Tick Size Constraints, Market Structure, and Liquidity[1]

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Abstract

We argue that a one-penny minimum tick size for all stocks priced above $1 (SEC rule 612) encourages high-frequency trading and taker/maker–fee markets. We find that non-high frequency traders (non-HFTers) are 2.7 times more likely than HFTers to provide best prices, thereby establishing price priority. However, while relatively large tick sizes constrain non-HFTers from providing better prices, HFTers' speed advantage helps them establish time priority over non-HFTers. Because liquidity providers can undercut prices by paying a maker fee, non-HFTers enter the taker/maker market more frequently than HFTers; this tendency is even stronger when tick size constraints are high. When stock splits increase relative tick size, speed competition in liquidity provision increases and volume shifts to the taker/maker market, although without improving liquidity. Thus recent proposals to increase tick size will not improve liquidity. Instead, they will generate further speed competition and taker/marker markets.

Key Words: tick size, high-frequency trading, maker/taker fees, liquidity

1. Introduction

Under standard Walrasian equilibrium, price is infinitely divisible but time is not; all agents are assumed to arrive at the market at the same time. However, the reality regarding financial markets is exactly the opposite: price competition is restricted by tick size regulations but time becomes divisible at the nanosecond level. This paper shows that two sources of friction, discrete prices and (almost) continuous time under canonical Walrasian equilibrium, help to explain two important features of the U.S. stock market: high-frequency trading (HFT) and taker/maker fees. Currently, there are heated debates over 1) whether we should increase tick size and 2) whether HFT and taker/maker fees should be regulated and what form such new regulation should take. To the best of our knowledge, our paper is the first to show that HFT and taker/maker fees are the consequences of existing tick size regulations, and we argue that increasing tick size through new regulatory action would further encourage speed competition by discouraging price competition and leading to a proliferation of markets with taker/maker fees.

Tick size in the United States is regulated through SEC rule 612 (Minimum Pricing Increment) of regulation NMS. The rule prohibits stock exchanges from displaying, ranking, or accepting quotations, orders, 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-penny tick size constraint is surprisingly binding: 50 percent of S&P stocks priced below \$100 per share have one-penny quoted spreads (Avramovic, 2012). The clustering of quoted spreads on one penny suggests that many of those stocks should have an equilibrium bid-ask spread of less than one

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

penny if there are no tick size constraints. The minimum pricing increment rule imposes a price floor on the lowest price for liquidity in the public exchange. A surplus represents a natural response to a binding price floor (supply exceeds demand). Because a price floor prevents the pricing system from rationing the available supply, other mechanisms must take its place. Rockoff (2008) summarizes four possible responses to price controls: queuing, the emerging of markets that bypass the regulation, evading, and rationing. HFT and taker/maker fees are just two examples of this general economic principle. HFT is a form of queuing through which traders with high speed capacity can move to the front of the queue at a constrained price. Taker/maker fees make it possible to bypass tick-size regulations, allowing traders to quote at sub-penny levels.

We first demonstrate that tick-size constraints are among the driving forces of HFT liquidity provision. Displayed limit orders in the NASDAQ market observe price and time priority.[3] Among orders with the same price and display status, orders arriving first have the highest priority. Therefore, a large tick size increases the importance of speed competition but discourages price competition. Because SEC rule 612 mandates a one-cent tick size for all stocks, the regulation imposes high tick size constraints for two types of stocks: 1) low-priced stocks, for which a fixed nominal tick size leads to a higher relative tick size, and 2) large stocks, for which the equilibrium bid-ask spread can be below one tick. We find that high-frequency traders (HFTers) with their speed advantage take a higher market share in terms of volume relative to lower-frequency traders in low-priced stocks with large caps.

Tick size constraints and the comparative advantages of non-HFTers and HFTers are the main economic mechanisms driving this cross-sectional variation. We first find that non-HFTers

3 Displayed orders take priority over non-displayed orders when they have the same price. For want of space, we do not discuss order display strategy here. Yao (2013) offers an empirical examination of display vs. hidden orders.

are 2.7 times more likely than HFTers to quote better prices and the likelihood that non-HFTers to provide better prices increases as relative tick size decreases. Therefore, a small tick size helps non-HFTers to establish price priority over HFTers. For large stocks with low prices, or stocks with large relative tick size, non-HFTers are still more likely to quote better prices than HFTers (2.8% vs. 1.9%), but the relatively larger tick size of those stocks apparently imposes a constraint on non-HFTers' ability to undercut HFTers.[4] For this stock category, 95.4% of the time HFTers and non-HFTers both provide the best price, which implies that time is needed as a secondary priority rule for allocating resources. Next, we find that the volume of HFTer liquidity providers is the highest for this category (49.29%), but the number decreases to 35.53% for large stocks with small relative tick sizes. In summary, we find that HFTers are less likely to provide better prices than non-HFTers, but large tick sizes enable them to quote the same price as non-HFTers and their speed helps them establish time priority at constrained prices. Therefore, tick size constraints favor HFTer liquidity provision by encouraging speed competition and discouraging price competition.

Taker/maker fees are another market design response to tick-size constraints. It provides liquidity providers with a means of undercutting prices by paying the stock exchange the maker fee, which is used by the stock exchange to partially subsidize liquidity takers. The impact of tick size constraints is demonstrated using the following identification strategy.[5] Direct Edge, a stock exchange that executes 12% of U.S. equity trading volume, operates twin trading platforms: EDGA and EDGX. These two trading platforms are almost identical except for the fee structure. In our sample period, EDGA, like most other exchanges, uses a maker/taker fee structure, which

[4] This might be either because undercutting is too costly or because there is no room to undercut the price when the bid-ask spread is exactly one penny.
[5] Internalization, dark pools, mid-point peg orders, and the Retail Price Improvement Program are also exempted from SEC rule 612.

pays liquidity makers 0.26 cents and charges liquidity takers 0.3 cents. EDGA, however, has an inverted taker/maker fee structure whereby the maker of liquidity, or the passive (limit) order, is charged a fee of 0.025 cents and the taker of liquidity, or the aggressive (market) order, obtains a rebate of 0.015 cents. Two interesting questions immediately emerge. First, why are some liquidity providers paid whereas others need to pay when providing liquidity for the same stock? Second, what forces determine the competition for order flow between these two markets?

We find the evidence that non-HFTers enter the taker/maker market more frequently than HFTers, while non-HFTers are more likely to pay the maker fee when tick size constraints are high. This (imperfect) separating equilibrium is generated through the comparative advantage enjoyed by HFTers. Holding all else equal, the unit profit obtained to make the market is higher in the maker/taker market conditional on execution, but such execution needs to be at the front of the queue. Non-HFTers do not have the speed advantage to move to the front of the queue. Retail traders, for example, usually have very low execution probability in maker/taker markets (Battalio, Corwin and Jennings, 2013). However, non-HFTers can choose to pay a fee and enter taker/maker market. For low priced stocks, Non-HFTers rely more on taker/maker market to undercut the price because of tick size constraints. Therefore, non-HFTers are more likely to pay to provide liquidity, whereas HFTers are more likely to get paid by providing liquidity because of their speed advantage. We also find that tick size constraints play a prominent role in determining competition for order flow. Taker/maker market has a surprisingly high market share for stocks with relatively high tick sizes. For low-priced large-cap stocks, EGDA executes 64.28% of the volume leaving the EDGX market share at only 35.72%. As stock prices increase, the impact of EDGA decreases. The result is consistent with the seminal theoretical work of Foucault, Kadan, and Kandel (2013). Their model posits an optimal bid-ask spread, which is the bid-ask spread that maximizes trading volume. Mandated tick sizes impose a constraint that prevents the bid-ask spread from freely adjusting, but stock exchanges can change taker/maker fees to move the spread to the optimal size. When tick size is too large, charging makers and subsidizing takers (taker/maker model) can increase trading volume. An increase in stock prices decreases relative tick size, which reduces the need to adjust the relative tick size closer to the optimal size by charging makers. Therefore, volume increases in markets with maker/taker fees.

