High-Frequency Traders' Single-Dealer Platforms and Market Quality

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Abstract

High-frequency traders (HFTs) primarily operate on public exchanges, where multiple third-party buying and selling interests interact. Since the European regulatory changes in 2018 (Markets in Financial Instruments Directive II), HFT single-dealer platforms have emerged, enabling HFTs to engage in bilateral trading as dealers. Our findings indicate that trading on HFT dealer platforms negatively affects liquidity but enhances price efficiency on public stock exchanges. HFTs manage inventory imbalances from their dealer operations by trading more aggressively and reducing their liquidity supply on exchanges, which harms liquidity but improves price efficiency.

Keywords: High-frequency traders, Dealers, Liquidity, Efficiency, Inventory management

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1 Introduction

High-frequency traders (HFTs) use sophisticated, high-speed computer programs to trade in their own accounts. They are known for their large trading volumes, short investment horizons, and tight inventory management (Securities and Exchange Commission (2010)). Menkveld (2016) associates the rise of HFT with the expansion of electronic trading and market fragmentation, allowing stocks to be traded not only on traditional exchanges but also on multilateral trading facilities, dark pools, crossing networks, and systematic internalizer (SI) dealer platforms.

The literature discusses various strategies employed by HFTs, primarily based on their activities on multilateral trading venues such as exchanges, where multiple third-party buying and selling interests interact.[2] Although we have a good understanding of the roles of HFTs and the nature of their activities on exchanges, less is known about their off-exchange strategies in bilateral trading settings. The European regulatory reform of the Markets in Financial Instruments Directive II (MiFID II) in 2018 led to the emergence of HFT single-dealer platforms in the form of SIs run by HFTs. With this operation, an HFT firm has its own trading platform, acts as a dealer, conducts bilateral trading, and is subject to more regulation compared to electronic liquidity providers in the U.S.[3]

We investigate the role of HFT single-dealer platforms in equity markets. Our focus is on the characteristics of HFT single-dealer platforms and how their operations affect HFTs'

[2] Menkveld (2013) demonstrates that HFTs primarily function as market makers. Hagströmer and Nordén (2013) argue that HFTs utilize their speed advantage to both provide and take liquidity. Other studies confirm that HFTs trade based on information (Hu, Pan, and Wang (2017)), can predict order flow (Hirschey (2021)), and contribute to improved liquidity and price efficiency (e.g., Brogaard, Hendershott, and Riordan (2014); Brogaard, Hagströmer, Nordén, and Riordan (2015)).
[3] Battalio, Hatch, and Sağlam (2023) analyze the bilateral interaction between a U.S. investment firm and market-making HFTs, also known as electronic liquidity providers.

inventory management behavior, liquidity provision on public exchanges, and ultimately, market quality.

We find that trading activity on HFT single-dealer platforms makes HFTs to manage their inventory imbalances by taking liquidity and reducing their liquidity supply on exchanges. Quoted bid–ask spreads thus widen and order books become thinner, while the actual trading cost at exchanges is virtually unchanged. This strategy, however, improves price efficiency by reducing the deviation of prices from the fundamental values, as measured by return autocorrelations and excess variance ratios.

Our investigation utilizes data on transactions in the 45 large-cap Swedish stocks with the highest average daily turnover during 2018. The data are obtained from the Swedish Financial Supervisory Authority, Finansinspektionen, and identify transactions by distinct trading firms on exchanges and single-dealer platforms.[4] We follow Baron, Brogaard, Hagströmer, and Kirilenko (2019) and identify HFTs as trading firms that are members of the Futures Industry Association's European Principal Traders Association (FIA EPTA), which is an industry organization for principal trading firms, or firms that describe themselves as HFTs on their websites. We classify HFT dealers as HFTs that operate SI platforms and HFT non-dealers as HFTs that do not operate SI platforms. On average, our results show that HFT dealers trade larger volumes, change their inventory positions more often, and experience better execution quality on exchanges than HFT non-dealers.

We investigate whether exchange liquidity is affected by the trading activity of HFT dealers. We measure liquidity in the consolidated order book, constructed from exchanges

[4] The exchanges are Nasdaq Stockholm, BATS Europe, Chi-X, Turquoise, and Aquis. Nasdaq has market shares of 61% of the exchange SEK trading volume and 53% of the number of exchange trades in our sample. The corresponding SEK volume market shares (number of trades) for the other exchanges are 22% (25%) for Chi-X, 8% (12%) for BATS Europe, 6% (7%) for Turquoise, and 3% (3%) for Aquis.

both ex-ante, as the displayed order book liquidity, and ex-post, as the actual cost of trading.[5] Accordingly, we use half the relative quoted bid–ask spread and the depth at the best bid and offer (the SEK value of the volume available at the best bid price plus that at the best offer price) in the consolidated order book as our measures of displayed liquidity. Moreover, we use the effective spread, which equals the relative signed difference between the price of each traded stock and the corresponding best bid–ask midpoint in the consolidated order book at the time of the trade, as our measure of actual cost of trading.

Our results show that trading on HFT single-dealer platforms harms displayed exchange liquidity.[6] Specifically, a one standard deviation increase in the market share of HFT dealers is associated with a 3.12% increase in the quoted half-spread (from 3.03 to 3.12 basis points, or bps, on average) and an 18% decrease in depth at the best quotes (from SEK 0.41 million to SEK 0.34 million, on average). These results are statistically significant at the 1% level. For a trade of USD 5,000 (roughly SEK 43,750), the results imply an increase in the round-trip cost from USD 3.03 to USD 3.12 for trading at the displayed order book quotes.[7] Additionally, the 18% decrease in depth corresponds to a decrease in the average trade size required to move a stock price from USD 23,405 to USD 19,209 (SEK 205,000 to SEK 168,250).

Despite the reduction in displayed exchange liquidity, the actual cost of trading on exchanges is virtually unchanged when exposed to a one standard deviation increase in the market share of HFT dealers. Even for slow traders (non-HFTs), the effective spread increases only slightly in statistical terms, and economically, the difference is only 1.27%.

[5] For each stock and at each point in time, the highest bid and the lowest ask quotes across exchanges are collected as the best bid and ask prices, respectively, of the consolidated order book.

[6] We ensure that all the liquidity results are robust to the potential endogeneity problem where dealer trading volume is affected by liquidity at exchanges by employing the instrumental variable estimation technique used by Comerton-Forde and Putniņš (2015) and Hasbrouck and Saar (2013) in our analyses.

[7] The round-trip cost equals the traded amount multiplied by the quoted spread. We use the SEK/USD exchange rate of 8.7587 observed on January 1, 2018, which marks the beginning of our sample period, in our calculations.

Hence, the reduction in displayed liquidity following an increase in the market share of HFT dealers is not reflected in the actual trading costs.

We also examine the impact of HFT single-dealer platforms on price efficiency in the consolidated order book. We use high-frequency measures of price efficiency proxied by return autocorrelations and excess variance ratios, which are based on the notion that stock prices should follow a random walk process. The return autocorrelations are the first-order logarithmic return autocorrelations, and the excess variance ratio measures the deviation of the variance ratio from one, indicative of an efficient market.

The findings show that an increase in the market share of HFT dealers reduces the deviation of prices from a random walk process, leading to more informative prices. A one standard deviation increase in the market share of HFT dealers decreases the values of return autocorrelation by 9% (from 0.04 to 0.03) and 13.33% (from 0.06 to 0.05) for 30-second and 60-second time horizons, respectively. Additionally, a one standard deviation increase in the market share of HFT dealers reduces the excess variance ratio by 41.40 % (from 0.05 to 0.03) and 17.25% (from 0.16 to 0.13) for the time horizons of (30-second, 60-second) and (60-second, 300-second), respectively.

We argue that the market quality effects are largely driven by HFT dealers' inventory management. When HFT dealers have a lot of platform trading activity, they need to manage their inventory imbalances by trading more aggressively and reducing their liquidity supply on exchanges, which, in turn, harms liquidity and enhances efficiency. To demonstrate how this channel explains the market quality effects, we investigate how HFT dealers' trading activity affects their inventory management behavior and their liquidity supply.

First, we analyze the connection between dealer activity and HFT inventory management. For this purpose, we count the number of times the inventory switches sign for each trading firm, stock, and day in our sample. Our results show that the inventory crosses zero more often for HFT dealers than for other HFTs. Hagströmer and Nordén (2013) show that market making HFTs' inventories switch signs more often than other HFTs'. Thus, our results indicate that the HFT dealers act as market makers on exchanges. However, their market-making behavior decreases significantly on days and for stocks that HFT dealers have trading activities on their respective single-dealer platforms. Specifically, HFT dealers' inventories cross zero less often, indicating that HFT dealers engage less in market making on stock-days with dealer platform trading.

Second, we investigate if trading on single-dealer platforms affects HFT dealers' liquidity provision on exchanges. We measure a trading firm's liquidity provision with the volume it passively trades on exchanges, both in the Swedish currency SEK (passive volume), and as a fraction of the firm's total volume (liquidity supply ratio). Our results show that HFT dealers' liquidity provision is significantly negatively related to their dealer trading. On days when a stock is trading on an HFT dealer platform, the HFT dealer's liquidity provision on exchanges is lower. This effect is intensified significantly with an increase in the HFT dealer's trading volume. Compared to a day without any dealer trading on an HFT platform in a stock, a one standard deviation increase in an HFT dealer's volume reduces the average passive volume (liquidity supply ratio) by 37% (18%), which is economically significant. These results are consistent with HFTs trading more aggressively on exchanges to manage the inventory imbalances caused by trading on their dealer platforms. The results are in line with the findings of Hendershott and Menkveld (2014), who show that market makers return their inventory positions to the desired level by setting more aggressive quotes in the opposite direction and less aggressively in the same direction of their inventories.

