Tick Size Constraints, High-Frequency Trading, and Liquidity[1]

First Draft: November 18, 2012

This draft: August 4, 2014

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Abstract

This paper demonstrates the causal effect of the relative tick size (one cent divided by price) on speed competition. Non-high-frequency traders (non-HFTers) are more likely than HFTers to provide the best quotes. A large relative tick size constrains non-HFTers from establishing price priority but helps HFTers establish time priority. Profits from liquidity provision are higher for lower-priced stocks. We use splits/reverse splits of ETFs as exogenous shocks to the relative tick size, with paired ETFs that track the same index as controls, finding that an increase in the relative tick size decreases liquidity but increases HFT liquidity provision.

JEL Classification: G10, G14, G18

Key words: High Frequency Trading, Tick Size, Liquidity

1. Introduction

The literature on high-frequency trading (HFT) identifies two overarching effects of speed competition. 1) Price competition effect: speed allows high-frequency traders (HFTers) to be the low-cost providers of liquidity; 2) information effect: speed enables HFTers to trade on advance information and adversely select slow traders (Jones, 2013, Biais and Foucault, 2014). We contribute to the HFT literature by establishing another channel for speed competition: tick size constraints. From this perspective, speed enables HFTers to achieve time priority over non-HFTers when price competition is constrained. The purpose of this paper is to demonstrate the causal impact of tick size regulations on HFT, particularly on its liquidity-supplying behavior. This newly identified channel for HFT, in turn, leads to a new perspective in the policy debate on market structure: the current policy debate focuses on whether and how to pursue additional regulation of HFT; our paper, however, demonstrates that HFT can be a response to an *existing* regulation.

An important yet often neglected assumption for Walrasian equilibrium is infinitely divisible price. In reality, price competition is constrained by the tick size regulation. SEC rule 612 (the Minimum Pricing Increment) of regulation NMS prohibits stock exchanges from displaying, ranking, or accepting quotations for, orders for, or indications of interest in any NMS stock priced in an increment smaller than \$0.01 if the quotation, order, or indication of interest is priced equal to or greater than \$1.00 per share.[2] A recent study by Credit Suisse demonstrates that this one-cent tick size is surprisingly binding: fifty percent of S&P stocks priced below \$100 per share have one-cent quoted spreads (Avramovic, 2012). The clustering of quoted spreads on one cent suggests that many low-priced liquid stocks should have a natural bid-ask spread of less than one tick. The minimum pricing increment rule imposes a floor on the lowest price for

[2] There are some limited exemptions, such as the Retail Price Improvement (RPI) Program and mid-point peg orders.

liquidity in the public exchange, and a surplus (whereby supply exceeds demand) arises as a natural response. Rockoff (2008) summarizes four possible responses when controls prevent price systems from rationing supply: queuing, black markets, evading, and rationing. We observe speed competition as a form of queuing through which traders with the capacity to trade at high speeds compete for a position at the front of the queue at a constrained price.

A binding tick size is not restricted to a scenario involving a one-cent spread. Such constraints exist wherever one trader's ability to provide a better price is hindered by the tick size, for the tick size stops traders from bidding a securities price up or down to its marginal valuation. The uniform one-cent tick size implies that the relative tick size, or one cent divided by the nominal price, is higher for stocks with lower prices. For example, in January 2010, Citigroup had a nominal price level of around \$3.30. Its 30-basis-point relative tick size is 18 times wider than that of HSBC, which has a nominal price of around \$59. Limit-order submitters, who would have differentiated themselves by price with a small relative tick size, may be forced to quote the same price with a large relative tick size. In that case, speed generally serves as the secondary priority in the allocation of supplies. As a result, a large relative tick size generates two interrelated effects: it hinders price competition and encourages speed competition.

We find that traders are more likely to quote identical prices for low-priced stocks, indicating that stocks with a large relative tick size indeed undergo more constrained price competition. For large stocks with low prices, HFTers and non-HFTers both quote the best price 95.9% of the time, and the priority for supplying liquidity is determined by the ability to submit orders at the top of the queue. A small relative tick size, however, encourages price competition.

The best quotes from HFTers and non-HFTers are the same only 45.5% of the time for large stocks with high prices, indicating that HFTers and non-HFTers diverge on price 54.5% of time.

The price competition channel operates on the assumption that a speed advantage enables HFTers to provide better quotes. The literature has indentified three channels for price improvements: avoiding adverse selection (Hendershott, Jones and Menkveld, 2011), better inventory management (Brogaard, Hagströmer, Nordén and Riordan, 2013), and low operations costs (Carrion, 2013). Contrary to this common belief, we find that non-HTFers are the more frequent providers of best quotes. The likelihood that non-HFTers are unique providers of the best price is 2.62 times greater than the likelihood that HFTers are. More direct evidence involves running tests using the relative tick size. Suppose that speed encourages better liquidity prices; in that case HFTers should take a more important role as the unique providers of best prices for stocks with a smaller relative tick size, which reduces constraints aimed at undercutting prices. Our empirical results, however, indicate the opposite: HFTers are less likely to be the unique providers of the best prices relative to non-HFTers as the relative tick size decreases. This result is surprising, because a recent editorial by Chordia, Goyal, Lehmann, and Saar (2013) raises the concern that *"HFTers use their speed advantage to crowd out non-HFT liquidity provision when the tick size is small and moving in front of standing limit orders is inexpensive."* Our results show that non-HFTers are more likely to move to the front of the price queue when the tick size is relatively small. In addition, the market share taken by non-HFTers is the highest for stocks with the smallest relative tick size, in terms of both the depth provided by non-HFTers and the volume with non-HFTers as liquidity providers. As the relative tick size increases, non-HFTers face constraints when seeking to undercut HFTers, and HFTers enjoy a comparative advantage for establishing time priority at the constrained price. Indeed, O'Hara, Saar, and Zhong (2013) find that HFTers are likely to improve the best bid and offer (BBO) when the relative tick size is large. Our results indicate that such an improvement does not necessarily entail price competition, because non-HFTers also intend to provide the same best price—but HFTers' speed advantage helps them be the first to improve the BBO. The existing literature does not differentiate between the following two scenarios: 1) Both HFTers and non-HFTers are willing to provide the best price for a stock, but HFTers' speed advantage enables them to post the order at the top of the queue; 2) HFTers can provide a better price than non-HFTers. HFTers improve the BBO in both cases, but the first case generates speed competition while the second case generates price competition. To draw a conclusion about who is clearly the best quote provider, we need to examine whether one type of trader is more likely to provide a better price than the other type, particularly when the constraints on price competition are not binding.

The causal impact of the relative tick size on HFT is further demonstrated using two identifications: twin ETFs that track the same underlying indexes and a diff-in-diff analysis using ETF splits/reverse splits. The twin ETF test finds that the lower-priced ETF within an index group experiences a higher level of HFT activity. Because the twin ETFs share the same underlying fundamentals, such differences in HFT activity can be ascribed to the higher relative tick size of the low-priced ETFs. This result is further strengthened by a diff-in-diff test using ETF splits/reverse splits as exogenous shocks to relative tick size, with ETFs that track the same index but experience no splits/reverse splits as the control group.

The tests based on ETFs demonstrate a non-information channel of speed competition.[3] Low-priced ETFs should not have more information than their high-priced twins that track the

[3] The information channel has been modeled extensively (Biais, Foucault and Moinas, 2013; Martinez and Rosu, 201; Foucault, Hombert, and Rosu, 2012). The empirical work focuses on the type of information used by HFTers,

same indexes, but the former experience higher levels of HFT activity. Similarly, ETFs splits/reverse splits should not increase the information content of affected ETFs relative to their controls, but splits result in an increase in HFT activity whereas reverse splits reduce HFT activity. In addition, we find that HFTers take a lower share in market making relative to non-HFTers for stocks with higher probability of informed trading (PIN).

The identifications using ETFs also show that a larger relative tick size decreases liquidity. The results for liquidity, in turn, provide a further intuition for understanding the economic mechanism that generates the HFT results. A split should not change the economic fundamentals of an ETF relative to its non-splitting counterpart. Therefore, the proportional spread, or the transaction costs for a fixed dollar amount, should not change after splits when there is no friction. Therefore, the nominal spread should decrease by the same ratio as the decline in the nominal price, keeping the proportional spread unchanged after splits. We find that the nominal quoted spread decreases following splits, but to a lesser degree than the decrease in the nominal price, thereby increasing the proportional quoted spread. The higher proportional spread is also associated with greater depth of the constrained spread, or a longer queue for providing liquidity at the best price on a coarser grid. The effective spread, or the real transaction cost faced by liquidity demanders, increases after splits. Therefore, we confirm the results of Schultz (2000) and Kadapakkam, Krishnamurthy, and Tse (2005) that splits harm liquidity, but the control group in our sample provides a cleaner identification of endogeneity.

Our main contribution to the literature on tick size, however, is showing that an increase in the relative tick size leads to a change in HFT behaviors. Splits increase the proportional

such as dislocation of separate financial instruments that track the same index (Budish, Cramton and Shim, 2013) triangular arbitrage opportunities (Chaboud, Chiquoine, Hjalmarsson and Vega, 2014; Foucault, Kozhan and Tham, 2014), order flow (Hirschey, 2013; Brogaard, Hendershott and Riordan, 2013), and macro news announcements (Brogaard, Hendershott and Riordan, 2013).

quoted spread as well as the length of the queue to supply liquidity, which encourages speed competition at the constrained price. Therefore, splits harm liquidity but increase HFT market-making activity. Reverse splits, on the other hand, have the opposite effect. The increase in the nominal spread following a reverse split is smaller than the increase in the nominal price, leading to a decline in the proportional spread. Also, a finer grid implies that liquidity providers who were forced to quote the same price before can now differentiate themselves by price, shortening the queue at the best price. A decrease in the quoted spread and depth at the best price also is followed by a decrease in HFT market-making activity.

Competition on speed appeals to a general finance audience because of its direct impact on the real economy. The literature reveals three channels whereby microstructure matters for real economic variables: liquidity, information risk, and ambiguity (Easley and O'Hara, 2010; O'Hara, 2007). All three of these channels affect asset prices and, by extension, a firm's cost of capital and real decisions. Speed competition, however, directly affects the allocation of physical as well as human capital.[4] The current literature ascribes this arms race to rents from instant access or quick responses to information (Biais, Foucault and Moinas, 2013, Budish, Cramton and Shim, 2013). Ours is the first study to show that such profits can come from a non-information channel. We demonstrate that a large relative tick size leads to higher profits for providing liquidity. In our sample, the daily market making profit for stocks with highest relative tick size is 4.7 basis points higher than that for stocks with median relative tick size.

Current debate focuses on whether additional regulation is required for HFT, and if so, how to pursue it. Our paper is also the first study to point out that HFT can be regarded as a market design response to existing regulations. Therefore, one possible solution is *deregulation*

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[4] We have witnessed aggressive investment in speed through co-location, the installation of a cable connecting New York and London, microwave towers between New York and Chicago, and competition for top programmers, inter alia.

instead of more regulation. At the minimum, we believe the first step towards pursuing additional regulations should be to evaluate current regulations. We are concerned that U.S. regulation is moving in the opposite direction. The Jumpstart Our Business Startups Act (the JOBS Act) encourages the SEC to examine the possibility of increasing the tick size, and a pilot program to increase the tick size to five cents for small stocks has been announced.[5]

Our results suggest that the SEC should also consider a pilot program that would decrease tick size for low-priced liquid stocks. Proponents of increasing tick size argue that a larger tick size controls the growth of HFT (Weild, Kim and Newport, 2012), but our results indicate that larger tick size can *encourage* HFT. The second argument for increasing tick size is that a larger tick size increases liquidity, but this paper demonstrates that a large relative tick size reduces liquidity. The final argument for increasing tick size is that it increases market-making revenue and supports sell-side equity research and, eventually, increases the number of IPOs (Weild, Kim and Newport, 2012). Economic theories suggest that constrained prices should facilitate non-price competition,[6] but we doubt that non-price competition would take the form of providing better research, especially when speed exists as a more direct form of non-price competition.

