High-Frequency Traders and Single-Dealer Platforms

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This version: October 30, 2021

Abstract

High-frequency traders (HFTs) mainly operate on public exchanges, where multiple third-party buying and selling interests interact with each other. Following recent European regulatory changes (Markets in Financial Instruments Directive II), HFT single-dealer platforms have emerged on which HFTs conduct bilateral trading as dealers. We find that trading on HFT dealer platforms is detrimental to liquidity 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.

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

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1 Introduction

High-frequency traders (HFTs) use sophisticated high-speed computer programs to trade in their own accounts. According to the U.S. Securities and Exchange Commission (SEC (2010)), HFTs are characterized by large trading volumes, short investment horizons, and the maintenance of tight inventories. Menkveld (2016) asserts that the development of high-frequency trading (HFT) over the last decade is intimately related to the concurrent growth in electronic trading and market fragmentation. Alongside technological development, regulatory reforms have enabled the fragmented equity market we see today, where it is possible to buy and sell stocks not only on traditional exchanges, but also on, for example, multilateral trading facilities, dark pools, crossing networks, and systematic internalizer (SI) dealer platforms.

The literature documents diverse strategies for HFTs, which are mainly based on their activities in multilateral trading-based venues such as exchanges, where multiple third-party buying and selling interests interact with each other. According to Menkveld (2013), an HFT firm operates primarily as a market maker. Hagströmer and Nordén (2013) find that some HFTs have market making as their main line of business, while others do not. They also show that, in their different roles, HFTs use their superior trading speed to consume liquidity and act as liquidity takers, whereas, at other times, they also act as liquidity providers. Other studies confirm that HFTs are active in arbitrage across assets and venues (Dahlström, Hagströmer, and Nordén (2020)), trade on information (Hu, Pan, and Wang (2017)), can predict order flow (Hirschey (2021)), and contribute to better liquidity and price efficiency (e.g., Brogaard, Hendershott, and Riordan (2014); Brogaard, Hagströmer, Nordén, and Riordan (2015)). In addition, Baron, Brogaard, Hagströmer, and

Kirilenko (2019) show that HFTs are persistently profitable and that a relative speed advantage enhances HFT profitability.

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. As an exception, Battalio, Hatch, and Sağlam (2019) analyze the bilateral interaction between one U.S. investment firm and market-making HFTs, so-called electronic liquidity providers. They show that the exposure of parts of a large institutional order to electronic liquidity providers leads to a higher trading cost for the entire order. In Europe, the 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 the electronic liquidity providers in the United States.

The objective of this paper is to investigate the role of HFT single-dealer platforms in equity markets. We focus on the characteristics of HFT single-dealer platforms and how their operation affects HFTs' inventory management behavior, liquidity provision on public exchanges, and, ultimately, market quality. Our main findings are that trading activity on HFT single-dealer platforms leads HFTs to manage their inventory imbalances by taking liquidity and, at the same time, reducing their liquidity supply on exchanges. Quoted bid–ask spreads thus widen and order books become thinner. However, the actual trading cost at exchanges is virtually unchanged.

Our investigation uses 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.[2] We follow Baron et al. (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. 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 analyze the connection between dealer activity and HFT inventory management. For this purpose, we construct three measures of inventory for each trading firm, stock, and day: the number of times the inventory switches sign, 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 the ratio of the maximum intraday absolute inventory relative to the firm's total trading volume on that stock–day. Hagströmer and Nordén (2013) show that HFTs keep a tighter inventory than non-HFTs. Adding to their finding, we show that HFT dealers manage a tighter inventory than other HFTs, both on an intraday basis and at the end of the trading day. Moreover, the inventory crosses zero more often for HFT dealers than for other HFTs.

On days and for stocks with trading activity on the respective single-dealer platform, HFT dealers have a significantly larger end-of-day inventory and maximum intraday inventory than otherwise. This indicates that dealer activities make it more difficult for HFT dealers to keep the inventory flat. However, our results show that these inventory effects decrease with dealer trading volume. Hence, larger inventory positions prompt HFT dealers to manage their inventory position more carefully. In addition, HFT dealers' inventory

[2] The exchanges are Nasdaq Stockholm, BATS Europe, Chi-X, Turquoise, and Aquis.

crosses zero less often when there is trading on the dealer platform, which indicates that HFT dealers engage less in market making on stock-days with dealer platform trading.

We also examine the impact of dealer market competition on HFT dealers' inventory management. We find that dealer competition is good for inventory management, in the sense that higher competition is associated with significantly lower end-of-day and maximum intraday inventory. These effects are accentuated on days and for stocks with trading on the respective HFT single-dealer platform. Moreover, 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 the dealer platform. Thus, when competition is high among dealers, HFT dealers are inclined to offload their positions more frequently to control their inventory costs.

We investigate if trading on single-dealer platforms affects HFT firms' liquidity provision on exchanges. We measure a trading firm's liquidity provision with the volume it passively trades on exchanges, both in Swedish kronor, or SEK (passive volume), and as a fraction of the firm's total volume (liquidity supply ratio). Our results show that HFTs' liquidity provision is significantly negatively related to dealer trading. Hence, on days when a stock is trading on an HFT dealer platform, the HFT firm's liquidity provision is lower on exchanges. In addition, greater dealer volume is associated with lower liquidity provision. The effects are economically large. Compared to a day without any dealer trading on an HFT platform in a stock, the passive volume (liquidity supply ratio) by an average HFT dealer is reduced by 37% (18%) for a one standard deviation increase in (standardized) dealer volume. These results are consistent with HFTs trading more aggressively on exchanges to manage the inventory imbalances caused by trading on dealer platforms.