We contribute to literature on the role of HFTs in equity markets. The literature shows that, while HFT market making improves liquidity (e.g., Brogaard et al. (2015); Jovanovic and

Menkveld (2016); Hendershott, Jones, and Menkveld (2011)), HFT trading on short-term information reduces liquidity on exchanges (e.g., Foucault, Hombert, and Rosu (2016); Foucault, Kozhan, and Tham (2017); Biais, Foucault, and Moinas (2015)). Moreover, Korajczyk and Murphy (2019) and van Kervel and Menkveld (2019) find evidence that HFTs profit by with-wind trading in the presence of investors with large institutional orders and make their trading costlier. Analyzing dark markets, Aquilina, Foley, O'Neill, and Ruf (2024) show that HFTs mainly act as liquidity takers and barely provide liquidity, taking advantage of stale quotes in dark pools. While all these studies are on HFT activities in the context of multilateral trading, we analyze the trading strategies of HFTs in a situation in which they run their own single-dealer trading platforms and trade bilaterally with counterparties.

Our research also contributes to the ongoing discussion in the U.S. regarding the effects of order flow segmentation on market quality. In the U.S. context, the retail (or uninformed) flow is predominantly captured off-exchange by a few leading HFT wholesalers, as detailed by Hu and Murphy (2022). Hu and Murphy (2022) and Green, Roseman, and Wu (2022) show that such a mechanism harms exchange liquidity. Dealer platforms operating as SIs can choose their counterparties under the SI regime based on their estimated risk, enabling HFTs to selectively engage with uninformed flow away from exchanges to reduce their adverse selection costs. Aramian and Nordén (2023) find that SIs interact more with uninformed than informed traders. The preference for lower-risk interactions and potentially reduced adverse selection costs likely motivates HFT dealers to engage more with the uninformed flow. Consequently, the SI regime creates opportunities for HFTs to segment order flow, leading to a higher engagement with uninformed orders.

We also contribute to the literature on dealer markets. From an inventory management perspective, previous studies show that there is a strong relation between the inventory level and quote submission behavior (e.g., Amihud and Mendelson (1980); Ho and

Stoll (1983); Hansch, Naik, and Viswanathan (1998)). In addition, Reiss and Werner (1998) find that dealers engage in interdealer trading for the purpose of risk sharing to reduce their inventory costs. Our paper differs from previous research on dealer markets in two ways. First, previous papers focus on the aggregated trading strategy of all dealers, whereas we investigate the trading behavior of a specific type of dealers, namely, HFT dealers, with respect to liquidity provision and inventory management. Second, most previous studies are from the time when equity markets were not as fragmented as today. Hence, we contribute by analyzing the cross-venue behavior of dealers in a fragmented market.

Our study is one of the few on SIs. Aramian and Nordén (2023) argue that SIs and exchanges are substitutes, and document that SIs capture more volume when the quoted bid–ask spread is large, volatility is low, and the tick size is not binding on exchanges. The authors also show that SI trades carry less information than exchange trades, indicating that SIs are sources of liquidity for large traders who need to decrease the price impact of their orders. Johann, Putniņš, Sagade, and Westheide (2019) document that a fraction of dark pools' order flows migrated to SIs following MiFID II's implementation of the double volume cap in dark pool trading and that the liquidity effect of the double volume cap is benign. Different from these studies, we focus on the activity of SI platforms run by HFTs and analyze the effects on market quality through their liquidity provision and inventory management.

2 Empirical framework

This section describes the institutional details for the venues on which it is possible to trade Swedish stocks. The main emphasis is on the single-dealer platforms (SIs), and the exchanges, namely, Nasdaq Stockholm, Bats Europe, Chi-X, Turquoise, and Aquis. The section also contains a presentation of the data, summary statistics and key variables for the analyses.

2.1 Institutional details

The empirical setting is the Swedish stock market in the year 2018. Today, it is, as it was in 2018, possible to trade Swedish stocks on several trading platforms including exchanges and SIs. Nasdaq Stockholm is the listing exchange for the Swedish stocks and is a regulated market (RM) offering an auction mechanism and continuous trading. The continuous trading takes place in a pre-trade transparent limit order book from 9:00 AM to 5:25 PM. The execution priority of submitted limit orders is set based on price, internal, visibility, and time.[8] Trading is open every weekday except for Swedish public holidays. On a weekday before a Swedish public holiday, the market closes early at 1:00 PM. The MTFs are pan-European exchanges running transparent limit order books and initiated equity trading following the introduction of MiFID I in 2007. Chi-X was the first pan-European exchange launched in 2007 and Bats Europe, Turquoise and Acquis soon followed. The execution priority of limit orders on the MTFs follows price, visibility, and time. The exchanges are venues providing full pre-trade transparency for visible limit order book trading.[9]

Stock trading is also possible on single-dealer platforms (SIs), which are different from the exchanges in several respects. First, SIs trade bilaterally with their clients' orders outside the exchanges. In other words, while exchanges facilitate trading by allowing the interaction of multiple third-party buying and selling interests, SIs execute clients' orders against their own books. According to the ESMA's Questions and Answers (Q&A) on the SI networking issue on April 5, 2017, "*SI activity is characterized by risk facing transactions that impact the profit and loss account for them".* It is also stated that rules *"prevent SIs from*

[8] Internal priority means internalization of orders within a trading firm. If a trading firm who submits a market order also has a limit order posted in the book at the same price level, that limit order gets priority even if other limit orders at the same price level were posted earlier.
[9] MTFs typically utilize a make-take fee model, where "maker" fees are paid by the MTF to non-marketable limit order submitters, while "taker" fees are imposed on those submitting marketable orders.

operating any system that would bring together third party buying and selling interest in a functionality similar to a trading venue".

Second, SIs are obliged to make quotes public for liquid stocks, and during normal trading hours while quotes for illiquid ones are only required to be published upon request. In addition, the pre-trade transparency obligation is limited to sizes up to the Standard Market Size (SMS), which is EUR 10,000 for the Swedish stocks in the sample. They are also required to post quotes for a size at least equal to 10% of the SMS. Pre-trade transparency is waived for orders larger than the SMS.[10]

The third distinction between SIs and exchanges relates to tick size. While exchanges must follow the MiFID II tick size regime for orders of all sizes, SIs' quotes, price improvements and execution prices must comply with the tick size regime for orders up to the large-in-scale (LIS).[11] This requirement came into force in June 2020, and prior to that (during our sample) SIs were advised to follow the tick size regime only for orders up to the SMS. Specifically, although there was not a written rule for SIs to follow MiFID II tick size regime prior to June 2020, in its Q&A and for orders up to the SMS, ESMA clarifies that "price improvements on quoted prices are only justified when they are meaningful and reflect the minimum tick size applicable to the same financial instrument traded on a trading venue".

[10] Regarding post-trade transparency, and based on the article 14 of RTS1, ESMA states that "since systematic internalisers are competing with trading venues over customers' order flow, it is important to provide a level playing field in post-trade transparency. Therefore, trading venues and systematic internalisers using similar technology and systems should process transactions for post-trade publication at the same speed" (Question 8, General Q&As on transparency topics, https://www.esma.europa.eu/sites/default/files/library/esma70-872942901-35_qas_transparency_issues.pdf).

[11] An order in a share is large-in-scale (LIS) if it is equal to or larger than the minimum qualifying size of orders set out in Table 1, ANNEX II, RTS1 (https://eur-lex.europa.eu/eli/reg_del/2017/587/oj). LIS is determined based on a share's average daily turnover.

2.2 Data

We focus on the trading activity of the 45 large-cap Swedish stocks with the highest average daily turnover from January 3 to December 28, 2018. We collect data from two main sources, the Transaction Reporting System (TRS) and the LSEG Tick History (TH) databases. According to the MiFID II transaction reporting regime, all firms that conduct securities business and trading venues/market operators that trade financial assets on their platforms and through their own systems must report their transactions. Specifically, they must report the details of these transactions to the TRS of their home supervisory authorities as quickly as possible, no later than the close of the following working day. We obtain access to the TRS data from the Swedish supervisory authority *Finansinspektionen*. The Swedish supervisory authority replaced TRS with TRS2 in the post-MiFID II period.

The use of the TRS2 database is essential. First, it provides us with granular information about the trading venues at which all transactions take place. This helps us to identify the SI platform responsible for each SI trade and to distinguish between trades by HFT dealers and non-HFT dealers, a feature that is not covered by the TH database. Second, the TRS2 database contains information on the legal entity identifier (LEI) of the trading entity reporting each transaction. This feature enables us to classify HFT firms and to process their trading activities on dealer platforms and exchanges. Apart from the trading venue and LEI, the database also includes information on the trade price, volume, date, time, and currency; the trading capacity, which shows if a firm is trading on its own account or is acting as an agent on behalf of a client; and a buyer/seller identifier.

In this study, we rely only on SI transactions with addressable liquidity. Transactions with non-addressable liquidity are restricted to the trading interest of predetermined counterparties and/or transactions due to purely technical reasons. Hence, using the flags provided in the data, we exclude these trades, including, for example, trades that do not contribute to price discovery and technical trades. Transactions with non-addressable liquidity are limited to those executed by non-HFT dealers.

We obtain tick-by-tick quotes and trades on exchanges from the TH database. The trade data contain the trade price, volume, flags, date, and the time of the execution. Using trade flags, we collect only transparent trades taking place in the limit order books. The TH quote data set has information about prices and volumes at the best bid and ask prices during the continuous trading session, timestamped at a microsecond frequency. We construct a consolidated order book using the best bid and ask prices from the primary exchange and MTFs. For each stock and at each point in time, the highest bid and lowest ask prices across exchanges are collected as the consolidated order book's best bid and ask prices.

We match TH exchange trades to the TRS2 exchange records to find the trading entity responsible for each side of a trade (passive/active side). In addition, the order book information from TH enables us to calculate liquidity measures such as the effective spread for different trader types. We determine the trade direction of TH trades using the procedure outlined by Lee and Ready (1991).[12] Section A1 in the Appendix describes the details of the TRS2 data cleaning and matching procedures.

