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High frequency trading and the *new market* makers[☆]

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Abstract

This paper characterizes the trading strategy of a large high frequency trader (HFT). The HFT incurs a loss on its inventory but earns a profit on the bid–ask spread. Sharpe ratio calculations show that performance is very sensitive to cost of capital assumptions. The HFT employs a cross-market strategy as half of its trades materialize on the incumbent market and the other half on a small, high-growth entrant market. Its trade participation rate in these markets is 8.1% and 64.4%, respectively. In both markets, four out of five of its trades are passive i.e., its price quote was consumed by others.

JEL classification: G10

Keywords: High frequency trading; Market maker; Multiple markets

Equity trading fragmented substantially in the first decade of the twenty-first century. Fig. 1 illustrates how NYSE market share in its listed stocks was still 80% in 2005 and declined to 25% in 2010. In Europe, equity trading started fragmenting somewhat later as, for example, the

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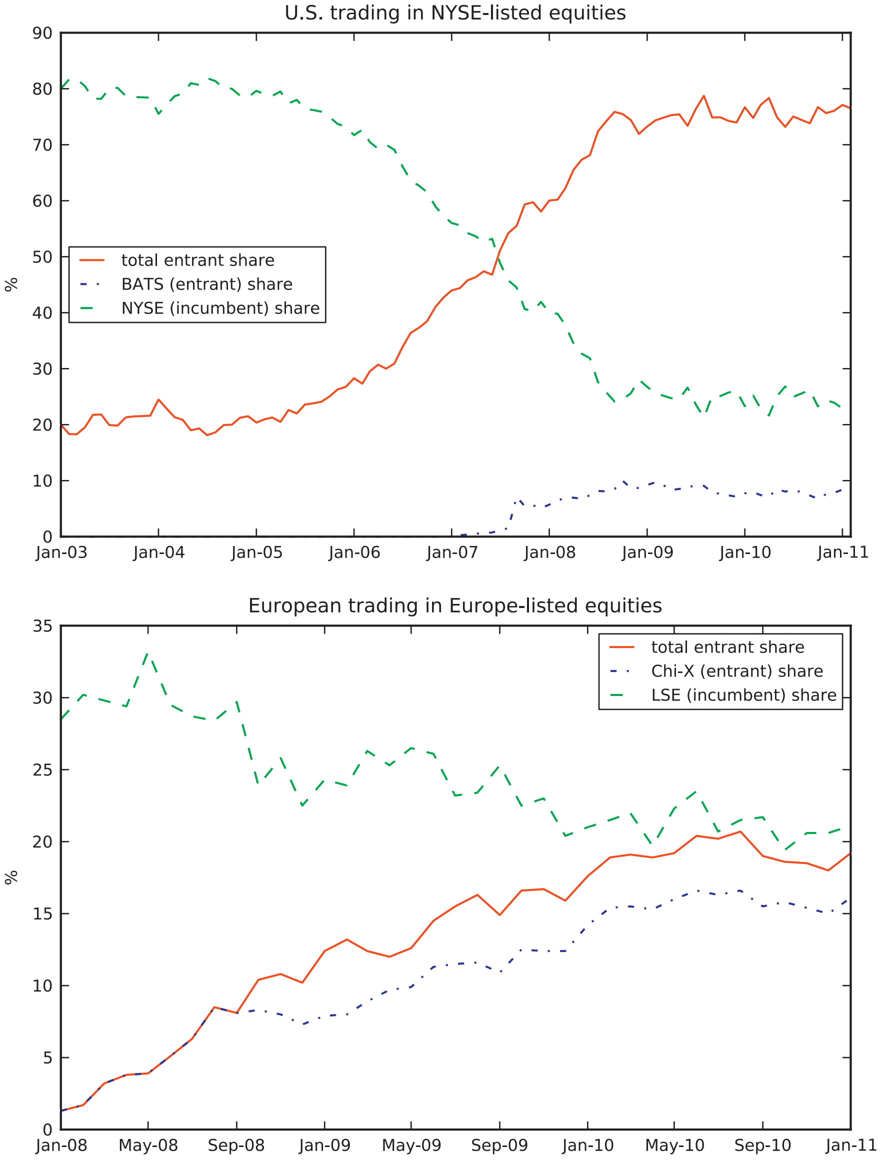

Fig. 1. Market fragmentation Europe and U.S. This figure illustrates the recent fragmentation in equity markets. The top graph plots incumbent and entrant market share in NYSE-listed stocks. The bottom graph does the same for European listed stocks. *Source*: Barclays Capital and Federation of European Exchanges.

London Stock Exchange market share dropped from 30% at the start of 2008 to about 20% at the end of 2010. New, high-tech entrant markets, such as BATS in the U.S. and Chi-X in Europe, captured a substantial part of the market share lost by incumbents. In 2011, Chi-X became the largest European equity market according to trade statistics published by the Federation of European Exchanges.

Another important development in the same decade is the arrival and explosive growth of a new type of trader: the high frequency trader. The Securities and Exchange Commission (SEC) refers to them as "professional traders acting in a proprietary capacity that engage in strategies that generate a large number of trades on a daily basis… characteristics often attributed to proprietary firms engaged in HFT are… the use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders… very short time-frames for establishing and liquidating positions… ending the trading day in as close to a flat position as possible" (SEC, 2010, p. 45). In the report, the SEC estimates that HFT volume in U.S. equity markets in the second half of the first decade is 50% of total volume or higher.

One particularly large and global HFT firm, Getco, claims that the two trends are intimately related.[1] In a public hearing on the merger proposal of BATS and Chi-X, Getco stated that these markets had "brought two main benefits to the market: technology and price pressures." It is no surprise that an HFT firm cheers lower fees and faster systems. It gets more interesting when Getco claims that it would invest in new markets for strategic reasons. It did, in fact, invest in BATS and Chi-X when these new markets entered. And, pushing it further, Getco stated that entry barriers for new markets are "very small" and, should consolidation turn out bad, it sees "plenty of opportunity to increase competition either by launching another platform or backing somebody else[2] doing so."[3]

Why now and not before? In pre-electronic securities trading, the search process was particularly costly and a single, centralized market could capitalize on a large network externality (Pagano, 1989) that, in effect, created a high entry barrier for rival markets. In the electronic age, search cost is almost trivial as a rival market price is easily checked by a computer. Yet, not all investors have the technology to poll other markets and new entrants might fail if their strictly better prices are overlooked (e.g., Foucault and Menkveld, 2008). HFTs might, as claimed by Getco, indeed have an important role in 'upstairs linking' multiple markets and thus make real competition between markets possible (Stoll, 2001). More specifically, they could produce the strictly lower asks and higher bids that a new market needs to take off i.e., as new market makers they could 'make' the new market.

This paper is a case study that characterizes the trading strategy of one large HFT that started trading after Chi-X entered as a new venue for European equities. A proprietary dataset with anonymized trader IDs for a large incumbent market NYSE-Euronext and the entrant market Chi-X allows for a rich and detailed analysis of what actually happened. Indeed, as Getco suggested, Chi-X growth took off when the HFT entered both the incumbent and the entrant market at the same time. Chi-X market share was 1–2% in the first months after its launch but jumped to a double-digit share when this happened. Moreover, the HFT's participation share closely mirrors Chi-X market share, both in magnitude and through time. The HFT's entry not only fragmented trading, but it also coincided with a 50% drop in the bid–ask spread.[4]

[1]On its website, Getco claims to be "consistently among the top 5 participants by volume on many venues, including the CME, Eurex, NYSE Arca, NYSE ARCA Options, BATS, Nasdaq, Nasdaq Options, Chi-X, BrokerTec, and eSpeed."

[2]Getco, for example, was the largest trader in Chi-X just after its Australian debut (see "Bourse Newcomer Chi-X Passes 2pc Mark," The Australian, November 21, 2011).

[3]"*BATS/Chi-X Merger Inquiry*: *Summary of Hearing with Getco on 19 July 2011*," published by the UK Competition Commission, July 19, 2011.

[4]This evidence that new trader entry both increases fragmentation and improves the bid–ask spread identifies one channel by which fragmentation and market quality might be related. It is consistent with O'Hara and Ye (2011) who show that, in the cross-section, the degree of fragmentation in U.S. equity trading positively correlates with market quality.

The remainder of the paper provides an in-depth analysis of this HFT that seemed crucial for the success of Chi-X.

First, the new trader fits the SEC profile of a high frequency trader. It is lightning fast with a latency (inter-message time) upper bound of 1 millisecond, it only engages in proprietary trading, it generates many trades (it participates in 14.4% of all trades, split almost evenly across both markets), and it starts and ends most trading days with a zero net position.

Second, micro-economic analysis of its trading strategy shows that the HFT is primarily a modern, multi-venue market marker. Its 'operation' uses capital to produce liquidity. The production side is analyzed by a standard decomposition of trade revenue into a bid–ask spread earned (or paid if the order consumed liquidity) and a 'positioning' revenue based on midquote changes in the life of the nonzero position (a midquote is the middle of the best bid and ask quote). The variable costs due to exchange and clearing fees are then subtracted to arrive at a 'gross profit' i.e., the profit does not account for the (unknown) fixed costs of, for example, development of the algorithm, acquisition of hardware, and clearing house/exchange membership fees. The 'capital-intensity' is explored by calculating the capital tied up in the operation due to margin calls in both markets' clearing houses. The HFT cannot net positions across these clearing houses which is shown to increase capital requirements by a factor of 100.[5] Combining the daily gross profits with the maximum capital draw-down yields an annualized (gross) Sharpe ratio of 7.62. Further analysis reveals that this Sharpe ratio is quite sensitive to the assumptions underlying HFT cost of capital.

Third, the HFT characterization as a modern market maker is detectable also in the overall price process. Midquotes are pressured downwards if the HFT is on a long position, upwards if it is on a short position. This pattern is consistent with dynamic inventory control models where a risk-averse market maker trades off the subsidy required to steer traffic to get out of a nonzero position against the idiosyncratic price risk associated with staying on such a position (e.g., Ho and Stoll, 1981; Hendershott and Menkveld, 2011).

It is important to view the surprisingly strong empirical results—high HFT profitability and the correlation between HFT position and price pressure—in the context of new market entry. A natural interpretation is that the documented profitability is a return for entrepreneurial risk. If there is a large fixed cost to building the technology to connect to both the incumbent and the entrant market and to design the optimal algorithm to run the operation, then one should expect temporary excess returns' to make it a positive net present value (NPV) project. In addition, there was considerable risk as, at the time, it was not at all clear that Chi-X would be a successful entry given that at least one earlier initiative had failed i.e., the London Stock Exchange introduced EuroSETS to compete with the NYSE-Euronext system in 2004 (Foucault and Menkveld, 2008). If such risk cannot be fully diversified, it leads to an additional required return. The market entry context also explains the HFT's large presence in the market (14.4% of all trades) and its position's effect on prices. Subsequent entry of other HFT firms should dilute the identified HFT's relative weight and bring down its rents to a competitive level. The sample is too short to identify any such effect.