U.S. regulators recently proposed increasing tick sizes, arguing that large ticks improve liquidity, facilitate stock research, and ultimately increase IPOs.[6] MiFID II of Europe also proposes increasing tick sizes with the goal of controlling HFT.[7] We test these two hypotheses using stock splits as exogenous shocks to tick-size constraints. We find that an increase in the relative tick size due to stock splits does not improve liquidity. First, the proportional spread increases because the decrease in the spread is less than the decrease in the nominal stock price. The depth, or the queue of traders able and willing to provide liquidity, increases when the quoted spread increases. With increased quoted spread and depth, the key to comparing liquidity is through the effective spread, or the actual transaction cost to liquidity demanders. We find that the effective spread increases, particularly when liquidity demanders also need to pay the taker fee. Therefore, an increase in the relative tick size does not improve liquidity. Meanwhile, we observe an increase in the speed of liquidity provision, which is consistent with our results using a cross-sectional variation of the relative tick size. Finally, there is a migration of volume from EDGX to EDGA. In summary, an increase in the relative tick size does not improve liquidity, but instead it drives speed competition and the migration of volume to the trading platform that bypasses the tick size constraints.

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[6] "Exchanges Said to Prepare Pilot Programs for Changing Tick Sizes," *Bloomberg News*, June 13, 2013.
[7] "MiFID II aims to slow HFT with increase in minimum tick sizes," *Markets Media,* October 10, 2012

Several recent studies also address the tick size issue, including Bartlett and McCray (2013), O'Hara, Saar, and Zhong (2013), and Buti, Consonni, Rindi, and Werner (2013). Our paper is, however, the first to link tick size with both HFT and taker/maker fees, and also the first to empirically examine the economic mechanism that drives the results: HFTers' comparative speed advantage and non-HFTers' comparative price advantage. O'Hara, Saar, and Zhong (2013) and Buti, Consonni, Rindi, and Werner (2013) also examine order flow competition between exchanges and trading venues that can quote sub-penny prices. However, our paper has the advantage of cleaner identification: EDGA and EDGX are identical except for the fee structure, whereas the trading platform on which these other studies are based differs along other dimensions such as information revelation and the trading mechanism.

To the best of our knowledge, our paper is the first empirical study that provides a coherent explanation linking the three streams of literature on tick size, HFT, and taker/maker fees. Tick size constraints create rents for supplying liquidity and an oversupply of liquidity at constrained prices. Traders who achieve higher speeds are able to supply liquidity because of time priority. Tick-size constraints also induce some traders to pay a fee in order to make the market. This explains the proliferation of markets with inverted fees. As expected, HFTer liquidity provision is strongly correlated with the taker/maker market share relative to the maker/taker market share because they are both driven by tick size constraints. By sorting the relevant stocks into five portfolios, we find that the highest EDGA-to-EDGX market-share quintile experiences twice as much HFT market-making activity as the lowest EDGA-to-EGDX market-share quintile.

Our study represents two contributions to the policy debate on tick size, maker/taker fees, and HFT. First, this is the first empirical study that demonstrates the linkage between these three policy issues.[8] Second, instead of discussing whether and how we should regulate HFT and maker/taker fees, our paper is the first to propose that these two phenomena may be a consequence of existing tick size regulations. Economic reasoning and our empirical evidence can show, step by step, how various regulations create these two phenomena. At infinitely small tick sizes, fees would be neutralized by differences in the nominal bid-ask spread: the maker/taker market would have a lower nominal spread and the taker/maker market would have a higher nominal spread, but the cum fee bid-ask spread is the same for both markets (Angel, Harris, and Spatt, 2011; and Colliard and Foucault, 2012). However, SEC rule 611 states that orders should be routed to the market with the best displayed (nominal) spread. In that case, all orders should be routed to the maker/taker market and the taker/marker market should be empty. However, rule 612 prohibits sub-penny pricing, so the maker/taker and taker/maker markets can display the same nominal bid-ask spread.[9] In addition, rule 611 imposes price priority only across markets, but time priority is imposed only on the individual market. Under tick-size constraints, the queue in the maker/taker market can be very long and order execution becomes the privilege of liquidity providers who trade at higher speeds. The taker/maker market provides a means of jumping ahead in the queue by paying a fee.

This paper is organized as follows. Section 2 describes the data used in the study. Section 3 examines the relationship between tick size constraints and HFT. Section 4 studies tick size constraints and taker/maker fees. Section 5 examines the impact of tick-size constraints on

[8] On high-frequency trading, see Biais, Foucault, and Moinas (2011), Jovanovic and Menkveld (2010), Pagnotta and Philippon (2012), Chaboud, Chiquoine, Hjalmarsson, and Vega (2009), Hendershott and Riordan (2009 and 2011), Hasbrouck and Saar (2013), and Hendershott, Jones, and Menkveld (2013), among others. For maker/taker markets, see Foucault, Kadan, and Kandel (2013), Colliard and Foucault (2012), Brolley and Malinova (2012), Park and Malinova (2013), and Halmrast, Malinova, and Park (2013), among others.

[9] For example, if the equilibrium spread without tick size is 0.3 cents on the maker/taker market and 0.8 cents on the taker/maker market, both markets will quote a one-cent spread due to price constraints.

liquidity as well as HFT and taker/maker fees using stock splits as an exogenous shock on relative tick size. Section 6 concludes the paper and discusses the policy implications.

2. Data

This paper uses four main datasets: a NASDAQ HFT dataset that identifies whether a liquidity maker/taker is an HFTer, daily TAQ data with a millisecond time stamp, NASDAQ TotalView-ITCH with a nanosecond time stamp, and CRSP.

The NASDAQ HFT dataset provides information on limit-order books and trades for 120 stocks selected by Hendershott and Riordan. The sample includes 40 large stocks from the 1000 largest Russell 3000 stocks, 40 medium stocks from stocks ranked from 1001–2000, and 40 small stocks from Russell 2001–3000. Among these stocks, 60 are listed on the NASDAQ and 60 are listed on the NYSE. Because the sample was selected in early 2010, three stocks actually disappear in our sample period so we have 117 stocks in our sample. 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. This enables us to examine the 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.

The consolidated trades file of daily TAQ data provides information on execution across separate exchanges for trades greater than or equal to 100 shares (O’Hara, Yao, and Ye, 2013). We use such data to calculate EDGA’s market share relative to that of EDGX. In our sample period, EDGX, like most exchanges, has a maker/taker fee structure whereby liquidity demanders pay a fee of 0.30 cents per share while liquidity providers get a rebate of 0.26 cents per share; EDGA has a taker/maker (or inverted) fee structure whereby liquidity suppliers pay a fee of 0.025 cents per share while liquidity demanders get a rebate of 0.015 cents per share.

The results we use to examine the cross-sectional variation in HFT and taker/maker fees are based on trades involving the 117 stocks in October 2010. NASDAQ high-frequency data provide the market shares of high-frequency liquidity provision for the 117 stocks for 2008–2009, February 22–26, 2010 and October 2010. EDGA and EDGX volumes are included in the TAQ data from July 2010. Therefore, we have measures of both high-frequency liquidity provision and market shares of the taker/maker market relative to that of the maker/taker market for October 2010. The summary statistics on these stocks are presented in Panel A of Table 1.

Insert Table 1 about Here

We also study the impact of relative tick size on liquidity, HFT, and the taker/maker market using stock splits as exogenous shocks to nominal stock prices, but these 117 shocks do not provide a large enough sample of splits. We examine all NYSE and NASDAQ firms that declared a two-for-one or greater stock split between January 2010 and November 2011 in the CRSP universe. Each of our pre- and post-event windows is comprised of the 30 trading days immediately before the stock-splitting date and the 30 trading days immediately after the stock-splitting date, including the splitting date. We exclude stocks that split more than once during the sample period. Among these stocks, 86 firms list trading data in the ITCH dataset. The summary statistics on these stocks are presented in Panel B of Table 1. Because the data on EDGA and EDGX is available only for trades occurring after July 1, 2011, we have 66 firms with data on EDGA and EDGX volumes.

We do not have high-frequency liquidity-provision data for these split stocks. Fortunately, Foucault, Kadan, and Kandel (2013) provide a proxy for high-frequency liquidity-making. In their model, an increase in tick size increases liquidity makers' profits. As a consequence, the monitoring intensity of liquidity-makers increases. This reduces time in the liquidity-making cycle, which in turn reduces the time gap between an execution of a limit order and the submission of another limit order. This time gap is measured using NASDAQ TotalView-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 with nanosecond resolution, which is the foundation for calculating liquidity. In particular, using NASDAQ TotalView-ITCH data allows us to construct the depth measure away from the best bid and ask. This is important for comparing the depth level before and after a split. For example, the depth within 20 cents of the best bid and offer for a stock with $20 is equivalent to the depth within 10 cents of $10 after a two-for-one split.