2.3 HFT identification

Following Baron et al. (2019), we identify HFT firms as those that are either members of the Futures Industry Association European Principal Traders Associations (FIA EPTA) or which

[12] We use the extended version of the method of Lee and Ready (1991) to determine the buyer/seller initiation of each trade. On each exchange, if a trade price is lower (higher) than the midpoint at the time of the trade on the corresponding exchange's order book, the trade is seller (buyer) initiated. For trades at the midpoint, the trade return is used to determine the trade direction; if the trade return is positive (negative), it is buyer (seller) initiated.

describe themselves as HFTs on their websites, by engaging only in low-latency proprietary trading.[13] Previous research applies different classification methods to identify HFTs. While Korajczyk and Murphy (2019), Comerton-Forde, Malinova, and Park (2018), and Malinova, Park, and Riordan (2018) identify HFTs based on operating speeds, van Kervel and Menkveld (2019) use exchange member identities, whereas others classify HFTs based on trading behavior (Brogaard and Garriott (2019); Kirilenko, Kyle, Samadi, and Tuzun (2017)). Baron et al. (2019) show that their HFT identification has an advantage, because it meets certain HFT criteria defined by the SEC (2010), including large trading volumes, tight inventory management, and short investment horizons.

2.4 Descriptive statistics

Table 1 presents summary statistics of the trading activity on single-dealer platforms and exchanges for the stock–days in our sample. The table shows that, while dealers account for only 3.65% of the total number of trades (on dealer platforms and exchanges), they capture 13.49% of the total SEK volume, which indicates that trade sizes on dealer platforms tend to be larger than those on exchanges.

Insert Table 1 here

Table 2 reports the average stock–day number of trades and the trading volume, in millions of SEK, on all single-dealer platforms, alongside the corresponding numbers for different types of dealers. The dealer platforms contain a stock–day average of 325.31 trades whereof 167.22 (51.40%) trades occur on HFT single-dealer platforms, and 158.09 (48.60%) trades take place on non-HFT dealer platforms. These trades account for an average stock–

[13] Baron et al. (2019) use the TRS data provided by the Swedish supervisory authorities during MiFID I. Their data contain client information too, such that, if a broker trades on behalf of a client, the information of the client is also provided in the data. However, the TRS2 database does not contain client information.

day volume of SEK 54.94 million, with SEK 12.71 million (23.13%) for HFT dealers and SEK 42.23 million (76.87%) for non-HFT dealers.

Insert Table 2 here

2.5 Key variables

Our goal is to analyze how HFT single-dealer operations affect market quality in equity markets. Specifically, we first examine the effects from HFT dealer operations on liquidity and price efficiency on exchanges. Then, we propose a channel through which the HFT dealer operations affect market quality, namely that the operations affect their inventory management and liquidity provision on exchanges. Measures of liquidity, price efficiency, inventory, and liquidity supply, are the key variables in our analyses.

2.5.1 Liquidity measures

When analyzing market quality, we consider both the displayed consolidated order book liquidity and the actual cost of trading. To measure displayed liquidity, we use the variable *Quoted Spread*, which equals half the relative quoted bid–ask spread, that is, the difference between the best offer and bid prices, divided by the midpoint between the best offer and the best bid available in the consolidated order book. We also use the variable *Depth,* which equals the SEK value of the volume available at the best bid price plus that at the best offer price in the order book. For each stock–day, *Quoted Spread* and *Depth* are obtained as averages from the end-of-minute quotes between 9:05 AM and 5:25 PM. We exclude the first and last five minutes of the exchanges' trading hours in the calculations of the liquidity measures to avoid potential issues related to the opening and closing of trading.

For our measure of the actual cost of trading, we use the variable *Effective Spread*, which is the signed difference between each trade price and the midpoint in the consolidated order book at the time of the trade, divided by the midpoint quote, expressed in bps. For each stock–day, *Effective Spread* is obtained as the volume-weighted average across all exchange trades between 9:05 AM and 5:25 PM.

Insert Table 3 here

Table 3 presents descriptive statistics for the liquidity measures. The average quoted spread is 3.03 bps, and the average effective spread is 2.47 bps. Thus, ex ante, the cost of a round–trip stock transaction is roughly equal to six bps on average, while, ex post, it is almost equal to five bps. The corresponding average depth equals 0.41 MSEK, which implies that it takes, on average, about SEK 200,000 to consume the liquidity available at either the bid or the ask price in the consolidated exchange limit order book.

2.5.2 Efficiency measures

An efficient equity market is where stock prices reflect all available information about fundamental values. We use two efficiency measures based on return autocorrelations and variance ratios that are common in the literature (e.g., Boehmer and Kelley (2009); O'Hara and Ye (2011)).

The return autocorrelations are the first-order logarithmic return autocorrelations. The measure is based on the notion that stock prices should follow a random walk process, which means that returns should not be predictable from past information. Thus, prices are considered efficient and close to stocks' fundamental values when the return autocorrelations are close to zero. Negative and positive return autocorrelations indicate the over- and underreaction of prices to information, respectively. Following previous studies (e.g., O'Hara and Ye (2011)), we consider the absolute value of the return autocorrelations as a proxy for price efficiency, as follows:

$$Autocorr[x] = \left|corr(ret_{x,s}, ret_{x,s-1})\right|,$$

where $ret_{x,s}$ is the s^{th} logarithmic return of length x for a stock-day, and $Autocorr[x]$ is computed for each stock-day and at the intraday frequencies of $x \in (30, 60)$ seconds.

The proxy for price efficiency based on variance ratios, called the excess variance ratio (EVR), is defined as:

$$EVR[qx] = |VR[qx] - 1| = \left|\frac{\sigma_{qx}^2}{\sigma_x^2} - 1\right|,$$

where σ_{qx}^2 and σ_x^2 are the variances of qx- and x-second logarithmic returns, respectively. In an efficient market, where prices follow a random walk process, the variance ratio (VR) equals one. This means that the variance of the qx-second logarithmic returns should be q times as large as the variance of the x-second logarithmic returns, and hence $EVR[qx]$ should be equal to zero. A $VR[qx]$ larger than one shows that prices underreact to information, whereas a $VR[qx]$smaller than one suggests that prices overreact to information.

The value of $EVR[qx]$ is computed for each stock-day and at the intraday frequencies of $(x, qx) \in (30\ seconds, 60\ seconds)$, $(60\ seconds, 300\ seconds)$. The applied intraday frequencies are based on the different frequencies used in previous studies, particularly Comerton-Forde and Putniņš (2015) and Hatheway et al. (2017). In addition, $Autocorr[x]$ and $EVR[qx]$ are calculated using the midpoint prices of the best bid and ask quotes in the consolidated order book from 09:05 AM to 5:25 PM.

Table 3 presents descriptive statistics for the efficiency measures. The average autocorrelations for the 30- and 60-second time horizons are 0.04 and 0.06, respectively. A two-tailed t-statistic test shows that these values are statistically significantly different from zero at the 1% level, suggesting market inefficiency. Each t-test assesses whether the average autocorrelation is significantly different from zero, indicating an efficient market. The average EVRs are 0.05 for the (30-, 60-second) interval and 0.16 for the (60-, 300-second) interval, each significantly different from zero at the 1% level using the t-test. As a point of comparison, Foley and Putniņš (2016) report average values of 0.05 for 10-second autocorrelations and 0.13 for the (10-, 60-second) EVR in the Canadian market.

2.5.3 Inventory measures

We measure inventory at the firm level, and we assume that each trading firm starts each trading day with zero inventory of each stock and that intraday buying and selling generate changes in the stock inventory. Our key variable *Inventory crosses zero* measures the number of times a trading firm's inventory switches sign during a trading day for each stock. In descriptive analyses, we also present two other inventory measures: *End-of-day inventory* is the ratio of each trading firm's absolute inventory (in SEK) at the end of each trading day for each stock to its total SEK volume for that stock–day; and *Max intraday inventory* is the ratio of the maximum intraday absolute inventory (in SEK) of each firm during each trading day for each stock to its total volume on that stock–day. The inventory measures are obtained using all proprietary (i.e., trading for their own accounts) lit trades, on exchanges and SIs between 9:00 AM and 5:30 PM.

2.5.4 Liquidity provision

Since we cannot identify the trading firms behind the quotes in the exchange order books, we use our trade data to construct measures of liquidity provision. We proxy for a trading firm's liquidity provision on exchanges with two variables. First, we use the variable *Passive volume*, which measures the SEK volume traded by the firm through passive trading on exchanges. Second, we use the variable *Liquidity supply ratio*, which is the fraction of *Passive volume* to the total SEK volume traded by the firm on exchanges. The liquidity provision measures are calculated for each firm on each stock–day using all lit trades on exchanges during the continuous trading session between 9:00 AM and 5:25 PM.

3 Empirical results

3.1 HFTs' single-dealer platform activity and market quality

We analyze two aspects of market quality: liquidity and price efficiency on exchanges. Specifically, we investigate if dealer trading volume is detrimental to each of these measures of market quality. To address the potential endogeneity issue that might arise if dealer trading volume is affected by exchange liquidity and/or price efficiency, we employ two-stage least squares instrumental variable regressions.[14] The first-stage regression is:

$$DV\_Sh_{i,t} = \delta_0 + \delta_1 \overline{DV\_Sh_{-\iota,t}} + \delta_2 DV\_Sh_{i,t-1} + \theta X_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where $DV\_Sh_{i,t}$ is the fraction of the SEK volume on HFT dealer platforms relative to the total SEK volume (through dealers and on Nasdaq) in stock *i* on day *t*. Following Comerton-Forde and Putniņš (2015), Hasbrouck and Saar (2013), and Buti, Rindi, and Werner (2022), our first instrument is denoted as $\overline{DV\_Sh_{-\iota,t}}$ and equals the average fraction of the HFT dealer volume to the total volume for all stocks except stock *i* on day *t*. This variable meets the requirements for an instrumental variable in the sense that the level of the HFT dealer volume in other

[14] Previous studies (e.g., Comerton-Forde and Putniņš (2015); Buti et al. (2022); Foley and Putniņš (2016)) have used 2SLS regression to analyze the impact of dark pools on price efficiency.

stocks is correlated with the level of the HFT dealer volume in a specific stock; however, it is unlikely that this level in other stocks is driven by the market quality of a specific stock.