We investigate whether exchange liquidity is affected by the trading activity on HFT dealer platforms. We consider liquidity on the Nasdaq Stockholm exchange (henceforth Nasdaq) both ex ante, as the displayed order book liquidity, and ex post, as the actual cost of trading.[3] 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 Nasdaq 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 order book at the time of the trade, as our measure of actual cost of trading.

Our results show that the trading activity on HFT single-dealer platforms harms displayed exchange liquidity.[4] Specifically, a one standard deviation increase in the HFT dealer volume share is associated with an almost 3.0% increase in the quoted half-spread (from 3.01 to 3.09 basis points, or bps, on average) and a 14% decrease in depth at the best quotes (from SEK 0.50 million to SEK 0.43 million). The results that show the trading activity of HFT dealers damages the displayed exchange liquidity (quoted spread and depth) 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 3.01 to USD 3.09 for trading at the displayed order book quotes.[5] In addition, the 14% decrease in depth corresponds to a decrease in the average trade size required to move a stock price from USD 28,269 to USD 24,311 (SEK 247,600 to SEK 212,936).

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[3] 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.

[4] 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-Ford and Putniņš (2015) and Hasbrouck and Saar (2013) in our analyses.

[5] 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.

Despite the reduction in displayed exchange liquidity, the actual cost of trading at exchanges is virtually unchanged. The effective spread increases slightly in statistical terms, but in economic terms the difference is only 1.10% for slow traders (non-HFTs) and 1.15% for fast traders (HFTs). Hence, the reduction in displayed liquidity following an increase in HFT dealer volume share is not reflected in the actual trading costs.

Our study contributes to the 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)), HFT trading on short-term information reduces liquidity on exchanges (e.g., Biais, Foucault, and Moinas (2015); Foucault, Hombert, and Rosu (2016); Foucault, Kozhan, and Tham (2017)). 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. Aquilina, Foley, O'Neill, and Ruf (2021) show that HFTs mainly act as liquidity takers in dark pools, taking advantage of stale quotes. 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 off exchange.

This study is related to the recent debate in the United States on the use of payment for order flow by HFT firms and its possible impact on the equity market quality. In this setting, large HFT firms pay a fee to brokerage firms for first access to their order flow, which is mainly from retail investors. These orders are usually not informative, and Eaton, Green, Roseman, and Wu (2021) find that HFTs' payment for order flow has a detrimental impact on liquidity. HFTs are motivated to using payment for order flow because it allows them to use the order flow to predict future price movements and to engage in relatively low-risk activity by interacting with more uninformed and small orders. The ability of dealer platforms operating as SIs to avoid interactions with certain counterparties under the SI regime helps HFTs to cream-skim uninformed traders away from public exchanges. Aramian and Nordén (2021a) show that SIs are more likely to interact with uninformed traders than with informed ones. Hence, although MiFID II's rule in the context of best execution is interpreted as a de facto ban on payment for order flow, the SI regime provides similar opportunities for HFTs to interact with uninformed orders outside of exchanges and to reduce their risk of adverse selection.

We also contribute to the literature on dealer markets. From an inventory management perspective, theoretical and empirical studies show that dealer inventory is mean-reverting and 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 research also joins the very few studies on SIs. Aramian and Nordén (2021a) argue that SIs and exchanges are substitutes of each other, 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 how their SI operations affect their liquidity provision, inventory management, and market quality.

The empirical results presented in this paper are relevant to regulators in two ways. First, MiFID II aims to reduce liquidity fragmentation and to create a stronger transparency regime for equity instruments, 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. 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. This result relates to a recent consultation paper by the European Securities and Markets Authorities (ESMA) that raises concerns that a large fraction of SI trades has no pre-trade transparency. ESMA proposes to modify the SI regime to make dealer activities more transparent.

Second, despite the positive effects of HFTs cited by many academics and practitioners, regulators believe that HFTs have 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, led 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.

2 Literature review

In this section, we present previous research that helps us address the impact of HFT single-dealer operations on HFTs' inventory management, liquidity provision on exchanges, and, ultimately, market quality. First, we discuss the association between HFT single-dealer trading activity and HFTs' inventory management. Then, we turn to the discussion on the relation between HFT single-dealer trading and the supply of liquidity on exchanges, as well as the effects on market quality.

2.1 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 when it comes to large orders. Early theoretical work on dealer markets emphasizes that dealers can face competition from other dealers supplying liquidity (e.g., Garman (1976); Stoll (1978); Amihud and Mendelson (1980)). Dealers' profits depend not only on the risk arising from uncertainty about the returns on their inventories, but also on the actions of other dealers. Competition among dealers to attract more order flow motivates them to post more competitive quotes, which results in lower transaction costs for traders (e.g., O'Hara and Zhu (2021)).