3. Tick Size Constraints and High-Frequency Liquidity Provision

This section argues that high-frequency liquidity provision is a consequence of tick size constraints. Tick size plays a central role in separating price competition from speed competition. For example, suppose there are three liquidity providers, one of whom (trader A) is willing to provide liquidity at 0.1 cents, another of whom (trader B) is willing to provide liquidity at 0.5 cents, and a third of whom (trader C) is willing to provide liquidity at 1 cent. When tick size is smaller or equal to 0.5 cents, trader A has price priority over traders B and C. When tick size is more than 0.5 cents but smaller than 1 cent, both traders A and B are willing to offer liquidity at the same constrained price, and the priority between A is B is determined by time. When tick size is greater than or equal to 1 cent, all three traders quote the same price and it is their speed in providing liquidity that determines whose order is executed first. Therefore, a large tick size dilutes the impact of the trader who is able to quote the best price.. Meanwhile, a large tick size increases the importance of speed competition.

We first formalize our argument by examining the relative market share of HFTers and non-HFTers in terms of volume. We find that HFTers take a higher market share for low-priced stocks with market caps. The analysis of quotes and depth provide more details about the economic mechanisms that drive the results on volume.

3.1. Tick Size Constraints Measure

An intuitive measure of tick size constraints is price. Because stocks with prices above one dollar have a tick size of one cent, lower-priced stocks have a large relative tick size. Also, tick-size constraints are more likely to be binding for large stocks, for which the equilibrium bid-ask spread can be below one tick.

Our empirical study design is justified by Benartzi, Michaely, Thaler, and Weld (2009), who argue that nominal share prices are exogenous with respect to firm fundamentals other than the market cap.[10] Baker, Greenwood, and Wurgler (2009) posit a catering theory of nominal stock prices, according to which firms split when investors place higher valuations on low-priced firms, and vice versa. However, the catering theory focuses more sharply on time-series

[10] Their paper states that the nominal share price is a puzzle because it cannot be explained by the marketability hypothesis, the pay-to-play hypothesis, or signaling. The marketability hypothesis states that low-priced stocks are more attractive to individual investors. (Baker and Gallagher, 1980; Baker and Powell, 1993; Fernando, Krishnamurthy, and Spindt, 1999 and 2004; Lakonishok and Lev, 1987; and Byun and Rozeff, 2003). The pay-to-play hypothesis posits that firms can split their stocks to achieve optimal relative tick size. A higher relative size motivates more dealers to make markets and investors to provide liquidity by placing limit orders, despite its placing a high floor on the quoted bid-ask spread (Angel, 1997). The signaling hypothesis (Brennan and Copeland, 1988; Lakonishok and Lev, 1987; and Kalay and Kronlund, 2013) states that insiders use stock splits to signal information.

variations in stock prices while our analysis focuses on cross-sections. Campbell, Hilscher, and Szilagyi (2008) find that prices may predict distress risk when they are very low, but the same paper also acknowledges that such a prediction no longer applies when the price rises above $15. In summary, prior literature indicates that cross-sectional variations in nominal stock prices are orthogonal to firm fundamentals other than the market cap. Therefore, we use price and market cap as our measure of tick size constraints.

3.2 Tick Size Constraints and Volume

NASDAQ high-frequency data indicate, for each trade, the maker and taker of liquidity. We are interested in the percent of volume with high-frequency liquidity provision. The original 120 stocks selected by Hendershott and Riordan include 40 large stocks from the 1000-largest Russell 3000 stocks, 40 medium stocks from stocks ranked from 1001–2000, and 40 small stocks from Russell 3000 stocks 2001–3000. A natural way to conduct the analysis is to sort the stocks 3 by 3 based on the market cap and the price level of the stock. We then 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.

Suppose 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, the volume share with HFTers as liquidity providers relative to total volume is defined as:

$$HFTliquidityvolumeshare_J = \frac{\sum_{i\in J}\sum_{t=1}^{T}(NH_{it} + HH_{it})}{\sum_{i\in J}\sum_{t=1}^{T}(NH_{it} + HH_{it} + HN_{it} + NN_{it})} \tag{1}$$

Table 2 demonstrates that the volume with HFTers as liquidity providers decreases monotonically with stock prices and the market cap. For large-cap stocks, 49.29% of the volume is due to HFTers as liquidity providers for low-priced stocks; the number decreases to 38.48% for medium-priced stocks and further decreases to 35.53% for high-priced large-cap stocks. For low-priced stocks, 39.15% of the volume is from HFTers as liquidity providers for mid-cap stocks, while the number is only 23.40% for small-cap stocks. The volume results suggest that HFTer liquidity provision is indeed more active in stocks with high tick size constraints. Next, we analyze the economic mechanism that drives this cross-sectional variation by examining the quoting strategy of HFTers and non-HFTers.

Insert Table 2 about Here

3.3 Tick Size Constraints, Best Quotes, and Depth

This section provides the economic mechanism that drives the results on volume. Our main finding is that non-HFTers enjoy a price advantage. They are more likely to quote better prices than HFTers. As relative tick size decreases, non-HFTers are more likely to quote better prices than HFTers, thereby establishing price priority. When relative tick size is large, however, HFTers and non-HFTers are more likely to quote the same constrained price, which suggests that time determines the priority for providing liquidity. Because HFTers are less likely to quote better prices but still enjoy a speed advantage when price competition is constrained by tick size, a relatively large tick size favors HFTers and increases their market share.

NASDAQ high-frequency book data provides one-minute snapshots of the limit order book. At each ask and bid price, the data indicates the depth provided by both HFTers and non-HFTers. For each stock on each day, there are 391 best ask prices and 391 best bid prices. Our analysis starts by dividing the best price (bid or ask are treated independently) into three types: 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. Next, we aggregate the number of observations into each category for all stocks and dates in each portfolio.

Insert Table 3 about Here

Table 3 reveals that non-HFTers enjoy a price advantage over HFTers, and the advantage increases when relative tick size decreases. A comparison between columns 1 and 2 reveals that non-HFTers are more likely to display the best price than HFTers for eight of these nine categories. This result is very surprising because there are a number of theoretical and empirical results suggesting that HFTers are more likely to quote better prices than non-HFTers, either because they can minimize adverse selection cost (Hendershott, Jones and Menkveld, 2011) or because they can better manage their inventory cost (Brogaard, Hagstromer, Norden and Riordan, 2013). More importantly, non-HFTers are even more likely to quote better prices when relative tick size decreases. Column 4 demonstrates the ratio of the best price from HFTers relative to the best price from non-HFTers. For large- and medium-cap stocks, the ratio is a decreasing function of relative tick size. For example, for large-cap stocks with medium relative tick size, non-HFTers offer better prices 20.1% of the time and HFTers offer better prices 13.1% of the time, resulting in a ratio of 1.53 (20.1%/13.1%). For large stocks with high prices, the incidence of best prices being displayed by HFTers increases slightly to 16.6%, but that of best prices being displayed by non-HFTers increases dramatically to 38.8%. Therefore, the ratio of Non-HFTers as unique providers of best prices increases dramatically to 2.34 (38.8%/16.6%). Taken together, non-HFTers are more likely to provide better prices than HFTers, increasing the incidence of non-HFTers' quoting the best price as relative tick size decreases. Therefore, non-

HFTers enjoy a price advantage over HFTers. When relative tick size is small, non-HFTers can quote better prices than HFTers and achieve price priority. This explains why the volume of liquidity provision from non-HFTers increases when relative tick size decreases.

When relative tick size or the market cap increases, however, HFTers become more and more likely to quote the same price as non-HFTers. This implies that price and market cap together is indeed a good proxy for tick size constraints, because time is needed to decide the priority between HFTers and non-HFTers. We still find that non-HFTers are more likely to offer better prices than HFTers, but large relative tick size constrains their ability to undercut the price.[11] Non-HFTers offer better prices than HFTers 2.8% of the time, whereas HFTers offer better prices than non-HFTers 1.9% of the time. For 95.4% of the time, both HFTers and non-HFTers offer the same best price, and the speed advantage of HFTers implies that they will have priority over non-HFTers. Therefore, HFTers are less likely to quote better prices than non-HFTers do, but a large tick size allows them to quote the same price as non-HFTers. A large tick size, therefore, shifts the priority from non-HFTers to HFTers.