This paper is organized as follows. Section 2 discusses the study's hypotheses as well as the empirical strategy for testing them. Section 3 describes the data used in the study. Section 4 presents preliminary results pertaining to the relationship between the relative tick size and HFT liquidity provision using double sorting. Section 5 examines the determinants of HFT liquidity provision and profits using regression analysis. Section 6 provides a robustness check on causal relationships between the relative tick size, liquidity, and HFT using twin ETFs and a diff-in-diff test. Section 7 concludes the paper and discusses the policy implications.

[5] "SEC Provides Details of 5-Cent Tick Test," *Wall Street Journal*, June 25, 2014.
[6] Airlines, for example, offer better service when price competition is constrained (Douglas and Miller, 1974).

2. Testable hypothesis and empirical design

The fundamental hypothesis underlying the price competition channel is that the speed advantage enjoyed by HFTers allows them to provide better prices for liquidity due to lower operation costs (Carrion, 2013), lower adverse selection risk (Hendershott, Jones and Menkveld, 2011), or better inventory management (Brogaard, Hagströmer, Nordén and Riordan, 2013). Surprisingly, this hypothesis has not been directly tested despite its vital importance. One reason for this omission is that existing empirical evidence seems to support this hypothesis. Hendershott and Riordan (2013) suggest that HFTers are more likely to improve the BBO, and O'Hara, Saar and Zhong (2013) show they are more likely to improve the BBO when the relative tick size is large. However, the literature has not distinguished two distinct scenarios. In the first scenario, both HFTers and non-HFTers would like to improve the BBO. HFTers move faster and are therefore able to place their orders at the top of the queue, while non-HFTers join the BBO after the HFTers do. In the second scenario, HFTers are the only providers of the best price and non-HFTers neither match nor undercut that price. HFTers are the first to improve the BBO in both cases, but only the second case supports the price competition hypothesis, whereas the first case generates speed competition. Results documented by the literature that exogenous speed improvement increases liquidity also seem to support the price competition effect (Hendershott, Jones, and Menkveld, 2011; Boehmer, Fong and Wu, 2013; Brogaard, Hagströmer, Nordén, and Riordan, 2013). However, the technology shocks in these experiments operate at millisecond or full-second scale, whereas speed for our sample operates at nanosecond scale. A companion paper by Gai, Yao, and Ye (2013) finds that speed enhancement does not improve liquidity. More importantly, there are distinct differences between speed enhancement as a cause of increased liquidity and traders with higher speed as a cause of increased liquidity, because the price improvement may come from traders who operate more slowly. Slower traders lose time priority when they quote the same price as a fast trader, which gives them a greater incentive to undercut the price and achieve price priority. Therefore, there is not enough support in the literature for the claim that HFTers provide better liquidity prices, which brings us to our first hypothesis to be tested:

Hypothesis 1: HFTers quote better prices than non-HFTers.

The second hypothesis extends hypothesis 1. Suppose that HFTers are better providers of liquidity. In that case their market share in liquidity provision should increase when tick size decreases, because a finer tick size reduces the constraints that enable HFTers to undercut non-HFTers. A recent survey conducted by Chordia, Goyal, Lehmann, and Saar (2013) raises the concern that non-HFTers may be crowded out by HFTers when the tick size is small. The crowding-out effect can be tested by the second hypothesis.

Hypothesis 2: HFTers take a larger market share of liquidity provision relative to non-HFTers when the relative tick size is small.

Hypotheses 1 and 2 are both conjectures related to the price competition channel, which presupposes that speed competition encourages price competition. The tick size channel, however, presupposes that speed competition is a consequence of constrained price competition. The main hypothesis of this paper is that a lower nominal price, or a larger relative tick size, leads to higher levels of HFT market marking, which is the alternative for hypothesis 2.

Hypothesis 2a: a larger relative tick size causes more HFT liquidity provision.

Hypothesis 2a is the main causal relationship this paper aims to establish. We refer to this causal relationship as the *tick size constraints hypothesis*. The key challenge in testing the tick size constraints hypothesis is possible endogeneity originating from simultaneity bias or omitted variables (Roberts and Whited, 2012). In our scenario, the simultaneity bias arises when HFT market making leads to a lower nominal price, or when both HFT market making and the nominal price are determined in equilibrium. Such a case of reverse causality is unlikely to exist in reality: we are not aware of any studies or arguments that HFT market making has the first-order effect of reducing the nominal price. In addition, the diff-in-diff test presented in section 6 addresses the simultaneity bias concern.

Biases induced by omitted variables arise from excluding observable or unobservable variables that are 1) correlated with the nominal price and 2) have explanatory power for HFT market making. These criteria provide us with two lines of inquiry along which to search for the independent variables to be included: the nominal share price literature and the literature on the determinants of HFT market making. Interestingly, a recent paper by Benartzi, Michaely, Thaler, and Weld (2009) find that the average normal price for a share of stock on the New York Stock Exchange has remained roughly constant since the Great Depression. They also find that several popular hypotheses pertaining to nominal prices, such as the marketability hypothesis, the pay-to-play hypothesis, and the signaling hypothesis, cannot explain nominal prices. The main cross-sectional result they established is that large firms have higher prices.[7] This finding dramatically reduces the number of variables that need to be controlled for, because it implies that the impact of the nominal price on HFT market marking can be estimated consistently after controlling for the market cap. The preliminary analysis presented in section 4 is based on double sorting, first on the market cap and then on the price. The regression analysis in section 5 controls for more variables that may impact the nominal price or HFT market making.

[7] Benartzi, Michaely, Thaler, and Weld (2009) also find that a firm splits when its price deviates from those of other firms in the same industry. However, there are no splits in our 117 NASDAQ HFT sample.

Section 6 provides two clean tests for hypothesis 2a based on ETFs. The first test compares HFT activity in twin ETFs tracking the same index but with heterogeneous nominal prices. The index-by-time fixed effect, therefore, controls for both observable and unobservable factors that affect HFT activity through their common underlying fundamentals. The results are further strengthened in our second test involving diff-in-diff analysis using splits/reverse splits as an exogenous shock to nominal prices, where the ETFs that split/reverse split are the pilot group and the non-split ETFs that track the same index are the control group.

ETF tests are particularly interesting not only because they are exogenous but also because they differentiate the tick size channel hypothesis from the information-based explanation. ETFs tracking the same index should have the same fundamental information, either with or without splits/reverse splits. Therefore, the variation in HFT activity under ETF tests should not be driven by information. We acknowledge the importance of the information channel, and the diversity of HFTers (Hagströmer and Nordén, 2013) implies that there should be more than one driver of HFT activity. This paper is designed to reveal an important new channel of HFT activity.

The ETF tests also provide a clean environment within which to identify the impact of splits/reverse splits on liquidity, which is an interesting result in its own right. The literature finds mixed results on the impact of splits on liquidity (Berk and DeMarzo, 2013). One possible reason for such inconclusiveness is a counterfactual: it is hard to know what happens to a security if it does not split. We contribute to this literature by finding securities with identical fundamentals that do not split. Our conjecture on liquidity is motivated by the theoretical argument of Foucault, Pagano, and Röell (2013), which shows that a large tick size increases spread as well as the depth at a given price level. Our tick size constraints hypothesis also implies that HFT market-making activity increases after splits. Therefore, we have our third hypothesis:

Hypothesis 3: Splits increase the quoted spread, depth, and effective spread as well as HFT market-making activity; reverse splits reduce the quoted spread, depth, and effective spread as well as HFT market-making activity.

The hypothesis pertaining to reverse splits is the mirror image of the hypothesis pertaining to splits under tick size constraints.

The final component of this study relates to the profits of HFTers. The question is important because these profits drive the arms race in speed, which requires investments in both equipment and talent. One fundamental question for finance is whether activities in financial markets are sideshows or affect real resource allocation decisions. The literature has revealed three indirect mechanisms through which the market microstructure affects real decisions: liquidity, information risk, and ambiguity (O'Hara, 2007; Easley and O'Hara, 2010). [8] Speed competition attracts the attention of a broader finance and economics audience because it has a direct real impact. A recent article in the *Financial Times* estimates that a 1-millisecond advantage is worth up to $100 million in annual gains.[9] The common belief is that profits are produced by fast access to information, and this paper aims to show that profits can come from the tick size, a non-informational source. This hypothesis is motivated by the theoretical predictions of Foucault, Pagano, and Röell (2013), which show that market-making profits increase with tick size.

Hypothesis 4: Market-making profits increase with tick size.

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[8] For liquidity, see Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Amihud and Mendelson (1986), Chordia, Roll, and Subrahmanyam (2000), Chordia, Sarkar, and Subrahmanyam (2005). The role of information risk in asset pricing is demonstrated in Easley, Hvidkjaer, and O'Hara (2003), O'Hara (2003), and Easley and O'Hara (2004). For the ambiguity channel, see Easley and O'Hara (2010).

[9] "Speed fails to impress long-term investors," *Financial Times*, September 22, 2011.

3. Data and institutional details

This paper uses three main datasets: a NASDAQ HFT dataset, the NASDAQ TotalView-ITCH with a nanosecond time stamp, and Bloomberg. CRSP and Compustat are also used to calculate stock characteristics. The sample period for our analysis is October 2010 unless indicated otherwise.

3.1. Sample of stocks and NASDAQ HFT data

The NASDAQ HFT dataset provides information on limit-order books and trades for 120 stocks selected by Hendershott and Riordan. The original sample includes 40 large stocks from the 1000 largest Russell 3000 stocks, 40 medium stocks ranked from 1001–2000, and 40 small stocks ranked from 2001–3000. Among these stocks, 60 are listed on the NASDAQ and 60 are listed on the NYSE. Since the sample was selected in early 2010, three stocks disappeared from our sample period. Panel A of Table 1 contains the summary statistics for the 117 stocks.

Insert Table 1 about Here

The limit-order book data offer one-minute snapshots of the book with an indicator that breaks out liquidity providers into HFTers and non-HFTers at each price level, which facilitates the analysis of best quotes and depth provided by HFTers and non-HFTers. The trade file provides information on whether the traders involved in each trade are HFTers or non-HFTers. In particular, trades in the dataset are categorized into four types, using the following abbreviations: “HH”: HFTers who take liquidity from other HFTers; “HN”: HFTers who take liquidity from non-HFTers; “NH”: non-HFTers who take liquidity from HFTers; and “NN”: non-HFTers who take liquidity from other non-HFTers.

One limitation of the NASDAQ HFT data is that the NASDAQ identifies a firm as an HFT firm if it engages only in proprietary trading. HFT desks in large and integrated firms (e.g. Goldman Sachs and Morgan Stanley) may be excluded because these large institutions also act as brokers for customers and engage in proprietary low-frequency strategies, and their orders cannot be clearly identified as HFT or non-HFT business. The other omission involves orders from small HFTers that route their orders through these integrated firms. The inclusion of some HFTers in the non-HFTers group tends to bias the estimate of their differences towards zero. Therefore, NASDAQ HFT data should underestimate the true differences between HFTers and non-HFTers. However, we still detect economically and statically significant differences between their activities.