The paper's focus is on one type of HFT: a modern market maker. It is part of a rapidly growing literature that encompasses various types of HFT. Brogaard (2010) studies trading of 26 NASDAQ-labeled HFT firms in the NASDAQ market in 2008–2010. He concludes that, as a group, HFTs tend to improve market quality. Three follow-up studies use the same

[5]See Duffie and Zhu (2011) for an analysis of netting efficiency and counterparty risk for single vs. multiple central clearing counterparties (CCPs).

data: Brogaard, Hendershott, and Riordan (2012) document that HFTs contribute to price efficiency; Carrion (2013) shows that HFTs "provide liquidity when it is scarce and consume liquidity when plentiful," and Zhang (2012) studies what type of information HFTs and non-HFTs are best at processing. Hasbrouck and Saar (2013, this issue) propose a new measure of low-latency activity as a proxy for HFT trading and find that it correlates positively with traditional measures of market quality. Kirilenko, Kyle, Samadi, and Tuzun (2011) study the behavior of HFTs in the E-mini S&P 500 stock index futures on May 6, 2010, the day of the flash crash. Hagströmer and Nordén (2013) study HFT activity in the NASDAQ OMX Stockholm market and document that most of it is market-making. Jovanovic and Menkveld (2011) use exactly the same data as used in the current manuscript (i.e., Euronext and Chi-X data). They also study HFT entry after Chi-X started operating but with a different focus. They propose an equilibrium model that endogenizes both HFT trading and the trading of others (in response to HFT presence). Model calibration suggests that HFT entry had a positive but modest welfare effect.[6] The current paper's contribution to this HFT literature is its focus on cross-market activity, market structure development, and its detailed analysis of the operation's production capital i.e., the capital tied up through margin requirements. This latter part is particularly important in view of the literature on the link between funding and market liquidity (e.g., Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009).

The paper also fits into a broader literature on algorithmic or automated trading. Foucault and Menkveld (2008) study smart routers that investors use to benefit from liquidity supply in multiple markets. Hendershott, Jones, and Menkveld (2011) show that algorithmic trading (AT) causally improves liquidity and makes quotes more informative. Chaboud, Chiquoine, Hjalmarsson, and Vega (2009) relate AT to volatility and find little relation. Hendershott and Riordan (2009) find that both AT demanding liquidity and AT supplying liquidity makes prices more efficient. Boehmer, Fong, and Wu (2012) study a 2001-2009 international sample and find that greater AT intensity improves liquidity and informational efficiency, and increases volatility.

The remainder of the paper is structured as follows. Section 1 reviews the institutional background and presents the data. Section 2 discusses the methodology. Section 3 presents the empirical results. Section 4 presents the conclusions.

1. Institutional background

The classic market-making literature views the bid–ask spread, a substantial part of investors' transaction cost, as a compensation for the cost a market maker incurs. It is comprised of essentially three components: order-handling cost (e.g., the fee an exchange charges to process an order), the cost of being adversely selected on a bid or ask quote, and the premium risk-averse market makers require for price risk on nonzero positions (e.g., Madhavan, 2000). Market makers prefer to operate in a system where these costs are low (e.g., low fees or fast access, see discussion below). In human-intermediated markets, however, it is hard for new venues to compete as humans) creates a participation externality: traders prefer to be where the other traders are (Pagano, 1989). A trader risks missing a trade opportunity when checking off-exchange prices (by phone, for example).

Technology has dramatically changed the nature of competition among trading venues. Participation externalities are severely reduced when markets change from 'humans on floors'

[6]Pure theory papers on HFT include Biais, Foucault, and Moinas (2011), Cartea and Penalva (2012), Foucault, Hombert, and Roşu (2012), Hoffmann (2012), Martinez and Roşu (2012), and Menkveld and Yueshen (2012).

to 'machines connected to electronic venues'; search costs are substantially reduced.[7] This creates more scope for new markets to compete through, for example, lower fees that reduce the order-processing costs. But they can also be competitive on the other two cost components of market-making. A fast matching engine enables a market-making strategy to quickly update quotes on the arrival of public information and thus reduce the risk of being adversely selected. And, a fast response time (referred to as 'low latency') makes the venue available to a market-making machine that wants to 'quickly poll' for investor interest when trying to offload a costly nonzero inventory position.

The increased ability to compete could explain the proliferation of venues both in the U.S. and in Europe. Investors are likely to benefit from such competition in two ways. First, fees might be reduced as a result of competitive pressure. Second, new venues might tailor to the needs of different types of investors and produce additional investor utility (e.g. Stoll, 2001). Such venue heterogeneity however is beyond the scope of this study; the focus is on competition between largely similar systems and the role of a market-making HFT in the viability of new systems.

1.1. Start of Chi-X

The European Union aimed to create a level playing field in investment services when it introduced the Markets in Financial Instruments Directive (MIFID) on November 1, 2007. In effect, it enabled the various national exchanges to compete and encouraged new markets to enter.

Instinet pre-empted MIFID when it launched Chi-X on April 16, 2007. Chi-X operates a trading platform which initially only traded Dutch and German index stocks.[8] By the end of the year, it allowed a consortium of the world's largest brokers to participate in equity through minority stakes.[9] Before Chi-X, Instinet had operated the Inet ECN successfully in the U.S. which distinguished itself through subsidization of passive orders (see fee discussion below) and system speed. At the time of its first anniversary Chi-X claimed it was "up to 10 times faster than the fastest European primary exchange."[10] In 2005 Instinet sold the U.S. license to NASDAQ. It kept the international license which led to the start of Chi-X.

In its first 14 months, my sample period, Chi-X traded Belgian, British, Dutch, French, German, and Swiss local index stocks. It captured 4.7% of all trades and was particularly successful in Dutch stocks with a market share of 13.6%. In terms of volume, Chi-X overall market share was 3.1% and its Dutch share was 8.4%. Chi-X appears to have used the Dutch index stocks, my sample stocks, to launch what ultimately became a pan-European operation.

Prior to Chi-X entry, Euronext was by far the main trading venue for Dutch stocks. It operated an electronic matching engine similar to Chi-X. Some Dutch stocks also traded as American Depositary Receipts (ADRs) in the U.S. and in the German Xetra system. They did not yet trade in NASDAQ OMX, Turquoise, or BATS-Europe which are venues that entered after Chi-X on a business model similar to Chi-X: low fees and fast systems. The broker identified as HFT in this study was a substantial participant in Chi-X. In my sample period, it participated in 43.7 million

[7]The search cost has not disappeared entirely; Hasbrouck and Saar (2013) compare the 2–3 milliseconds it takes for participants to respond within a market to the distance between New York and Chicago (both important market centers) which is about 8 milliseconds at the speed of light.

[8]"Chi-X Successfully Begins Full Equity Trading, Clearing and Settlement," Chi-X press release, April 16, 2007.

[9]These brokers were: BNP Paribas, Citadel, Citi, Credit Suisse, Fortis, Getco, Goldman Sachs, Lehman Brothers, Merrill Lynch, Morgan Stanley, Optiver, Société Générale and UBS (see press release referred to in, footnote 10).

[10]"Chi-X Europe Celebrates First Anniversary," Chi-X press release, April 7, 2008.

out of 99.2 million Chi-X trades. It was particularly active in Dutch stocks with participation in 4.9 million out of 8.6 million Chi-X trades.

1.2. Matching engine and exchange fee structure

The matching engines of Chi-X and Euronext both run an electronic limit order book. Investors submit a limit order to the system which summarizes their trade interest. An example of a limit is a buy order for 2,000 shares with a price ‘limit’ of €10. The order is either matched with a standing sell order with a limit price of (weakly) less than €10 and executes immediately at the limit sell price or it is added to the stack of limit buy orders on the buy side of the book. If executed immediately, it is labeled an aggressive order that consumes liquidity. If not, it is a passive order that supplies liquidity. Also, the matching of orders is such that standing orders are ranked by price-time priority. In the example, the standing sell orders with the lowest price get executed first and, among these, the ones that arrived earliest take priority. See Biais, Hillion, and Spatt (1995) for a detailed description of generic limit-order markets .

The fees that the exchanges charge differ significantly both in structure and level. Euronext charges a fixed fee of €1.20 per trade which for an average size trade (~€25, 000) amounts to 0.48 basis point. Highly active brokers benefit from volume discounts which can bring the fixed fee down to €0.60 per trade, the fee used for the HFT in subsequent analysis. In addition, Euronext charges a variable fee of 0.05 basis point. The act of submitting an order or cancelling it is not charged (i.e., only executions get charged) unless, on a daily basis, the cancellation-to-trade ratio exceeds 5. In this case, all orders above the threshold get charged a €0.10 fee (~0.04 basis point).

Chi-X conditions on the incoming order's type when charging its fee in what is called a maker-taker model: an aggressive order gets charged 0.30 basis point whereas a passive order receives a rebate of 0.20 basis point in case it leads to an execution. The platform is therefore guaranteed a 0.10 basis point revenue per transaction; the optimality of such fee structure is discussed in Foucault, Kadan, and Kandel (2010). Chi-X does not charge for limit order submissions and cancellations.

1.3. Post-trade cost: clearing fee and margin requirement

A trade is not finished once two limit orders have been matched. The actual transfer of the security and the payment is effectuated three days after the transaction; the trade is cleared and settled. This process leads to two types of cost: clearing fees and margin requirements. Chi-X and Euronext also compete at this end of the trading process as they use different clearing houses: EMCF and LCH-Clearnet, respectively. EMCF started as a clearing house at the same time Chi-X entered as a new trading venue: April 16, 2007.

The entry of EMCF triggered a clearing fee war with incumbent clearer LCH-Clearnet. EMCF started by charging €0.30 per trade, 36% less than the LCH-Clearnet fee: €0.47 per trade. Note that these fee levels are substantial as they compare to, for example, the per-trade fee of €1.20 charged by Euronext (see discussion above). On October 1, 2007, six months after EMCF entry, LCH-Clearnet responded by reducing its fee by 34% to €0.31 per trade. At the same time, EMCF reduced its fee to €0.28 per trade. Half a year later, on April 1, 2008, EMCF reduced its fee by 32% to €0.19 per trade; at the same time, LCH-Clearnet reduced its fee by 26% to €0.23. Overall, clearing fees were reduced by 50-60% in the first year after Chi-X entry.

LCH-Clearnet and EMCF are both central counterparty (CCP) clearing houses. A CCP effectively insures all market participants against the risk of counterparty default in the period between the limit order match and the actual transfer of the securities (and funds). In my sample, this period is three days. The clearing house itself manages this risk by requiring participants to keep margin accounts with the clearer. The capital held in these accounts is confiscated should the participant become insolvent. The margin requirement is therefore linked to the value owed in as of yet uncleared transactions. LCH-Clearnet uses the SPAN methodology developed by the Chicago Mercantile Exchange which charges for 'specific risk' and 'general market risk.' At the start of the sample, LCH-Clearnet charged 4.8% on the marked-to-market value of the net position in each stock and 3.3% on the marked-to-market value of the overall net position. For example, suppose a broker's yet-to-clear, marked-to-market position is long €10 million in security XYZ and €20 million short in security ABC at a particular point in the day. In this case, its margin account needs to have at least €$4.8\%(|10|+|-20|)+3.3\%|10-20|=$ €1.77 million. On February 9, 2008, LCH-Clearnet increased the specific risk parameter to 6.3% and the general market risk parameter to 4.85%. EMCF on the other hand uses a proprietary system that is opaque to its clearing members. The empirical analysis therefore applies the SPAN methodology to also calculate the margin requirement on the HFT EMCF positions assuming that the schedules are competitive.[11]

2. Data, summary statistics, and approach

2.1. Data

The main sample consists of trade and quote data on Dutch local index stocks for both Chi-X and Euronext from January 1, 2007 through June 17, 2008. The quote data consist of the best bid and ask price and the depth at these quotes. The trade data contain trade price, trade size, and an anonymized broker ID for both sides of the transaction, and a flag to indicate which side of the trade was the passive order (i.e., the price quote that got consumed). The broker ID anonymization was done for each market separately and broker IDs can therefore not be matched across markets—say the first market uses 1, 2, 3 and the second one uses A, B, C. The Euronext sample also contains a flag that indicates whether the broker's transaction was proprietary (own-account) or agency (for-client). The Chi-X sample also contains information on all order submissions and cancellations. The time stamp is to the second in Euronext and to the millisecond in Chi-X. In the analysis, Chi-X data is aggregated to the second to create a fair comparison across markets. A similar sample for Belgian stocks, except for trader ID information, is used for benchmark purposes.