The second instrument is $DV\_Sh_{i,t-1}$, which is the previous day's fraction of the HFT dealer volume to the total volume in stock *i*. Our second instrument is like those used by Sarkar and Schwartz (2009) and Foley and Putniņš (2016). The term $X_{i,t}$ contains stock–day control variables, including the relative tick size, $Rel.TS_{i,t}$ (the tick size divided by the midpoint quote in the limit order book, observed at the end of every minute), volatility (the realized volatility of one-minute midpoint logarithmic returns), and the natural logarithm of the total SEK volume traded.

Table 4 reports the results from the first-stage regression according to Eq. (1). The dealer volume share, $DV\_Sh_{i,t}$, is significantly positively related to both instrumental variables, indicating that they are valid instruments. The results also show a significant negative relation between volatility and the HFT dealers' market share. This finding is in line with the literature, where, in times of high volatility, traders are more likely to trade on the exchanges, which have more concentrated liquidity than the dealer platforms (e.g., Buti et al. (2022); He and Lepone (2014); Aramian and Nordén (2023)).[15]

Insert Table 4 here

Next, we turn to the second-stage regression to examine the impact of the HFT dealer volume on market quality, which takes the following form:

$$MQ_{i,t} = \delta_0 + \delta_1 \widehat{DV\_Sh}_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}, \quad (2)$$

[15] In addition, we find a significantly higher trading volume on HFT single-dealer platforms when the relative tick size is larger on exchanges. This result is consistent with the fact that a larger relative tick size makes it more expensive for both liquidity makers and takers to submit limit and market orders, and traders are more likely to move to trading venues that offer lower trading costs.

where $MQ_{i,t}$ is one of the liquidity measures *Quoted Spread*, *Depth*, and *Effective Spread*, or the price efficiency measures return autocorrelation ($Autocorr$) and excess variance ratio (EVR) in stock *i* on day *t*; $\widehat{DV\_Sh}_{i,t}$ is the fitted value from the first-stage regression in Eq. (1) in stock *i* on day *t*; and $X_{i,t}$ contains the same stock–day control variables as in the first stage.

Table 5 presents the results from the regressions with the liquidity measures according to Eq. (2). They indicate that the trading activity of HFT single-dealer platforms is detrimental to liquidity on exchanges. The impact of HFT dealers' market share is significantly positive on *Quoted Spread* and significantly negative on *Depth* at the 1% level, and the magnitudes are economically meaningful. A one standard deviation increase in the market share of HFT dealers is associated with an increase of 3.12% in the quoted spread (from 3.03 bps to 3.12 bps, on average) and an 18% decrease in depth at the best quotes (from SEK 0.41 million to SEK 0.34 million, on average). For a trade of USD 5,000 (SEK 43,750), the results imply an increase in the round-trip cost from USD 3.03 to USD 3.12 for trading at the displayed order book quotes.[16] In addition, the 18% decrease in depth corresponds to a decrease in the average trade size required to move a stock price from USD 23,405 to USD 19,209 (SEK 205,000 to SEK 168,250).

Insert Table 5 here

Trading activity of HFT dealers also has a significantly positive effect on *Effective Spread*, but only at the 10% level, and the impact is smaller than that on *Quoted Spread*. The regression results imply that a one standard deviation increase in the market share of HFT dealers is associated with less than a 1% increase in the effective spread (from 2.47 bps to

[16] The round-trip cost equals the traded amount multiplied by the quoted spread. We use the SEK/USD exchange rate of 8.7587 observed on January 1, 2018, which marks the beginning of our sample period, in our calculations.

2.48 bps, on average). Even so, the results show that the trading activity of HFT dealers harms both the displayed liquidity and execution quality on exchanges.

Our results for the association between liquidity measures and the control variables support the previous findings in the literature, where a larger relative tick size and volatility result in a wider quoted spread and thinner depth on exchanges (e.g., Van Ness, Van Ness, and Pruitt (2000); Anderson and Peng (2014)).

We also run regressions according to Eq. (2) with *Effective Spread* for different trader types when they take liquidity (active trading) as the dependent variable. The results are presented in Table 6.

Insert Table 6 here

The effective spread for HFTs, both for those with, and those without dealer platforms, is not significantly related to the market share of HFT dealer platforms. The lack of significance shows that HFTs are skilled enough to time liquidity equally well and achieve similar execution costs, even in a situation involving dealer trading, and the displayed exchange liquidity is deteriorated. However, for non-HFTs, *Effective Spread* is significantly positively related to HFT dealers' market share at the 10% level. A one standard deviation increase in the market share of HFT dealers leads to a 1.27% increase in *Effective Spread* for non-HFTs (from 2.59 bps to 2.62 bps, on average). Hence, dealer activities incur somewhat higher execution costs on exchanges for slow traders.

Table 7 contains the results from the second-stage regressions with the price efficiency measures as dependent variables. The results indicate that the trading activity of HFT single-dealer platforms improves price efficiency on exchanges. The coefficients for the HFT dealers' market share are significantly negative on $Autocorr$ and EVR at both intraday frequencies. The negative coefficients indicate a reduction in deviations from zero in each measure (a reduction in deviations from a random walk process) as the HFT dealers' market share increases.

Insert Table 7 here

The magnitude of the effect of HFT dealer platforms on price efficiency is economically meaningful. A one standard deviation increase in the market share of HFT dealers is associated with a decrease of 9.00% (13.33%) in autocorrelation at the 30-second (60-second) frequency. In terms of *EVR*, the corresponding impact is a decrease of 41.40% (17.25%) with the 30, 60 (60, 300) combination, from 0.05 (0.16) to 0.03 (0.13).

3.2 HFTs' inventory management and single-dealer platform activity

How do HFT single-dealer operations affect the inventory management of HFTs? We know that HFTs try to keep their inventory close to zero at any time throughout the trading day (SEC (2010)). Moreover, in a competitive dealer market, dealers are motivated to offer competitive quotes to attract more trading volume, which can result in lower costs for traders (O'Hara and Zhu (2021)). Facing competition from other dealers can force HFT dealers to adopt a different inventory management behavior as they trade for their own accounts and incur inventory risk. We investigate if trading activity on the single-dealer platform and competition among dealers instigate different inventory management behaviors for an HFT firm, using the following regression:

$$Inventory_{i,j,t} = \gamma_0 + \gamma_1 Dealer_{i,j,t} + \gamma_2 Comp_{i,t} + \gamma_3 DVol_{i,j,t} \times Dealer_{i,j,t} + \gamma_4 Comp_{i,t} \times Dealer_{i,j,t} + \gamma_5 Dealer_j + \varepsilon_{i,j,t}, \tag{3}$$

where $Inventory_{i,j,t}$ is measured by the variable *Inventory crosses zero* in stock *i* for HFT firm *j* on day t; $Dealer_j$ is a dummy variable that is equal to one if HFT firm *j* is a dealer, and zero otherwise; $Dealer_{i,j,t}$ is a dummy variable that is equal to one if HFT firm *j* is a dealer *and* has a nonzero trading volume on its single-dealer platform in stock *i* on day *t,* and zero otherwise; and $DVol_{i,j,t}$ is the dealer trading volume of HFT firm *j* in stock *i* on day t.

We construct a daily Herfindahl–Hirschman Index (*HHI*) based on the volume share of each dealer on its single-dealer platform to proxy for the level of competition among dealers in each stock. The variable $HHI_{i,t} = \sum_{k=1}^{K} Volume\ Share_{i,k,t}^2$ is calculated as the squared share of the SEK volume across K single-dealer platforms in stock *i* on day t, and it varies between $1/K$ and one. We use $Comp_{i,t} = 1 - HHI_{i,t}$ to measure the level of competition among dealers, where the presence of a single dominant dealer indicates zero competition (i.e., a monopoly and high market concentration), while $1 - 1/K$ shows the highest level of competition (with a SEK volume shared equally among all dealers). The variable *HHI* is commonly used in the literature to measure market concentration and competition (e.g., Weston (2000); Chung and Kim (2005)). The stock–day average, median, and standard deviation of competition ($Comp_{i,t}$) in our sample are 0.65, 0.70, and 0.11, respectively. Given that the competition measure in our sample varies from zero to 0.96 ($1 - 1/K$), the average and median competition values of 0.65 and 0.70 indicate a high level of competition for order flow among dealers.

In the regression according to Eq. (3), our main coefficients of interest are those associated with the variable $Dealer_{i,j,t}$ (γ_1) and the interaction variables $DVol_{i,j,t} \times Dealer_{i,j,t}$ (γ_3) and $Comp_{i,t} \times Dealer_{i,j,t}$ (γ_4). Each of the continuous explanatory variables is standardized to have a zero mean and a standard deviation equal to one. Each regression is run with stock and day fixed effects, and standard errors are double clustered by stock and day, following Petersen (2009) and Thompson (2011).

Insert Table 8 here

The regression results are presented in Table 8. The coefficient for the variable $Dealer_{i,j,t}$ is significantly negative (at the 1% level). On stock–days when there is trading activity on the single-dealer platforms in question, HFT dealers' inventory crosses less often when there is trading on the dealer platform. This result indicates that HFT dealers engage less in market making on stock–days with dealer platform trading activity.

The results in Table 8 also show that the inventory measure is significantly negatively related to the interaction variable $DVol_{i,j,t} \times Dealer_{i,j,t}$ at the 1% level. The larger the HFT dealer volume, the less often its inventory crosses zero. Hence, greater dealer volume intensifies the reduction in market making activities by the HFT dealer. In the following section, we delve more closely into the market making activities of HFTs by analyzing how trading on dealer platforms affects the liquidity supply of HFT dealers.