3.2. Sample of stocks and NASDAQ HFT data

To clearly identify the causal impact of the relative tick size on HFT liquidity provision, we introduce two identifications: twin ETFs and a diff-in-diff test. The first test involves twin ETFs which track the same underlying index but are traded at different nominal prices. We start the collection of these twin ETFs from the Bloomberg terminal. Although Bloomberg provides the ticker names for ETFs, it omits information about the underlying indexes for some ETFs. As a result, we supplement Bloomberg with hand-collected information from ETF Database (http://etfdb.com/indexes/), an authoritative ETF information website. We exclude ETFs with fewer than 100 trades per day, which leads to 18 ETFs in eight pairs in our sample. For brevity, we refer to them as twin ETFs, even though some indexes have more than two ETFs.

The diff-in-diff test uses ETFs that have undergone splits/reverse splits, and treats them as the pilot group, whereas the control group contains ETFs that track the same indexes and do not split/reverse split. Splits/reverse splits are frequent among leveraged ETFs, which amplify the daily returns of the underlying indexes.[10] Leveraged ETFs are issued prominently by Proshares and Direxion, and often appear in pairs that track the same index but in opposite directions. For example, the ETFs SPXL and SPXS both track the S&P 500, but SPXL amplifies S&P 500 returns by 300% while SPXS does so by -300%. The amplification effect results in frequent divergence of their nominal prices. The issuers often use splits/reverse splits to keep their nominal prices aligned with each other. We search the Bloomberg and ETF Database to collect information on leveraged ETF pairs that track the same index with an identical multiplier, and the data are then merged with CRSP to identify their splitting/reverse splitting events. We identify 5 splits and 21 reverse splits from January 2010 through November 2011 after the 100-trade cut-off. Reverse splits occur more frequently, because their issuers are often concerned about the higher trading cost of low-priced ETFs.[11]

Since the NASDAQ HFT dataset does not provide HFT information for ETFs, we compute HFT activities based on methodologies introduced by Hasbrouck and Saar (2013) using NASDAQ ITCH data, which is a series of messages that describe orders added to, removed from, or executed on the NASDAQ. We also use ITCH data to construct a limit-order book at nanosecond-scale resolution, which is the calculation upon which liquidity is based. Detailed information about how to link to these messages can be found in Gai, Yao, and Ye (2013) and Gai, Choi, O'Neal, Ye, and Sinkovits (2013). Summary statistics for twin ETFs and leveraged ETFs are presented in Panels B and C of Table 1, respectively.

[10] We find only one split and one reverse split for non-leveraged ETFs that track the same index, and the results are consistent with our hypothesis.

[11] "Why has ProShares decided to reverse split the shares of these funds?" (http://www.proshares.com/resources/reverse_split_faqs.html)

4. Double sorting

Our preliminary analysis starts with 3-by-3 double sorting based first on the market cap and then on the price level of the stock. We sort the 117 stocks first into small, medium, and large groups based on the average market cap of September 2010, and each group is further subdivided into low, medium, and high sub-groups based on the average closing price of September 2010. Section 4.1 contains the results for best quotes. Section 4.2 provides the results for depth at best quotes. Section 4.3 presents the share of volume with HFTers as liquidity providers.

4.1. Who provides the best price?

A fundamental question in the HFT literature is whether the speed advantage enjoyed by HFTers enables them to provide better liquidity prices relative to non-HFTers. The cost of liquidity comes from three sources: information asymmetry, inventory risk, and order-processing costs (Stoll, 2000). The price competition channel presupposes that HFTers can reduce these costs.[12] The literature, however, overlooks the possibility that speed competition may discourage price competition. The U.S. market prioritizes price over time. HFTers can achieve time priority when they quote the same price as non-HFTers, which reduces their incentive to undercut the price; non-HFTers are less likely to move to the front of the queue at the same price as HFTers, giving them a greater incentive to improve on the price. Hypothesis 1 tests whether HFTers play a more prominent role in providing best quotes than non-HFTers.

The test strategy for hypothesis 1 involves the relative tick size: suppose HFTers take a more prominent role in quoting the best price; they should then be more likely to be the unique best price provider as the relative tick size decreases. A large relative tick size hinders price

[12] See Hendershott, Jones, and Menkveld (2011) for information asymmetry, Brogaard, Hagströmer, Nordén, and Riordan (2014) for inventory risk, and Carrion (2013) for the argument on order-processing costs.

competition and forces traders with different valuations to quote the same price. A small relative tick size encourages price differentiation and alleviates constraints on establishing price priority. By construction, this methodology not only tests hypothesis 1, but also tests hypothesis 2 and its alternative hypothesis 2a, which involves the relationship between the provision of the best price and the relative tick size.

The one-minute snapshots of the limit-order book in the NASDAQ high-frequency book data indicate the depth provided by both HFTers and non-HFTers at each bid and ask price. Our analysis starts by categorizing the best price (the bid and the ask are treated independently) in these 391 minute-by-minute snapshots for each stock and each day into three groups according to the following criteria: 1) both HFTers and non-HFTers display the best price, 2) only HFTers display the best price, and 3) only non-HFTers display the best price. The number is then averaged across all the stocks in each portfolio for each day, resulting in 21 daily observations for each of the 3-by-3 portfolios.

The results are presented in Table 2. Column 1 presents the percentage of time that HFTers are unique providers of the best quotes, column 2 presents the percentage of time that non-HFTers are unique providers of the best quotes, and column 3 presents the percentage of time that both display the best quotes. Columns 1, 2, and 3 sum to 100 percent. Column 4 presents the ratio whereby non-HFTers are the unique providers of the best price relative to HFTers (column 2/column 1). Column 5, defined as column 2 minus column 1, shows the differences in percentage between non-HFTers as unique providers of the best price and HFTers as the unique providers of the best price. Column 6 contains the statistical inferences for column 5 based on 21 daily observations.

Table 2 shows that HFTers and non-HFTers are more likely to quote the same price with a large relative tick size: both provide the best price 95.9% of the time for low-priced large stocks. This result implies that a large relative tick size is associated with lower price differentiation. The table also shows that HFTers and non-HFTers quote the same best price 45.5% of time for high-priced large stocks, implying that a small relative tick size is associated with more price competition:. Therefore, price priority is sufficient to differentiate HFTers from non-HFTers 54.5% of the time for high-priced large stocks, but price priority is sufficient only 4.1% of the time for low-priced large stocks. This evidence suggests that price competition is indeed more constrained for stocks with a large relative tick size.

Insert Table 2 about Here

Column 4 shows that non-HFTers are more likely to display the best price than HFTers. The last row of Column 4 shows that non-HFTers are 2.62 times more likely to display better prices than HFTers.[13] More convincing evidence involves the pattern across relative tick sizes. As the relative tick size decreases, non-HFTers play a more prominent role than HFTers in providing the best price for large and medium stocks, both in terms of the ratio (column 4) and the difference (column 5), which suggest non-HFTers are more likely to jump ahead in the price queue when the relative tick size is small. This result belies the common belief that a smaller relative tick size leads to penny-jumping behavior on the part of HFTers when stepping in front of standing limit orders is inexpensive (Chordia, Goyal, Lehmann and Saar, 2013).

[13] Non-HFTers can be the unique provider of best quotes because they fail to update their quotes after an information event. Such a scenario is unlikely to drive the results based on snapshot data. Stale quotes tend to be immediately picked off in the current market. As a consequence, they are unlikely to be observed in snapshots of the limit order book. If stale quotes were able to account for the fact that non-HFTers are more likely than HFTers to provide best quotes in aggregate, there should be significant amount of information at exactly these one minute snapshots. In addition, stale quotes are hard to explain the cross sectional variation in liquidity provision.

The first row of Table 2 demonstrates that non-HFTers are also more likely to offer better prices than HFTers for low-priced large stocks (2.5% vs. 1.6%). The difference (0.9%) is statistically significant but economically trivial, because 95.9% of the time they quote the same price. Time priority determines the execution sequence in these scenarios. It is natural to expect that HFTers enjoy a comparative advantage for establishing time priority when price competition is constrained, and a recent paper by O'Hara, Saar, and Zhong (2013) found that HFTers take on an increasing share of limit orders that improve the best price when the relative tick size is large. Taking our results together with those of O'Hara, Saar, and Zhong (2013), the evidence suggests that HFTers are more likely to improve the BBO whereas non-HFTers intend to quote the same price as well, except that non-HFTers do not have a speed advantage when it comes to being the first to improve on the quote. The competition between the two types of traders is on the speed dimension instead of the price dimension. To summarize, a small relative tick size helps non-HFTers achieve price priority, and a large relative tick size leads non-HFTers and HFTers to quote the same price, helping HFTers to establish time priority. This intuition helps in understanding the results reported in section 4.3, which show that the volume share with HFTers as liquidity providers is the highest for low-priced stocks.

4.2. Best depth provided by HFTers and non-HFTers

This section analyzes the best depth, or the quantity provided at the best price. We denote the depth provided by HFTers and non-HFTers as $\{HFTdepth_{itm}, NonHFTdepth_{itm}\}$, where i is the stock, t is the date, and m is the time of day. The share-weighted average first sums the HFT liquidity provision for all stocks in the portfolio and then divides the number by the total liquidity provision for all stocks in the portfolio for each day.[14]

[14] The depth result is share weighted. We also try Equal-weighted depth and the results are similar.

The average depths from HFTers and non-HFTers for stock *i* on day *t* are:

$$HFTdepth_{it} = \frac{1}{M}\sum_{i=1}^{M} HFTdepth_{itm} \quad \text{and} \quad NonHFTdepth_{it} = \frac{1}{M}\sum_{i=1}^{M} NonHFTdepth_{itm} \quad (1)$$

The depth provided by HFTers relative to the total depth of portfolio *J* on day *t* is:

$$HFTdepthshare_{Jt} = \frac{\sum_{i\in J} HFTdepth_{it}}{\sum_{i\in J}(HFTdepth_{it} + NonHFTdepth_{it})} \quad (2)$$

Table 3 shows the average percentage of depth provided by HFTers for each of the 3-by-3 portfolios. The result indicates that the depth provided by HFTers increases monotonically with the relative tick size. The depth from HFTers is as high as 55.66% for large stocks with a large relative tick size, while the figure is only 35.07% for large stocks with a small relative tick size. The difference is 20.59% and the t-statistic based on the 21 observations runs as high as 22.10. The depth percentage provided by HFTers is 39.73% for mid-cap stocks with a large relative tick size, while the figure is 24.61% for mid-cap stocks with a small relative tick size. The difference is 15.13% with a t-statistic of 22.88. As the percentage of the depth offered by non-HFTers is 1 minus the percentage of the depth offered by HFTers, Table 3 shows that a smaller tick size increases the percentage of the depth offered by non-HFTers relative to HFTers. Taken as a whole, section 4.1 shows that a smaller tick size is associated with a greater chance that non-HFTers offer the best price, and this section demonstrates that the same pattern holds true for the quantity of shares offered at the best price.

Insert Table 3 about Here

4.3. Tick size constraints and volume

Sections 4.1 and 4.2 show that non-HFTers are more likely to quote better prices to achieve price priority over HFTers when the relative tick size is small. A large relative tick size, however, discourages price differentiation and increases the likelihood that these two types of traders will quote the same price, leaving it to time priority to determine the execution sequence. Although our data do not provide information on the liquidity provision queue, it is natural to assume that speed competition at the constrained price favors HFTers. These results in greater volume, providing additional evidence consistent with this claim: the volume with HFTers as liquidity providers increases with the relative tick size, and is highest for portfolios in which HFTers and non-HFTers quote the same price 95.9% of the time.