The final sample consists of 14 Dutch stocks and 18 Belgian stocks. The market capitalization of all Dutch index stocks is €371 billion which is about 80% of total Dutch market capitalization (including non-index stocks). The market capitalization of all Belgian index stocks is €214 billion which is more than 95% of total Belgian market capitalization. Appendix A contains a detailed list of all stocks that are analyzed.

[11]This assumption does not affect most of the paper's results. It only affects the Sharpe ratio analysis presented in Table 2 as the capital required might be lower if EMCF charges a lower margin. Table 3 reveals how the Sharpe ratio changes when the capital requirement assumption is changed. It shows that the ratio increases only modestly if the HFT capital buffer is close to the *realized* maximum margin. If the buffer is a lot larger, then the Sharpe ratio does increase substantially on a lower margin requirement.

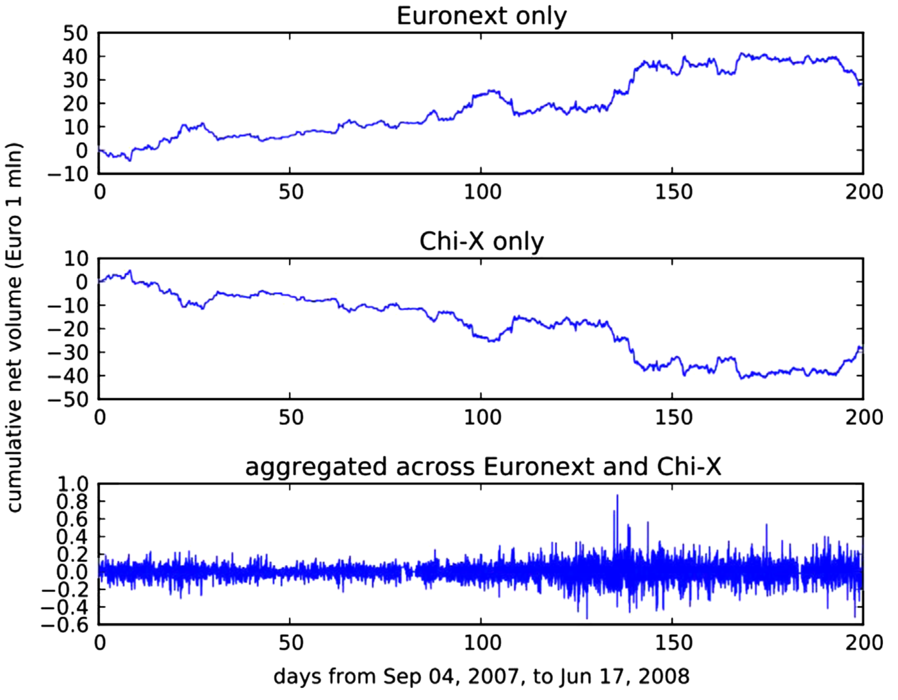

Fig. 2. Raw data plot of the high frequency trader's cumulative net volume by market. This figure plots, for the median week in the sample, one broker ID pair's cumulative net volume in Unilever, the median stock in the large size group. Net volume is defined as the sign of a trade (plus one for buys, minus one for sells) times its size. The plot depicts the pecuniary value by multiplying aggregate net volume (in shares) with the prevailing midquote (average of the lowest ask and the highest bid) at each point in time. It plots the series for each market separately and for the aggregate market. The broker ID pair is assumed to represent a single high frequency trader.

2.2. Summary statistics

Pairing broker IDs systematically across markets (1-A, 1-B,…,2-A, 2-B,…) yields one pair that has all the characteristics of a high frequency trader.[12] First, the series mean-reverts to zero. Fig. 2 plots the cumulative net volume in a large stock (Unilever) for the Euronext broker ID, for the Chi-X broker ID, and for the pair of these two broker IDs. The first two series look nonstationary and, more importantly, they seem to be each other's mirror image. Indeed, summing the series yields an aggregate net volume series—from now on referred to as the HFT net position—that mean-reverts to zero. Fig. 3 zooms in on this net position and plots it at various frequencies: minutes, hours, and days. The graphs lead to the following further observations. It seems that the position is zero at the start and end of each trading day. The HFT appears to be highly active as positions change frequently and reach up to €300,000 either long or short. These positions can last seconds, minutes, and even hours. Finally, the Euronext data show that all this broker ID's trades were proprietary (the Chi-X data unfortunately do not flag trades as either proprietary or agency). In sum, these observation for the broker ID pair match the

[12] I started with the most active broker ID in Chi-X, paired all Euronext broker IDs, and immediately discovered the HFT this way. It participated in about four out of five Chi-X trades and therefore became the focus of this study.

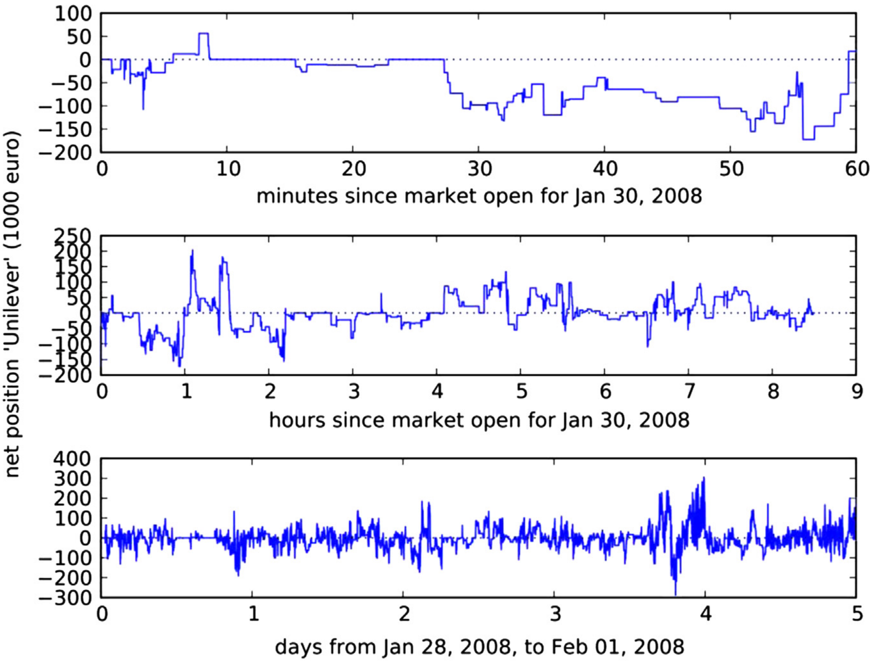

Fig. 3. Raw data plot high frequency trader net position by frequency. This figure plots, for the median week in the sample, the high frequency trader's net position in Unilever, the median stock in the large stock group. It plots the series for essentially three frequencies: minutes, hours, and days.

SEC characterization of high frequency trading and the pair will therefore be referred to as HFT in the remainder of the manuscript.

Fig. 4 illustrates how Chi-X entry coincided with a 50% decline in the bid–ask spread of Dutch stocks, but only at the time when the HFT started to participate. The top graph shows that Chi-X captured a 1–2% share of all Dutch trades in the first few months. It jumped to a double-digit share in August which is exactly the time that the HFT started to trade in both Chi-X and Euronext. The middle graph illustrates that the HFT is a major part of the new market as it participates in 70–80% of Chi-X trades. The bottom graph plots the evolution of the (inside) bid–ask spread of Dutch stocks (index-weighted) benchmarked against the bid–ask spread of Belgian stocks. The latter stocks serve as a useful control sample as they also trade in the Euronext system but get 'treated' with Chi-X entry only one year later on April 28, 2008 (which motivates the end date of the graph). Taken together, the plots illustrate that the HFT appears be the '*new market* maker.' Finally, note that whereas the *reach* lower spread levels were only obtained after HFT entry, these new levels appear viable even in their absence; on December 24 and 31, the HFT was virtually absent in the market, Chi-X share dropped to almost zero, yet spread levels did not bounce back to pre-event levels.[13] Fig. 6 in the online appendix shows that the substantial spread drop is not purely driven by passing on of the rebate that quote producers obtain in Chi-X,

[13]This finding suggests that others followed in the footsteps of the HFT identified in this study. Chakrabarty and Moulton (2012) document how at the NYSE, after automation, off-floor market makers step in when the NYSE specialist is "distracted."

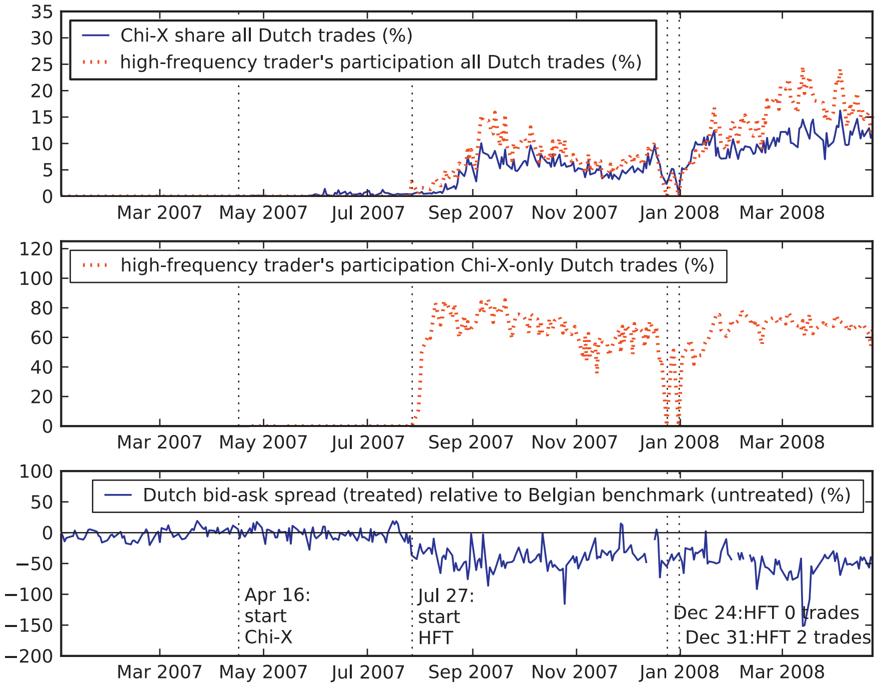

Fig. 4. Market share Chi-X, high frequency trader participation, and bid–ask spread. This figure plots four time series based on trading in Dutch index stocks from January 2, 2007, through April 23, 2008. The top graph depicts the market share of the entrant market Chi-X based on the number of trades; Chi-X started trading Dutch stocks on April 16, 2007. The graph also depicts the high frequency trader's participation in trades, based on its trading in both the entrant (Chi-X) and in the incumbent market (Euronext). The middle graph replots the high frequency trader's participation in trades, but now numerator and denominator are entrant market trades only. The bottom graph plots the average bid–ask spread of Dutch stocks relative to the spread of Belgian stocks. The incumbent market is the same for both sets of stocks (Euronext) but the Belgian stocks get delayed 'treatment with Chi-X'; they started trading in Chi-X one year later (April 24, 2008). The bid–ask spread is the inside spread i.e., the lowest ask across entrant and incumbent market minus the highest bid across these two markets. The spread is calculated daily as a cross-sectional weighted average where weights are equal to stock weights in the local index.

or by the entrant market alone. A detailed analysis of the change in liquidity supply and trade characteristics is beyond the scope of this study, but is available in Jovanovic and Menkveld (2011).