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)). These studies argue that a market maker with the most divergent inventory position relative to other market makers is more likely to post the most competitive quotes to reduce inventory costs and to 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.[6]

The literature on HFTs' inventory management is limited to their multilateral trading on exchanges and emphasizes how HFTs use their speed advantage to control their inventory costs. Ait-Sahalia and Saglam (2017) model high-frequency market making and analyze the effect of speed on HFTs' inventory management. They show that faster traders can reduce their inventory costs, since their speed and information processing advantages help them to revise their quotes. In line with this prediction, Brogaard et al. (2015) empirically find that, when market makers invest in the fastest trading technology (the colocation with the lowest latency), they keep their inventory positions for longer. Roşu (2019), on the other hand, predicts that inventory-averse fast informed traders do not hold their inventory positions for long and engage in "hot potato" trading, a process where an HFT firm passes its inventory to a slow trader shortly after the trade. Roşu argues that the difference in speed between fast and slow traders makes the hot potato effect possible; otherwise, the inventory-averse fast trader would have a negative expected profit.

There is no evidence on how HFTs manage their overall inventories when they act on single-dealer platforms and engage in bilateral trading in addition to their activities on

[6] Recent empirical studies of over-the-counter markets, particularly bond markets, document that dealers' inventories significantly affect liquidity and trading prices (see, e.g., Friewald and Nagler (2019)).

exchanges. If HFTs with single-dealer operations could hold their inventory positions without the need to offload them quickly, they would be able to offer better prices to their counterparties, attract more trading volume, and, eventually, lower their overall inventory costs. When operating their single-dealer platforms, HFTs build up additional inventory positions because of their dealer activities, which expose them to greater inventory risk. To control inventory risk, an HFT dealer might unwind its dealer position on exchanges. Specifically, for larger positions, HFT dealers can choose to reduce inventory risk exposure by taking liquidity on exchanges when the exchange order book is deep enough.

Moreover, in a competitive dealer market, dealers engage in more trading activities and offer competitive quotes to attract greater trading volumes. Such a situation could raise the need for better inventory management by HFT dealers, since they trade for their own accounts and face inventory risk. In the presence of competition among market makers, quoted prices change from one moment to another, and a dealer with a large inventory position could face higher uncertainty about the return on his/her inventory. Weston (2000) documents that both adverse selection and the inventory cost components of the bid–ask spread on Nasdaq increase following regulation implemented with the objective of increasing competition among Nasdaq dealers. To this end, we conjecture that it could be harder for HFT dealers to control their inventory costs and to hold their positions for longer if they face competition from other dealers.

2.2 Liquidity provision and market quality

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 HFT firms to know who they are trading with, which could subsequently reduce their adverse selection costs, since they can avoid trading with informed traders.

Previous research documents that, in dealer markets, trades are less informative relative to trades on exchanges (e.g., Grammig and Theissen (2005); Aramian and Nordén (2021a)). In other words, by moving their liquidity supply to their single-dealer platforms, HFT dealers would profit by interacting with counterparties while reducing their own adverse selection risk. Therefore, HFTs' liquidity provision on exchanges can be crowded out by the potentially profitable and less risky dealer platform alternative.

The other channel through which HFT dealers could affect liquidity on exchanges is through their inventory management. Specifically, when an HFT firm takes a position in a trade, especially a large trade, on its single-dealer platform, the firm can reduce the inventory cost by unwinding the position 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. Translating the quote adjustment of Hendershott and Menkveld (2014) to the inventory management of single-dealer HFTs, an HFT firm could decide to take liquidity or quote aggressively on exchanges following a trade on its single-dealer platform to unwind its position. We therefore hypothesize that the activity of HFT dealer platforms is associated with lower liquidity supply and, to a larger degree than normal, higher liquidity demand on exchanges.

When operating single-dealer platforms, HFTs run their own trading venues and interact with trading counterparties, alongside their activities on exchanges. The partial shift in trading by HFT dealers from exchanges to their dealer platforms can affect the liquidity on exchanges. Studies on the impact of off-exchange trading do not uniformly conclude that trading away from exchanges impairs market quality, particularly liquidity. For instance, while Foley and Putniņš (2016) show that dark trading improves liquidity, Degryse, De Jong, and van Kervel (2015) provide evidence that off-exchange (dark pool, broker–dealer internalization, and over-the-counter) trading is detrimental to liquidity on exchanges. Given that our conjecture on the reduction of liquidity provision on exchanges by HFT dealers holds, we expect dealer trading to be detrimental to exchange liquidity and to increase the execution costs on exchanges.

3 Empirical framework

This section provides a description of 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.

3.1 Institutional details

Nasdaq Stockholm is the listing exchange for Swedish stocks and is an RM offering a traditional call auction mechanism and continuous trading. Trading takes place continuously in a limit order book from 9:00 AM to 5:25 PM. The execution priority of the submitted limit orders is set based on price, internal, visibility, and time.[7] Trading is open every weekday, except for Swedish public holidays. On a weekday before a Swedish public holiday, the market is open for half the day and closes early, at 1:00 PM. Each trading day, Nasdaq also offers an opening call auction (with the uncrossing at 9:00 AM), a closing call auction (with the uncrossing at 5:30 PM), and a scheduled intraday call auction (with the uncrossing at 1:35 PM). On half-days, when the market closes at 1:00 PM, the scheduled

[7] Internal priority means the internalization of orders within a trading firm. If a trading firm submitting a market order also has a limit order posted in the book at the same price level, that limit order has priority, even if other limit orders at the same price level were posted earlier.

intraday call auction is omitted, and the market closes with the closing call auction uncrossed at 1:00 PM.