The NASDAQ high-frequency data indicate, for each trade, the maker and taker of liquidity. Recall that NH_{it}, HH_{it}, HN_{it}, and NN_{it} are the four types of share volume for stock *i* on each day *t*. For each portfolio *J* on day *t*, the volume with HFTers as liquidity providers relative to total volume is defined as:[15]

$$HFTliquidityshare_{Jt} = \frac{\sum_{i \in J}(NH_{it} + HH_{it})}{\sum_{i \in J}(NH_{it} + HH_{it} + HN_{it} + NN_{it})} \tag{3}$$

Table 4 shows the average percentage of volume with HFTers as the liquidity providers for each of the 3-by-3 portfolios. The result demonstrates a clear pattern according to which the volume with HFTers as liquidity providers increases with the relative tick size. For example, about half of the volume is due to HFTers' being liquidity providers for large stocks with a large relative tick size, but only 35.93% of the volume is due to HFTers' being liquidity providers for large stocks with a small relative tick size. The difference is 14.03% with a t-statistic of 15.54 for

[15] The equal-weighted average yields similar results. As a falsification test, we also perform double sorting for the percentage of volume with HFTers as liquidity takers. We do not find it increase with the relative tick size.

the 21 observations. Across all 3-by-3 observations, volume with HFTers as liquidity providers is highest for large stocks with a large relative tick size, in which case HFTers and non-HFTers quote the same price 95.9% of time (Table 2). In summary, our results show that liquidity provision by HFTers is more active for stocks with a large relative tick size, or stocks that face more tightly constrained price competition.

Insert Table 4 about Here

5. Regression analysis

The multivariate regressions in this section further confirm that low-priced stocks generate more HFT liquidity provision. In addition, we demonstrate that the profit for liquidity provision is also higher for low-priced stocks. We control for additional variables to overcome omitted variable bias. A sufficient condition for omitted variable bias to occur is that the missing variables are correlated with both the nominal price and HFTer market making. We are not aware of any papers that have touched on the variables correlated with both of these variables. Therefore, we start from the necessary condition that omitted variables be correlated with at least one of these two variables. The search for control variables is then guided by the nominal price literature and the HFT literature.

5.1. Control variables

The nominal price literature suggests that the industry norm is important in choosing the nominal price. Benartzi, Michaely, Thaler, and Weld (2009) find that a firm may split/reverse split if its price deviates from the industry average. The advantage of regression analysis is that we can control for this average using an industry fixed effect, where industries are classified using the Fama and French classification of 48 industries. Although Benartzi, Michaely, Thaler, and Weld (2009) argue that other hypotheses cannot explain nominal prices, to run a robustness check we nevertheless take five lines of studies in the nominal price literature into consideration, three of which suggest additional control variables for our analysis.[16] The summary of control variables from these hypotheses is presented in Table 1.

The optimal tick size hypothesis argues that firms choose the optimal tick size through splits/reverse splits (Angel, 1997). This hypothesis implies that firm characteristics can determine both HFT market making and the relative tick size. However, the optimal tick size hypothesis has been rejected by the following experiment. If firms could choose their optimal relative tick sizes, they would aggressively split their stocks when the tick size changes from 1/8 to 1/16 and then to one cent. Such aggressive splits have not occurred in reality (Benartzi, Michaely, Thaler, and Weld, 2009). Nevertheless, we include an idiosyncratic risk, the number of analysts that may affect the choice of the optimal tick size, from this study.[17]

The marketability hypothesis argues that a lower price appeals to individual traders. Tests of this hypothesis find mixed results.[18] Nevertheless, we include the measure of small investor ownership suggested by Dyl and Elliott (2006), which is equal to the logarithm of the average book value of equity per shareholder.

[16]Two other lines of research do not suggest additional variables to control for in our study. The catering hypothesis proposed by Baker, Greenwood, and Wurgler (2009) discusses time-series variations in stock prices: firms split when investors place higher valuations on low-priced firms and vice versa, but our analysis focuses on cross-sectional variation. Campbell, Hilscher, and Szilagyi (2008) find that an extremely low price predicts distress risk, but the 117 firms in our sample are far from default, and the distress risk should not affect the ETFs in our sample.

[17] Angel also argues that the relative tick size also depends on whether a firm is in a regulated industry, and this effect has been taken care of by including an industry-by-time fixed effect. Angel uses firm book value as a control for size, which is similar to the market cap for which we have controlled. When book value is included as an additional control, the results are similar.

[18] Some papers find that individuals prefer low-priced stocks (Dyl and Elliott, 2006), whereas Lakonishok and Lev (1987) find no long-term relationship between nominal prices and retail ownership. Byun and Rozeff (2003) suggest that if there are any short-term effects of low prices, they are very small.

The signaling hypothesis states that firms use stock splits to signal good news. The empirical literature, however, does not reach a definitive conclusion as to whether splits serve as a signal or, if so, what types of news prompt firms to signal.[19] In addition, the 117 stocks in our sample do not split. Although our ETF sample contains splits, these splits should not be regarded as information driven, particularly when compared with ETFs that track the same index but do not split. Nevertheless, we use PIN offered by Easley, Kiefer, O'Hara and Paperman (1996) to control for information asymmetry.

We then introduce additional control variables from the HFT literature. We include turnover and volatility in our regression following Hendershott, Jones, and Menkveld (2011). PIN is also an interesting variable from an HFT prospective. The literature has reached a consensus that HFTers' speed advantage allows them to reduce the pick-off risk by cancelling their quotes before being adversely selected, but it does not predict whether HFTers take a higher or lower market share for stocks with higher probability of informed trading. The regression also covers past returns to examine the impact of returns on HFT market making.[20] The method used for calculating the variables from the HFT literature is also summarized in Table 1.

5.2. Regression results for HFT liquidity provision.

The regression specification is

$$y_{i,t} = u_{j,t} + \beta \times tick_{relative_{i,t}} + \Gamma \times X_{i,t} + \epsilon_{i,t} \tag{4}$$

[19] See Brennan and Copeland (1988), Lakonishok and Lev (1987), and Kalay and Kronlund (2013).

[20] We thank an anonymous reviewer for the Texas Finance Festival for the suggestion to add past returns.

where $y_{i,t}$ is the daily percentage of depth provided by HFTers (*HFTdepth*) or the percentage of volume with HFTers as liquidity providers (*HFTvolume*) for each stock i on date t.[21] $u_{j,t}$ are industry-by-time fixed effects.[22]

The key variable of interest, $tick_{relative_{i,t}}$, is the daily inverse of the stock price. $X_{i,t}$ are the control variables presented in Table 1.

Insert Table 5 about here

Table 5 confirms that *HFTdepth* and *HFTvolume* both increase with the relative tick size, which is consistent with our tick size constraints hypothesis. Large-cap stocks also show higher *HFTdepth* and *HFTvolume*. Column 3 shows that the sign for retail trading ($logbv_{average}$) is mixed: more retail trading leads to a decrease in *HFTdepth* but an increase in *HFTvolume*. Column 4 indicates that firm age is the only variable that predicts both *HFTdepth* and *HFTvolume* under the relative tick size hypothesis: HFTers tend to provide more liquidity for older firms. Columns 1–7 show that no other variables can consistently predict the market share of HFTers other than the relative tick size, market cap, and PIN.

Columns 5 and 7 show that a higher PIN, alone or combined with other control variables, reduces *HFTvolume* and *HFTdepth*. This intriguing result suggests that the speed advantage enjoyed by HFTers when updating their quotes does not lead to higher market share for stocks with higher information asymmetry. The main takeaway from Table 5 is that HFTers concentrate their activity on stocks with a large relative tick size and lower information asymmetry.

[21] We also analyze who provides the best price using multinomial logit and probit models and obtain similar results. The results are not reported but are available upon request.
[22] We do not include firm fixed effects because the focus of this paper is on understanding the cross-sectional variation in HFT market-making activity, and firm fixed effects defeat this purpose (Roberts and Whited, 2012).

5.3 Relative tick size and profits

Hypothesis 4 argues that market-making profits increase with the relative tick size (Foucault, Pagano and Röell, 2013). We test this hypothesis using the following specification.

$$y_{i,t,n} = \beta_1 \times tick_{relative_{i,t}} + \beta_2 \times HFTdummy_{i,t,n} + \beta_3 \times tick_{relative_{i,t}} \times HFTdummy_{i,t,n}$$

$$+u_{j,t} + \Gamma \times X_{i,t} + \epsilon_{i,t,n} \quad (5)$$

In addition to hypothesis 4, regression (5) also tests two interesting hypotheses: 1) whether the profit from liquidity provision is higher for HFTers than for non-HFTers and 2) whether the difference between the profits for HFTers and non-HFTers depends on the relative tick size. In the specification, $y_{i,t,n}$ is the unit profit for each stock *i* on date *t* for trader type *n*. Therefore, we have two daily observations for each stock: a unit profit for HFTers and a unit profit for non-HFTers. $HFTdummy_{i,t,n}$ equals 1 if it is the profit for HFTers and 0 otherwise. The key variable of interest, $tick_{relative_{i,t}}$, is the relative tick size of stock *i* at day *t* minus the average of the relative tick size of the sample. We demean the relative tick size to facilitate the interpretation of β_2, which captures the difference in profit between HFTers and non-HFTers for stocks with average relative tick size.[23] The interaction term $tick_{relative_{i,t}} \times HFTdummy_{i,t,n.}$ captures the differences in profits between HFTers and non-HFTers for stocks for which the relative tick size differs. $u_{j,t}$ are industry-by-time fixed effects. $X_{i,t}$ are control variables presented in Table 1.

[23] Without demeaning the data, β_2 is interpreted as the difference in profit between HFTers and non-HFTers for stocks with 0 tick size, or infinite price.

Our profit measure comes from Brogaard, Hendershott, and Riordan (2014), Menkveld (2013), and Baron, Brogaard, and Kirilenko (2014). The HFT market-marking profit for an individual stock during one day for a certain time interval *t* is defined as

$$\pi^{HFT,t} = \sum_{n}^{N} -(HFT_n^t) + INV\_HFT_n^t \times P_{mid}^t \tag{6}$$

The profit comes from two components. The first term, $\sum_n^N -(HFT_n^t)$, captures total cash flows throughout the interval, with *n* indicating each of the *N* transactions within each interval.[24] The second term, often referred as "positioning profit," cumulates value changes associated with net position. In our analysis, $INV\_HFT_n^t$ or the interval *t* is cleared at the end of the interval midpoint quote P_{mid}^t. The positioning profit is negative when liquidity providers are adversely selected (e.g., Glosten and Milgrom, 1985), or if liquidity providers are willing to mean-revert out of nonzero position (Ho and Stoll, 1981).

The unit profit for HFT market making for each stock-day is calculated as:

$$\pi^{HFT} = \sum_{t}^{T} \pi^{HFT,t} / DolVol \tag{7}$$

where *T* is the total number of intervals during trading hours 9:30–15:59 and $DolVol$ is the total dollar volume with HFTers as liquidity providers for one stock on one day. For example, if the interval *t* is taken to be 30 minutes long, cash flows are calculated for each of the 30-minute intervals and inventories accumulated are emptied at the end of the 30-minute interval; the total number of intervals *T* equals 13. We calculate multiple daily unit profit measures taking *t* at

[24] We also add a liquidity rebate when calculating the first part of the profit. NASDAQ has a complex fee structure and we use a fee of 0.295 cents per share, but the results are similar at other fee levels.

varying lengths: five-minute, 30-minute, one-hour, and one-day lengths, respectively.[25] The market-making profit per dollar volume of non-HFT is calculated analogously.