As the HFT appears crucial to both Chi-X take-off and liquidity improvement, the remainder of the analysis is focused on its activity. The analysis is based on its trading for 200 days starting on September 4, 2007 and ending on June 17, 2008. The sample of index stocks is cut into two equal-sized bins of small and large stocks according to their weight in the local index. The remaining analyses are done stock by stock and the results are presented in the tables through index-weighted averages across stocks. The tables also report cross-sectional dispersion by reporting the range (i.e., the lowest and the highest value in a bin) in parentheses (cf. Hasbrouck and Sofianos, 1993).

Panel A of Table 1 presents statistics to further support the claim that the trader ID combination is a *high frequency* trader. The HFT trades on average 1397 times per stock per day and is more active in large stocks (1582 times per day) as compared to small stocks (315 times per day). It is

Table 1
Summary statistics.
This table reports summary statistics on trading in Dutch index stocks from September 4, 2007 through June 17, 2008. Panel A presents statistics on the HFT's transactions; Panel B reports aggregate trading statistics. For each stock size group, it reports the variable weighted average (where index weights are used) and, in parentheses, the cross-sectional range i.e., the group's minimum and maximum value. The incumbent market refers to Euronext and the entrant market refers to Chi-X. Variable units are reported in parentheses.

Variable	Large stocks	Small stocks	All stocks
Panel A: High frequency trader statistics			
Fraction of days with zero closing inventory (%)	66.1 (50.5,87.5)	91.0 (86.0,97.0)	69.8 (50.5,97.0)
Daily closing inventory (100-share lots)	−0.35 (−1.00,0.68)	0.04 (−0.05,0.17)	−0.29 (−1.00,0.68)
St. dev. daily closing inventory (100-share lots)	12.9 (2.4,38.4)	1.2 (0.8,2.0)	11.2 (0.8,38.4)
High frequency trader #trades per day	1582 (344,2458)	315 (93,434)	1397 (93,2458)
High frequency trader trade participation rate (%)	15.7 (8.6,19.0)	6.9 (2.1,9.8)	14.4 (2.1,19.0)
High frequency trader trade participation rate incumbent market (%)	8.8 (5.7,11.0)	4.2 (1.2,6.6)	8.1 (1.2,11.0)
High frequency trader trade participation rate entrant market (%)	65.5 (63.1,69.1)	57.5 (41.4,63.6)	64.4 (41.4,69.1)
Panel B: Aggregate market statistics (based on all traders' activity)			
Daily total number of trades incumbent market (1000)	17.0 (7.6,23.4)	8.5 (5.3,10.7)	15.8 (5.3,23.4)
Daily total number of trades entrant market (1000)	2.5 (0.4,3.9)	0.5 (0.2,0.6)	2.2 (0.2,3.9)
Avg trade size incumbent market (€1,000)	31.4 (14.7,41.7)	15.1 (10.6,20.2)	29.0 (10.6,41.7)
Avg trade size entrant market (€1,000)	16.8 (7.8,21.9)	8.1 (6.7,10.1)	15.5 (6.7,21.9)
Half spread (0.5 * (ask–bid)) incumbent market (€)	0.007 (0.006,0.011)	0.016 (0.011,0.025)	0.008 (0.006,0.025)
Relative half spread incumbent market (basis points)	1.6 (1.3,2.5)	2.2 (1.6,3.6)	1.7 (1.3,3.6)
Avg transaction price (€)	22.97 (11.01,27.24)	37.39 (19.41,52.72)	25.08 (11.01,52.72)

fast as its latency is at most one millisecond (this is the granularity of the timestamp on Chi-X order events).[14] It is a large market participant as this activity represents a 14.4% participation rate in trades, 15.7% in large stocks and 6.9% in small stocks. The average closing position is −29 shares with a cross-sectional range of −100 shares to +68 shares. This shows that the HFT does not build up towards a long-term position but rather aims at mean-reverting its position quickly. It seems particularly eager to avoid overnight positions as on 69.8% of all trading stock-days it ends the day flat. The average standard deviation of its closing position is 1120 shares which is small judged against how actively it trades. Interestingly, the HFT seems to be particularly eager to avoid overnight positions for small stocks as it ends flat 91.0% of the days with an end-of-day position standard deviation of only 120 shares.

[14] Latency is proxied for by the time between a cancellation and a resubmission of a bid or ask quote (e.g., to change the price or quantity on the quote). These cancel-and-resubmit events are identified as a cancelled order followed by a new one in the same direction, of the same size, and within 1000 milliseconds of the cancelled order (cf., 'strategic runs' in Hasbrouck and Saar, 2013). HFT latency is then calculated based on the subset of runs that end up in a trade by the HFT. The latency measure can unfortunately not be calculated on *all* HFT runs as there is no trader identity available for orders, only for trades. Latency is calculated across all stocks for January 2008, the median month in the sample.

Panel B presents some more general trading statistics on the Dutch index stocks to show that these are highly liquid securities. The average stock in the sample trades 15,800 times a day in the incumbent market and 2,200 times a day in the entrant market. Average trade size is €29, 000 in the incumbent market and €15, 500 in the entrant market. Half the bid–ask spread is, on average, €0.008 which is 1.7 basis points.

2.3. Approach

This study's main objective is to understand the main source of HFT profitability by documenting its various components. It takes a micro-economics perspective by separately analyzing the revenue or gross profit[15] generated by the HFT operation and the capital that is required for it. The profit and capital are then combined to arrive at a standard profitability measure: the (gross) Sharpe ratio.

Inspired by Sofianos (1995), the HFT's revenue is decomposed into a spread component and a positioning component. Let n_t^a cumulate HFT aggressive trades (buy at the ask or sell at the bid, *ergo* pay the half-spread) through time t and let n_t^p cumulate its passive trades (buy at the bid or sell at the ask, *ergo* earn the half-spread). If started off on a zero position, this implies that the HFT net position at time t is $n_t = n_t^a + n_t^p$ shares.

HFT average trading profit over T time units is simply the average net cash flow (assuming it starts and ends at a zero position):[16]

$$\overline{\pi}^* = \frac{1}{T}\sum_{t=1}^{T} -\Delta n_t P_t \tag{1}$$

where $\overline{\pi}^*$ is the average gross profit per time unit (not accounting for trading fees), n_t is the (end-of-time-unit) net inventory position, P_t is the transaction price. Rewriting this sum allows for a natural decomposition of its trading profit into a spread and a 'positioning' profit:

$$\overline{\pi}^* = \frac{1}{T}\sum_{t=1}^{T} n_{t-1}\Delta p_t - \left|\Delta n_t^a\right| p_t s_t + \left|\Delta n_t^p\right| p_t s_t \tag{2}$$

where p_t is the midquote price (the average of the bid and the ask quote) and s_t is the relative effective half-spread (i.e., $|P_t - p_t|/p_t$).[17] In other words, Eq. (2) reads

$$\begin{aligned}\text{profit} = {} & \text{realized positioning profit} - \text{paid spread aggressive orders}\\ & + \text{earned spread passive orders}\end{aligned}$$

The HFT revenue decomposition is particularly useful to distinguish two contrasting common views on HFT: a friendly view that considers HFT as the new market makers and a hostile view that claims HFT is aggressively picking off other investors' quotes. These views

[15]This revenue or gross profit does not account for the (unknown) fixed costs of, for example, development of the algorithm, acquisition of hardware, exchange and clearing house membership fees.

[16]In the data, the HFT closes a day with a zero net position 69.8% of the time (see Table 1). For the days that it does not, it is standard practice to mark-to-market its position at the start and at the end of a trading day. This introduces an additional term in the equation: $n_T p_T - n_0 p_0$ where p_t denotes the midquote price. These terms are added in the empirical analysis, but omitted in the main text for exposition reasons.

[17]These equations hold under the assumption that the HFT engages in either one aggressive trade or one passive trade at each instant of time (each second in my data sample). The equation is trivially extended to deal with multiple trades per time unit at the cost of a more burdensome notation.

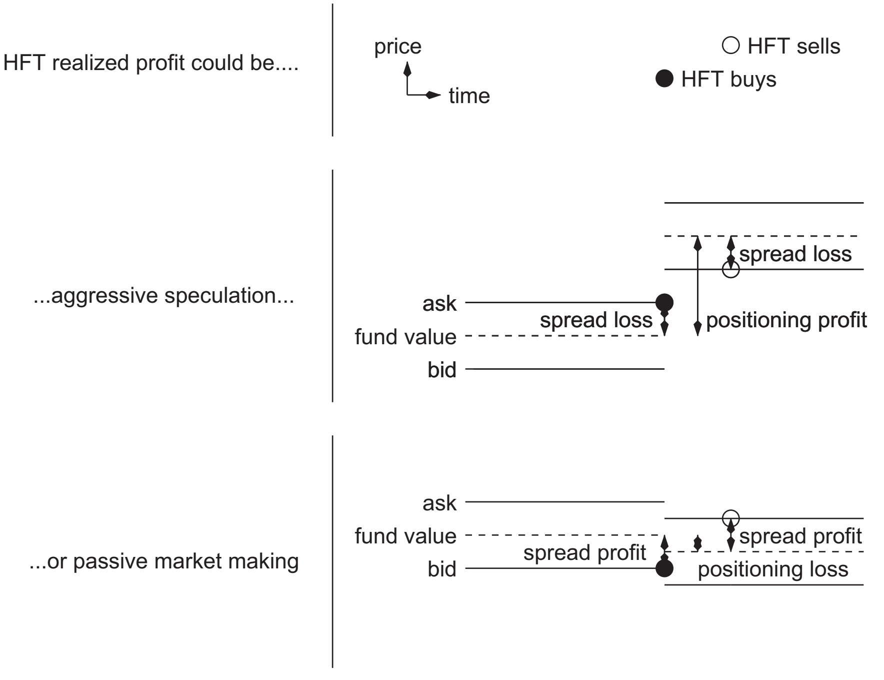

Fig. 5. Trade revenue decomposition: spread vs. positioning revenue. This figure illustrates the decomposition of a high frequency trader's gross profit into a spread and a positioning profit by analyzing the two extremes of how an HFT might generate profit. One extreme is that the HFT aggressively speculates; it consumes liquidity to pursue a fundamental value change that it observes and trades on quickly: spread revenue is negative, positioning revenue is positive. The other extreme is that the HFT passively makes a market; it produces liquidity by submitting bid and ask quotes and suffers a positioning loss when adversely selected by an incoming informed market order (e.g., Glosten and Milgrom, 1985). An alternative well-understood source of negative positioning profit is a price concession that a market maker willingly incurs to mean-revert its position (e.g., Ho and Stoll, 1981).

are illustrated in Fig. 5. The top graph plots the simplest inventory cycle for which the HFT generates a profit: it buys one share at a particular price and sells it some time later for a strictly higher price. The subsequent two graphs illustrate two ways (the extremes) by which the HFT might have generated this profit (by providing context to the prices drawn in the top graph).

In the middle graph the HFT aggressively picked off on an ask quote that had become stale after the fundamental value jumped. It unloads the position by hitting the bid quote after the bid and ask quotes fully reflect the new fundamental value. The HFT aggressively picked off quotes; it paid the half-spread twice, but made up for it through a (speculative) positioning profit.