The MTFs are pan-European exchanges. Chi-X was the first pan-European exchange, launched in 2007, and BATS Europe, Turquoise, and Aquis soon followed. MTFs usually do not offer traditional call auctions, and trading days start directly with a continuous trading session. MTFs' trading hours are in line with the trading hours of the continuous trading session of the RM (i.e., Nasdaq Stockholm). The execution priority of all MTFs' limit order books is based on price, visibility, and time, except for Aquis, whose limit order book follows price and time priority.

Trading is also possible through SIs. While exchanges facilitate trading by allowing the interaction of multiple third-party buying and selling interests, SIs conduct bilateral trading and execute orders against their own inventories. ESMA emphasizes that, under the market structure of SIs, trading is characterized by risk-taking activity, according to which each SI is obliged to take positions in transactions and to execute orders against its own inventory, which influences its profit and loss account (ESMA (2020)).

SIs are obliged to continuously publish real-time two-way quotes only for liquid stocks during the continuous trading session of the most relevant market in terms of these stocks' liquidity.[8] The pre-trade transparency obligation is, however, limited to orders with sizes up to the standard market size (SMS), which is EUR 10,000 for all Swedish stocks in the sample, except for one stock whose SMS is EUR 30,000. SIs are also required to post quotes with sizes greater than or equal to 10% of the SMS. They should make quotes public through one of the Approved Publication Arrangement (APA) reporting services. SIs can

[8] According to Article 4 of RTS1, the most relevant market in terms of liquidity for a stock is the trading venue with the highest turnover within all European markets for that stock. Nasdaq is the most relevant market for the sample of stocks in this study, except for two, for which Chi-X and the London Stock Exchange are the relevant markets.

choose any APA, but most opt to use the main one, namely, the Cboe trade reporting service (BXTR), which accounts for the majority of SIs active in European equities. The pre-trade transparency obligation is waived for orders larger than the SMS for both liquid and illiquid stocks, and quotes are provided upon request. Different from SIs, limit order books of exchanges are obliged to provide pre-trade transparency for all stocks (liquid and illiquid) and for all order sizes.

Regarding post-trade transparency, similar to exchanges, SIs are required to make each trade's information public as close to real time as technically possible, following Article 6 of Markets in Financial Instruments Regulation (MiFIR) and Article 14 of RTS1. ESMA emphasizes this further that a level playing field in post-trade transparency is required, since SIs compete directly with other trading venues for customers' order flow. Hence, according to the rules, ``trading venues and SIs using similar technology and systems should process transactions for post-trade publication at the same speed'' (ESMA (2021), 24).

The regulation provides a degree of flexibility for SIs to decide whom they trade with (for all order sizes) based on their commercial policies, such as counterparties' credit status or counterparty risk.[9] For instance, for orders up to the SMS, when SIs make their quotes public through an APA, the quotes are visible to everyone, but it is not possible for an investor to interact with the APA quotes, since, for this, they need direct trading connectivity to the SI. This process normally involves both an order entry connection and a market data connection. Via the market data connection, the investor receives quotes from the SI which it can trade with by sending orders via the order entry connection. It is via this direct connectivity that SIs operate their commercial discretion regarding the

[9] This flexibility is based on Article 17 of MiFIR. According to this article, SIs are also allowed to limit the number of transactions with the same counterparty, to reduce the risk of exposure to multiple transactions from the same client.

counterparties with which to trade. Quotes for orders above the SMS are also accessible through market data connections upon request, and then SIs use their commercial discretion regarding whether to trade with the counterparty.

When it comes to the minimum price improvement (tick size), although 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 minimum large-in-scale threshold.[10] This requirement came into force in June 2020, and previously SIs were advised to follow the tick size regime only for orders up to the SMS. Specifically, although there was no written rule for SIs to follow the MiFID II tick size regime prior to June 2020, ESMA (2020) clarifies that price improvements on quoted prices can only be justified when they reflect the minimum tick size applicable to the same stock traded on a trading venue.

SIs and exchanges have different trading fee structures, with diversity within each group as well. For an exchange trade, a broker pays a trading fee directly to the exchange (the exchange fee), a fee to the central clearing party (either directly or via their clearer) for clearing the trade, and then a settlement fee. SIs generally do not charge a platform fee or other connectivity costs for sessions that exchanges charge, and they also do not normally charge for market data. SI counterparties, however, still need to cover their own costs for clearing and settling trades.

If an investor interacts with an SI through its broker, the investor does not pay the clearing and settlement fees, which is similar to trading on exchanges. In other words, the investor pays the broker a commission on each trade and the broker then pays all the costs,

[10] The minimum qualifying sizes for LIS orders under MiFID II are presented in Table 1, Annex II, Regulatory Technical Standards 1 (RTS1; see https://eur-lex.europa.eu/eli/reg_del/2017/587/oj). The minimum LIS threshold is determined based on a share's average daily turnover.

including clearing and settlement fees. Hence, in such cases, there should normally be no difference in the costs from interacting with an SI or an exchange for the end investor.

Nasdaq Stockholm and MTFs also differ in their applied trading fee models. MTFs usually have a make-take fee model, in which the exchange pays a rebate to liquidity providers for making the market and charges liquidity takers a fee. However, Nasdaq Stockholm does not have a make-take fee model.

