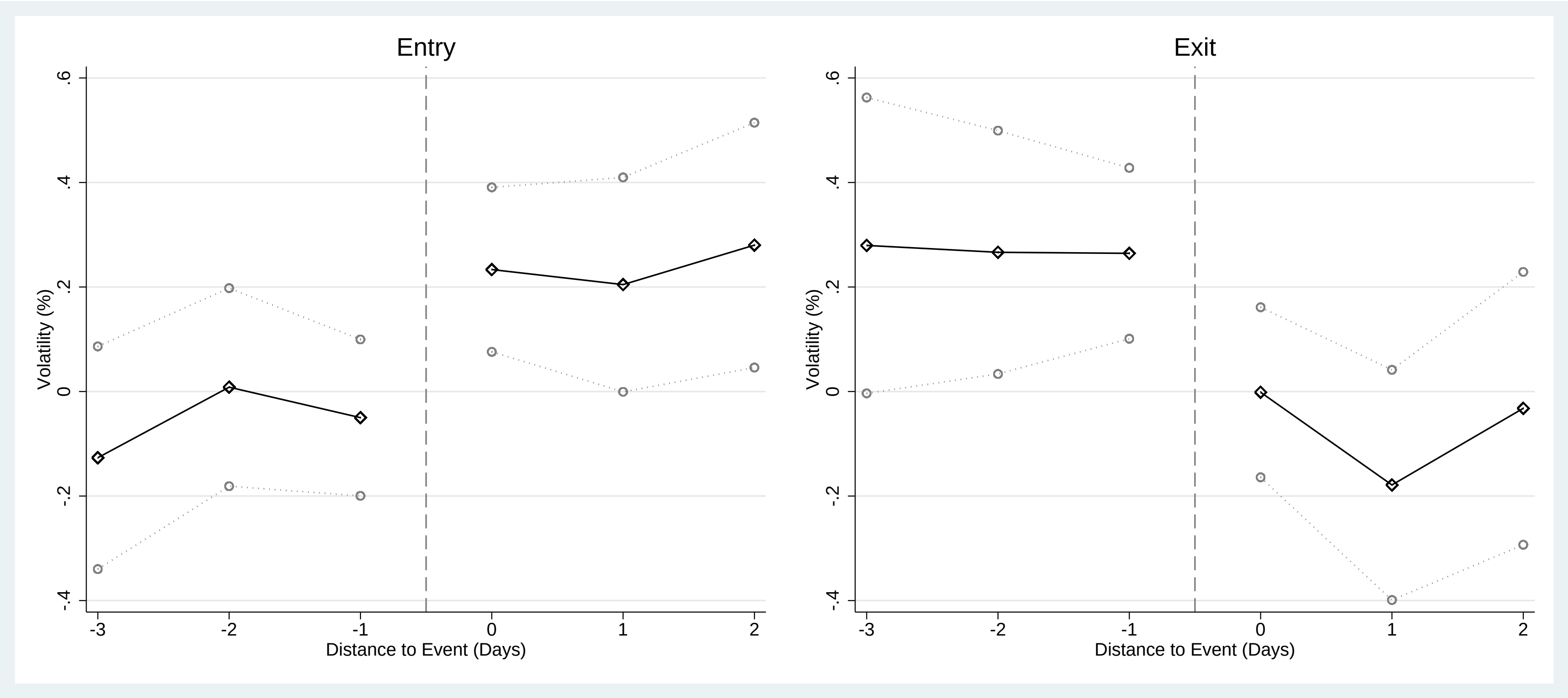

Figure 11: Dynamic Impact of Entry and Exit on Order-execution Time

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

$$y_{ist} = \beta_1 d_{is}^{-5} + \beta_2 d_{is}^{-4} + \cdots + \beta_{10} d_{is}^{5} + X_{ist}\Gamma + p_t + m_s + u_{ist},$$

which allows for multiple time periods and multiple treatment groups (Bertrand, Duflo, and Mullainathan (2004)). With i indexing entry (the change from HFT monopoly to HFT duopoly and vice versa), s being the security and t the time. d_{is}^{j} is an indicator for the distance, j, if an HFT entry or exit affected security s at time t. p_t are daily time fixed effects and m_g are security fixed effects. X_{ist} is the vector of covariates and u_{ist} is the error term. The dependent variable, y_{ist}, is hourly volatility computed from hourly intraday returns. On the left, we show the median order-execution time decrease after entry and on the right we show the median order-execution time increase after exit.