Table 6 shows that the unit profit for market making increases with the relative tick size for all profit measures. The regression coefficient for profits measured on the assumption that inventories are cleared at the end of the day is 29.734 basis points. The economic magnitude of this coefficient can be interpreted as follows. The stock with the lowest price in our sample has a relative tick size of about 0.192 (price around $5), and the median relative tick size in our sample is about 0.034 (price around $30), and their difference in daily market-making profits is 29.734*0.192-29.734*0.034 = 4.7 basis points per dollar volume.

Insert Table 6 About Here

Whether HFTers enjoy a higher unit profit than non-HFTers, however, depends on the assumption regarding the frequency of inventory clearance. The first column in able 6 shows that the unit profit for HFTers is 0.762 basis points higher than that for non-HFTers if inventory can be cleared at a frequency of five minutes. The positively significant coefficient of 7.054 for the interaction term suggests that the difference in the unit profit between HFTer and non-HFTers increases with the relative tick size. The economic and statistical significance of the *HFTdummy* and the interaction term both decrease with the time horizon. Indeed, one important feature of HFTers is their "very short time-frames for establishing and liquidating positions" SEC (2010). One possible source for the higher profit HFTers enjoy over non-HFTers at a short horizon can be attributed to their speed advantage and time priority. A limit order at the front of the queue at a given price has a greater expected profit than other limit orders in the queue since its execution probability is higher (Foucault, Kadan and Kandel, 2013; Sandås, 2001).

[25] Because each day has 6.5 trading hours, the first interval for one-hour profit unit is from 9:30 to 10:00.

6. Identifications using ETFs

This section offers two clean identifications to test the causal impact of the relative tick size on HFT market-making activity (hypothesis 2 and 2a): twin ETFs and a diff-in-diff test using ETF splits. The same identification strategy also facilitates the analysis of the causal relationship between the relative tick size and liquidity (hypothesis 3). The question of liquidity is not only important in its own right, but it also offers additional economic insights to help us understand the relationship between the relative tick size and HFT. Section 6.1 illustrates how HFT activity and liquidity are measured. Section 6.2 presents the twin ETFs test, which uses ETFs that track the same index but with different nominal prices.[26] Section 6.3 presents the diff-in-diff test using the splits/reverse splits of leveraged ETFs as exogenous shocks to the relative tick size.

6.1. Measure of HFT activity and liquidity

Because the NASDAQ HFT dataset does not contain HFT information for ETFs, we use "strategic runs," proposed by Hasbrouck and Saar (2013), as a proxy for HFT market-making activity. A strategic run is a series of submissions, cancellations, and executions that are likely to form an algorithmic strategy. The link between submissions, cancellations, and executions are constructed based on three criteria: (1) Limit orders with their subsequent cancellations or executions are linked by reference numbers provided by data distributors.[27] (2) The point of inference comes in deciding whether a cancellation can be linked to either a subsequent submission of a nonmarketable limit order or a subsequent execution that occurs when the same

[26] In reality, ETFs that track the same index may have slightly different portfolios due to tracking errors, but slight differences between holdings should not determine HFT activity.

[27] We have a more recently updated version of the data relative to those reported in Hasbrouck and Saar (2013). Therefore, if a trader chooses to use the "U" (update) message to cancel an order and add another one, we know that the addition and cancellation comes from the same trader.

order is re-sent to the market priced to be marketable. We follow Hasbrouck and Saar (2013), and infer such a link when a cancellation is followed within 100 ms by a limit-order submission of the same size and same direction or by an execution of a limit order of the same size but in the opposite direction. (3) If a limit order is partially executed and the remainder is cancelled, we apply criterion (2) based on the cancelled quantity. *RunsInProcess* is the sum of the time length of all strategic runs with 10 or more messages divided by the total trading time of that day (Hasbrouck and Saar, 2013).

To test whether *RunsInProcess* is a good proxy for HFT market-making activity, we calculate *RunsInProcess* for the 117 stocks for which we have both ITCH data and NASDAQ HFT data. Table 7 presents the cross-sectional correlation between *RunsInProcess* and three measures of HFT activity. HFTvolume (making) and HFTdepth are measures of HFT liquidity provision, and HFTvolume (taking) are measures of the percentage of volume with HFTers as takers of liquidity.[28] Table 7 also contains the correlation test for two other widely used HFT proxies: the quote-to-trade ratio (Angel, Harris and Spatt, 2010 and 2013) and negative dollar volume divided by total number of messages (Hendershott, Jones, and Menkeveld, 2011; Boehmer, Fong, and Wu, 2013), both of which are based on the intuition that HFTers tend to cancel more orders than non-HFTers. Surprisingly, these two measures have either low or negative correlations with HFT market making.[29] However, *RunsInProcess* has a positive correlation of 0.65 with the percentage of depth provided by HFTers and the correlation runs as

[28] The measure is defined as the sum of volume from HN and HH types relative to total volume.

[29] Both the quote-to-trade ratio and negative dollar volume divided by total number of messages are excellent proxies for distinguishing trader types if the comparison is made within the same security or to measure time-series variation in HFT activity. Cross-sectional comparison of HFT market-making activity can be affected by the relative tick size. A large relative tick size attracts HFTers to move to the front of the queue, but HFTers are less likely to cancel an order once they are in the queue, since their positions in the queue will be lost by cancellation. A smaller relative tick size discourages HFT liquidity provision, but remaining HFTers cancel more frequently because a smaller relative tick size implies more frequent price movement. One additional contribution of our paper is that we put forward the notion of carefully interpreting results that use quote-to-trade ratios and negative dollar volume divided by total number of messages in cross-sectional comparisons.

high as 0.765 with the volume with HFTers as liquidity providers. A high *RunsInProcess* combines three factors: a fast response (within 100 ms), frequent cancellation (10 messages or more), and persistent interest in supplying liquidity (staying in the queue to provide liquidity conditional on fast and frequent cancellation). Therefore, it becomes a good proxy for HFT market making activity.

RunsInProcess has a correlation of 0.283 with HFT market-taking activity, indicating that it also captures some liquidity-taking activity on the part of HFTers. However, the lower correlation for liquidity taking implies that *RunsInProcess* is a better proxy for liquidity-making activities than for liquidity-taking activities. Indeed, pure submissions of market orders are not considered strategic runs, because all "runs" start with limit orders. The 10 message cut-off and the time weight also increase the correlation of *RunsInProcess* with patient liquidity-providing algorithms. Impatient liquidity-demanding algorithms may also use limit orders, but these algorithms are more likely to switch to market orders once the initial limit orders fail to be executed. Therefore, strategic runs that arise from liquidity-demanding algorithms should contain fewer messages. Even if they contain more than 10 messages, it is natural to expect that they span a shorter period of time and carry lower time weight in *RunsInProcess*. Therefore, we use *RunsInProcess* as a proxy for liquidity making, but we are also aware that it may capture some liquidity-demanding HFT activity as well.

Insert Table 7 about Here

Stock market liquidity is defined as the ability to trade a security quickly at a price that is close to its consensus value (Foucault, Pagano, and Röell, 2013). The spread is the transaction cost faced by traders, and is often measured by the quoted bid-ask spread or the trade-based effective spread. Depth reflects the market's ability to absorb large orders with minimal price impact, and is often measured by the quoted depth. These liquidity measures come from a message-by-message limit-order book we construct from ITCH data.

The quoted spread (*Qspread*) is measured as the difference between the best bid and ask at any given time. The proportional quoted spread (*pQspread*) is defined as the quoted spread divided by the midpoint of the best bid and ask. In addition to earning the quoted spread, a market maker also obtains a rebate from each executed share from the NASDAQ. Therefore, we compute two other measures of the quoted spread: $Qspread_{adj}$ and $pQspread_{adj}$, which are spreads adjusted by the liquidity supplier's rebate.[30] Specifically,

$$Qspread_{adj_{i,t}} = Qspread_{i,t} + 2 * liquidity\ maker\ rebate \tag{8}$$

$$pQspread_{adj_{i,t}} = (Qspread_{i,t} + 2 * liquidity\ maker\ rebate)/midpoint_{it} \tag{9}$$

All four of these quoted spreads are weighted by the duration of a quote to obtain the daily time-weighted average for each stock.

The effective spread (*Espread*) for a buy is defined as twice the difference between the trade price and the midpoint of the best bid and ask price. The effective spread for a sell is defined as twice the difference between the midpoints of the best bid and ask and the trade price. The proportional effective spread (*pEspread*) is defined as the effective spread divided by the midpoint. The effective spread measures the actual transaction costs for liquidity demanders. However, a liquidity demander on the NASDAQ also pays the taker fee.[31] Therefore, we compute the fee-adjusted effective spread and the fee-adjusted proportional effective spread:

[30] For each stock on each day, the liquidity maker's rebate is 0.295 cents per execution, but the results are qualitatively similar at other rebate levels.
[31] We set the taker fee at 0.3 cents per share.

$$Espread_{adj_{it}} = Espread_{it} + 2 * liquidity\ taker\ fee \tag{10}$$

$$pEspread_{adj_{it}} = (Espread_{it} + 2 * liquidity\ taker\ fee)/midpoint_{it} \tag{11}$$

Our main measures of depth are the time-weighted average of dollar depth at the best bid and offer.

6.2. Twin ETFs test

The twin ETFs test demonstrates that among ETF pairs that track the same index, the one with the lower price has higher proportional spread and depth as well as more HFT liquidity-provision activity. To see this, denote $y_{i,t,j}$ as the HFT market-making or liquidity measure for ETF *j* in index *i* at day *t*. $u_{i,t}$ is the index-by-time fixed effect that controls for both observable and unobservable characteristics that affect liquidity or HFT liquidity-provision activity.[32] Therefore, Regression (12) compares the differences in HFT market making or liquidity between ETFs that track the same index *i*, which are explained by differences in the relative tick size and the market cap.

$$y_{i,t,j} = u_{i,t} + \beta \times tick_{relative_{i,t,j}} + \rho \times logmktcap_{i,t,j} + \epsilon_{i,t,j} \tag{12}$$

Insert Table 8 about Here

The key variable of interest is the relative tick size, the results for which are presented in the first row of Table 8. Columns 1 and 2 show that the nominal spread is lower for ETFs with a higher relative tick size. The coefficient is -23.567, implying that for two ETFs, one with a normal price of $20 and the other with a nominal price of $40, the difference in the normal spread is -0.589 cents (1/20*(-23.567)-1/40*(-23.567) = -0.589 cents). However, low-priced

[32] We choose interactive index-by-time fixed effects instead of an individual index fixed effect and a time fixed effect to allow the time fixed effect to differ across the index for each day.

ETFs also have higher proportional spreads, particularly after fee adjustments. Indeed, the fee is the same for all securities, implying a higher proportional fee for lower-priced ETFs. In this sense, the fees on the NASDAQ have an economic impact that is similar to that of tick size. The coefficient shown in column 4 for the relative tick size is 146.354 basis points, implying that the proportional quoted spread after a fee adjustment of a $20 ETF is 3.66 basis points higher than that of a $40 ETF (1/20*146.354-1/40*146.354). The second row of Table 6 shows that ETFs with larger caps have lower spreads, greater depth, and higher levels of HFT liquidity-providing activity. The fact that low-priced ETFs have lower nominal spreads and higher proportional spreads is particularly interesting. Without tick size constraints, two ETFs that track the same index should have the same proportional spread due to their common fundamentals. This implies that their nominal spread should be at the same proportion relative to their prices, reflecting the same transaction cost measured proportionately. Our results suggest that lower-priced ETFs do have a lower nominal spread, but the nominal spread does not decrease as much as the nominal price, leading to a higher proportional spread. One explanation of this result is that the coarse tick size for the lower-priced ETFs prevents the nominal spread from fully adjusting.