3.2 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 Refinitiv Tick History (RTH) databases. According to the MiFID II transaction reporting regime, all firms that conduct securities business and trading venues/market operators that trade financial instrument 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 on which all transactions take place, including single-dealer platforms (SIs), exchanges, dark venues, and off exchange. 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 RTH database. Second, the TRS2 database contains information on the identifier (i.e., legal entity identifier, or 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 remove non–price-forming SI transactions (or transactions that do not contribute to the price discovery process) from the sample by using the flags provided in the data. According to ESMA, non–price-forming transactions include transactions whose execution prices are not determined based on the current value of the stock (e.g., prices are calculated over multiple time instances based on a given benchmark price) and transactions with non-addressable liquidity. Transactions with non-addressable liquidity are those restricted to the trading interests of predetermined counterparties and/or transactions conducted for purely technical reasons. These transactions are limited to non-HFT dealers.

We also obtain tick-by-tick quotes and trades on exchanges from the RTH database. The trade data contain information on 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 RTH quote data include information about prices and volumes at the best bid and ask prices during the continuous trading session, timestamped at a microsecond frequency.

We match RTH 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 availability of order book information from RTH enables us to calculate liquidity measures such as the effective spread for different trader types. We determine the trade direction of RTH trades using the procedure outlined by Lee and Ready (1991).[11] Section A1 in the Appendix describes the details of the TRS2 data cleaning and matching procedures.

3.3 HFT identification

Following Baron et al. (2019), who use a similar database, we identify HFT firms as those that are either members of the Futures Industry Association European Principal Traders Associations (FIA EPTA) or which describe themselves as HFTs on their websites, by engaging only in low-latency proprietary trading.[12] 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 (Kirilenko, Kyle, Samadi, and Tuzun (2017); Brogaard and Garriott (2019)). Baron et al. (2019) argue and 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.

3.4 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

[11] 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.

[12] 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.

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–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

In Table 3, we present descriptive statistics of the trading activity on dealer platforms with respect to different trade sizes. We note that the average stock–day number of trades for HFT dealers is distributed almost equally between trade size ranges of up to SEK 500,000, with few trades larger than SEK 500,000. In Table 3, we recognize that about 25% of trades by HFT dealers are categorized as large trades, namely, trades above the standard market size (SEK 100,000).

Insert Table 3 here

3.5 Key variables

Our goal is to analyze HFT single-dealer operations in equity markets. Specifically, we first examine the effects of HFT single-dealer operations and competition on HFTs' inventory management. Next, we focus on whether and how HFT dealer operations affect HFTs' liquidity provision on exchanges and the possible effects on market quality. Measures of inventory, liquidity supply, and market quality are the key variables that we use to conduct our analyses.

3.5.1 Inventory measures

We use three variables to measure different nuances of inventory at the firm level. All inventory measures 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. The variable *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 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 trades, i.e., when trading firms are trading for their own accounts, on exchanges and SIs between 9:00 AM and 5:30 PM.

3.5.2 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 trades on exchanges between 9:00 AM and 5:30 PM.

3.5.3 Market quality

In our analysis of market quality, we focus on liquidity on the Nasdaq exchange and consider liquidity both ex ante, as the displayed order book liquidity, and ex post, as 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 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 on Nasdaq 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 Nasdaq 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 trades on Nasdaq between 9:05 AM and 5:25 PM.

4 Empirical results

4.1 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 subsequently reduce their adverse selection costs, since they can avoid trading with informed traders. What characterizes HFTs that operate on single-dealer platforms? To answer this, we present the characteristics of single-dealer HFTs and HFTs that do not operate as single dealers by focusing on factors such as trading activity, inventory management, liquidity provision, and trading costs.

Table 4 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 4 here

Panel A of Table 4 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 4, 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.

The liquidity measures in Panel C of Table 4 are obtained for the active and passive trading of each trading firm group. The effective spread 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. Following Glosten (1987), we decompose the effective spread into the realized spread and the price impact. The realized spread compensates passive traders for supplying liquidity to active traders. It is measured as the signed difference between the trade price and the midpoint quote in the order book 15 seconds after the reported time of the trade, divided by the midpoint quote. The price impact quantifies the losses to passive traders incurring adverse selection costs from informed active traders. It is the signed difference between the midpoint quote in the order book 15 seconds after the reported time of the trade and the midpoint quote at the time of the trade, divided by the midpoint quote at the time of the trade.

Relative to non-HFTs, HFTs pay a lower effective spread in active trading and obtain a higher effective spread in passive trading. Moreover, HFTs are compensated for by a negative active realized spread and a positive passive realized spread, whereas non-HFTs pay for liquidity supply, even when they supply it themselves. HFTs also incur a relatively lower price impact in passive trading and a higher active price impact following active trading. These results are 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 providers can avoid being adversely selected by informed traders (e.g., Menkveld (2013); Hoffmann (2014); Jovanovic and Menkveld (2016)), while 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 4, dealers face significantly lower transaction costs than non-dealers. The tests for differences between the groups show that dealers are significantly better off in active trading and slightly worse off in passive trading than non-dealers.

4.2 HFTs' inventory management and single-dealer platform activity

How do 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 framework:

$$Inventory_{i,j,t} = \gamma_0 + \gamma_1 Dealer_{i,j,t} + \gamma_2 Comp_{i,t} + \gamma_3 DVol_{i,j,t} \times Dealer_{i,j,t} + \gamma_4 Comp_{i,t} \times Dealer_{i,j,t} + \gamma_5 Dealer_j + \varepsilon_{i,j,t}, \quad (1)$$

where $Inventory_{i,j,t}$ is one of the inventory measures *Inventory crosses zero*, *End-of-day inventory,* and *Max intraday inventory* 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;[13] $Dealer_{i,j,t}$ 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,

[13] The variable $Dealer_j$ is used in the regressions in Table 4 to test for differences across HFT dealers and non-dealers.