Moreover, Table 8 shows that competition among dealers affects the respective HFT dealer's inventory management on stock–days when the HFT dealer is active on its own dealer platform. Each of the coefficient of the variable $Comp_{i,t}$ and the coefficient of the variable $Comp_{i,t} \times Dealer_{i,j,t}$ is significantly positive. Hence, an increase in competition is associated with the inventory crossing zero significantly more often for HFT dealers, both in general and even more so when there is trading on their own dealer platform. One interpretation of this effect is that when competition is high among dealers, dealer trades are more spread out among the dealers, so that each dealer has less disturbances to inventory, and, thus, to their market making behavior.

The coefficient for the variable $Dealer_j$ is significantly positive in the regression for *Inventory crosses zero*. This implies that HFT dealer inventory changes from a short to a long position, and vice versa, more often than non-dealers'.

3.3 HFTs' liquidity supply and single-dealer platform activity

In this part, we analyze if HFTs' liquidity provision on exchanges is affected by their single-dealer operations. Specifically, we hypothesize that HFT dealers reduce their liquidity provision, both in an absolute sense and relative to their liquidity demand, to manage inventory. Therefore, we expect to see less passive trading on exchanges for an HFT dealer firm *j* when the single-dealer volume is large in stock *i* on day *t*.

We investigate if trading on the single-dealer platform affects the liquidity provision of an HFT firm, with the following regression:

$$LS_{i,j,t} = \phi_0 + \phi_1 Dealer_{i,j,t} + \phi_2 DVol_{i,j,t} \times Dealer_{i,j,t} + \phi_3 Dealer_j + \varepsilon_{i,j,t}, \qquad (4)$$

where $LS_{i,j,t}$ is one of the liquidity supply measures *Liquidity Supply Ratio* and *Passive Volume* in stock *i* for HFT firm *j* on day *t*. For each firm–stock–day, *Liquidity Supply Ratio* is the fraction of the passive exchange trading volume relative to the total exchange volume, and *Passive Volume* is the total volume through passive trading on exchanges, in millions of SEK.

Insert Table 9 here

Table 9 presents the regression results according to Eq. (4). As before, the explanatory variable $DVol_{i,j,t}$ is standardized to have a zero mean and a standard deviation equal to one. The regression is run with stock and day fixed effects, and standard errors are double clustered by stock and day. The results show that the provision of HFT dealer liquidity is significantly lower on stock–days when there is trading activity on the dealer platform run by the HFT firm, both in an absolute sense and relative to its total exchange volume on that stock–day. In addition, the liquidity supply ratio is significantly negatively related to the corresponding dealer trading volume. We also note that HFT dealers have a significantly lower liquidity supply ratio than HFT non-dealers, since the coefficient for the variable $Dealer_j$ is significantly negative at the 1% level. However, in an absolute sense, HFT dealers trade a significantly larger passive volume than non-dealers.

The effects of dealer trading on the liquidity supply on exchanges are substantial. The average liquidity supply ratio (passive volume) for HFT non-dealers is estimated as the constant term in Table 9 (corresponding to the coefficient ϕ_0 in Eq. (4)) and is equal to the value 0.6176 (SEK 2.3993 million). The corresponding average liquidity supply ratio (passive volume) for HFT dealers, $\phi_0 + \phi_3$, is equal to 0.4994 (SEK 20.6472 million). For a one standard deviation increase in the (standardized) dealer volume from the zero (standardized) dealer volume, the regression results show a combined reduced liquidity supply ratio and total passive volume for HFT dealers at the level of 0.41 $(0.4994 - 0.0748 - 0.0135)$ and SEK 13.093 million $(20.6472 - 8.7069 + 1.1536)$, which are reductions of 18% and 37%, respectively.

As a comparison, Hagströmer and Nordén (2013) find that market making HFTs have a liquidity supply ratio in the range of 0.68 to 0.71, while opportunistic HFTs, according to their definition—HFTs that do not have market making as their main business model—have a liquidity supply ratio in the range of 0.32 to 0.36. Although we do not claim that the HFT dealers in our study are market making HFTs according to the definition of Hagströmer and Nordén (2013), we note that a HFT dealer's liquidity supply ratio when there is trading activity on its dealer platform makes the HFT look a lot more opportunistic than otherwise.

The combined results from Tables 8 and 9 are consistent with HFT dealers managing their inventory imbalances caused by trading on their dealer platforms by increased active trading and/or decreased passive trading on exchanges. Engaging in less risky trading activity on dealer platforms (Grammig and Theissen (2005); Aramian and Nordén (2023)) and inventory management (Hendershott and Menkveld (2014)) are two possible channels leading HFT dealers to provide liquidity to their counterparties on their own dealer platforms and to reduce it on exchanges.

The findings in Table 9 support our hypothesis that a reduction in HFT dealers' liquidity supply, and a significant increase in relative aggressive trading, on exchanges for stock–days with trading on their dealer platforms induces exchanges' liquidity to shrink and improves price efficiency. The results are also consistent with the empirical evidence in the literature that HFTs' liquidity-taking harms liquidity but improves price informativeness (e.g., Foucault et. al. (2017); Brogaard et al. (2014)).

3.4 HFTs with single-dealer platforms versus other HFTs

The high speed of acquiring, processing, and reacting to information is an HFT trademark. In multilateral trading on exchanges, liquidity-supplying HFTs use their speed advantage to revise and update their quotes to avoid being adversely selected by informed traders (e.g., Menkveld (2013); Hoffmann (2014); Jovanovic and Menkveld (2016)), while HFT liquidity takers use it to react to news more quickly than others and to make a profit (e.g., Foucault et al. (2016); Foucault et al. (2017)). However, due to the bilateral nature of trading under the SI regime, speed might not be the key factor for the operation of an HFT single-dealer platform. Instead, other factors, such as the ability to trade with selected counterparties bilaterally, helps HFT dealers to know who they are trading with, which could reduce their adverse selection costs, since they can avoid trading with informed traders. Here, we present characteristics of single-dealer HFTs and HFTs that do not operate as single dealers by focusing on trading activity, inventory management, liquidity provision, and trading costs.

Table 10 presents descriptive statistics for the characteristics of different types of trading firms during our sample period. The left-hand side of the table compares HFTs with non-HFTs, and the right-hand side divides HFTs into those that operate single-dealer platforms (dealers) and those that do not (non-dealers). The focus is on the comparison between dealers and non-dealers, and this comparison is facilitated by a test for the difference between the groups for each characteristic.

Insert Table 10 here

Panel A of Table 10 presents statistics for the average firm–stock–day trading activity of the different trading firm groups in our sample. Consistent with evidence from Hagströmer and Nordén (2013), HFTs trade more often and with smaller trade sizes than non-HFTs. On average, HFT dealers conduct significantly more trades, for a significantly greater volume and a significantly smaller trade size than corresponding non-dealers.

In Panel B of Table 10, we present the average firm–stock–day trading behavior measures. HFT dealer inventory changes from a short to a long position, and vice versa, more often than non-dealers'. In addition, HFT dealers have significantly lower end-of-day and maximum intraday inventories than non-dealers. This result indicates that dealers behave more like market makers than non-dealers do. Consistent with the evidence of Hagströmer and Nordén (2013), HFTs trade both actively and passively. The result that the average liquidity supply ratio is significantly lower for HFT dealers than for non-dealers is consistent with dealers supplying liquidity on their own platforms too.

In Panel C of Table 10 we focus on the effective spread, i.e., the cost of active trading for each trading firm group. Relative to non-HFTs, HFTs pay a lower effective spread in active trading. This result is consistent with the findings of Hagströmer and Nordén (2013) and Brogaard et al. (2015) and show that HFTs are better than non-HFTs at timing liquidity. Specifically, the results are in line with the adverse selection channel in the literature arguing that HFT liquidity takers force higher adverse selection costs onto slow market makers (e.g., Foucault et al. (2016); Foucault et al. (2017)). Separating between the two groups of HFTs in Panel C of Table 10, dealers face significantly lower transaction costs than non-dealers. The test for difference between the groups shows that dealers are significantly better off in active trading than non-dealers.

4 Discussion and motivation

HFT dealers run their own single-dealer platforms, provide liquidity to counterparties, and trade with them bilaterally off-exchange, alongside their activities on exchanges. The trading activities of HFT dealers, who are also essential market participants on exchanges, have implications for market quality through different channels.

A channel through which HFT dealers can affect market quality (i.e., liquidity and price efficiency) on exchanges is their inventory management. Transactions in dealership markets rely on dealers' willingness to provide liquidity to impatient traders. Although dealers profit from this interaction by earning the bid–ask spread, their capacity to bear inventory risk is limited, especially for large orders. Dealers build up inventory positions when they interact with traders. Inventory models of competitive dealership markets predict a strong correlation between dealers' relative inventory positions and their contemporaneous trading activity (e.g., Biais (1993); Ho and Stoll (1983); Laux (1995)). Studies show that a market maker with the most divergent inventory position relative to other market makers is likelier to post the most competitive quotes to reduce inventory costs and return to his/her desired position. Specifically, the dealer holding the largest long position would offer the lowest ask price, whereas the dealer with the largest short position would quote the highest bid price.

HFTs build up additional inventory positions because of their dealer activities, which may expose them to greater inventory risk than if they are only trading on exchanges. Menkveld (2013) argues that fast market makers unwind their large positions by applying price pressure. Hendershott and Menkveld (2014) show that when market makers' inventories deviate from their target levels, they control the inventory risk by quoting aggressively in the opposite direction and less aggressively in the same direction. An HFT dealer might unwind its dealer position on exchanges to control inventory risk. Specifically, HFT dealers can choose to reduce inventory risk exposure, especially for larger positions, by taking liquidity on exchanges when the exchange order book is deep enough. Translating the quote adjustment of Hendershott and Menkveld (2014) to the inventory management of HFT dealers, our results are consistent with them taking liquidity or quoting aggressively on exchanges following a trade on their single-dealer platform to unwind the inventory position.