Column 5 reveals that a large relative tick size results in greater dollar depth provided at the best bid and ask, implying a longer queue for providing liquidity at the best price. A large relative tick size for low-priced ETFs implies that traders who are able to quote a range of prices under a finer grid may have to quote a single price under a coarse grid, which increases the queue at the best price for low-priced ETFs.

Column 10 shows that HFT activity is higher for ETFs with a larger relative tick size. Such a difference cannot be ascribed to information, because the low-priced and high-priced ETFs should have similar fundamental information. We argue that the source of the difference is tick size constraints. At a constrained price, ETFs at lower prices have higher proportional spreads and longer queues for providing liquidity, and speed competition plays a prominent role when price competition is more constrained.

The literature generally agrees that securities with lower quoted spreads and greater depth are more liquid. Because lower-priced ETFs have higher quoted spreads and greater depth, the key variable of interest turns out to be the effective spread, the measure for the actual transaction costs incurred by liquidity demanders. Columns 6–9 show that the nominal effective spread is lower for ETFs with a large relative tick size, but their proportional effective spread is higher. In summary, we show that a large relative tick size reduces liquidity while increasing HFT market-making activity.

6.3. Diff-in-Diff test using leveraged ETF splits

This section establishes the causal relationship between the relative tick size and HFT liquidity provision using a diff-in-diff test. ETF splits provide us with a cleaner environment within which to isolate the effects of the tick size constraints channel than stock splits do, since stock splits may also be motivated by information (Grinblatt, Masulis, and Titman, 1984; Brennan and Hughes, 1991; Ikenberry, Rankine and Stice,1996). The splits for ETFs, however, are much less likely to be motivated by informational reasons. Furthermore, the ETFs that track the same index but do not split provide an ideal control even if related splits involve information. Among ETFs, splits/reverse splits are more frequent for leveraged ETFs. The reason that splits occur is completely transparent. The bear and bull ETFs for the same index are usually issued by the same company at similar IPO prices, but large cumulative movements of an index result in the divergence of their nominal prices. The issuers of leveraged ETFs usually use splits/reverse splits to align the nominal prices of bull and bear ETFs. Splits/reverse splits can be regarded as exogenous after controlling for past returns.

The regression specification for the diff-in-diff test is:

$$y_{i,t,j} = u_{i,t} + \gamma_j + \rho \times D_{trt_{i,t,j}} + \theta \times return_{i,t,j} + \epsilon_{i,t,j} \tag{13}$$

where $y_{i,t,j}$ is HFT market-making activity or the liquidity measure for ETF j in index i at time t. u_{it}, the index-by-time fixed effects, controls for the time trend that may affect each index. The new element, γ_j, is the ETF fixed effect that absorbs the time-invariant differences between two leveraged ETFs that track the same index. After controlling for index-by-time and ETF fixed effects, the only real differences between the bull and bear ETFs that track the same indexes are returns, $return_{i,t,j}$. $D_{trt_{i,t,j}}$, the treatment dummy, equals 0 for the control group. For the treatment group, the treatment dummy equals 0 before splits/reverse splits and 1 after splits/reverse splits. Therefore, coefficient ρ captures the treatment effect. The leveraged bull ETF is in the treatment group, and the leveraged bear ETF is in the control group if the leveraged bull ETF splits, and vice versa.

Panel A of Table 9 reports the splits results. Columns 1 and 2 show that the nominal quoted spread decreases by 9.686 cents following splits. However, the proportional quoted spread increases by 0.998 basis point following a split, and the proportional quoted spread after a fee adjustment increases by 1.205 basis points. Without the friction of an increased relative tick size, we would expect the nominal spread to decrease by the same ratio as the decrease in the nominal price, keeping the proportional spread unchanged. Our results indicate that the nominal quoted spread does not adjust by the same proportion as the decrease in the nominal price, which can be attributed to the large relative tick size following splits. Column 5 shows that the average dollar depth increases by 15,000 dollars. The nominal effective spread decreases by 5.385 cents following a split, but the proportional effective spread, or the transaction cost for a fixed transaction dollar amount, increases by 0.801 basis points. Again, we observe an increase in HFT activity along with an increase in the proportional spread and depth. We argue that this occurs because an increase in tick size constraints leads to a larger proportional spread and a longer queue for providing liquidity, which in turn generates more HFT market-making activity.

Insert Table 9 about Here

Panel B of Table 9 displays the results for reverse splits. Columns 1 and 2 show that reverse splits increase the quoted spread by 1.198 cents, but the proportional quoted spread decreases by 2.611 basis points (Column 3) and 5.030 basis points after adjusting the fee (Column 4). We ascribe this result to the reduction in the relative tick size following the reverse split. Reverse splits create new possible levels of the proportional spread for the fixed nominal spread, which encourages price competition. For example, for a stock offered at five dollars, the first nominal tick of one cent implies a proportional tick of 20 basis points. A one-for-five reverse split reduces the first proportional tick to four basis points, the second one to eight basis points and so on until it reaches 20 basis points at the fifth proportional tick. The depth at the best price decreases by 324,000 dollars, implying a shorter queue to provide liquidity at a less constrained price. This result, along with the reduction in the proportional quoted spread, constitutes evidence that traders who were forced to quote the same price under a large relative tick size can now choose to differentiate themselves by price, leading to a reduction in depth at the new but less constrained best price. Columns 6 and 7 show an increase in the effective spread by 0.692 cents, but Columns 8 and 9 show a reduction in the proportional spread of 2.958 basis points and 5.418 basis points after adjusting for the fee. The results show that the transaction cost for liquidity demanders falls after reverse splits. Column 10 reports a reduction in HFT activity following the reverse splits, and the intuition follows the results established in previous sections. A reduction in the relative tick size enhances price competition and reduces the queue for supplying liquidity at the constrained best price, which weakens the incentives to be at the top of the queue at the constrained price. Therefore, we see less HFT market-making activity following reverse splits.

In summary, we find that splits decrease liquidity whereas reverse splits increase liquidity. We also find that splits attract HFT market-making activity whereas reverse splits reduce HFT market-making activity. These results should not be interpreted as having a negative impact on HFTers regarding liquidity provision, because they are based on exogenous shocks to the tick size and not HFT activity. The correct economic interpretation is that a large relative tick size reduces liquidity but attracts HFTers.

7. Conclusion

We contribute to the HFT literature by providing a tick size–based explanation of speed competition in liquidity provision. Contrary to the common belief that HFTers provide liquidity at lower cost, we find that non-HFTers play a more prominent role in providing liquidity at better prices than HFTers do, particularly when the relative tick size is small. An increase in the relative tick size, however, constrains non-HFTers' abilities to undercut price and helps HFTers achieve price priority when they quote the same price as non-HFTers. As a consequence, HFTers provide a larger fraction of liquidity for low-priced stocks in which a one-cent uniform tick size implies a larger relative tick size. For ETFs that track the same index, HFTers are more active in trading lower-priced ETFs. In addition, splits increase HFT liquidity-providing activity and the quoted spread and lengthen the queue for providing liquidity; reverse splits decrease the quoted spread and reduce depth and also decrease HFT liquidity-providing activity. We also find that HFTers are less active in market making for stocks with higher PIN, suggesting that quick access to information does not give market-making HFTers a more prominent role in liquidity provision with a higher probability of informed trading.

The tick size constraints channel provides a new possibility for explaining the results reported in the extant literature. The literature on HFT finds that speed improvement increases liquidity and the common belief about the source of improvement is that it comes from traders with higher speed, which is at odds with the results of the current paper. There are two possible reconciliations of this discrepancy. First, the extant literature is based on technology shocks at millisecond or full-second scale, whereas speed competition in our sample is recorded at nanosecond scale (Gai, Yao and Ye, 2013), implying a diminishing return for speed (Jones, 2013). A more intriguing conjecture is that the source of liquidity improvement may come from traders who decline to improve their speed in the face of those technology shocks. Traders who pay for technology enhancement enjoy time priority and a lesser need to undercut the price, whereas traders who choose not to pay for speed need to undercut the price more often. A test for this conjecture based on account-level data would be very interesting.

The tick size constraints channel provides new insights into the policy debate over HFT. The current policy debate focuses on whether additional regulation is required, and if so how to pursue it. Our paper points to a new direction: HFT may simply be a consequence of the existing tick size regulation and one possible policy solution would be deregulation instead of additional regulation. At the minimum, the first step in pursuing additional regulation would involve due diligence to evaluate the impact of the existing tick size regulation on HFT.

This paper also provides a benchmark for evaluating the economic consequences of increasing tick size. The JOBS Act encourages the SEC to examine the possibility of increasing tick size, and a pilot program is under way for less liquid stocks. Proponents of a wider tick size have offered three rationales for this position (Weild, Kim and Newport, 2012). First, a larger tick size controls the growth of HFT. Second, a larger tick size should increase liquidity. Our paper shows that a larger tick size *encourages* HFT without improving liquidity. The third argument for increasing tick size is that a larger tick size increases market-making revenue, supports sell-side equity research, and increases the number of IPOs. The economic argument that controlling prices leads to non-price competition is valid, but we doubt that non-price competition would take the form of stock research or more IPOs. The causal impact of the tick size on IPOs has never been proved by academic research, but speed competition under constrained price competition is well established by this paper. We believe that an increase in tick size would create more rents for time priority, and would fuel another round of the arms race in speed.

Our paper can be extended in various ways. First, current theoretical work on speed competition focuses on the role of information. Our paper points out another channel for speed competition: tick size constraints. Models using discrete prices can be constructed to indicate the value of speed and the impact of tick size constraints on market quality. Second, speed competition is not the only market design response to tick size constraints (Buti, Consonni, Rindi, Wen and Werner, 2014). In a companion paper, we examine the causal impact of tick size constraints on the taker/maker fee market or the market that charges liquidity providers but subsidizes liquidity demanders (Yao and Ye, 2014). The literature on market microstructure focuses on liquidity and price discovery under certain market designs, but market design is also endogenous, and it should prove fruitful to examine why certain market designs exist in the first place. Finally, the SEC recently announced a pilot program for increasing tick size for a number of small stocks, believing that tick size may need to be wider for less liquid stocks. We encourage the SEC to consider decreasing tick size for liquid stocks in the pilot program, particularly for large stocks with lower prices.

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Table 1. Summary Statistics

This table presents the summary statistics for all stocks and ETFs. Panel A contains stocks in the NASDAQ HFT sample. Panel B provides the summary statistics for the non-leveraged ETF sample used in the twin ETFs test. Panel C lists the summary statistics for the leveraged ETF sample used in the diff-in-diff test. All the variables are measured for each stock per day unless otherwise indicated. *HFTdepth* is the percentage of depth at the best bid/ask provided by HFTers. *HFTvolume* is the percentage of trading volume with HFTers as liquidity providers. $tick_{relative}$ is the reciprocal of price. *logmcap* is the log value of market capitalization. *turnover* is the annualized share turnover. *volatility* is the standard deviation of open-to-close returns based on the daily price range, that is, high minus low, proposed by Parkinson (1980). $logbv_{average}$ is the logarithm of the average book value of equity per shareholder at the end of the previous year (December 2009). *idiorisk* is the variance on the residual from a 60-month beta regression using the CRSP Value Weighted Index. *age* (in 1k days) is the length of time for which price information is available for a firm on the CRSP monthly file. *numAnalyst* is the number of analysts providing one-year earnings forecasts calculated from I/B/E/S. *pastreturn* is the past one-month return. *PIN* is the probability of informed trading. *return* is the contemporaneous daily return. *Qtspd* represents the time-weighted quoted spread. *pQtspd* represents the time-weighted proportional quoted spread. $Qtspd_{adj}$ and $pQtspd_{adj}$ represent the time-weighted quoted spread and the time-weighted proportional quoted spread after adjusting for fees. *SEffspd* represents the size-weighted effective spread and *pSEffspd* represents the size-weighted proportional effective spread. $SEffspd_{adj}$ and $pSEffspd_{adj}$ represent the size-weighted effective spread and the size-weighted proportional effective spread after adjusting for fees. *Depth* represents the time-weighted dollar depth at the best bid and ask. *RunsInProcess* is the proxy for HFT market-making activity. The sample period for Panel A and Panel B is October 2010 and the sample period for Panel C is 30 days before leveraged ETFs splits/reverse splits during 2010 and 2011.