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 each regression according to Eq. (1), 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 5 here

The regression results are presented in Table 5. The coefficient for the variable $Dealer_{i,j,t}$ is significantly different from zero (at the 1% level) in each regression equation for each measure of inventory. On stock–days when there is trading activity on the single-dealer platforms in question, HFT dealers have a significantly larger end-of-day inventory and maximum intraday inventory than on other stock–days. This result is consistent with the fact that HFT dealers build up additional inventory positions by operating their own dealer platforms and careful inventory management could be needed to keep inventory flat. In addition, HFT dealers' inventory crosses zero to a lesser degree 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 5 also show that all inventory measures are significantly negatively related to the interaction variable $DVol_{i,j,t} \times Dealer_{i,j,t}$ at the 1% level. Interestingly, the negative association between the dealer volume and the end-of-day inventory (and maximum intraday inventory) implies that large dealer trades somewhat mitigate the positive effect of the variable $Dealer_{i,j,t}$. This result is consistent with larger dealer trades (and thus larger inventory positions) prompting HFT dealers to manage their inventory position more carefully to reduce their positions. In addition, 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 5 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. Specifically, on such stock–days, the higher level of competition forces HFT dealers to offload their positions more often to control their inventory costs, since the coefficient of the variable $Comp_{i,t} \times Dealer_{i,j,t}$ is significantly positive for the *Inventory crosses zero* variable. We also find that, despite competition in the dealer market on stock–days when there is trading on the dealer platform, HFT dealers are still able to keep their inventories flat and to experience a similar end-of-day inventory and a significantly smaller maximum intraday inventory relative on other stock–days.

The coefficient for the variable $Dealer_j$ is significantly positive in the regression for *Inventory crosses zero* and significantly negative in the regressions for *End-of-day inventory* and *Max intraday inventory*. Hence, the addition of variables related to dealer trading activity and competition do not alter the results from Table 4 regarding differences between HFT dealers and non-dealers.

4.3 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 total volume, 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 high 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:

$$LS_{i,j,t} = \phi_0 + \phi_1 Dealer_{i,j,t} + \phi_2 DVol_{i,j,t} \times Dealer_{i,j,t} + \phi_3 Dealer_j + \varepsilon_{i,j,t}, \quad (2)$$

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*.

Insert Table 6 here

Table 6 presents the regression results according to Eq. (2). 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, according to Petersen (2009) and Thomson (2011). 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 6 (corresponding to the coefficient ϕ_0 in Eq. (2)) 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 so-called 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 the 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 5 and 6 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 (2021a)) 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. Whether the behavior of HFT dealers is detrimental to market quality or not is investigated next.

4.4 HFTs' single-dealer platform activity and market quality

Our results show that HFT dealers reduce their liquidity provision on exchanges on stock–days with trading activity on their single-dealer platforms and that liquidity supply is decreasing in the dealer trading activity. We now turn to analyze if the partial shift in the liquidity provision of HFT dealers from exchanges to their dealer platforms affects liquidity on exchanges. Specifically, we investigate if the trading activity of HFT dealers is detrimental to liquidity on the primary exchange, namely, Nasdaq.

To address the potential endogeneity issue that could arise if dealer trading volume is affected by exchange liquidity, we employ two-stage least squares instrumental variable regressions. The first-stage regression is in the form

$$DV\_Sh_{i,t} = \delta_0 + \delta_1 \overline{DV\_Sh_{-\iota,t}} + \delta_2 DV\_Sh_{i,t-1} + \theta X_{i,t} + \varepsilon_{i,t}, \quad (3)$$

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 (2016), 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*. Arguably, this variable meets the requirements for an instrumental variable in the sense that the level of the HFT dealer volume in other 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 liquidity 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 7 reports the results from the first-stage regression according to Eq. (3). The HFT 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 dealer volume share. This finding is in line with the literature, where, in times of high volatility, traders are more likely to trade on the biggest venue, which has more concentrated liquidity (e.g., He and Lepone (2014); Buti et al. (2016); Aramian and Nordén (2021a)).[14]

Insert Table 7 here

Next, we turn to the second-stage regression to examine the impact of trading activity on HFT single-dealer platforms on liquidity on Nasdaq, which takes the following form:

[14] 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.

$$Liq_{i,t} = \delta_0 + \delta_1 \widehat{DV\_Sh}_{i,t} + \theta X_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where $Liq_{i,t}$ is one of the liquidity measures *Quoted Spread*, *Depth*, and *Effective Spread* in stock i on day t on Nasdaq; $\widehat{DV\_Sh}_{i,t}$ is the fitted value from the first-stage regression according to Eq. (3) in stock i on day t; and $X_{i,t}$ contains the same stock–day control variables as in the first stage.

Table 8 presents the results from the regressions according to Eq. (4). They indicate that the trading activity on single-dealer platforms is indeed detrimental to liquidity on Nasdaq. The impact of HFT dealer volume share is significantly positive on *Quoted Spread* and significantly negative on *Depth* at the 1% level. The magnitude of the effect of dealer volume on the displayed order book liquidity is economically meaningful. A one standard deviation increase in HFT dealer volume share is associated with an increase of almost 3.0% in the quoted spread (from 3.01 bps to 3.09 bps, on average) and a 14% decrease in depth at the best quotes (from SEK 0.50 million to SEK 0.43 million).