HFTs stand out due to their ability to process information faster than other market participants and to time liquidity, giving them an edge in identifying and acting on profitable trading opportunities (Carrion (2013); Biais et al. (2015)). They use this advantage to take liquidity from the market, leading to a decrease in liquidity (e.g., Foucault et al. (2017)). However, their ability to anticipate short-term future price movements results in price efficiency improvement on exchanges through taking liquidity (e.g., Brogaard, Hendershott, and Riordan (2014)). Therefore, our results are in line with the notion that HFTs' inventory management due to the dealer's activities harms liquidity but improves price efficiency.

A single-dealer platform can be an attractive alternative to exchanges for a market making HFT's liquidity supply. SI features, such as the ability to trade with selected counterparties bilaterally, help HFTs to know who they are trading with, which can subsequently reduce their adverse selection costs. Since trades with dealers (SIs) are not anonymous, and dealers usually have ongoing relationships with their counterparties, they can know where the orders originate.

Previous research documents that, in dealer markets, trades are less informative relative to trades on exchanges (e.g., Chordia and Subrahmanyam (1995) and Easley, Kiefer, and O'Hara (1996); Aramian and Nordén (2023)). Collin-Dufresne, Hoffmann, and Vogel (2019) also show fewer interactions between informed traders and dealers in a foreign exchange market than between uninformed traders and dealers. The authors argue that this can be due to the high cost of information leakage for informed traders. Hence, HFTs' liquidity provision on exchanges can be crowded out by the potentially profitable and less risky dealer platform alternative. Our results are also consistent with the crowding out channel, that HFTs' dealer activities are associated with lower liquidity supply relative to liquidity demand on exchanges.

5 Concluding remarks

HFTs play an important role in today's equity markets. According to Biais and Woolley (2012), HFTs represent between 40% and 70% of the trading volume in U.S. equity markets. From the literature, we know that HFTs are primarily operating as market makers (Menkveld (2013)), but at other times they also consume liquidity (Hagströmer and Nordén (2013)). HFTs mainly operate on exchanges where multiple third-party buying and selling interests interact with each other. However, the regulatory reform of MiFID II in Europe leads to the emergence of HFT single-dealer platforms in the form of SIs run by HFTs. In this paper, we analyze the role of HFT single-dealer platforms in equity markets. Specifically, we focus on how trading on HFT single-dealer platforms affect liquidity and price efficiency on exchanges.

We find that trading by HFTs on their single-dealer platforms, on the one hand, harms the liquidity by widening the quoted and effective spreads and reducing the depth, but on the other hand, improves price efficiency on exchanges. Our results suggest that the mechanism behind the reduced exchange liquidity is that the HFT dealer trading makes HFT dealers decrease their liquidity provision, and market making activities, on exchanges. In addition, HFTs increase their liquidity taking, at the cost of a decreased liquidity supply, on exchanges to keep their inventory positions tight. HFTs' increased aggressiveness on exchanges is in line with the increased price efficiency.

Our empirical results are relevant to regulators in two ways. First, MiFID II aims to reduce liquidity fragmentation and to create a stronger transparency regime for equities, with the objectives of providing fair competition across trading venues and improving the price formation process. The promotion of partially transparent single-dealer platforms (SIs) as alternative trading venues to exchanges under MiFID II has resulted in a significant increase in their market shares (Johann et al. (2019)). Our findings imply that promoting dealers not only contributes to greater fragmentation of liquidity, but also leads to a reduction in liquidity transparency on exchanges.

Second, despite the positive effects of HFTs cited by many academics and practitioners, regulators believe that HFT has the potential to distort the market suddenly and significantly. Specifically, concerns over the activities of HFTs, such as the ability to withdraw liquidity at any time and increased volatility, lead regulators to impose new requirements in MiFID II for HFTs and the trading venues on which they trade, to prevent possible damage by them. Our results are informative to regulators considering the role of HFTs when they act as single dealers and their subsequent effects on the market.

This study is also relevant to exchanges. As imposed by MiFID II, exchanges should enter into a written agreement with market makers engaging in algorithmic trading and specify their market making obligations. Our findings on the changes in the liquidity supply of HFT dealers could be of interest to exchanges to evaluate the role of their HFT members, especially when it comes to market making.

Appendix

A1 TRS2 data processing

A1.1 Data cleaning

In the TRS2 database, depending on the trading capacity of the investment firm and whether it acts as a principal or agent, a transaction can be reported more than once. For example, when a firm is trading in its own account on behalf of a client on an exchange and buys a stock, the trade is reported to TRS2 twice: the first time is the market-side report, where the firm reports a buy with the capacity of the principal on the exchange and with one of the central clearing parties or the exchange as the counterparty. The second entry is the client-side report, where the firm reports a sell off exchange with the capacity of the principal and with the client's information as the counterparty. This scenario is similar when it comes to SI platforms. When a firm is trading with an SI on behalf of a client, the trade can have two entries in TRS2, one on the SI and one off exchange. In this study, to avoid such cases, we focus only on TRS2 transactions reported for SIs and exchanges and filter out all off-exchange trades.

We also only consider transactions reported in SEK for SIs and the exchanges, since most Swedish stocks trade exclusively in SEK. TRS2 also contains an ID unique to each transaction in the whole database, and we use this to avoid counting the same reported transaction twice. In addition, the data contain buyers' and sellers' LEIs, which help us extract a buy/sell indicator for each trade from the perspective of reporting firms. However, the LEI of buyers/sellers is anonymized if the reporting firm is not a buyer/seller or the counterparty is not one of the central clearing parties. Therefore, we are not able to identify the buy/sell indicator for 1% of all exchange trades and almost 2% of all SI trades.

Moreover, there are cases in which both sides of the SI transaction report the trade. We find these cases and put both sides in one entry. To find such cases, we require the SI transactions to involve the same stock, date, SI platform, price, and volume, different reporting firms, and opposite directions (buy/sell) and the timestamps of the two transactions to be within one second.

A1.2 Time adjustment

The timestamps of the transactions reported to TRS2 are not always in the same time zone since the reporting firms can operate in different time zones. We adjust the timestamps of the TRS2 transactions to Stockholm time (CET), where the exchanges operate from 09:00 AM to 5:30 PM. For all TRS2 exchange transactions, we observe the hour of the first and last trades of each firm on each day and obtain the median daily first and last trade hours of each firm. We adjust the timestamps of reporting firms that do not have their median daily first and last trade hours synchronized with the exchanges' opening and closing hours. For example, for a firm whose first and last trade hours have the median of 8 AM and 4:30 PM, we adjust its timestamps by +1 hour. We adjust the timestamps of TRS2 SI transactions using information obtained for the time adjustment of the corresponding firms on exchanges.

A1.3 Matching TH records with TRS2 transactions

We match the TH exchange records with TRS2 exchange transactions and obtain the IDs of the firms on the active and passive sides of the TH trades. For the active side, we require a TRS2 transaction to have the same stock, date, venue, price, volume, and trade direction as the TH record, and we allow the timestamps of the two databases to vary by up to five seconds. If more than one TRS2 transaction is matched to the same TH record, we consider the TRS2 entry that is closest in time to the TH record. To determine the TRS2 entry on the passive side of TH trades, we follow the same procedure, except we require the trade directions of the TH and TRS2 records to be opposite each other.

A1.4 Trading firms

Throughout the paper, we perform the analyses of trading firms at the corporation level. Specifically, we first find the business identification code (BIC) corresponding to each LEI in the TRS2 database. BICs are usually 11-letter codes and the reporting firms that belong to the same corporation share the first four letters of the BIC code. Hence, we truncate the BIC codes to the first four letters.

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Table 1: Trading activity on dealer platforms and exchanges

The table presents the average stock–day trading activity on dealer platforms (SIs) and exchanges. All statistics are calculated as averages across the 45 large-cap sample stocks from January 3 to December 28, 2018. The averages are obtained using all trades between 9:00 AM and 5:30 PM. The exchanges are Nasdaq Stockholm, BATS Europe, Chi-X, Turquoise, and Aquis.

	Trading Volume		Number of Trades	
Trading Mechanism, Venue Type	SEK (M)	Percent	#	Percent
Exchange	352.47	88.50	8,648.08	97.07
Dealer platform (SI)	45.81	11.50	260.35	2.93
All	398.28	100.00	8,908.43	100.00

Table 2: Dealer trading activity

This table cites the average stock–day trading activity on dealer platforms (SIs) that are operated by HFTs and other trading firms (non-HFTs). HFTs are trading firms that are members of FIA EPTA or which describe themselves as HFTs on their websites. All statistics are calculated as averages across the 45 large-cap Swedish stocks from January 3 to December 28, 2018.

	Trading Volume		Number of Trades	
Operator	SEK (M)	Percent	Number	Percent
HFTs	8.21	17.92	118.17	45.39
Non-HFTs	37.60	82.08	142.18	54.61
All	45.81	100.00	260.35	100.00

Table 3: Measures of liquidity and price efficiency

The table displays the mean, standard deviation (St. Dev.), and quartile points (P25, Median, and P75) at the stock-day level for liquidity and price efficiency measures used in the analyses. *Quoted Spread* is half the difference between the ask and bid prices in the consolidated order book, divided by the midpoint in this order book, expressed in bps. *Depth* is the volume available at the best bid and ask prices in the consolidated order book, in millions of SEK. *Effective Spread* is the signed difference between each trade price and the midpoint in the consolidated order book at the time of the trade, divided by the midpoint quote, expressed in bps. *Active effective Spread* is the effective spread for active trades and is presented as the volume-weighted average across all trades on all exchanges. *Autocorrelation* is the absolute value of the first-order logarithmic midpoint return autocorrelations at the intraday frequencies of 30 and 60 seconds. $EVR(x, qx) = \left|\sigma_{qx}^2 / q\sigma_x^2 - 1\right|$, where σ_{qx}^2 and σ_x^2 are variances of the qx- and x-second logarithmic midpoint returns, respectively. The (x, qx) combinations are (30 seconds, 60 seconds) and (60 seconds, 300 seconds). The midpoint logarithmic returns are calculated using the midpoint of the best bid and ask prices in the consolidated order book. The consolidated order book is built using the top of the order book of all exchanges. All variables are calculated across the 45 large-cap sample stocks from January 3 to December 28, 2018.