	Mean	Median	Std.	Min.	Max.
Panel A. NASDAQ HFT Sample					
HFTdepth(in pcg)	0.321	0.298	0.166	0.006	0.744
HFTvolume(in pcg)	0.285	0.273	0.134	0	0.728
$tick_{relative}$	0.048	0.034	0.038	0.002	0.192
logmcap	22.01	21.473	1.893	19.371	26.399
turnover	2.367	1.801	2.179	0.074	33.301
volatility	0.015	0.013	0.009	0.002	0.099
$logbv_{average}$	13.148	13.196	2.112	8.822	17.881
idiorisk	0.013	0.008	0.017	0.001	0.139
age (in 1k days)	9.751	7.671	7.839	0.945	30.955
numAnalyst	13.731	12	10.048	1	48
pastreturn	0.105	0.096	0.073	-0.077	0.336
PIN	0.118	0.111	0.052	0.021	0.275
Panel B. Twin ETF Sample					
$tick_{relative}$	0.021	0.012	0.018	0.007	0.078
logmcap	21.994	22.781	2.303	17.107	25.139
Qtspd (in cent)	2.614	2.034	1.916	1.007	10.474
pQtspd (in bps)	5.270	2.784	5.664	0.832	31.889

Qtspd$_{adj}$ (in cent)	3.204	2.624	1.916	1.597	11.064
pQtspd$_{adj}$ (in bps)	6.516	3.368	6.166	1.280	33.680
SEffspd (in cent)	2.002	1.421	1.429	0.964	8.178
pSEffspd (in bps)	4.029	2.061	4.043	0.850	19.347
SEffspd$_{adj}$ (in cent)	2.602	2.021	1.429	1.564	8.778
pSEffspd$_{adj}$ (in bps)	5.296	2.841	4.674	1.312	21.158
Depth (in mn dollars)	0.985	0.433	1.458	0.044	9.194
RunsInProcess	84.244	24.234	133.056	0.967	654.986

Panel C. Leveraged ETF Sample

	Mean		Median	
	Treatment	Control	Treatment	Control
Split Sample				
return	-0.002	0	0.006	-0.007
Qtspd (in cent)	20.259	2.062	18.232	1.938
pQtspd (in bps)	11.544	9.797	9.657	10.082
Qtspd$_{adj}$ (in cent)	20.849	2.652	18.822	2.528
pQtspd$_{adj}$ (in bps)	11.881	12.868	9.994	13.476
SEffspd (in cent)	11.846	1.526	10.732	1.423
pSEffspd (in bps)	6.673	7.477	6.039	7.156
SEffspd$_{adj}$ (in cent)	12.446	2.126	11.332	2.023
pSEffspd$_{adj}$ (in bps)	7.015	10.6	6.38	9.835
Depth (in mn dollars)	0.179	0.188	0.141	0.114
RunsInProcess	15.607	37.570	15.042	13.401
Reverse Split Sample				
return	0	0	-0.002	0.002
Qtspd (in cent)	1.362	4.415	1.066	2.333
pQtspd (in bps)	13.839	9.464	12.6	9.645
Qtspd$_{adj}$ (in cent)	1.952	5.005	1.656	2.923
pQtspd$_{adj}$ (in bps)	20.224	11.837	17.958	11.644
SEffspd (in cent)	1.179	3.031	1	1.635
pSEffspd (in bps)	12.191	7.185	10.815	6.389
SEffspd$_{adj}$ (in cent)	1.779	3.631	1.6	2.235
pSEffspd$_{adj}$ (in bps)	18.683	9.598	16.124	8.105
Depth (in mn dollars)	1.304	0.512	0.412	0.095
RunsInProcess	106.230	63.938	66.973	36.252

Table 2. Who Provides the Best Quotes?

This table displays the percentage of time HFTers and non-HFTers provide the best bid and ask quotes to the NASDAQ limit-order book. The sample includes 117 stocks in the NASDAQ HFT data from October 2010. Stocks are sorted first into 3-by-3 portfolios by average market cap and then by average price from September 2010. For each portfolio and each trading day, we calculate the percentage of time that HFTers are the sole providers of the best quotes, the percentage of time that non-HFTers are the sole providers of the best quotes, and the percentage of time that both provide the best quotes. Column (1) presents the average percentage of time that HFTers are the sole providers of the best quotes and column (2) presents the average percentage of time that non-HFTers are the sole providers of the best quotes. Column (3) presents the average percentage of time that both HFTers and non-HFTers provide the best quotes. Column (4) shows the ratio of column (2) figures to column (1) figures. Column (5) shows the difference between column (1) figures and (2) figures. *t*-statistics for column (5) based on 21 daily observations are presented in column (6). *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Relative Tick Size	(1) HFT Only	(2) Non-HFT Only	(3) HFT & Non-HFT	(4) Ratio	(5) Non-HFT minus HFT	(6) *t*-stat
Large Cap	Large (Low Price)	1.6%	2.5%	95.9%	1.55	0.9%***	7.27
	Medium (Medium Price)	11.9%	18.6%	69.6%	1.57	6.7%***	14.01
	Small (High Price)	16.8%	37.7%	45.5%	2.25	20.9%***	37.81
Middle Cap	Large (Low Price)	18.0%	15.2%	66.8%	0.84	-2.9%***	-3.52
	Medium (Medium Price)	20.0%	56.6%	23.4%	2.83	36.6%***	36.03
	Small (High Price)	20.7%	63.7%	15.7%	3.08	43.0%***	67.15
Small Cap	Large (Low Price)	11.3%	54.7%	34.1%	4.86	43.4%***	27.55
	Medium (Medium Price)	20.2%	55.8%	24.0%	2.77	35.7%***	30.11
	Small (High Price)	18.6%	70.7%	10.7%	3.80	52.1%***	66.79
Total		15.4%	41.7%	42.9%	2.62	26.3%***	18.31

Table 3. Market Share of BBO Depth Provided by HFTers

This table presents the percentages of depth at the NASDAQ best bid and offer (BBO) provided by HFTers. The sample includes 117 stocks in the NASDAQ HFT data from October 2010. The stocks are sorted first by average market cap and then by average price from September 2010. To calculate the share-weighted average for each portfolio on each day, we aggregate the number of shares provided by HFTers at the BBO and then divide it by the total number of shares at the BBO for that portfolio. *t*-statistics are calculated based on 21 daily observations. *, **, and *** represent statistical significance of large-minus-small differences at the 10%, 5%, and 1% levels, respectively.

	Large Relative Tick Size (Low Price)	Medium Relative Tick Size (Medium Price)	Small Relative Tick Size (High Price)	Large-Small Relative Tick Size (Low-High Price)	*t*-stat
Large Cap	55.66%	45.44%	35.07%	20.59%***	22.10
Middle Cap	39.73%	29.24%	24.61%	15.13%***	22.88
Small Cap	25.78%	23.02%	20.78%	5.00%***	3.18
L-S Cap	29.88%***	22.43%***	14.29%***		
t-statistics	18.84	17.92	16.80		

Table 4. Percentage of Volume with HFTers as the Liquidity Providers

This table presents the trading volume percentage due to HFTers as liquidity providers. The sample includes 117 stocks in the NASDAQ HFT data from October 2010. The stocks are sorted first by average market cap and then by average price from September 2010 into 3-by-3 portfolios. To calculate the volume-weighted average for each portfolio on each day, we aggregate the volumes due to HFT liquidity providers and then divide that figure by the total volume for that portfolio. *t*-statistics are calculated based on 21 daily observations. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels of large-minus-small differences, respectively.

	Large Relative Tick Size (Low Price)	Medium Relative Tick Size (Medium Price)	Small Relative Tick Size (High Price)	Large-Small Relative Tick Size (Low-High Price)	*t*-stat
Large Cap	49.96%	38.23%	35.93%	14.03%***	15.54
Middle Cap	39.30%	24.03%	24.33%	14.97%***	18.74
Small Cap	24.11%	18.88%	18.49%	5.62%***	5.38
L-S Cap	25.84%***	19.35%***	17.43%***		
t-statistics	21.33	21.76	18.22		

Table 5. HFT Liquidity Provision

This table presents the results of the regressions of HFT liquidity provision on relative tick size (reciprocal of price). The regressions use the NASDAQ HFT data sample as of October 2010 and merges it with all the other variables calculated from databases including CRSP, COMPUSTAT, etc. Panel A presents the results for the daily percentage of depth provided by HFTers. Panel B contains the results for the daily percentage of trading volume with HFTers as liquidity providers. The regression specification is:

$$y_{i,t} = u_{j,t} + \beta \times tick_{relative_{i,t}} + \Gamma \times X_{i,t} + \epsilon_{i,t}$$

where $tick_{relative_{i,t}}$ is the daily inverse of the stock price. $u_{j,t}$ represents industry-by-time fixed effects. The definitions for the control variables $X_{i,t}$ are presented in Table 1. *t*-statistics are shown in parenthesis; *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. HFT Liquidity Provision as in HFT Trading Depth

Dep. Var	*HFTdepth* (in percentage)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$tick_{relative}$	0.678***	0.699***	0.673***	0.691***	0.641***	0.677***	0.658***
	(5.48)	(5.60)	(5.40)	(5.16)	(5.26)	(5.44)	(4.98)
logmcap	0.038***	0.037***	0.038***	0.032***	0.032***	0.038***	0.023***
	(16.57)	(15.13)	(16.56)	(7.86)	(12.15)	(16.37)	(4.90)
turnover		0.001					0.001
		(0.62)					(0.83)
volatility		-0.837*					-0.531
		(-1.75)					(-1.13)
$logbv_{average}$			-0.003				0.002
			(-1.48)				(0.99)
idiorisk				-0.290			-0.308
				(-1.33)			(-1.46)
age				0.005***			0.005***
				(7.40)			(7.83)
numAnalyst				-0.001			-0.001
				(-0.96)			(-1.09)
PIN					-0.358***		-0.435***
					(-4.05)		(-4.71)
pastreturn						-0.069	-0.117**
						(-1.33)	(-2.26)
R^2	0.461	0.462	0.462	0.485	0.466	0.462	0.494
N	2268	2268	2268	2268	2268	2268	2268
Industry*time FE	Y	Y	Y	Y	Y	Y	Y