Insert Table 8 here

Trading activity on HFT single-dealer platforms 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 HFT dealer volume share is associated with a 1% increase in the effective spread (from 2.56 bps to 2.58 bps, on average). Even so, the results show that the trading activity of HFT dealers damages both the displayed liquidity and execution quality on Nasdaq. The findings in Table 8 support our hypothesis that a reduction in HFT dealers' provision of liquidity on exchanges on stocks–days with active trading on their dealer platforms induces the exchange liquidity to shrink. In addition, the results support the empirical evidence in the literature, where the presence of HFTs improves market quality (e.g., Hendershott, Jones, and Menkveld (2011); Jovanovic and Menkveld (2016)), since we find that the lack of HFT liquidity supply is detrimental to exchange liquidity.

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)).

Insert Table 9 here

We also run regressions according to Eq. (4) with *Effective Spread* for different trader types when they take liquidity (active trading) as the dependent variable. The results are presented in Table 9. The effective spread for HFT dealers is significantly positively related to HFT dealer volume share only at the 10% level. A one standard deviation increase in HFT dealer volume share is associated with a 1.15% increase in *Effective Spread* (from 2.43 bps to 2.45 bps, on average). The increase in execution costs for HFT dealers is most likely a result of their shift from passive to active trading when there is trading on their dealer platforms.

The effective spread for other HFTs, those without dealer platforms, is not significantly related to the dealer activity. The lack of significance shows that other 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 dealer volume share at the 10% level. A one standard deviation increase in HFT dealer volume share leads to a 1.10% increase in *Effective Spread* for non-HFTs (from 2.65 bps to 2.68 bps, on average). Since HFT dealers act more like market makers relative to other HFTs, their decision to diminish their supply of exchange liquidity leads slow traders to incur somewhat higher execution costs.

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 the characteristics of HFT single-dealer platforms and how their operations affect HFTs' inventory management and provision of liquidity on exchanges and, subsequently, market quality.

We find that, on average, HFT dealers trade more and experience better execution quality on exchanges than HFT non-dealers. Our results also show that the trading activity of HFT dealers on their own dealer platforms complicates their inventory management, in the sense that it makes it harder to end the trading day with a lower inventory position, relative to days with no trading on their dealer platforms. In addition, we find that greater competition among single-dealer platforms is associated with lower end-of-day HFT dealer inventory positions. Thus, competition among dealers eases their inventory management.

Our results also indicate that HFT dealers reduce their supply of liquidity on exchanges in stocks and on days when they trade on their dealer platforms. The provision of liquidity to their counterparties on their dealer platforms and inventory management costs are the two channels that make HFT dealers decrease their liquidity provision on exchanges. We document that such a reduction in liquidity supply harms the liquidity of the primary exchange (Nasdaq) by widening the quoted and effective spreads and reducing the depth. We also examine how this affects trading costs for different types of traders. The results show that the dealer activities of HFTs induce higher transaction costs for non-HFTs on the exchange, but do not affect the trading costs for other HFTs.

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 RTH records with TRS2 transactions

We match the RTH exchange records with TRS2 exchange transactions and obtain the IDs of the firms on the active and passive sides of the RTH trades. For the active side, we require a TRS2 transaction to have the same stock, date, venue, price, volume, and trade direction as the RTH 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 RTH record, we consider the TRS2 entry that is closest in time to the RTH record. To determine the TRS2 entry on the passive side of RTH trades, we follow the same procedure, except we require the trade directions of the RTH 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	352.05	86.51	8,580.46	96.35
Dealer platform (SI)	54.94	13.49	325.31	3.65
All	406.99	100.00	8,905.77	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	12.71	23.13	167.22	51.40
Non-HFTs	42.23	76.87	158.09	48.60
All	54.94	100.00	325.31	100.00

Table 3: Dealer trading activity with respect to trade size

This table lists the average stock–day trading activity with respect to trade size 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 describe themselves as HFTs on their websites. The number of trades is calculated as the average across the 45 large-cap Swedish stocks from January 3 to December 28, 2018.

	Dealer Operators' Number of Trades					
	HFTs		Non-HFTs		All	
Trade Size (*SEK*)	Trades	%	Trades	%	Trades	%
≤10,000	39.05	12.00	43.54	13.38	82.58	25.39
10,000–50,000	48.89	15.04	54.98	16.90	103.87	31.93
50,000–100,000	36.94	11.35	31.56	9.70	68.52	21.06
100,000–500,000	40.61	12.48	23.75	7.30	64.35	19.78
500,000–1,000,000	1.43	0.44	1.56	0.48	2.99	0.92
1,000,000–5,000,000	0.30	0.09	1.65	0.52	1.95	0.60
>5,000,000	0.00	0.00	1.05	0.32	1.05	0.32
All	167.22	51.40	158.09	48.60	325.31	100.00