The results pertaining to best depth further confirm this intuition. We find that HFTers are more likely to be at the best depth for low-priced large-cap stocks. The depth data provide one-minute snapshots of the depth provided by HFTers and non-HFTers, {HFTdepth_{itm}, NonHFTdepth_{itm}}, where i is the stock, t is the date, and m is the time of day. The average depths provided by HFTers and non-HFTers for each stock on each day are:

$$HFTdepth_{it} = \frac{1}{M}\sum_{i=1}^{M} HFTdepth_{itm} \quad \text{and} \quad NonHFTdepth_{it} = \frac{1}{M}\sum_{i=1}^{M} NonHFTdepth_{itm} \qquad (2)$$

The depth provided by HFTers relative to the total depth of portfolio J is then defined as:

11 It can either because undercutting is too costly or because there is no room to undercut the price when the bid-ask spread is exactly a penny.

$$HFTdepthshare_J = \frac{\sum_{i \in J} \sum_{t=1}^{T} HFTdepth_{it}}{\sum_{i \in J} \sum_{t=1}^{T} (HFTdepth_{it} + NonHFTdepth_{it})} \quad (3)$$

Table 4 reveals that the depth provided by HFTers decreases monotonically in price and market cap. For low-priced large-cap stocks, HFTers provide greater depth than non-HFTers (55.62% vs. 44.38%), whereas HFTers provide only 33.16% of such depth for high-priced large-cap stocks. The number decreases to 23.67% for high-priced mid-cap stocks, and further decreases to 21.83% for high-priced small-cap stocks.

Insert Table 4 about Here

In summary, we find that non-HFTers are more likely to quote better prices and achieve price priority when tick size is relatively small. When price competition is constrained to a greater extent by tick size, however, the priority moves to HFTers, who can quickly post orders at constrained prices. Therefore, we believe that tick size constraints facilitate HFTer liquidity provision.

4. Tick Size Constraint, HFT and Taker/Maker Market

We argue that the taker/maker market is another natural response to tick size constraints. It provides liquidity providers with a means of undercutting prices by paying the stock exchange (the maker fee), which allows the stock exchange to use part of the maker fee to subsidize liquidity takers. The market we examined in section 3 is a traditional maker/taker market, in which liquidity providers are paid. Three exchanges—Boston, BATS-Y, and EDGA—have inverted fee structures that charge liquidity providers and subsidize liquidity demanders. Two interesting questions immediately emerge. First, why are some liquidity providers paid whereas others need to pay when providing liquidity for the same stock? Second, what forces determine the competition for order flow between these two markets?

We offer three hypotheses following the intuitions established in section 3. First, we conjecture that:

H1: HFTers are more likely to make the market in the maker/taker market, in which liquidity providing is paid. Non-HFTers are more likely to make the market in the taker/maker market, in which they need to pay to provide liquidity.

This (imperfect) separating equilibrium is generated through the comparative advantage enjoyed by HFTers. Holding all else equal, the unit profit obtained to make the market is higher in the maker/taker market conditional on execution, but such execution needs to be at the front of the queue. Non-HFTers do not have the speed advantage to move to the front of the queue. However, they can choose to pay a fee. Interestingly, we can observe how they jump ahead in the queue in terms of both price priority and time priority. Because each trading platform has its own time priority, traders at the back of a queue in the maker/taker market can be at the head of the queue in the taker/maker market by paying a fee. What is more, trading platforms charging liquidity providers usually subsidize liquidity demanders. If the nominal spread in the taker/maker market is the same as the maker/taker market, a liquidity demander with a smart router (Foucault and Menkveld, 2008) would go first to the taker/maker market because of the subsidy. Therefore, the taker/maker fee is another natural force in the price system that makes it possible to bypass tick size constraints.

Section 3 shows that a relatively large tick size constrains non-HFTers from undercutting HFTers. For stocks with larger tick size constraints, we expect that the taker/maker market plays a more important role in undercutting the price. When relative tick size decreases, it becomes easier to undercut the price and weakens dependence on the taker/maker market, which brings us to our second hypothesis:

H2: The market share taken by Non-HFTers in the taker/maker market is high for low-priced stocks, decreasing as the stock price increases.

Finally, we conjecture that the volume in the taker/maker market relative to that in the maker/taker market is also an increasing function of relative tick size.

H3: EDGA volume relative to that of EDGX increases with relative tick size.

This conjecture is consistent with the tick size constraints hypothesis of Foucault, Kadan, and Kandel (2013), but is contrary to the agency hypothesis of Angel, Harris, and Spatt (2011) and Battalio, Corwin, and Jennings (2013). We will give a detailed explanation in section 4.2.

Next, we provide tests for these three hypotheses. We use the twin trading platforms EDGA and EDGX to inform our identification strategy. These two trading platforms have similar infrastructures with the major difference being in the breakdown of maker/taker fees. EDGA charges liquidity makers 0.025 cents per share whereas it provides a 0.015 cent rebate to liquidity takers. EDGX provides liquidity makers with 0.26 cents per share but charges liquidity takers 0.3 cents per share. Therefore, the competition for order flow between these two trading platforms can be explained only by differences in fee structure.

4.1. HFTers' Activity in the Taker/maker Market Relative to that in the Marker/taker Market

The TAQ data do not provide an identifier for HFTers. We use two commonly known measures for HFTer activity from TAQ data: the quote-to-trade ratio (Angel, Harris, and Spatt, 2013) and negative dollar volume divided by total number of messages (Hendershott, Jones, and

Menkeveld, 2011; Boehmer, Fong, and Wu, 2013). These are both relative measures. If there is an increase in activity on the part of non-HFTers relative to that of HFTers, both measures should decrease because HFTers are more likely to have a higher quote-to-trade ratio and a higher number of messages relative to dollar volume.

Because these two measures are proxies for HFTer activity, they are subject to some limitations. First, neither measure separates liquidity-providing HFTers from liquidity-demanding HFTers. However, Brogaard, Hagströmer, Norden, and Riordan (2013) show that liquidity-providing HFTers have a much higher order cancellation ratio than liquidity-taking HFTers. Because the quote-to-trade ratio and the total number of messages divided by trading volume are mainly driven by cancellations, we expect liquidity-making HFTers to be the main drivers of these two variables. Also, these two measures can also be affected by stock characteristics (O'Hara, Saar, and Zhong, 2013). Our empirical specification, however, controls for both stocks and time fixed effects and the comparison is made between stocks on the same day across two trading platforms. Denoting the HFTer measure for stock *i* on trading platform *j* on day *t* as HFT_{ijt} , we have:

$$\begin{aligned}\mathrm{HFT}_{ijt} &= u_i + \gamma_t + \alpha + \beta_1 DummyEDGA_{ijt} + \beta_2 DummyEDGA_{ijt} * Prc_{-i} \\ &\quad + \beta_3 DummyEDGA_{ijt} * logmktcap_{-i} + \varepsilon_{ijt} \qquad (4)\end{aligned}$$

Here u_i is the firm fixed effect, which controls for the fact that some firms undertake HFT activity. γ_t is the time fixed effect, which presupposes that some days have more cancellations or messages than other days. $DummyEDGA_{ijt}$ equals 1 if the quote-to-trade ratio is from EDGA and 0 otherwise. Prc_{-i} is the average price level of stock *i* in September 2010 minus the median average price of the 117-stock sample. The variable $logmketcap_{-i}$ is the log of the market cap of stock *i* in September 2010 minus the log of the median market cap of the

117 stocks in the sample. Both variables are normalized to facilitate the interpretation of β_1.[12] Because of the controls for both firm and time fixed effects, the regression measures the difference between relative HFT activity in EDGA and relative HFT activity in EDGX. β_1 measures the overall difference between EDGA and EDGX in terms of relative HFTer activity, and β_2 and β_3 measures how the differences depend on the price level and market cap of the results.

Table 5 shows that EGDA experiences a relatively lower level of HFTer activity than EDGX. Column (1) shows that EDGA exhibits a much lower quote-to-trade ratio than EDGX. The constant term (EDGX) is 30.63 and the EDGA dummy is -9.35, which implies that for an firm with median price and median market cap, the quote-to-trade ratio of EDGX is 30.63 to 1 and the quote-to-trade ratio of EDGA is 21.28 (30.63-9.35) to 1. This result is consistence with hypothesis 1. Column (2) shows that the dollar volume to message ratio in EDGA is higher than EDGX by 0.69, which implies that EDGA have higher dollar volume to message than EDGX, which is also consistent with hypothesis 1.