	Mean	St. Dev.	P25	Median	P75
Panel A: Liquidity					
Quoted spread (bps)	3.03	0.31	2.04	2.68	3.58
Depth (MSEK)	0.41	0.09	0.26	0.41	0.64
Effective spread (bps)	2.47	0.26	1.69	2.23	2.82
Panel B: Price Efficiency					
Autocorrelation 30-second	0.04***	0.03	0.02	0.04	0.06
Autocorrelation 60-second	0.06***	0.05	0.03	0.05	0.09
EVR(30 seconds, 60 seconds)	0.05***	0.08	0.02	0.04	0.07
EVR(60 seconds, 300 seconds)	0.16***	0.18	0.06	0.12	0.22

Table 4: First-stage regression

This table reports the results from the first stage of the two-stage least squares regressions according to the equation:

$$DV\_Sh_{i,t} = \delta_0 + \delta_1 \overline{DV\_Sh_{-\iota,t}} + \delta_2 DV\_Sh_{i,t-1} + \theta X_{i,t} + \varepsilon_{i,t},$$

where $DV\_Sh_{i,t}$ is the fraction of the SEK volume on HFT dealer platforms relative to the total SEK volume (dealers and exchanges) in stock *i* on day *t*; $X_{i,t}$ contains the stock–day control variables, including the relative tick size $Rel.TS_{i,t}$ (the tick size divided by the midpoint quote in the limit order book observed at the end of every minute), $Volatility_{i,t}$ (the realized volatility of one-minute midpoint logarithmic returns), and the natural logarithm of the total SEK volume $Volume_{i,t}$; and $\overline{DV\_Sh_{-\iota,t}}$ and $DV\_Sh_{i,t-1}$ are instrument variables and are defined, respectively, as the average fraction of the HFT dealer volume to the total volume in all stocks except for stock *i* on day *t* and the previous day's fraction of the HFT dealer volume to the total volume in stock *i*. HFTs are firms that are members of FIA EPTA or which describe themselves as HFTs on their websites. Dealers are HFTs that operate single-dealer platforms (SIs). All variables are calculated across the 45 large-cap sample stocks during the period from January 3 to December 28, 2018. All continuous independent variables are standardized. Each regression is run with stock fixed effects, and standard errors (in parentheses) are double clustered by stock and day. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	$DVol_{i,t}$
$\overline{DV\_Sh_{-\iota,t}}$	0.9604***
	(0.0565)
$Rel.TS_{i,t}$	0.2582***
	(0.0641)
$Volatility_{i,t}$	-0.0891***
	(0.0249)
$Volume_{i,t}$	0.0269**
	(0.0503)
$DV\_Sh_{i,t-1}$	0.4440***
	(0.0403)
Constant	1.9575***
	(0.0151)
Stock fixed effects	Yes
Adj. R^2	0.3844
# Observations	10,560

Table 5: Liquidity effect regression

This table reports the results from the second stage of the two-stage least squares regressions according to the equation:

$$MQ_{i,t} = \delta_0 + \delta_1 \widehat{DV\_Sh}_{i,t} + \theta X_{i,t} + \varepsilon_{i,t},$$

where $MQ_{i,t}$ is one of the (consolidated) exchange liquidity measures *Quoted Spread*, *Depth*, and *Effective Spread* in stock i on day t. For each stock–day, *Quoted Spread* and *Depth* are obtained as averages of end-of-minute quotes, and *Effective Spread* is the volume-weighted average across all trades on exchanges between 9:05 AM and 5:25 PM. The variable *Quoted Spread* is half the difference between the ask and bid prices, divided by the midpoint in the order book and expressed in bps; *Depth* is the volume available at the best bid and ask prices, in millions of SEK; *Effective spread* is the signed difference between each trade price and the midpoint in the consolidated order book at the time of the trade, divided by the midpoint quote, expressed in bps; $\widehat{DV\_Sh}_{i,t}$ is the fitted value of $DV\_Sh_{i,t}$ from the first-stage regression, where $DV\_Sh_{i,t}$ is the fraction of the SEK volume on HFT dealer platforms relative to the total SEK volume (dealers and exchanges) in stock i on day t; and $X_{i,t}$ contains stock–day control variables, including the relative tick size $Rel.TS_{i,t}$ (the tick size divided by the midpoint quote in the limit order book observed at the end of every minute), $Volatility_{i,t}$ (the realized volatility of one-minute midpoint logarithmic returns), and the natural logarithm of the total SEK volume $Volume_{i,t}$. In the first stage, the instrument variables are the average fraction of the HFT dealer volume to the total volume in all stocks except for stock i on day t and the previous day's fraction of the HFT dealer volume to the total volume in stock i, and the control variables are the same as in the second stage. HFTs are firms that are members of FIA EPTA or which describe themselves as HFTs on their websites. Dealers are HFTs that operate single-dealer platforms (SIs). All variables are calculated across the 45 large-cap sample stocks during the period from January 3 to December 28, 2018. All continuous independent variables are standardized. Each regression is run with stock fixed effects, and standard errors (in parentheses) are double clustered by stock and day. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Quoted Spread	*Depth*	*Effective Spread*
$\widehat{DV\_Sh}_{i,t}$	0.0944***	−0.0735***	0.0105*
	(0.0333)	(0.0139)	(0.0271)
$Rel.TS_{i,t}$	0.4716***	0.1901***	0.4088***
	(0.0421)	(0.0378)	(0.0392)
$Volatility_{i,t}$	0.5556***	−0.1066***	0.5880***
	(0.0605)	(0.0153)	(0.0522)
$Volume_{i,t}$	−0.5288***	0.1388***	−0.3536***
	(0.0881)	(0.0175)	(0.0679)
Constant	2.5720***	0.8002***	2.2592***
	(0.0445)	(0.0114)	(0.0371)
Stock fixed effects	Yes	Yes	Yes
Adj. R^2	0.8522	0.6605	0.8304
# Observations	10,560	10,560	10,560

Table 6: Liquidity regression at the trader level

This table reports the results from the second stage of the two-stage least squares regressions according to the equation:

$$MQ_{i,t} = \delta_0 + \delta_1 \widehat{DV\_Sh}_{i,t} + \theta X_{i,t} + \varepsilon_{i,t},$$

where $MQ_{i,t}$ is the effective spread for either HFT dealers, HFT non-dealers, or non-HFTs in stock *i* on day *t*. For each stock–day, *Effective Spread* is the volume-weighted average across all active trades on exchanges between 9:05 AM and 5:25 PM. The variable *Effective Spread* is the signed difference between each trade price and the midpoint in the consolidated order book at the time of the trade, divided by the midpoint quote, expressed in bps; $\widehat{DV\_Sh}_{i,t}$ is the fitted value of $DV\_Sh_{i,t}$ from the first-stage regression, where $DV\_Sh_{i,t}$ is the fraction of the SEK volume on HFT dealer platforms relative to the total SEK volume (dealers and exchanges) in stock *i* on day *t*; and $X_{i,t}$ contains the stock–day control variables, including the relative tick size $Rel.TS_{i,t}$ (the tick size divided by the midpoint quote in the limit order book observed at the end of every minute), $Volatility_{i,t}$ (the realized volatility of one-minute midpoint logarithmic returns), and the natural logarithm of the total SEK volume $Volume_{i,t}$. In the first stage, the instrument variables are the average fraction of the HFT dealer volume to the total volume in all stocks except for stock *i* on day *t* and the previous day's fraction of the HFT dealer volume to the total volume in stock *i*, and the control variables are the same as in the second stage. HFTs are HFT firms that are members of FIA EPTA or which describe themselves as HFTs on their websites. Dealers are HFTs that operate single-dealer platforms (SIs). All variables are calculated across the 45 large-cap sample stocks during the period from January 3 to December 28, 2018. All continuous independent variables are standardized. Each regression is run with stock fixed effects, and standard errors (in parentheses) are double clustered by stock and day. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	HFT Dealers	HFT Non-Dealers	Non-HFTs
$\widehat{DV\_Sh}_{i,t}$	0.0388	−0.0479	0.0330*
	(0.0333)	(0.0265)	(0.0276)
$Rel.TS_{i,t}$	0.4430***	0.4096***	0.4848***
	(0.0518)	(0.0372)	(0.0472)
$Volatility_{i,t}$	0.5024***	0.5209***	0.6072***
	(0.0521)	(0.0267)	(0.0529)
$Volume_{i,t}$	−0.3590***	−0.2737***	−0.4337***
	(0.0816)	(0.0496)	(0.0922)
Constant	2.3891***	2.7400***	2.6728***
	(0.0427)	(0.0250)	(0.0431)
Stock fixed effects	Yes	Yes	Yes
Adj. R^2	0.5833	0.6684	0.8008
# Observations	10,560	10,560	10,560