Table 4: 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, or 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 measures are the volume-weighted averages across all trades on exchanges between 9:05 AM and 5:25 PM. The variable *Active effective spread* (*Passive effective spread*) for each active (passive) 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. The variable *Active realized spread* (*Passive realized spread*) is the signed difference between the trade price and the midpoint quote in the order book 15 seconds after the reported time of the active (passive) trade, divided by the midpoint quote. The variable *Active price impact* (*Passive price impact*) is the signed difference between the midpoint quote in the order book 15 seconds after the reported time of the active (passive) trade and the midpoint quote at the time of the trade, divided by the midpoint quote at the time of the trade. 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. The regressions for the realized spread and price impact are run on data winsorized at the first and 99th percentiles. ***, **, 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	73.55	574.67	48.91	11.64***
SEK volume (millions)	9.74	6.23	25.02	2.54	8.53***
Trade Size (thousands of SEK)	64.38	1,187.81	58.96	66.93	−8.78***
Panel B: Trading Behavior					
Inventory crosses zero	9.73	1.62	14.43	2.77	20.84***
End-of-day inventory	0.38	0.58	0.17	0.69	−51.10***
Max intraday inventory	0.43	0.65	0.22	0.74	−48.17***
Liquidity supply ratio	0.59	0.46	0.52	0.61	−23.43***
Panel C: Liquidity Measures					
Active effective spread (bps)	2.37	2.59	2.35	2.49	−4.79***
Active realized spread (bps)	−0.82	0.42	−0.85	−0.59	−9.18***
Active price impact (bps)	3.19	2.17	3.20	3.08	8.19***
Passive effective spread (bps)	2.68	2.36	2.65	2.79	−5.15***
Passive realized spread (bps)	0.77	−0.23	0.68	1.22	−0.63
Passive price impact (bps)	1.91	2.59	1.97	1.57	1.78*

Table 5: Inventory regression

This table reports the results from the regressions 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 one of the inventory measures *Inventory crosses zero*, *End-of-day inventory,* and *Max intraday inventory* in stock *i* for HFT firm *j* on day *t*; *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; $Comp_{i,t}$ 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, or 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. Each 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	End-of-day inventory	Max intraday inventory
$Dealer_{i,j,t}$	−13.5797***	0.0396***	0.0743***
	(1.0019)	(0.0110)	(0.0101)
$Comp_{i,t}$	0.8303***	−0.0074**	−0.0075**
	(0.3011)	(0.0027)	(0.0031)
$DVol_{i,j,t} \times Dealer_{i,j,t}$	−0.3985***	−0.0076***	−0.0105***
	(0.1194)	(0.0018)	(0.0026)
$Comp_{i,t} \times Dealer_{i,j,t}$	0.7632**	−0.0072	−0.0124**
	(0.3465)	(0.0043)	(0.0048)
$Dealer_j$	18.3802***	−0.5300***	−0.5470***
	(1.1926)	(0.0140)	(0.0148)
Constant	2.0828***	0.6935***	0.7401***
	(0.2757)	(0.0034)	(0.0039)
Stock fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Adj. R^2	0.1725	0.4192	0.4638
# Observations	91,566	91,566	91,566

Table 6: 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, or 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 7: 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 Nasdaq) 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, or 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.

	$DVol_{i,t}$
$\overline{DV\_Sh_{-\iota,t}}$	0.0187***
	(0.0017)
$Rel.TS_{i,t}$	0.0050***
	(0.0015)
$Volatility_{i,t}$	-0.0034***
	(0.0006)
$Volume_{i,t}$	0.0043***
	(0.0012)
$DV\_Sh_{i,t-1}$	0.0127***
	(0.0013)
Constant	0.0426***
	(0.0003)
Stock fixed effects	Yes
Adj. R^2	0.4572
# Observations	10,800

Table 8: Liquidity effect regression

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

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

where $Liq_{i,t}$ is one of the 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 Nasdaq 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 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 Nasdaq) 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, or 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*
$\widehat{DV\_Sh}_{i,t}$	0.0773***	−0.0692***	0.0202*
	(0.0247)	(0.0119)	(0.0182)
$Rel.TS_{i,t}$	0.4879***	0.1966***	0.4366***
	(0.0427)	(0.0375)	(0.0383)
$Volatility_{i,t}$	0.4117***	−0.0807***	0.4787***
	(0.0438)	(0.0111)	(0.0361)
$Volume_{i,t}$	−0.4013***	0.1196***	−0.2580***
	(0.0708)	(0.0154)	(0.0533)
Constant	3.0097***	0.4952***	2.5581***
	(0.0063)	(0.0023)	(0.0047)
Stock fixed effects	Yes	Yes	Yes
Adj. R^2	0.8956	0.7295	0.8894
# Observations	10,800	10,800	10,800

Table 9: 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

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

where $Liq_{i,t}$ 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 Nasdaq 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 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 Nasdaq) 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, or 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
$\widehat{DV\_Sh}_{i,t}$	0.0278*	0.0130	0.0280*
	(0.0160)	(0.0172)	(0.0191)
$Rel.TS_{i,t}$	0.4250***	0.4264***	0.4637***
	(0.0377)	(0.0303)	(0.0380)
$Volatility_{i,t}$	0.4146***	0.4736***	0.4995***
	(0.0319)	(0.0264)	(0.0368)
$Volume_{i,t}$	−0.1988***	−0.2090***	−0.2776***
	(0.0449)	(0.0428)	(0.0555)
Constant	2.4254***	2.5924***	2.6529***
	(0.0042)	(0.0074)	(0.0050)
Stock fixed effects	Yes	Yes	Yes
Adj. R^2	0.8770	0.7102	0.8818
# Observations	10,800	10,792	10,800