Insert Table 5 About Here

β_2 is positive and significant, which means that EDGA exhibits an even a lower level of relative HFT activity compared with EDGX when the stock price is low because β_1 is negative. An increase in the stock price, however, increases the relative level of HFT activity in EDGA compared with that in EDGX, which is consistent with hypothesis 2. For low priced stocks, Non-HFTers rely more on taker/maker market to undercut the price because of tick size constraints. Therefore, we observe that EDGA have a relatively larger non-HFT activity or relatively less HFT activity when stock price is low. As stock prices increases, non-HFTers rely less on

[12] Without this normalization, β_1 is interpreted as the coefficient for a stock with price 0 and market cap 0.

taker/maker market to undercut the price, which increase the relative level of HFT activity in EDGA compared with that in EDGX. Column (2) shows that the sign for market cap is also consistent with hypothesis 2. An increase in market cap increases tick size constraints. Therefore, non-HFTers rely more on the taker/maker market to undercut the price. Therefore, there is an increase in the volume-to-message ratio (or a decrease in the –volume-to-message ratio) in EDGA relative to EDGX because non-HFTers tend to trade at a higher volume for the same number of messages.

4.2 Volume of Taker/maker Market Relative to Marker/taker Market

Hypothesis 3 states that the volume of taker/maker relative to marker/taker increases in relative tick size. To show this, we first sort the 117 stocks 3 by 3 by average market cap and then by average price on September 2010. Next, we aggregate the EDGA and EDGX volumes for stocks in the portfolio for all days. EDGAratio is defined as the ratio of the aggregated EDGA volume divided by the aggregated EDGA volume plus the aggregated EDGX volume. Table 6 reveals two interesting patterns. First, the taker/maker market has a surprisingly large market share in stocks with large-cap stocks with high relative tick size. Large-cap low-priced stocks take 64.28% of the EDGA volume, implying that EDGX accounts for only 35.72% of the volume. The taker/maker market also has a higher market share relative to the maker/taker market for low-priced mid-cap stocks (55.94% vs. 44.06) and medium-priced large-cap stocks. Second, as stock prices increase, volume shifts from the taker/maker market to the maker/taker market. For example, EDGX beats EDGA in large-cap high-priced stocks. EDGA accounts for only 28.98% of the volume with the remaining 71.02% in EDGX. Therefore, the taker/maker fee market takes a relatively higher market share in low-priced stocks, whereas the maker/taker fee market takes a relatively higher market share in high-priced stocks. This demonstrates that liquidity providers are more willing to pay a fee to make a market for low-priced stocks.

Our result is consistent with the seminal theoretical paper on maker/taker fees by Foucault, Kadan, and Kandel (2013). Their model posits an optimal bid-ask spread without tick size constraints, or a spread that maximizes trading volume.[13] Tick size constraints the adjustment to the optimal bid-ask spread, but exchanges can adjust maker/taker fees to achieve the optimal spread. When the mandated tick size is too high, charging liquidity makers and subsidizing liquidity takers can increase trading volume. Based on the intuition of the model, the fact that large stocks have higher volume in the taker/maker market relative to the maker/taker market implies that a one-penny tick size might be too high for these stocks. As stock prices increase, relative tick size decreases and we observe a migration of volume from the taker/maker market to the maker/taker market due to smaller tick size constraints.

Insert Table 6 about here

We are aware, however, that there exist a competing hypothesis for explaining the market share of the taker/maker market relative to that of the maker/taker market based on fee structure. The agency hypothesis proposed by Angel, Harris, and Spatt (2013) and Battalio, Corwin, and Jennings (2013) argues that brokerage firms have an incentive to route non-marketable limit orders from retail traders to the maker/taker market because retail traders usually do not claim the rebate. The agency hypothesis is, however, unlikely to explain the cross-sectional variation of market shares in the taker/maker market relative to the maker/taker market. Existing empirical evidence either argues that retail traders are more likely to trade low-priced stocks (Baker and Gallagher, 1980; Baker and Powell, 1993; Fernando, Krishnamurthy, and Spindt, 1999 and

[13] Page 316, equation (22) of *Journal of Finance*, February, 2013.

2004) or retail traders are indifferent between high-priced and low-priced stocks (Lakonishok and Lev, 1987; Benartzi, Michaely, Thaler, and Weld, 2009). In the first case, the agency hypothesis predicts that the maker/taker market should have higher market share in low-priced stocks. The agency hypothesis yields no prediction pertaining to cross-sectional variation in market share when retail traders are indifferent between low-priced and high-priced stocks. We find that the maker/taker market is more active for high-priced stocks, which is not consistent with the agency hypothesis.

Because high-frequency liquidity provision and the taker/maker market are driven by the same common factors, they are highly correlated. We first calculate the average percentage of BBO depth provided by high frequency traders for each stock, and then sort the 117 stocks into five quintiles based on the percentage. Stocks in quintile 1 exhibit the lowest percentage of the BBO depth provided by high frequency traders, and stocks in quintile 5 exhibits the highest percentage of BBO depth provided by high frequency traders. For each stock in the quintile, we find the average percentage of the EDGA trading volume relative to the total volume of EDGA and EDGX, and we equally weight the stocks in each quintile. Figure 1 demonstrates that the portfolio with the highest HFT liquidity provision (quintile 5) has the highest market share in the taker/maker market (56%). The market share of the taker/maker market decreases monotonically with HFT liquidity provision. Quintile 1, or the stock with lowest HFT liquidity provision, only has 28% of volume in taker/maker market.

Insert Figure 1 about Here

5. The Impact of Tick Size Constraints on Liquidity

We engage with recent policy debates over whether an increase in tick size improves liquidity (SEC, 2012) by using a stock-splitting event as an exogenous shock to relative tick size. Following stock splits, outstanding shares are multiplied while nominal stock prices are reduced by the same factor. Therefore, tick size constraints become more binding after stock splits. In addition, we use the increase in relative tick size after splits as a robustness check for our results on cross-sectional variations in HFT and taker/maker market share.

The HFT dataset we used in previous sections cover only 117 stocks and only one of those stocks has experienced a stock split. In order to study the general trend, we examine all firms that declared a two-for-one, three-for-one, or four-for-one stock split between January 2010 and November 2011 in the CRSP universe. Each of our pre- and post-event windows is comprised of the 30 trading days immediately before the stock-splitting date and the 30 trading days immediately after the stock-splitting date, including the splitting date. We exclude stocks that split more than once during the sample period. Among these stocks, 86 firms list trading data in the ITCH dataset and 66 list data on EDGA and EDGX volumes.[14] To address potential issues regarding the time trend in our sample period, we also match splitting stocks one-to-one with stocks that do not split based on price, market cap, and listing exchange. Therefore, for each stock that splits, we match it with a stock listed on the same exchange with minimal matching error D_{ij}, where the matching error is defined as:

$$D_{ij} = \left|\frac{MCAP_i}{MCAP_j} - 1\right| + \left|\frac{PRC_i}{PRC_j} - 1\right| \qquad (5)$$

[14] We have fewer data on EDGA and EDGX volumes because the data were not available from January 2010–June, 2010.

Section 5.1 examines the impact of splits on liquidity, and section 5.2 examines the impact of splits on HFT and taker/maker volume. Section 5.3 provides a brief discussion to explain the economic linkage between the results reported in section 5.1 and those reported in section 5.2.

5.1. Tick Size Constraints and Liquidity

We explore the relation between tick size constraints and liquidity using the diff-in-diff approach. We run the following regression:

$$Liquidity_{it} = \alpha + \beta_1 treatment_i + \beta_2 after_t + \beta_3 treatment_i * after_t + e_{it} \qquad (6)$$

where $treatment_i$ is equal to 1 for stocks that split and 0 for the matched sample, $after_t$ is equal to 1 after the splitting day for stock 1 and 0 before the split. The variable of interest is β_3, which measures the impact of the tick size constraints on liquidity. Stock market liquidity is defined as the ability to trade a security quickly at a price close to its consensus value (Foucault, Pagano, and Röell, 2013). 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.