The situation in the bottom graph is quite the opposite. The HFT buys the security when an incoming limit sell is matched with the standing HFT bid quote. The fundamental value drops at the time of the incoming order which indicates that the sale might have been information-motivated. The HFT offloads the position when an incoming buy order hits its ask quote. The HFT acts as a market maker; it earned the half-spread twice but suffered a positioning loss as the first incoming market order was information-motivated. The graphs are just illustrations of how both positioning and order types can be a source of profit or loss to an HFT.

In the analysis, the exchange and clearing fees are subtracted from the spread to arrive at a so-called 'net spread' paid or earned:

$$\overline{\pi} = \frac{1}{T}\sum_{t=1}^{T} n_{t-1}\Delta p_t - \left|\Delta n_t^a\right| p_t(s_t+\tau^a) + \left|\Delta n_t^p\right| p_t(s_t-\tau^p) \tag{3}$$

where $\overline{\pi}$ is the gross profit per time unit (after accounting for trading fees), τ^a denotes the sum of the (proportional) exchange fee and the clearing fee that need to be paid for an aggressive order, τ^p is the equivalent of τ^a for a passive order (and might, in fact, be negative due to rebates).

The first term captures HFT 'positioning' profit. It cumulates value changes associated with its net position. If it engages in speculative trading this is expected to be positive; on average, it will trade into a long position when the fundamental value is below the midquote and vice versa. The positioning profit might equally be negative if it is adversely selected on its quotes (e.g., Glosten and Milgrom, 1985). Or, a negative positioning profit might be willingly incurred to mean-revert out of a nonzero position (e.g., Ho and Stoll, 1981). Hendershott and Menkveld (2011) show that in an ongoing market a risk-averse intermediary trades off staying one more time unit on a nonzero position and suffer the price risk versus subsidizing traffic to get out of the nonzero position. In the process it collects the spread but (willingly) suffers a loss on positions (due to the subsidy it hands out when skewing quotes).

The last two terms in profit Eq. (3) sum up the HFT result on the 'net spread.' An aggressive, liquidity-demanding order leads to a negative contribution whereas a passive, liquidity-supplying order might lead to a profit. Aggressive trades pay the effective spread i.e., the distance between the transaction price and the midquote, pay the clearing fee, and pay the aggressive exchange fee. Passive trades on the other hand earn the effective spread, pay the clearing fee, and either pay an exchange fee (Euronext) or collect a rebate (Chi-X).

To further understand HFT trading profit it would be useful to decompose its positioning profit according to trading horizon. Does the HFT make money on positions it turns around in a matter of seconds, but perhaps lose money on positions it gets stuck with for hours? If so, how much does each trading horizon's result contribute to overall positioning revenue? Frequency domain analysis is the most natural way to create such decomposition. Hasbrouck and Sofianos (1993) were the first to propose such decomposition of trading revenue and applied it to NYSE specialist trading (e.g., Hau, 2001; Coughenour and Harris, 2004). The approach taken here differs slightly in that it is applied only to positioning profit (after stripping out 'net spread' revenues)[18] instead of the full trading profit and it runs the analysis on the natural clock as opposed to the transaction clock. The positioning profit is decomposed into bins of position durations with boundaries set at five seconds, one minute, one hour, and one day. A detailed description of the methodology is in Appendix B.

3. Empirical results

3.1. Gross profit, capital employed, and Sharpe ratio

Table 2 documents the HFT's performance, including the revenue generated, the capital required, and ultimately the Sharpe ratio. Panel A presents the average daily gross profit net of exchange/clearing fees (see Eq. (3)). It amounted to €9,542 per day.

[18]The net spread part of profit is instantaneous and, if desired, is therefore trivially attributed to the shortest-term bucket.

Table 2
Gross profit, capital employed, and Sharpe ratio.

This table reports statistics on the high frequency trader's gross profit (Panel A), the capital tied up in the operation due to margin requirements (Panel B), and, using both the profit and the capital results along with the risk-free rate, the implied Sharpe ratio based on daily return (Panel C) and half-hour return (Panel D). The Sharpe ratios have been annualized to correct for first-order autocorrelation based on Lo (2002, Table 2).

Panel A: Gross profit	
Gross profit per day (only net of exchange/clearing fees) (€)	9,542
Panel B: Capital employed	
Actual capital employed	
Avg margin specific risk (€1,000)	2,023
Avg margin gen market risk (€1,000)	618
Avg margin overall (€1,000)	2,641
Max margin overall (€1,000)	9,462
Capital employed if netting across markets were allowed	
Avg margin specific risk (€1,000)	22
Avg margin gen market risk (€1,000)	7
Avg margin overall (€1,000)	29
Max margin overall (€1,000)	452
Panel C: Sharpe ratio (based on daily return and maximum capital employed)	
Avg daily net return in excess of riskfree rate (bps)	9.65
St. dev. daily return (bps)	9.69
Autocorr daily return	0.63
Annualized Sharpe ratio based on daily return	7.62
Panel D: Sharpe ratio (based on half-hour return and maximum capital employed)	
Avg half-hour net return in excess of riskfree rate (bps)	0.59
St. dev. half-hour return (bps)	1.27
Autocorr half-hour return	0.26
Annualized Sharpe ratio based on half-hour return	23.43

Panel B of Table 2 presents statistics on the capital employed in the operation due to margin requirements. The average margin for specific risk is €2.023 million; for general market risk it is €0.618 million. The differential is partially due to an average 38% higher margin charge for specific risk (see Section 1). The other part is due to diversification in the HFT's position across stocks. The sample period maximum capital employed is a more relevant measure as it is (a lower bound on) the amount of capital the HFT needs to make available for the operation. It is roughly four times as high as the average margin required (€9.462 million vs. €2.641 million) which is perhaps surprisingly low given that this maximum is taken over *every second* in the 200 day sample period. This indicates that the HFT is particularly skillful in keeping its position in check.

The HFT has to keep margin in both clearing systems which is a source of a substantial inefficiency. Panel B reports the hypothetical margin requirements in case the HFT could net its position across the two clearing houses. The average capital margin is approximately a factor 100 lower for both specific risk and general market risk. The maximum margin is a factor 20 lower.

Panel C presents Sharpe ratios based on HFT gross profit. The ratio needs the daily excess return which is based on the sample maximum capital employed which is an indication of the standby capital required in the operation, the daily profit where a nonzero end-of-day position is marked-to-market based on the latest midquote in the day, and the capital's required return is set

Table 3
Sharpe ratio analysis.

This table presents the Sharpe ratio of the HFT strategy as a function of capital employed and the required return on the HFT capital tied up in the firm. Panel A presents Sharpe ratios for daily returns and panel B for half-hour returns. The Sharpe ratios have been annualized to correct for first-order autocorrelation based on Lo (2002, Table 2). The baseline Sharpe ratio reported in Table 2 appears in a box in both panels.

		Capital buffer, factor times actual maximum capital employed			
		0.5	1	5	10
Panel A: Sharpe ratio based on daily return					
Required return based on	$\beta=0$	7.80	$\boxed{7.62}$	6.14	4.34
	$\beta=0.5$	7.34	6.69	1.60	−4.50
	$\beta=1$	6.89	5.80	−2.81	−13.12
	$\beta=1.5$	6.46	4.93	−7.10	−21.52
Panel B: Sharpe ratio based on half-hour return					
Required return based on	$\beta=0$	23.43	$\boxed{23.43}$	23.41	23.39
	$\beta=0.5$	22.06	20.68	9.68	−4.08
	$\beta=1$	20.72	18.01	−3.67	−30.76
	$\beta=1.5$	19.43	15.42	−16.63	−56.70

equal to the risk-free rate which is downloaded from Kenneth French' website. The assumption is that the HFT can fully diversify its (entrepreneurial) risk. This assumption is unrealistic and the Sharpe ratio therefore serves as an upper bound in this respect. This issue is further analyzed in Table 3. The average daily excess return is 9.65 basis points, its average standard deviation is 9.69 basis points, and the average annualized Sharpe ratio is 7.62. The latter was corrected for a positive first-order autocorrelation of 0.63 based on Lo (2002, Table 2).[19]

Panel D reports the Sharpe ratio based on half-hour returns instead of daily returns. The higher frequency ratio seems appropriate given the speed of trading of HFTs.[20] The average return is unaffected as it is simply the daily average divided by 17, the number of half-hour intervals in a trading day. The standard deviation, however, seems to scale by almost double that factor. The first-order autocorrelation drops from 0.63 to 0.26. The Sharpe therefore rises from 7.62 to 23.43.

The large difference between half-hour and daily Sharpe ratios serves as a warning against solely relying on high-frequency Sharpe ratio analysis. The Lo (2002) correction for first-order autocorrelation appears to miss out on lower frequency persistence. Note that the first-order autocorrelation of daily returns is higher than its half-hour counterpart: 0.63 vs. 0.26, respectively. The autocorrelation function of half-hour returns captures such persistence through 'slow decay' of the autocorrelation at high lags. The AR(1) approximation does not seem to capture this tail behavior. It is therefore recommended to calculate daily or lower frequency

[19]The annualized Sharpe ratio is calculated as $(a*\mu(r_t)/\sigma(r_t))$ where a is the annualization factor taken from Lo (2002, Table 2), $\mu(\cdot)$ and $\sigma(\cdot)$ denote the mean and standard deviation and $r_t=(\pi_t-rf_t*max\_cap)$ where π_t is the daily gross profit as in Eq. (3) with start- and end-of-day positions marked to market, rf_t is the monthly risk-free rate, and max_cap is the full-sample stock-specific maximum capital employed.

[20]On August 1, 2012, the HFT firm Knight Capital was close to collapse after it suffered a $440 million loss on software that entered millions of faulty trades in less than an hour. See "Loss Swamps Trading Firm," *Wall Street Journal*, August 2, 2012.

Table 4
Gross profit, the cross-section and its components.
This table reports statistics on the high frequency trader's gross profit. For each stock size group, it reports the variable weighted average (where index weights are used) and, in parentheses, the cross-sectional range i.e., the group's minimum and maximum value.

Variable	Large stocks	Small stocks	All stocks
Gross profit per trade (only net of exchange/clearing fees) (€)	0.99 (−0.15,1.62)	0.19 (−0.18,0.78)	0.88 (−0.18,1.62)
Positioning profit per trade (€)	−0.69 (−0.90,−0.30)	−0.61 (−1.79,−0.07)	−0.68 (−1.79,−0.07)
Net spread per trade (€)	1.68 (0.76,2.15)	0.80 (0.25,1.64)	1.55 (0.25,2.15)

Sharpe ratios in addition to intraday Sharpe ratios.[21] In general, a substantially higher high-frequency Sharpe ratio relative to a low-frequency counterpart—after the Lo (2002, Table 2) correction—could serve as a red flag for HFT managers or regulators as trading losses can accumulate over time in a persistent manner.

Table 3 reveals how sensitive the Sharpe ratio is to the assumption on the required return on HFT capital and the capital buffer needed for margin requirements. For example, if instead of a capital buffer equal to the realized maximum margin requirement, one takes a more conservative approach and sets aside ten times that buffer, the daily Sharpe ratio drops from 7.62 to 4.34. Or, if the required return assumption is based on a beta of one instead of zero, the Sharpe ratio drops from 7.62 to 5.80. If both assumptions are changed simultaneously, the ratio drops to −13.12. Half-hour Sharpe ratios exhibit similar sensitivity.