Table 7: Efficiency effect regression

This table reports the results from the second stage of the two-stage least squares regressions according to the equation:

$$MQ_{i,t} = \delta_0 + \delta_1 \widehat{DV\_Sh}_{i,t} + \theta X_{i,t} + \varepsilon_{i,t},$$

where $MQ_{i,t}$ is one of the price efficiency measures *Autocorrelation* and *EVR* in stock *i* on day *t*. *Autocorrelation* is the absolute value of the first-order logarithmic midpoint return autocorrelations at the intraday frequencies of 30 and 60 seconds. $EVR(x,qx) = \left|\sigma_{qx}^2/q\sigma_x^2 - 1\right|$, where σ_{qx}^2 and σ_x^2 are variances of the qx- and x-second logarithmic midpoint returns, respectively. The (x,qx) combinations are (30 seconds, 60 seconds) and (60 seconds, 300 seconds). The midpoint logarithmic returns are calculated using the midpoint of the best bid and ask prices in the consolidated order book. The consolidated order book is built using the top of the order book of all exchanges. $\widehat{DV\_Sh}_{i,t}$ is the fitted value of $DV\_Sh_{i,t}$ from the first-stage regression, where $DV\_Sh_{i,t}$ is the fraction of the SEK volume on HFT dealer platforms relative to the total SEK volume (dealers and exchanges) in stock *i* on day *t*; and $X_{i,t}$ contains stock–day control variables, including the relative tick size $Rel.TS_{i,t}$ (the tick size divided by the midpoint quote in the limit order book observed at the end of every minute), $Volatility_{i,t}$ (the realized volatility of one-minute midpoint logarithmic returns), and the natural logarithm of the total SEK volume $Volume_{i,t}$. In the first stage, the instrument variables are the average fraction of the HFT dealer volume to the total volume in all stocks except for stock *i* on day *t* and the previous day's fraction of the HFT dealer volume to the total volume in stock *i*, and the control variables are the same as in the second stage. HFTs are firms that are members of FIA EPTA or which describe themselves as HFTs on their websites. Dealers are HFTs that operate single-dealer platforms (SIs). All variables are calculated across the 45 large-cap sample stocks during the period from January 3 to December 28, 2018. All continuous independent variables are standardized. Each regression is run with stock fixed effects, and standard errors (in parentheses) are double clustered by stock and day. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Autocorrelation		EVR	
	30 seconds	60 seconds	$EVR(30,60)$	$EVR(60,300)$
$\widehat{DV\_Sh}_{i,t}$	−0.0036***	−0.0080***	−0.0207***	−0.0276***
	(0.0010)	(0.0013)	(0.0043)	(0.0081)
$Rel.TS_{i,t}$	0.0037**	0.0042***	0.0117**	0.0123***
	(0.0024)	(0.0021)	(0.0056)	(0.0094)
$Volatility_{i,t}$	0.0043***	0.0042***	0.0050**	0.0052**
	(0.0013)	(0.0011)	(0.0042)	(0.0066)
$Volume_{i,t}$	−0.0001***	−0.0007**	−0.0097**	−0.0239**
	(0.0013)	(0.0017)	(0.0061)	(0.0108)
Constant	0.0760***	0.0888***	0.2102***	0.2973***
	(0.0013)	(0.0012)	(0.0043)	(0.0076)
Stock fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.0531	0.0107	0.0126	0.0158
# Observations	10,560	10,560	10,560	10,560

Table 8: Inventory regression

This table reports the results from the regression according to the equation:

$$Inventory_{i,j,t} = \gamma_0 + \gamma_1 Dealer_{i,j,t} + \gamma_2 Comp_{i,t} + \gamma_3 DVol_{i,j,t} \times Dealer_{i,j,t} + \gamma_4 Comp_{i,t} \times Dealer_{i,j,t} + \gamma_5 Dealer_j + \varepsilon_{i,j,t},$$

where $Inventory_{i,j,t}$ is the variable *Inventory crosses zero* in stock *i* for HFT firm *j* on day *t*, i.e., the number of times a trading firm's inventory switches sign during a trading day for each stock; $Comp_{i,t}$ equals one minus the sum of the squared share of the SEK volume ($Volume\ Share$) across *K* single-dealer platforms in stock *i* on day *t* and measures competition among single-dealer platforms; $Dealer_{i,j,t}$ is a dummy variable that is equal to one if HFT firm *j* is a dealer and has a nonzero trading volume on its single-dealer platform in stock *i* on day *t,* and zero if it is a dealer but has no trading activity on its platform in stock *i* on day *t*; $Dealer_j$ is a dummy variable taking the value of one if the HFT firm is a dealer and zero if it is not; and $DVol_{i,j,t}$ is the dealer SEK volume in stock *i* for HFT firm *j* on day *t*. HFTs are members of FIA EPTA or which describe themselves as HFTs on their websites. Dealers are HFTs that operate single-dealer platforms (SIs). All variables are calculated across the 45 large-cap sample stocks during the period from January 3 to December 28, 2018, and are obtained using all proprietary trades on exchanges and SIs between 9:00 AM and 5:30 PM. The exchanges are Nasdaq Stockholm, BATS Europe, Chi-X, Turquoise, and Aquis. All continuous independent variables are standardized. The regression is run with stock and day fixed effects, and standard errors (in parentheses) are double clustered by stock and day. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Inventory crosses zero
$Dealer_{i,j,t}$	−13.5797***
	(1.0019)
$Comp_{i,t}$	0.8303***
	(0.3011)
$DVol_{i,j,t} \times Dealer_{i,j,t}$	−0.3985***
	(0.1194)
$Comp_{i,t} \times Dealer_{i,j,t}$	0.7632**
	(0.3465)
$Dealer_j$	18.3802***
	(1.1926)
Constant	2.0828***
	(0.2757)
Stock fixed effects	Yes
Day fixed effects	Yes
Adj. R^2	0.1725
# Observations	91,566

Table 9: Liquidity supply regression

This table reports the results from the regressions according to the equation:

$$LS_{i,j,t} = \phi_0 + \phi_1 Dealer_{i,j,t} + \phi_2 DVol_{i,j,t} \times Dealer_{i,j,t} + \phi_3 Dealer_j + \varepsilon_{i,j,t},$$

where $LS_{i,j,t}$ is either *Liquidity Supply Ratio* (the fraction of the passive exchange trading volume relative to the total exchange volume) or *Passive Volume* (the volume through passive trading on exchanges, in millions of SEK) in stock *i* for HFT firm *j* on day *t*; $Dealer_{i,j,t}$ is a dummy variable that is equal to one if HFT firm *j* is a dealer and has a nonzero trading volume on its single-dealer platform in stock *i* on day *t* and zero if it is a dealer but has no trading activity on its platform in stock *i* on day *t*; $Dealer_j$ is a dummy variable taking the value of one if the HFT firm is a dealer and zero if it is not; and $DVol_{i,j,t}$ is the dealer SEK volume in stock *i* for HFT firm *j* on day *t*. HFTs are members of FIA EPTA or describe themselves as HFTs on their websites. Dealers are HFTs that operate single-dealer platforms (SIs). All variables are calculated across the 45 large-cap sample stocks during the period from January 3 to December 28, 2018, and are obtained using trades on exchanges between 9:00 AM and 5:30 PM. The exchanges are Nasdaq Stockholm, BATS Europe, Chi-X, Turquoise, and Aquis. All continuous independent variables are standardized. Each regression is run with stock and day fixed effects, and standard errors (parentheses) are double clustered by stock and day. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Liquidity Supply Ratio	Passive Volume
$Dealer_{i,j,t}$	−0.0748***	−8.7069***
	(0.0118)	(1.3439)
$DVol_{i,j,t} \times Dealer_{i,j,t}$	−0.0135***	1.1536*
	(0.0046)	(0.5906)
$Dealer_j$	−0.1182***	18.2479***
	(0.0080)	(2.3487)
Constant	0.6176***	2.3993***
	(0.0024)	(0.5499)
Stock fixed effects	Yes	Yes
Day fixed effects	Yes	Yes
Adj. R^2	0.0982	0.2160
# Observations	93,067	93,067

Table 10: Trading firm characteristics

This table reports the trading activity (Panel A), trading behavior (Panel B), and liquidity measures (Panel C) by trading firm type. The HFTs are firms that are members of FIA EPTA or which describe themselves as HFTs on their websites, while non-HFTs are other trading firms. Dealers are HFTs that operate single-dealer platforms (SIs), and non-dealers are other HFTs. All statistics are calculated across the 45 large-cap sample stocks during the period from January 3 to December 28, 2018. The variables *Number of trades, SEK volume,* and *Trade size* are the firm–stock–day averages for all transparent trades on exchanges (excluding auction trades) and SIs between 9:00 AM and 5:30 PM; *Inventory crosses zero* measures the number of times a trading firm's inventory switches sign during a trading day for each stock; *End-of-day inventory* is the ratio of a trading firm's absolute inventory (in SEK) at the end of each trading day for each stock to its total SEK volume on that stock–day; *Max intraday inventory* is the ratio of the maximum intraday absolute inventory (in SEK) of a firm during each trading day for each stock to its total volume on that stock–day; and *Liquidity supply ratio* is the fraction of the SEK volume traded through passive trading on exchanges, presented as the firm–stock–day average. The liquidity measure is the volume-weighted average across all trades on exchanges between 9:05 AM and 5:25 PM. The variable *Active effective spread* for each active trade is the signed difference between each trade price and the midpoint quote in the order book of the corresponding exchange at the time of the trade, divided by the midpoint quote, expressed in bps. Each *t*-statistic is the result of a test for the difference in each measure between dealers and non-dealers. The test is performed using the firm–stock–day ordinary least squares regression of each measure as the dependent variable and the dealer dummy as the explanatory variable, which takes the value one if the HFT firm is a dealer, and zero otherwise. Each regression is run with stock and day fixed effects, and standard errors are double clustered by stock and day. Each *t*-statistic tests the null hypothesis that each regression coefficient is equal to zero. The exchanges are Nasdaq Stockholm, BATS Europe, Chi-X, Turquoise, and Aquis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	All Trading Firms		Segments of HFTs		
	HFTs	Non-HFTs	Dealers	Non-Dealers	*t*-Statistic
Panel A: Trading Activity					
Number of trades	217.15	76.38	574.67	48.91	11.64***
SEK volume (millions)	9.74	6.28	25.02	2.54	8.53***
Trade Size (thousands of SEK)	64.38	1,544.76	58.96	66.93	−8.78***
Panel B: Trading Behavior					
Inventory crosses zero	9.73	1.64	14.43	2.77	20.84***
End-of-day inventory	0.38	0.57	0.17	0.69	−51.10***
Max intraday inventory	0.43	0.63	0.22	0.74	−48.17***
Liquidity supply ratio	0.59	0.46	0.52	0.61	−23.43***
Panel C: Liquidity Measure					
Active effective spread (bps)	2.37	2.59	2.35	2.49	−4.79***