The results are presented in Table 7. Panel A presents the analysis of the impact of changes in tick size constraints on the quoted spread. The dependent variable in each column is defined as follows. *pQspread* in Column (3) is the time-weighted proportional quoted spread for each stock on each day, where proportional quoted spread is defined as the quoted spread divided by the midpoint of the best ask and bid. In addition to earning the quoted spread, a market maker also obtains a rebate from each executed share from the exchange. Therefore, we compute two other measures of the quoted spread. *Qspread$_{adj}$* in Column (2) and *pQspread$_{adj}$* in Column (4) are the spreads adjusted by the liquidity supplier's rebate.[15] Specifically,

$$Qspread_{adj_{it}} = Qspread_{it} + 2 * liquidity\ maker\ rebate \tag{7}$$

$$pQspread_{adj_{it}} = (Qspread_{it} + 2 * liquidity\ maker\ rebate)/midpoint_{it} \tag{8}$$

Insert Table 7 About Here

Panel B presents the analysis of the impact of changes in tick size constraints on Nasdaq limit-order book depth. The variable *Depth* in Column (1) measures the sum of the shares at the best bid and ask prices except for the splitting firms before the stock splits. The variable *Depth10* in Column (2) measures the sums of shares at and within 10 cents from the best bid and ask prices except for the splitting firms before the stock splits. Because splits cause an increase in shares and a decrease in share price, we make the following adjustments, following Lipson (1999), for the depth prior to the split. The basic idea is to measure the depth within a certain percentage of the stock price. Therefore, *Depth* for splitting firms before the splitting event is the sum of the shares at and within one, two, and three cents from the best quote for two-for-one splits, three-for-one splits, and four-for-one splits, respectively.[16] *Depth10* represents splitting firms before splitting events as the sum of the orders at and within twenty, thirty, and forty cents from the best quote for two-for-one splits, three-for-one splits, and four-for-one splits, respectively. After the stock split, tick size constraints become more binding as nominal prices become a fraction of the pre-splitting level.

[15] For each stock on each day, the liquidity maker's rebate is 0.295 cent per execution, but the results are qualitatively similar with other rebate levels.

[16] We also measure *Depth* for the splitting firms before the splitting event as the best quote and the result is stronger, but for the sake of brevity we do not present it.

Panel C presents the analysis of the impact of changes in tick size constraints on the effective spread. The dependent variable in each column is defined as follows. The effective spread 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. *Espread* in Column (1) is defined as the size-weighted effective spread of all trades for each stock and each day. $Espread_{adj}$ in Column (2) is defined as the spreads adjusted by the liquidity taker's fee.

$$Espread_{adj_{it}} = Espread_{it} + 2 * liquidity\ taker\ fee \tag{9}$$

The proportional effective spread is defined as the effective spread divided by the midpoint. *pEspread* in Column (3) is defined as the size-weighted proportional effective spread of all trades for each stock and each day. $pEspread_{adj}$ in Column (4) are spreads adjusted by the liquidity taker's fee. Specifically,

$$pEspread_{adj_{it}} = (Espread_{it} + 2 * liquidity\ taker\ fee)/midpoint_{it} \tag{10}$$

Panel A shows that both the quoted spread and the adjusted quoted spread decrease by 5.86 cents after the split. This result is not surprising because a split results in a decrease in the nominal share price, and the quoted spread should decrease. However, the proportional quoted spread increases by 5 basis points and the adjusted quoted spread increases by 6.1 basis points. The adjusted proportional quoted spread increases more because of the fee. For example, suppose a $20 stock has a two-for-one split and a $2,000 transaction has a maker rebate of 29.5 cents (0.295 cents per share*100 shares), but the maker rebate increases to 59 cents after the split (0.295 cents per share *200 shares). Therefore, the maker fee causes a further increase in the proportional quoted spread after adjusting for the fee. Panel B shows that limit-order-book depth increases after the stock splits. This holds true both for depth at the best bid and ask prices and for the accumulative depth within 10 cents of the best bid and ask prices.

With an increase in both the quoted spread and depth, the key variable of interest becomes the effective spread, because it measures the transaction cost to traders. Panel C demonstrates a decrease in the effective spread after the split. However, this decrease in the effective spread is not as large as the decrease in the share price. The proportional effective spread then increases, particularly after adjusting for the fees. This shows that the proportional transaction cost increases after the split. Therefore, an increase in relative tick size does not improve liquidity.

5.2. Tick Size Constraints, HFT Liquidity Providing and Take/Maker Market Share

In this section, we examine the impact of changes in tick size constraints on HFT market marking and taker/maker market share. The sample we use in this section is the same as the one used in the previous section, namely, firms that split stocks and their matching stocks.

For those stocks, we do not have high-frequency liquidity provision data at hand, so we are not able to directly observe HFTer liquidity provision. Fortunately, Foucault, Kadan, and Kandel (2013) provide a proxy for the speed of liquidity-making. In their model, an increase in tick size increases liquidity makers' profits. As a consequence, the monitoring intensity of liquidity-makers increases. This reduces time in the liquidity-making cycle, which reduces the time gap between an execution of a limit order and the submission of another limit order. Following this model, we estimate the speed competition of liquidity provision as follows: suppose that an order is executed with an E message; we then look for the closest order submission with the same size and order side. Therefore, some resubmission time associated with each trade exists. Next, we calculate the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentiles of resubmission time for each stock on each day. Table 8 shows the correlation of the logarithm of the resubmission time with measures of high-frequency liquidity-making for the 117 stocks. The first column shows the correlation between resubmission time and the percentage of volume with HFTers as liquidity providers, and the second column shows the correlation between resubmission time and the percentage of depth provided by HFTers. The 1st–75th resubmission times are negatively correlated with high-frequency liquidity-making, which means that a lower resubmission time, or a higher resubmission speed, is associated with a larger fraction of high-frequency market-making. The correlation becomes insignificant from the 90th percentile to the 99th percentile. Therefore, we chose the 1st–50th resubmission time percentiles as our proxy for speed competition in liquidity making.

Insert Table 8 About Here

Next, using the diff-in-diff approach, we explore the effects of changes in tick size constraints on speed competition in liquidity making and on the market share of the taker/maker market. For speed competition, we run the following regression:

$$Speed_{it} = \alpha + \beta_1 treatment_i + \beta_2 after_t + \beta_3 treatment_i * after_t + e_{it} \tag{11}$$

where $treatment_i$ is equal to 1 for stocks that split and 0 for the matched sample, $after_t$ is equal to 1 after the splitting day for stock 1 and 0 before the split. The variable of interest is β_3, which measures the impact of the split on trading speed.

We run a similar regression on EDGA's market share relative to EDGX (Edgeratio) as the dependent variable:

$$Edgeratio_{it} = \alpha + \beta_1 treatment_i + \beta_2 after_t + \beta_3 treatment_i * after_t + e_{it} \qquad (12)$$

where $Edgeratio_{it}$ is defined as the EDGA volume divided by the sum of the EDGA and EDGX volumes.

The results are presented in Table 9. The first five columns present the results on speed. The constant term is the trading speed of the control group before the treatment. For example, the 1st percentile of the resubmission time is exp (-7.81) =.000406 seconds and the 50th percentile of the resubmission time is exp (-0.951) = 0.386 seconds. The time scale of the resubmission is too short to have been submitted by humans. Nor would the change in time be driven by economic fundamentals. We argue that the change is more likely to be driven by speed competition among HFTers. The coefficient β_1 is not significant for the 1st–25th percentiles and only marginally significant for the 50th percentile, meaning that the order resubmission time in the treatment group is very similar to the resubmission time of the control group before the split. This result suggests that price, market cap, and listing exchange provide an appropriate control group for trading speed. The variable $after_t$ is not significant, implying that there is no general trend regarding trading speed.

Insert Table 9 About Here

The coefficient of interest is β_3, which measures the average treatment effect of the stock split on order-resubmission time. Because the dependent variable representing speed is expressed in logarithmic format, the coefficient can be interpreted approximately as the percentage change in the resubmission time of the treatment group relative to that of the matched stocks that do not split. For example, the 1st percentile of the resubmission time of the split stocks decreases by 19.5% after the split, while the 50th percentile of the resubmission time decreases by 29.3%. The results show that, after the stock split, there is a dramatic increase in order-resubmission speed. The sixth column demonstrates the results for EDGEratio. We find that Edge A's volume increases by 7.32% relative to that of Edge X.