3.2. Gross profit, the cross-section and its components

Table 4 reports the HFT's average gross profit per trade and unfolds it both in the cross-section and along its two main components: positioning profit and net spread. The gross profit per trade is €0.88 which is the result of a net spread of €1.55 and a positioning loss of €0.68. The positioning loss is consistent across all stocks as the cross-sectional range is €−1.79 to €−0.07. It is robust evidence against the hostile view of HFT that is based on speculation where the HFT creates an adverse-selection cost for other market participants. In this case, the HFT appears to suffer a consistent positioning loss. The net spread result is consistently positive in the cross-section of stocks: it ranges from €0.25 to €2.15 per trade.

3.3. Gross profit: the positioning profit component

Table 5 zooms in on the positioning loss reported in Table 2 by decomposing it according to trading horizon. Panel A reports that the overall loss of €−0.68 is composed of a €0.45 profit on ultra-high frequency positions that last less than five seconds, but losses on almost all lower frequency bins. The ultra-high frequency profit is a robust result as the cross-sectional range, €0.15 to €0.59, is entirely in the positive domain. The five seconds to a minute bin shows mixed results with negative and positive values for both small and large stocks. The frequency bins with

[21]The alternative approach is to model the half-hour return process with an AR(p) model where $p > 1$ or with a long-memory model to capture the slow decay in the autocorrelation function. One might then do a Lo correction based on the more elaborate model. The drawback of such approach is that one needs to take a stance at the appropriate model.

Table 5
Positioning profit decomposition.

This table decomposes the high frequency trader's positioning profit (reported in Table 2) according to position durations using frequency domain analysis (Panel A). It further decomposes (unconditional) net position variance to establish how much 'mass' is in each duration bracket; this is naturally interpreted as a histogram of durations (Panel B). For each stock size group, it reports the variable weighted average (where index weights are used) and, in parentheses, the cross-sectional range i.e., the group's minimum and maximum value.

Variable	Large stocks	Small stocks	All stocks
Panel A: Positioning profit decomposition			
Ultra-high frequency, period $\leq$5 seconds (€)	0.49 (0.21,0.59)	0.24 (0.15,0.39)	0.45 (0.15,0.59)
High frequency, 5 seconds $<$ period $\leq$1 minute (€)	−0.30 (−0.41,0.04)	0.02 (−0.08,0.20)	−0.25 (−0.41,0.20)
Medium frequency, 1 minute $<$ period $\leq$1 hour (€)	−0.67 (−0.99,−0.05)	−0.65 (−1.56,−0.17)	−0.67 (−1.56,−0.05)
Low frequency, 1 hour $<$ period $\leq$1 day (€)	−0.18 (−0.40,−0.06)	−0.15 (−0.43,−0.08)	−0.17 (−0.43,−0.06)
Ultra-low frequency, 1day $<$ period (€)	−0.03 (−0.13,0.02)	−0.07 (−0.17,−0.01)	−0.04 (−0.17,0.02)
Total positioning profit per trade (€)	−0.69 (−0.90,−0.30)	−0.61 (−1.79,−0.07)	−0.68 (−1.79,−0.07)
Panel B: Net position variance decomposition			
Ultra-high frequency, period $\leq$ 5 sec- onds (mln shares^2)	0.042 (0.001,0.060)	0.001 (0.000,0.001)	0.036 (0.000,0.060)
High frequency, 5 seconds $<$ period $\leq$ 1 minute (mln shares^2)	0.539 (0.017,0.761)	0.007 (0.001,0.011)	0.461 (0.001,0.761)
Medium frequency, 1 minute $<$ period $\leq$ 1 hour (mln shares^2)	9.182 (0.362,20.336)	0.145 (0.024,0.307)	7.862 (0.024,20.336)
Low frequency, 1 hour $<$ period $\leq$ 1 day (mln shares^2)	4.503 (0.247,17.624)	0.085 (0.022,0.271)	3.858 (0.022,17.624)
Ultra-low frequency, 1 day $<$ period (mln shares^2)	1.885 (0.101,7.284)	0.045 (0.008,0.170)	1.616 (0.008,7.284)
Net position variance (mln shares^2)	16.150 (0.728,45.866)	0.284 (0.059,0.760)	13.833 (0.059,45.866)

durations longer than a minute are virtually all negative as ranges are consistently in the negative domain except for large stocks in the lowest duration bin where the range is $(-0.13, 0.02)$.

Panel B shows that the overall loss of €0.68 is mostly driven by the €0.67 loss in the one-minute-to-an-hour bin as this bin carries most weight. As a matter of fact, 7.862/13.833 = 56.8% of the unconditional variance of HFT net position falls into this bin. It further shows that the profit associated with the ultra-high frequency bin is negligible for the overall result as this bin carries only 0.3% of the HFT net position variance.

3.4. *Gross profit: the net spread component*

Table 6 dissects the net spread profit to study its various components. Panel A presents the bottom-line net spread earned (also reported in Table 2). This panel also shows that the HFT is equally active in both markets: 50.8% of its trades are generated in Chi-X, the remaining 49.2% are generated in Euronext.

Panels A and B of Table 6 present a net spread decomposition for Euronext and Chi-X respectively. Comparing across these two panels leads to a couple of observations. First, in both markets the vast majority of HFT trades are passive: 78.1% in Euronext and 78.0% in Chi-X. The gross spread earned on these passive trades is of similar magnitude: €2.09 in Euronext and €2.38

Table 6
Net spread decomposition.

This table decomposes the high frequency trader's net spread result (reported in Table 2) along three dimensions: (i) incumbent market (Euronext) or entrant market (Chi-X), (ii) passive or aggressive side of the trade (the passive side of a trade is the standing limit order in the book that is executed against an incoming (marketable) limit order; the latter order is the aggressive side), (iii) (gross) spread or fee. For each stock size group, it reports the variable weighted average (where index weights are used) and, in parentheses, the cross-sectional range i.e., the group's minimum and maximum value.

Variable	Large stocks	Small stocks	All stocks
Panel A: High frequency trader in both markets			
Entrant market (Chi-X) trade share (%)	49.8 (43.7,62.8)	56.5 (51.6,63.6)	50.8 (43.7,63.6)
Net spread per trade (€)	1.68 (0.76,2.15)	0.80 (0.25,1.64)	1.55 (0.25,2.15)
Panel B: High frequency trader in incumbent market (Euronext)			
#trades per day	770 (216,1189)	180 (48,276)	684 (48,1189)
Fraction of passive trades (%)	79.5 (70.5,82.5)	70.0 (58.7,81.6)	78.1 (58.7,82.5)
Net spread per trade (€)	0.72 (0.09,1.27)	−0.07 (−0.44,1.01)	0.61 (−0.44,1.27)
Net spread per trade, passive orders (€)	1.26 (0.31,2.03)	0.23 (0.05,1.50)	1.11 (0.05,2.03)
Gross spread per trade, passive orders (€)	2.25 (1.25,2.99)	1.17 (0.97,2.44)	2.09 (0.97,2.99)
Exchange fee per trade, passive orders (€)	−0.68 (−0.71,−0.65)	−0.64 (−0.66,−0.62)	−0.68 (−0.71,−0.62)
Clearing fee per trade, passive orders (€)	−0.30 (−0.32,−0.29)	−0.30 (−0.31,−0.29)	−0.30 (−0.32,−0.29)
Net spread per trade, aggressive orders (€)	−1.35 (−2.21,−0.80)	−0.75 (−1.12,−0.23)	−1.26 (−2.21,−0.23)
Gross spread per trade, aggressive trades (€)	−0.39 (−1.28,0.17)	0.16 (−0.23,0.66)	−0.31 (−1.28,0.66)
Exchange fee per trade, aggressive orders (€)	−0.67 (−0.70,−0.63)	−0.63 (−0.64,−0.62)	−0.67 (−0.70,−0.62)
Clearing fee per trade, aggressive orders (€)	−0.29 (−0.30,−0.26)	−0.28 (−0.29,−0.27)	−0.29 (−0.30,−0.26)
Panel C: High frequency trader in entrant market (Chi-X)			
#trades per day	812 (128,1269)	135 (45,183)	713 (45,1269)
Fraction of passive trades (%)	77.1 (71.4,81.8)	83.3 (79.0,90.7)	78.0 (71.4,90.7)
Net spread per trade (€)	2.63 (1.88,3.17)	1.92 (1.46,3.05)	2.52 (1.46,3.17)
Net spread per trade, passive orders (€)	2.63 (1.97,3.15)	1.87 (1.46,3.14)	2.52 (1.46,3.15)
Gross spread per trade, passive orders (€)	2.46 (1.97,3.05)	1.90 (1.49,3.17)	2.38 (1.49,3.17)
Exchange fee per trade, passive orders (€)	0.34 (0.18,0.45)	0.16 (0.11,0.21)	0.31 (0.11,0.45)
Clearing fee per trade, passive orders (€)	−0.16 (−0.18,−0.14)	−0.19 (−0.22,−0.17)	−0.17 (−0.22,−0.14)
Net spread per trade, aggressive orders (€)	2.61 (1.51,3.36)	2.21 (1.43,3.78)	2.55 (1.43,3.78)
Gross spread per trade, aggressive trades (€)	3.30 (1.91,4.11)	2.65 (1.83,4.18)	3.21 (1.83,4.18)
Exchange fee per trade, aggressive orders (€)	−0.48 (−0.61,−0.18)	−0.22 (−0.28,−0.18)	−0.45 (−0.61,−0.18)
Clearing fee per trade, aggressive orders (€)	−0.21 (−0.22,−0.19)	−0.21 (−0.23,−0.20)	−0.21 (−0.23,−0.19)

in Chi-X. This translates into a substantially higher net spread in Chi-X relative to Euronext primarily due to the strong fee differential for passive orders: in Chi-X these orders earn a rebate on execution whereas in Euronext they get charged; the average exchange fee is €−0.31 in Chi-X and €0.68 in Euronext. This difference of almost one euro is large relative to the amount earned in the gross spread. Fees turn out to be of first-order importance for the profitability of the HFT. The clearing fee is also substantially lower: €0.17 in Chi-X vs. €0.30 in Euronext. The result is that the net spread result is substantially different across markets: €2.52 in Chi-X vs. €1.11 in Euronext.

In terms of aggressive orders, the most salient difference across markets is that the Euronext gross spread is €−1.26 whereas, surprisingly, the Chi-X gross spread is positive and large: €3.21. The unusual finding of a positive spread for aggressive orders is an artefact of the accounting that takes the midquote in the incumbent market as a reference price.[22] This positive result therefore reveals that the average HFT aggressive order hits a 'stale' Chi-X quote if the incumbent midquote has moved past it. For example, the HFT aggressively buys and consumes a Chi-X ask quote of €30.00 if the Euronext midquote is €30.01 which generates a positive gross spread result.

Another unusual finding is a positive aggressive spread of €0.16 for Euronext small stocks. This is the result of imperfect data as the timestamp on Euronext quotes is registered only to the second. The Euronext trade file carries a flag on who is on the aggressive side of each trade. It could therefore happen that the trade file registers an HFT aggressive sell at a price above the prevailing (stale) midquote. The finding of a positive result on average is revealing of the HFT strategy for small stocks. It seems that the HFT immediately responds (within a second) and aggressively trades against sudden large quote changes.

3.5. HFT net position, permanent price change, and price pressure

The results thus far suggest that the HFT is predominantly a market maker: on average, it earns the spread as most of its trades are passive and it suffers losses on its net positions. This section studies whether the HFT position, given that it is a large intermediary (it participates in 14.4% of all trades, see Table 1), correlates with price change. The microstructure literature suggests it might do so in essentially two ways (e.g., Madhavan, 2000): adverse selection and price pressure.