Panel B. HFT Liquidity Provision as in HFT Trading Volume

Dep. Var	*HFTvolume* (in percentage)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$tick_{relative}$	0.937***	0.940***	0.943***	0.992***	0.893***	0.937***	0.956***
	(9.88)	(9.86)	(10.10)	(9.35)	(9.72)	(9.87)	(9.58)
logmcap	0.051***	0.048***	0.051***	0.042***	0.044***	0.051***	0.031***
	(33.54)	(29.38)	(33.52)	(13.68)	(23.63)	(33.47)	(9.43)
turnover		0.008***					0.007***
		(5.50)					(5.44)
volatility		-0.803**					-0.536
		(-2.34)					(-1.64)
$logbv_{average}$			0.003***				0.005***
			(2.68)				(4.01)
idiorisk				-0.495***			-0.547***
				(-3.00)			(-3.76)
age				0.002***			0.003***
				(3.77)			(6.37)
numAnalyst				0.001**			0.001**
				(2.25)			(2.04)
PIN					-0.423***		-0.407***
					(-6.64)		(-6.51)
pastreturn						-0.007	-0.034
						(-0.22)	(-1.09)
R^2	0.632	0.641	0.634	0.639	0.643	0.632	0.664
N	2268	2268	2268	2268	2268	2268	2268
Industry*time FE	Y	Y	Y	Y	Y	Y	Y

Table 6. Tick size and profits

This table presents the results of regressions of HFT unit profit on relative tick size (reciprocal of price). The regression uses the NASDAQ HFT data sample as of October 2010.The regression specification is:

$$y_{i,t,n} = \beta_1 \times tick_{relative_{i,t}} + \beta_2 \times HFTdummy_{i,t,n} + \beta_3 \times tick_{relative_{i,t}} \times HFTdummy_{i,t,n}$$
$$+u_{j,t} + \Gamma \times X_{i,t} + \epsilon_{i,t,n}$$

Columns (1)–(4) present regression results for daily unit profit measured on the assumption that inventories are emptied at 5-minute, 30-minute, 60-minute intervals and at daily closing. $tick_{relative_{i,t}}$ is the daily inverse of the stock price. $HFTdummy_{i,t,n}$ is equal to 1 if the profit measure is from HFTers and 0 otherwise. $u_{j,t}$ represents the industry-by-time fixed effects. The definitions for the control variables $X_{i,t}$ are presented in Table 1. *t*-statistics are shown in parenthesis; *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Dep. Var	*Unit Profit (bps)*			
	(1)	(2)	(3)	(4)
$tick_{relative}$	15.497***	17.513***	18.977***	29.734**
	(5.45)	(3.97)	(3.43)	(2.31)
HFTdummy	0.762***	0.421**	0.243	-0.094
	(6.43)	(2.29)	(1.06)	(-0.18)
$tick_{relative}$ * *HFTdummy*	7.054**	2.328	-0.261	-16.344
	(2.21)	(0.47)	(-0.04)	(-1.13)
logmcap	-0.160*	-0.129	-0.144	-0.233
	(-1.67)	(-0.87)	(-0.77)	(-0.54)
turnover	-0.085**	0.038	0.062	-0.178
	(-2.37)	(0.68)	(0.89)	(-1.11)
volatility	-19.509**	-91.450***	-105.805***	-179.865***
	(-1.97)	(-5.95)	(-5.48)	(-4.01)
$logbv_{average}$	0.036	0.017	0.082	0.314*
	(0.98)	(0.30)	(1.15)	(1.92)
idiorisk	2.883	11.624*	16.507*	26.079
	(0.65)	(1.70)	(1.92)	(1.31)
age	-0.008	-0.028	-0.019	-0.033
	(-0.61)	(-1.37)	(-0.76)	(-0.57)
numAnalyst	0.040**	0.033	0.033	0.063
	(2.54)	(1.33)	(1.07)	(0.89)
PIN	0.797	2.895	7.518**	9.835
	(0.44)	(1.02)	(2.11)	(1.19)
pastreturn	-1.658*	1.373	4.769**	9.321**
	(-1.66)	(0.89)	(2.45)	(2.06)
R^2	0.220	0.214	0.203	0.194
N	4484	4484	4484	4484
Industry*time FE	Y	Y	Y	Y

Table 7. Correlation Test

This table presents the cross-sectional correlations between HFT proxies and the HFT activity measures which are calculated from the NASDAQ HFT dataset. The HFT activity measures include the percentage of depth provided by HFTers, the percentage of volume with HFTers as liquidity providers, and the percentage of volume with HFTers as liquidity takers. The HFT proxies include *RunsInProcess* by Hasbrouck and Saar (2013), the Quote-to-Trade Ratio and the Dollar Volume (in $100)–to–Message Ratio multiplied by -1. *P*-values are shown under correlation coefficients; *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

HFT Measures	HFTdepth (liq. making)	HFTvolume (liq. making)	HFTvolume (liq. taking)
RunsInProcess	0.650***	0.765***	0.283***
	<.0001	<.0001	0.002
Quote / Trade Ratio	-0.385***	-0.390***	-0.082
	<.0001	<.0001	0.378
-Trading Vol. (in $100) / Message Ratio	0.031	-0.252***	-0.274***
	0.7403	0.0061	0.003

Table 8. Twin ETFs Test

This table presents the results of regressions of liquidity measures and HFT measure on relative tick size (the reciprocal of price) and market capitalization for twin ETFs. The sample period is October 2010. The regression specification is as follows:

$$y_{i,t,j} = u_{i,t} + \beta \times {tick_{relative}}_{i,t,j} + \rho \times logmktcap_{i,t,j} + \epsilon_{i,t,j}$$

${tick_{relative}}_{i,t}$ is the daily inverse of the price for ETF j. $logmktcap_{i,t,j}$ is the logarithm of ETF j's daily market capitalization. $u_{i,t}$ represents the index-by-time fixed effect. Column (1) - (9) present regression results for liquidity. *Qtspd* represents the time-weighted quoted spread. *pQtspd* represents the time-weighted proportional quoted spread. $Qtspd_{adj}$ and $pQtspd_{adj}$ represent the time-weighted quoted spread and the time-weighted proportional quoted spread after adjusting for fees. *SEffspd* represents the size-weighted effective spread and *pSEffspd* represents the size-weighted proportional effective spread. $SEffspd_{adj}$ and $pSEffspd_{adj}$ represent the size-weighted effective spread and the size-weighted proportional effective spread after adjusting for fees. *Depth* represents the time-weighted dollar depth at the best bid and ask in millions of dollars. Column (10) presents regression results for HFT activity, which is proxied by *RunInProcess* proposed by Hasbrouck and Saar (2013). *t*-statistics are shown in parenthesis; *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	(1) *Qtspd* (in cent)	(2) $Qtspd_{adj}$ (in cent)	(3) *pQtspd* (in bps)	(4) $pQtspd_{adj}$ (in bps)	(5) *Depth* (in mn)	(6) *SEffspd* (in cent)	(7) $SEffspd_{adj}$ (in cent)	(8) *pSEffspd* (in bps)	(9) $pSEffspd_{adj}$ (in bps)	(10) *RunInProc.*
$tick_{relative}$	-23.567***	-23.567***	87.354***	146.354***	76.275***	-27.059***	-27.059***	79.101***	139.101***	366.171***
	(-16.97)	(-16.97)	(29.42)	(49.29)	(20.72)	(-7.19)	(-7.19)	(32.88)	(57.81)	(3.92)
logmcap	-0.339***	-0.339***	-0.710***	-0.710***	0.245***	-0.218***	-0.218***	-0.394***	-0.394***	32.988***
	(-16.56)	(-16.56)	(-15.31)	(-15.31)	(10.63)	(-9.36)	(-9.36)	(-10.72)	(-10.72)	(7.90)
R^2	0.930	0.930	0.914	0.928	0.824	0.832	0.832	0.929	0.947	0.562
N	375	375	375	375	375	375	375	375	375	375
Index*time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 9. Diff-in-Diff Test Using Leveraged ETF Splits

This table presents the results of a diff-in-diff test using leveraged ETF split (and reverse-split) events in 2010 and 2011. Panel A reports the results for 5 splits and Panel B reports the results for 21 reverse splits. The event windows are 30 days before and 30 days after splits/reverse splits. The regression specification is:

$$y_{i,t,j} = u_{i,t} + \gamma_j + \rho \times D_{trt\,i,t,j} + \theta \times return_{i,t,j} + \epsilon_{i,t,j}$$

$u_{i,t}$ is the index by time fixed effects and γ_j is the ETF fixed effects. The treatment dummy D_{trt}, equals 0 for the control group. For the treatment group, D_{trt} equals 0 before splits/reverse splits and 1 after the splits/reverse splits. *return* is the daily return. The regression includes both an index-by-time fixed effect and an ETF fixed effect. Column (1) - (9) present regression results for liquidity. *Qtspd* represents the time-weighted quoted spread. *pQtspd* represents the time-weighted proportional quoted spread. $Qtspd_{adj}$ and $pQtspd_{adj}$ represent the time-weighted quoted spread and the time-weighted proportional quoted spread after adjusting for fees. *SEffspd* represents the size-weighted effective spread and *pSEffspd* represents the size-weighted proportional effective spread. $SEffspd_{adj}$ and $pSEffspd_{adj}$ represent the size-weighted effective spread and the size-weighted proportional effective spread after adjusting for fees. *Depth* represents the time-weighted dollar depth at the best bid and ask in millions of dollars. Column (10) presents regression results for HFT activity, which is proxied by *RunInProcess* proposed by Hasbrouck and Saar (2013). *t*-statistics are shown in parenthesis; *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A. Split Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Qtspd (in cent)	$Qtspd_{adj}$ (in cent)	*pQtspd* (in bps)	$pQtspd_{adj}$ (in bps)	*Depth* (in mn)	*SEffspd* (in cent)	$SEffspd_{adj}$ (in cent)	*pSEffspd* (in bps)	$pSEffspd_{adj}$ (in bps)	*RunInProc.*
D_{trt}	-9.686***	-9.686***	0.998*	1.205**	0.015	-5.385***	-5.385***	0.801*	1.012**	3.372***
	(-15.83)	(-15.83)	(1.89)	(2.23)	(1.41)	(-11.96)	(-11.96)	(1.96)	(2.40)	(3.28)
return	-9.307**	-9.307**	-6.954**	-8.112**	0.000	-5.235*	-5.235*	-5.482**	-6.660**	-3.725
	(-2.48)	(-2.48)	(-2.15)	(-2.45)	(-0.00)	(-1.89)	(-1.89)	(-2.19)	(-2.57)	(-0.59)
R^2	0.911	0.911	0.741	0.717	0.915	0.868	0.868	0.637	0.731	0.978
N	597	597	597	597	597	597	597	597	597	597
Index*time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ETF FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel B. Reverse Split Sample

	(1) *Qtspd* (in cent)	(2) $Qtspd_{adj}$ (in cent)	(3) *pQtspd* (in bps)	(4) $pQtspd_{adj}$ (in bps)	(5) *Depth* (in mn)	(6) *SEffspd* (in cent)	(7) $SEffspd_{adj}$ (in cent)	(8) *pSEffspd* (in bps)	(9) $pSEffspd_{adj}$ (in bps)	(10) *RunInProc.*
D_{trt}	1.198***	1.198***	-2.611***	-5.030***	-0.324***	0.692***	0.692***	-2.958***	-5.418***	-32.108***
	(8.45)	(8.45)	(-13.33)	(-18.27)	(-5.98)	(5.92)	(5.92)	(-12.45)	(-17.18)	(-9.72)
return	-1.478	-1.478	-3.551**	-4.449**	0.842**	-0.696	-0.696	-1.748	-2.661	18.536
	(-1.39)	(-1.39)	(-2.42)	(-2.16)	(2.08)	(-0.80)	(-0.80)	(-0.98)	(-1.13)	(0.75)
R^2	0.832	0.832	0.883	0.856	0.789	0.768	0.768	0.785	0.798	0.852
N	2517	2517	2517	2517	2517	2517	2517	2517	2517	2517
Index*time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ETF FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y