5.3. Summary

In summary, the results based on a stock-splitting event indicate that an increase in tick size constraints does not improve liquidity. However, the constrained price spurs speed competition because of time priority, while also resulting in an active taker/maker market.

6. Conclusion

We argue that tick size regulation is among the drivers of two important features of current stock markets: HFT and taker/maker markets. Because rule 612 of regulation NMS prohibits price competition at increments less than one cent, speed allocates executions when price competition is constrained. Moreover, the one-cent tick size applies to all stocks priced greater than one dollar, which implies heterogeneous tick size constraints for stocks with different market caps and price levels. We find that non-HFTers have a comparative advantage in supplying liquidity for stocks with small relative tick sizes because of their ability to quote better prices. A decrease in stock prices or an increase in relative tick size, however, favors HFTers. Higher tick size constraints eliminate non-HFTers' ability to undercut HFTers. Therefore, both HFTers and non-HFTers quote the same prices and HFTers can achieve priority because of their speed advantage. Stocks with higher tick size constraints also take larger market shares in the taker/maker market, in which the price constraint can be bypassed by paying a fee.

We also find that a decrease in the nominal share price due to a stock split is associated with an increase in trading speed and a migration of volume from the maker/taker market to the taker/maker market. These results, again, suggest that tick size constraints and time priority are the two common factors that drive speed competition and the taker/maker market.

Currently, regulators in the United States and Europe are considering increasing tick sizes with the following two arguments. First, a larger tick size increases liquidity, facilitates stock research, and ultimately increases IPO. Second, a larger tick size controls HFT. We argue that none of this argument is justified. We find that an increase in relative tick size does not improve liquidity. Instead, it increases competition in speed by constraining price competition. The argument that price constraints lead to non-price competition is valid, but we doubt whether non-price competition will involve publishing stock research. A more direct way to create non-price competition is speed competition. Also, an increase in tick size constraints would lead to a migration of volume to the taker/maker market, in which tick size constraints can be bypassed.

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, we explain the market share of taker/maker fees based on tick size constraints, and theoretical models can be built to understand why there exist separate equilibria for traders on separate trading platforms and how exchanges set fee structures in both markets to maximize total profits. Empirically, the relationship between tick size constraints, speed competition, and maker/taker versus taker/maker fees can be further explored. For example, the SEC recently announced a pilot program for increasing tick sizes for a number of small stocks, and it would be interesting to see the impact of this shock on speed competition and the taker/maker fee market.

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Table 1 Sample Summary Statistics

This table presents summary statistics of the sample data used in the paper. Panel A presents summary statistics of the 117 stock sample as of October 2010 using CRSP market data. Panel B presents descriptive statistics of both the split sample and matched firms 30 days prior to the split execution day using both CRSP and NASDAQ (Total View-ITCH) data.

Panel A: CRSP Summary Statistics of 117 Stocks as of October 2010				
	Market Cap ($Million)	Avg Closing Price ($)	Avg Daily Volume (1000s)	Avg Daily Return (%)
Mean	19352	41.5	5095	0.245
Medium	2032	27.22	573	0.23
Std	42246	64.41	11176	0.365
Min	282	5.72	24	-0.665
Max	275000	575.94	67028	1.331

Panel B: Descriptive Statistics of Split Sample & Matched Firms					
		Mean		Median	
	N	Sample	Match	Sample	Match
Split Factor	86	2.36	-	2	-
Pre-split Price ($)	86	84.14	65.19	71.76	54.44
CRSP					
Market Cap ($Million)	86	7065	6130	3440	2146
Avg Closing Price ($)	86	82.57	63.56	72.4	53.48
Avg Daily Volume (1000s)	86	917	1007	467	446
Avg Daily Return (%)	86	0.153	0.142	0.058	0.066
NASDAQ (Total View-ITCH)					
Avg Quoted Spread ($)	86	0.123	0.097	0.096	0.08
Avg Effective Spread ($)	86	0.048	0.04	0.029	0.023
Avg Best Depth	86	430	520	351	372
Avg Depth within 10 Cents from NBBO	86	3009	5708	1712	2591

Table 2: Percentage of Volume with High Frequency Traders as the Liquidity Providers by Market Cap and Relative Tick Size

This table presents the volume-weighted percentage of trading volume with high frequency traders as the liquidity providers. The sample includes 117 stocks in the NASDAQ high-frequency data in Oct 2010. The stocks are sorted first by average market cap and then by average price in September 2010 into 3 by 3 portfolios. To calculate the volume-weighted average, we first aggregate the volume with high-frequency traders as the liquidity providers and all volume in the portfolio for all days. Volume-weighted average is defined as the ratio of the volume with high-frequency traders as the liquidity providers divided by the aggregated overall volume.

	Large Relative Tick Size (Low Price)	Medium Relative Tick Size (Medium Price)	Small Relative Tick Size (High Price)
Large Cap	49.29%	38.48%	35.53%
Middle Cap	39.15%	23.56%	22.34%
Small Cap	23.40%	19.93%	18.74%

Table 3: Who Provides the Best Quotes?

This table displays the percentage of time high frequency traders and non-high frequency traders provide the best bid and ask quotes to the NASDAQ limit order book. The sample includes 117 stocks in the NASDAQ high-frequency data in Oct 2010. The data provide a one-minute snap shot to the limit order book indicating the order size and the type of traders that submit the order at each price level. Stocks are sorted first into 3 by 3 portfolios by average market cap and then by average price in September 2010. We aggregate the number of times that high frequency traders, and non-high frequency traders are the sole providers of the best quotes, and the number of times that both type traders provide the best quotes for each stock category. We then divide the number of the best quotes associate with each category by the aggregate number of snap shots in that category. Column (1) present the percentage of time that high frequency traders is the sole provider for the best quotes, and Column (2) presents the percentage of time that non-high frequency trader is the sole providers for the best quotes. Column (3) presents the percentage of time that both high frequency traders and non-high frequency traders provide the best quotes. Column (4) is the ratio of column (2) to column (1).

	Relative Tick Size	(1) HFT	(2) Non-HFT	(3) HFT and Non-HFT	(4) Ratio
	Large (Low Price)	1.9%	2.8%	95.4%	1.47
Large Cap	Medium (Medium Price)	13.1%	20.1%	66.9%	1.53
	Small (High Price)	16.6%	38.8%	44.7%	2.34
	Large (Low Price)	18.0%	15.2%	66.8%	0.84
Medium Cap	Medium (Medium Price)	20.0%	56.6%	23.4%	2.83
	Small (High Price)	20.7%	63.7%	15.7%	3.08
	Large (Low Price)	11.3%	54.7%	34.1%	4.84
Small Cap	Medium (Medium Price)	20.2%	55.8%	24.0%	2.76
	Small (High Price)	18.6%	70.7%	10.7%	3.80
Total		15.6%	42.1%	42.4%	2.70

Table 4: Market Share of Depth at BBO Provided by High Frequency Traders by Market Cap and Relative Tick Size

This table presents volume-weighted market shares of NASDAQ best bid and offer (BBO) depth provided by high-frequency traders. The sample includes 117 stocks in the NASDAQ high-frequency data in Oct 2010. The stocks are sorted first by average market cap and then by average price in September 2010 into 3 by 3 portfolios. To calculate the volume-weighted average, we first aggregate the depth provided by high-frequency traders and the depth provided by all traders for stocks in the portfolio for all days. Volume-weighted average is defined as the ratio of the aggregated depth provided by high frequency traders divided by the aggregated depth provided by all traders.

	Large Relative Tick Size (Low Price)	Medium Relative Tick Size (Medium Price)	Small Relative Tick Size (High Price)
Large Cap	55.62%	46.17%	33.16%
Middle Cap	39.60%	30.26%	23.67%
Small Cap	24.92%	23.19%	21.83%

Table 5: Does Tick Size Constraints Affect the Relative High Frequency Trading Activities Between EDGA and EDGX?