A market maker's quote might be hit by an informed trader in which case the market maker loses money; the intermediary is adversely selected. This implies that the permanent price change (i.e., information) is negatively correlated with the market maker's position change. For example, an information-motivated market sell order causes investors' to rationally infer a negative permanent price change and at the same time makes the market maker's position increase.

The market maker's position also correlates with transitory price changes as its solution to the inventory position control problem is to skew quotes relative to fundamental value i.e., apply price pressure. A risk-averse market maker who is long relative to his optimal position adjusts his quotes downwards to trade out of his position: a lowered ask increases the chance of someone buying and a lowered bid reduces the chance of someone selling. In essence, he subsidizes traffic to mean-revert his position where the size of the subsidy is determined by trading off the size of the subsidy against the loss of absorbing price risk on a nonoptimal position. For a closed-form solution to the stylized control problem, see Hendershott and Menkveld (2011).

[22]The analysis was redone with the inside market midquote instead of the incumbent market midquote as the reference price (Table 8 in the online appendix). The inside market midquote is defined as the midpoint of the lowest ask across both markets (i.e., incumbent and entrant) and the highest bid across both markets. The results show that the Chi-X gross spread is reduced from 3.21 to 2.44 basis points.

The interaction of the HFT net position, permanent price change, and price pressure is most naturally captured by estimating a state-space model as proposed in Hendershott and Menkveld (2011). The model is implemented at an intraday frequency, yet recognizes a continuous round-the-clock price process (cf. Menkveld, Koopman, and Lucas, 2007). The idea is simple. The *unobserved* 'fundamental' or 'efficient' price is characterized by a martingale:[23]

$$m_{t,\tau} = m_{t,\tau-1} + \kappa_\tau \tilde{n}_{t,\tau} + \eta_{t,\tau} \quad (\text{where } \tilde{n}_{t,\tau} := n_{t,\tau} - E_{t,\tau-1}(n_{t,\tau})) \tag{4}$$

where (t, τ) indexes time, t runs over days and τ runs over intraday time points (9:00, 9:05, 9:10, …), m is the efficient price, n is the HFT net position, $\tilde{n}$ is the residual of an AR(2) model applied to n (standard selection criteria indicate that AR(2) is the appropriate model), and η is a normally distributed error term. The efficient price equation uses the residual $\tilde{n}$ rather than n to ensure that m retains its martingale property. It also makes economic sense as a Bayesian update is based on the 'surprise' change, leaving out the forecasted change. The five-minute frequency is selected as most of the probability mass in the frequency domain analysis is on minute cycles as opposed to second, hour, or daily cycles (see Panel B of Table 5). For ease of exposition, let the time index $(t, \tau = -1)$ be equal to $(t-1, \tau_{max})$ where τ_{max} is the latest time point in the day. The system therefore runs around the clock and includes overnight price changes. The adverse selection argument predicts that the parameter κ_τ is negative (for an uninformed market maker).

A transitory deviation from the efficient price, the *unobserved* 'pricing error' (cf. Hasbrouck, 2007, p. 70) is modeled as

$$s_{t,\tau} = \alpha_\tau n_{t,\tau} + \varepsilon_{t,\tau} \tag{5}$$

where s is the (stationary) pricing error and ε is a normally distributed error term that is independent of η. The $\alpha_\tau n$ part of the pricing error reflects the price pressure exercised by the HFT to revert out of a nonzero position; the argument predicts α_τ to be negative.

Finally, the *observed* price is modeled as the sum of the efficient price and the pricing error:

$$p_{t,\tau} = m_{t,\tau} + s_{t,\tau} \tag{6}$$

Eqs. (4)–(6) make up a standard state-space model that is estimated with maximum likelihood using the Kalman filter (Durbin and Koopman, 2001). The parameterization recognizes potential time-of-day effects by making all parameters depend on τ (including the error terms' variance). To keep the estimation feasible, these parameters are pooled into four intraday time intervals: (open) 9:00–12:00, 12:00–15:00, 15:00–17:30 (close), 17:30–9:00 (+1).

The estimation results in Table 7 largely support the market-making character of the HFT operation. Panel A reveals that the size of HFT net position increases in the course of the day; its standard deviation is €57,500 in the morning, €71,300 by midday, and €84,400 in the afternoon. The first-order autoregressive coefficient (from the AR(2) model) reveals that roughly half of a shock to the HFT position disappears in five minutes which indicates that the five-minute frequency seems appropriate. It is 0.48 in the morning, 0.51 by midday, and 0.40 in the afternoon. The quicker reversals in the afternoon are consistent with the HFT aim to end the day 'flat' (see Table 1); it is too costly to carry an overnight position with its associated price risk. The overnight coefficient, the HFT opening position (after the opening auction) regressed on its

[23]The intercept is set to zero as the model samples at a five-minute frequency for one year of data. Merton (1980) shows that estimators of second moments (variance, covariances) are helped by frequent sampling, not estimators of first moments (mean). Hasbrouck (2007, p. 27) illustrates the trade-off between estimator bias associated with setting the 'high-frequency intercept' to zero against the estimator error of setting it equal to the sample mean. He considers it preferable to set it to zero for a one-year sample.

Table 7
HFT net position, permanent price change, and price pressure.

This table relates inter- and intraday price changes to the HFT net position to analyze whether the HFT can be characterized as a liquidity supplier. A state space model distinguishes transitory and permanent price changes and relates each of them to the HFT net position consistent with the canonical microstructure model of a supplier of liquidity (Hendershott and Menkveld, 2011):

$$p_{t,\tau} = m_{t,\tau} + s_{t,\tau}$$
$$m_{t,\tau} = m_{t,\tau-1} + \kappa_\tau \tilde{n}_{t,\tau} + \eta_{t,\tau} \quad (\text{where } \tilde{n}_{t,\tau} := n_{t,\tau} - E_{t,\tau-1}(n_{t,\tau}))$$
$$s_{t,\tau} = \alpha_\tau n_{t,\tau} + \varepsilon_{t,\tau}$$

where t indexes days, τ indexes intraday time points (9:00, 9:05, 9:10),…, p is the incumbent midquote price, m is a martingale that represents the unobserved 'efficient' price, n is the HFT net position, $\tilde{n}$ is the (surprise) innovation in HFT net position where last period's forecast is obtained based on an AR(2) model for the net position series n, and s represents the unobserved stationary pricing error process. For ease of exposition, let the time index $(t, \tau = -1)$ be equal to $(t-1, \tau_{max})$ where τ_{max} is the latest time point in the day. The error terms η and ε are assumed to be mutually independent normally distributed variables with a variance that depends on time of day (τ). In the estimation all time-of-day dependent parameters are pooled into four intraday time intervals: (open) 9:00–12:00, 12:00–15:00, 15:00–17:30 (close), 17:30–9:00 (+1). For each stock size group, the table reports the average parameter estimate and in parentheses its cross-sectional range i.e., the group's minimum and maximum value. Parameter units are in parentheses.

Variable	Time	Large stocks	Small stocks	All stocks
	Panel A: Net position			
St. dev. net position, $\sigma(n)$ (€1,000)	9:00–12:00	64.6 (22.7,80.3)	15.4 (7.2,20.4)	57.5 (7.2,80.3)
	12:00–15:00	80.3 (25.1,101.8)	19.0 (7.2,25.5)	71.3 (7.2,101.8)
	15:00–17:30	95.4 (24.8,128.9)	19.9 (7.3,26.7)	84.4 (7.3,128.9)
Ar1 coefficient net position, n	9:00–12:00	0.46 (0.38,0.68)	0.56 (0.48,0.73)	0.48 (0.38,0.73)
	12:00–15:00	0.50 (0.43,0.69)	0.56 (0.48,0.72)	0.51 (0.43,0.72)
	15:00–17:30	0.39 (0.30,0.64)	0.43 (0.35,0.62)	0.40 (0.30,0.64)
	17:30–9:00 (+1)	0.02 (−0.01,0.09)	0.04 (−0.03,0.12)	0.02 (−0.03,0.12)
	Panel B: Permanent price change (Δm)			
Cond adverse selection, κ (bp/€1,000)	9:00–12:00	−0.035 (−0.074,−0.023)	−0.096 (−0.421,−0.049)	−0.044 (−0.421,−0.023)
	12:00–15:00	−0.025 (−0.053,−0.010)	−0.066 (−0.213,−0.029)	−0.031 (−0.213,−0.010)
	15:00–17:30	−0.019 (−0.041,−0.010)	−0.069 (−0.270,−0.027)	−0.026 (−0.270,−0.010)
	17:30–9:00 (+1)	0.014 (−0.378,0.101)	0.106 (−0.433,3.475)	0.028 (−0.433,3.475)
Var adv selection, $\sigma^2(\kappa\tilde{n})$ (bp^2/hour)	9:00–12:00	41.3 (9.3,59.4)	12.8 (3.1,54.7)	37.1 (3.1,59.4)
	12:00–15:00	32.0 (2.6,68.5)	8.7 (1.2,22.4)	28.6 (1.2,68.5)
	15:00–17:30	31.0 (5.8,70.0)	12.9 (2.2,70.5)	28.3 (2.2,70.5)
	17:30–9:00 (+1)	0.3 (0.0,0.7)	0.7 (0.0,10.4)	0.3 (0.0,10.4)
Var perm price change, $\sigma^2(\Delta m)$ (bp^2/hour)	9:00–12:00	10871 (5423,15705)	7054 (3701,29342)	10313 (3701,29342)
	12:00–15:00	7371 (3182,15730)	3877 (2533,12513)	6861 (2533,15730)
	15:00–17:30	8036 (2923,17574)	5436 (2782,33261)	7656 (2782,33261)
	17:30–9:00 (+1)	691 (375,1071)	764 (435,3727)	702 (375,3727)

Table 7 (*continued*)

Variable	Time	Large stocks	Small stocks	All stocks
	Panel C: Price pressure (s)			
Cond price pressure, α (bp/€1,000)	9:00-12:00	−0.041 (−0.128,−0.016)	−0.144 (−0.536,−0.080)	−0.056 (−0.536,−0.016)
	12:00–15:00	−0.026 (−0.097,−0.006)	−0.095 (−0.426,−0.015)	−0.036 (−0.426,−0.006)
	15:00–17:30	−0.063 (−0.308,0.116)	0.028 (−0.696,2.147)	−0.050 (−0.696,2.147)
Var price pressure, $\sigma^2(\alpha n)$ (bp^2)	9:00–12:00	6.6 (0.7,12.0)	4.3 (1.5,27.8)	6.3 (0.7,27.8)
	12:00–15:00	4.2 (0.4,9.8)	2.7 (0.1,16.8)	4.0 (0.1,16.8)
	15:00–17:30	93.3 (0.0,439.9)	76.7 (0.2,246.5)	90.9 (0.0,439.9)
Var pricing error, $\sigma^2(s)$ (bp^2)	9:00-12:00	7.9 (1.1,27.4)	8.3 (1.9,28.3)	8.0 (1.1,28.3)
	12:00–15:00	10.2 (1.8,21.3)	16.5 (6.1,55.0)	11.1 (1.8,55.0)
	15:00–17:30	107.7 (15.2,459.2)	86.7 (0.8,266.0)	104.6 [a] (0.8,459.2)

[a]This AR coefficient is based on the HFT opening position (just after the opening auction) relative to its previous day closing position.

position at the previous day close, is 0.02 which is further evidence that the HFT manages its position within the day in such a way so as to avoid a nonzero overnight position.

Panel B reveals that the HFT incurs adverse selection cost most of the day except for when it acquires a position at the market open. The adverse selection parameter, κ_τ, is consistently negative for all stocks in the morning, midday, and afternoon (i.e., the range intervals are strictly in the negative domain). Its intraday pattern is largely monotonic as κ_τ is −0.044, −0.031, and −0.026 basis point per €1,000 (surprise) position change, respectively. This might explain why the size of the HFT position gradually rises during the day (cf. Panel A); the HFT increases its activity after the most intense price discovery in the opening hours is over. The HFT is best equipped to intermediate at times when the market is back to 'normal' so that it can rely on publicly available 'hard' information (e.g., quotes in same-industry stocks, index futures, FX, etc.) to refresh its quotes and thereby minimize adverse selection risk. This argument is developed in detail in Jovanovic and Menkveld (2011). Interestingly, the adverse selection parameter κ_τ is positive for the overnight innovation: 0.028.[24] The HFT seems to participate in the opening auction when there is an informational opportunity.

Panel C shows that the HFT net position generates (transitory) price pressure. The average estimate of the conditional price pressure, α_τ, is negative for all time intervals: −0.056, −0.036, and −0.050 basis point per €1,000 position for the morning, midday, and afternoon, respectively. In a stylized market maker model, the size of the conditional price pressure is the optimal control variable that trades off the cost of staying on the position one more time unit (lower pressure) and a higher revenue loss to mean-revert a suboptimal position more quickly (higher pressure) (Hendershott and Menkveld, 2011). This insight could explain the relatively

[24]The particularly large κ estimate for small stocks relative to large stocks is driven entirely by one particularly large estimate for the smallest stock. Absent this stock, the results are not much different across small and large stocks.

high pressure in the morning as volatility is highest in this period (see panel B) and holding inventory is therefore particularly costly (in utility terms). It could also explain elevated pressure in the afternoon as the risk of staying in a nonzero position overnight increases when the market close draws near. The negative α_τ result appears robust for all time intervals except for the afternoon session; the range of α_τ estimates is strictly in the negative domain for the morning and the midday, but not for the afternoon.

The effect of price pressure is economically significant. Its variance ($\alpha_\tau^2\sigma_\tau^2(n)$) is 6.3, 4.0, and 90.9 squared basis points for the morning, midday, and afternoon, respectively. To put them into perspective, these numbers are larger than the squared average half spread ($1.7^2=2.89$ squared basis points, see Table 1). Moreover, price pressure variance is at least two-thirds of total pricing error variance. Particularly striking is the large price pressure exercised in the afternoon, the period in which U.S. markets open. The HFT is particularly active as it enters large positions on average ($\sigma(n)=0.84$), larger than any of the other periods. At the same time it steers these positions back to zero more quickly; the AR1 coefficient is 0.40 (compared to 0.48 and 0.51 for the morning and midday periods, respectively). The more aggressive mean-reversion might be driven by the desire to not hold a position overnight. An alternative reason is that the HFT might be 'forced' to do it due to additional overall demand when U.S. markets are open. The HFT pays a high cost for the strong mean-reversion as conditional price pressure ($\alpha=-0.050$) is high compared to the midday period ($\alpha=-0.036$), but not as high as in the morning ($\alpha=-0.056$).

Taken together, these state space results indicate that the HFT does act as a modern market maker and its positions explain most of the transitory pricing error in five-minute midquote returns (i.e., price pressure variance is at least two-thirds of the total pricing error variance). To conclude, a couple of final observations. First, the HFT's weight in the market appears large or representative enough to generate visible overall price patterns. The HFT's large effect on pricing error is most likely due to it undercutting the best available rival quote on the side of market that mean-reverts its position; if it is long it will undercut the lowest ask in the market by one tick to increase the probability to get out of the position. The HFT skews the midquote downwards this way. This is, unfortunately, not testable with the data at hand as HFT quotes are not observed (only its trades). Second, the price variable was taken to be the incumbent market midquote (in order to be consistent with earlier analysis, Table 6 for example). As a robustness check, Table 9 in the online appendix repeats the analysis with the overall market midquote (thus including Chi-X quotes) as the price variable. The results appear largely unaffected. Third, five-minute HFT position changes correlate negatively with permanent price changes which is consistent with the positioning losses reported in Table 5; the market maker is adversely selected on its quotes.

4. Conclusion

This paper benefits from proprietary Chi-X and Euronext datasets that contain anonymized broker IDs for trades in Dutch index stocks for a sample period that runs from September 4, 2007 to June 17, 2008. One particular set of broker IDs matched across markets shows the characteristics of an HFT that acts as a market maker in both the entrant market (Chi-X) and the incumbent market (Euronext). In each market, four out of five of its trades are passive i.e., the HFT was the (liquidity-supplying) limit order in the book that got executed. Its lowest inter-message time is at most one millisecond. It trades actively with an average of 1397 trades per stock per day. It makes money on the spread but loses money on its positions. If this positioning loss is decomposed according to duration, one finds that positions that last less than five seconds generate a profit whereas the ones that last longer generally lose money. The HFT is equally active in both markets as roughly half of its trades are on Chi-X and the other half are on Euronext. Overall, it is a significant market participant as it shows up in 14.4% of all trades (aggregated across markets). It is particularly active in Chi-X where it participates in roughly every other trade.

The paper also focuses on the capital required for the operation. The fee structure and margin requirement of the each of the two clearing houses associated with the two markets were retrieved to the extent possible. The HFT cannot net its positions across markets and therefore is estimated to have to put up a 100 times more capital than what would have been needed if netting were possible. This might in effect explain why the U.S. equity market is most fragmented as netting is possible in the U.S. The maximum (across my sample period) of the capital tied-up due to margining is then taken as a natural measure for the standby capital needed in the operation. This capital measure along with the daily gross profits and the risk-free rate imply an average annualized Sharpe ratio of 7.62.

Round-the-clock price changes are modeled to analyze whether the HFT is visible in the security's market prices. The market making literature suggests that it might be in two ways: permanent price changes should correlate negatively with HFT position change (the HFT is adversely selected on its quotes) and transitory pricing errors should also correlate negatively with the HFT position (the HFT skews quotes to get out of its position). The evidence is supportive. In the trading day, the HFT position generates significant (transitory) price pressure. It is an economically meaningful amount as it is, for example, larger than half the average bid–ask spread. Also, the (surprise) HFT position change correlates negatively with permanent price changes throughout the trading day, but not in the overnight period for which the sign is reversed.

Finally the results show that fees are a substantial part of a high frequency trader's profit and loss account. It is therefore not surprising that new, low-fee venues have entered the exchange market as they are attractive to these ‘modern’ market makers. This evidence adds to the regulatory debate on high frequency traders and highlights that a subset is closely linked to the rapidly evolving market structure that is characterized by the entry of many new and successful trading venues.

Appendix A. List of the sample stocks

This table lists all stocks that have been analyzed in this paper. It reports the official ISIN code, company name, and the index weight that has been used to calculate (weighted) averages.

Dutch index stocks/‘treated’ sample			Belgium index stocks/‘untreated’ sample		
ISIN code	Security name	Index weight[a]	ISIN code	Security name	Index weight[a]
NL0000303600	ING Groep	22.3%	BE0003801181	FORTIS	17.5%
NL0000009470	Royal Dutch Petrol	20.1%	BE0003565737	KBC	15.8%
NL0000009538	Kon Philips Electr	12.1%	BE0003796134	Dexia	13.5%
NL0000009355	Unilever	11.3%	BE0003793107	Interbrew	9.5%
NL0000303709	AEGON	7.5%	BE0003470755	Solvay	6.5%

NL0000009082	Koninklijke KPN	7.4%	BE0003797140	GPE Bruxel.Lambert	5.7%
NL0000009066	TNT	4.8%	BE0003562700	Delhaize group	5.4%
NL0000009132	Akzo Nobel	4.2%	BE0003810273	Belgacom	4.4%
NL0000009165	Heineken	3.0%	BE0003739530	UCB	4.1%
NL0000009827	DSM	2.4%	BE0003845626	CNP	2.9%
NL0000395903	Wolters Kluwer	2.2%	BE0003775898	Colruyt	2.3%
NL0000360618	SBM Offshore	1.2%	BE0003593044	Cofinimmo	2.2%
NL0000379121	Randstad	1.1%	BE0003764785	Ackermans and Van Haaren	2.2%
NL0000387058	TomTom	0.6%	BE0003678894	BEFIMMO-SICAFI	2.1%
			BE0003826436	Telenet	2.1%
			BE0003735496	Mobistar	1.5%
			BE0003780948	Bekaert	1.1%
			BE0003785020	Omega Pharma	1.0%

[a] The index weights are based on the true index weights of December 31, 2007. The weights are rescaled to sum up to 100% as only stocks are retained that were a member of the index throughout the sample period. This allows for fair comparisons through time.

Appendix B. Frequency domain decomposition of positioning profit

The first term from Eq. (3) was labeled the positioning profit i.e.,

$$\overline{\pi}_{pos} = \frac{1}{T}\sum_{t=1}^{T} n_{t-1}\Delta p_t,$$

where t indexes all seconds in the sample (and T therefore equals 6.12 million)[25] (=200 days *8.5 hour*60 minute*60 second), Δp_t is the log midquote price change, and n_t is HFT net position.

The frequency domain decomposition of this 'covariance' term is standard and the discussion below is largely taken from Hasbrouck and Sofianos (1993). A useful reference on frequency domain analysis is Bloomfield (2000). The original series are relabeled x_t for n_{t-1} and y_t for Δp_t for ease of notation.

For an equally spaced time series of length T, the Fourier frequencies are given by $\omega_k = 2\pi k/T$, for $k = 0, 1, \ldots, T-1$. The period (length of cycle) corresponding to a frequency $\omega > 0$ is given by $2\pi/\omega$, so the lowest positive frequency in the data corresponds to a component that cycles once over the full sample. The Fourier transform of the data is

$$J_x(\omega_k) = \frac{1}{T}\sum_{t=1}^{T} x_t e^{-i\omega_k t}.$$

[25] Note that the nontrading seconds have been removed for numerical reasons. The procedure still takes overnight positioning profit into account and mechanically adds it to the one second bucket. This profit is however a relatively small part of overall profit as the HFT endogenously avoids overnight positions; Table 1 shows that HFT net position is zero at the end of 69.8% of the sample days.

$J_x(\omega_k)$ is the Fourier component of x_t at frequency ω_k. The data may be recovered using the inverse transform:

$$x_t = \sum_{k=0}^{T-1} J_x(\omega_k) e^{i\omega_k t}.$$

This expresses x_t as the sum of the components at various frequencies. The usual estimate of the cross-product between two series, x_t and y_t, is

$$\hat{M} = \frac{1}{T} \sum_{t=1}^{T} x_t y_t.$$

This estimate is computationally equal to the one formed from the Fourier transforms:

$$\hat{M} = \sum_{k=0}^{T-1} J_x(\omega_k) \overline{J_y(\omega_k)},$$

where the summation is over all Fourier frequencies and the overbar denotes complex conjugation. Written in this fashion, the contributions to the covariance from different frequencies is clearly visible. A particular subset of frequencies, such as the ones corresponding to a certain horizon, may be denoted by K, as subset of $\{k|k=0,1,\ldots,T-1\}$.

The Fourier transforms were implemented in Python using the library function matplotlib.mlab.csd. The Fourier transforms were smoothed by twice applying the Daniell filter of size 16*256 (e.g., Bloomfield, 2000, p. 194).

Appendix C. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org.10.1016/j.finmar.2013.06.006.

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