This table presents the impact of tick size constrains on the relative high frequency trading activities between Direct Edge's two trading platforms, EDGA and EDGX. EDGA charges liquidity providers and pays rebates to liquidity takers, whereas EDGX charges liquidity takers and pays rebates to liquidity makers. We use the following regression spefication:

$$\mathrm{HFT}_{ijt} = u_i + \gamma_t + \alpha + \beta_1 DummyEDGA_{ijt} + \beta_2 DummyEDGA_{ijt} * Prc_{-i} + \beta_3 DummyEDGA_{ijt} * logmktcap_{-i} + \varepsilon_{ijt}$$

We use two measures, *quote_to_trade_ratio* in Column (1), and *volume_to_message_ratio* in Column (2), as proxies for the high frequency trading activities. We measure *quote_to_trade_ratio* as the ratio between the number of quotes and the number of trades in each platform for each stock on each day. We measure *volume_to_message_ratio* as the negative of dollar trading volume (in $100) divided by the number of messages, where message is calculated as the sum of the number of quote and the number of trade, in each platform for each stock on each day. *dummyEDGA* is a dummy variable that equals one if the HFT measure is from EDGA, and equals to zero if the HFT measure is for EDGX. Prc_{-i} is the average price level of stock *i* in September 2010 minus the median average price of the 117-stock sample. The variable $logmktcap_{-i}$ is the log of the market cap of stock i in September 2010 minus the log of the median market cap of the 117 stocks in the sample. This table uses 117 stocks in Nsadaq High Frequency Trading Data. The dependent variable is constructed using TAQ data in Oct 2010. Standard errors are shown in parenthesis in the table; *, ** and *** represent statistical significance at 10%, 5% and 1% level respectively.

VARIABLES	(1) Quote_to_trade_ratio	(2) Volume_to_message_ratio
DummyEDGA	-9.350***	-0.690***
	(1.347)	(0.075)
DummyEDGA*prc	.0537***	.1353***
	(.0115)	(.014)
DummyEDGA*logmktcap	.8728	-.2035**
	(.5985)	(.092)
Constant	30.63***	-4.95***
	(2.809)	(.4082)
R-squared	0.227	0.784
Observations	4888	4888
Time effects	Yes	Yes
Firm effects	Yes	Yes

Table 6: The Market Share of Taker/maker Market by Market Cap and Relative Tick Size

This table presents the ratio of Direct Edge A (EDGA) volume to the total volume of Direct Edge (the volume of EDGA plus Direct Edge X (EDGX)). EDGA charges liquidity providers and pays rebates to liquidity takers, whereas EDGX charges liquidity takers and pays rebates to liquidity makers. The sample includes 117 stocks in the NASDAQ high-frequency data in Oct 2010. The 117 stocks are sorted first by market cap and then by price into 3 by 3 portfolios based on their average market cap and prices in September 2010. We aggregate the EDGA and EDGX volumes for stocks in each portfolio across all days. Volume weighted average is defined as the ratio of the aggregated EDGA volume divided by the aggregated EDGA volume plus the aggregated EDGX volume. Panel B is on equally weighted average. We first compute, for each stock i on each day t, the market share of EDGA relative to that of EDGA and EDGX. Then we average these observations equally across stocks and dates.

	Large Relative Tick Size (Low Price)	Medium Relative Tick Size (Medium Price)	Small Relative Tick Size (High Price)
Large Cap	64.28%	54.57%	28.98%
Middle Cap	55.94%	40.95%	38.33%
Small Cap	43.56%	29.79%	24.53%

Table 7: Impact of Tick Size Constraints on Market Liquidity

This table studies the impact of changes in tick size change on market liquidity. We use stock splitting event as an exogenous shock as the change of tick size constraints. We examine all firms that declared a two-for-one, three-for-one, or four-for-one stock split between January 2010 and November 2011 in the CRSP universe. Each of our pre- and post-event windows is comprised of the 30 trading days immediately before the stock-splitting date, and 30 trading days immediately after the stock-splitting date, including the splitting date. We excluded stocks that split more than once during the sample period. We employ the following diff-in-diff regression to study the relationship.

$$Liquidity_{it} = \alpha + \beta_1 treatment_i + \beta_2 after_t + \beta_3 treatment_i * after_t + e_{it}$$

$Treatment_i$ is equal to 1 for stocks that split and 0 for the matched sample, after_t equal to 1 after the splitting day for stock 1 and 0 before the stock split. We measure the liquidity variable for each stock i on each day t. In Panel A column (1), we measure liquidity variable *Depth* as the sum of the bid and ask offers at Nasdaq BBO. To make fair comparison, *Depth* before the splitting event has been adjusted by the splitting ratio for the splitting stocks. In Column (2), variable *Depth10* is measured as the sum depth at and within 10 cent of Nasdaq BBO. To make fair comparison, *Depth10* before the splitting event has been adjusted by the splitting ratio for the splitting stocks. In Panel B, *Qspread* in Column (3) stands for quoted spread and $Qspread_{adj}$ in Column (4) stands for the quoted spread adjusted for the liquidity maker's rebate. *pQspread* in Column (5) is proportional quoted spread and $pQspread_{adj}$ in Column (6) is the proportional quoted spread and adjusted for liquidity maker's rebate. In Panel C, *Espread* in Column (7) stands for effective spread and $Espread_{adj}$ in Column (8) stands for the effective spread adjusted for the liquidity taker's fee. *pEspread* in Column (9) is effective spread and $pEspread_{adj}$ in Column (10) is the proportional effective spread and adjusted for liquidity taker's fee.

Panel A: The Impact of Change in Tick Size Constrains on Quoted Spread

	(1)	(2)	(3)	(4)
VARIABLES	Qspread	$Qspread_{adj}$	pQspread	$pQspread_{adj}$
after	0.00293	0.00293	9.30e-05	9.27e-05
	(0.00250)	(0.00250)	(0.000120)	(0.000122)
treatment	0.0296***	0.0296***	-0.000249**	-0.000298**
	(0.00250)	(0.00250)	(0.000120)	(0.000122)
treatment*after	-0.0586***	-0.0586***	0.000500***	0.000610***
	(0.00354)	(0.00354)	(0.000170)	(0.000173)
Constant	0.0935***	0.0994***	0.00223***	0.00238***
	(0.00177)	(0.00177)	(8.48e-05)	(8.65e-05)
Observations	9,182	9,182	9,182	9,182
R-squared	0.051	0.051	0.003	0.004

Panel B: The Impact of Change in Tick Size Constrains on Limit Order Book Depth

VARIABLES	(1) Depth	(2) Depth10
after	50.33**	551.3**
	(19.63)	(277.3)
treatment	134.4***	-700.0**
	(19.62)	(277.2)
treatment*after	51.86*	3,497***
	(27.76)	(392.2)
Constant	505.4***	5,584***
	(13.87)	(196.0)
Observations	9,182	9,182
R-squared	0.018	0.026

Panel C: The Impact of Change in Tick Size Constrains on Effective Spread

VARIABLES	(1) Espread	(2) $Espread_{adj}$	(3) pEspread	(4) $pEspread_{adj}$
after	0.000733	0.000733	2.33e-05	2.32e-05
	(0.00289)	(0.00289)	(9.86e-05)	(0.000101)
treatment	0.0194***	0.0194***	-4.07e-05	-9.09e-05
	(0.00289)	(0.00289)	(9.85e-05)	(0.000101)
treatment*after	-0.0477***	-0.0477***	0.000223	0.000336**
	(0.00409)	(0.00409)	(0.000139)	(0.000143)
Constant	0.0725***	0.0785***	0.00158***	0.00173***
	(0.00204)	(0.00204)	(6.97e-05)	(7.13e-05)
Observations	9,164	9,164	9,164	9,164
R-squared	0.029	0.029	0.001	0.002

Table 8: Correlation between High Frequency Market Making and Resubmission Time

This table presents the correlation between limit order resubmission time and high-frequency liquidity provision. We first compute the logarithm of the quickest *i* percentile of a limit order submission subsequent to an execution for stock *i* on date *t*, and then take the average across days. For each stock, we obtain *logpi*,with i = 1, 5, 10, 25, 50, 75, 95, 99 by taking the average across days. For each stock ,we compute *HFT_Volume*, the average percentage of trading volume with high frequency traders as the liquidity provider, and *HFT_Depth*, the average percentage of depth at Nasdaq BBO provided by high frequency traders. The sample includes 117 stocks in the NASDAQ high-frequency data in Oct 2010.

	HFT_Volume	HFT_Depth
logp1	-0.654***	-0.672***
P-Value	(0.000)	(0.000)
logp5	-0.605***	-0.630***
P-Value	(0.000)	(0.000)
logp10	-0.614***	-0.619***
P-Value	(0.000)	(0.000)
logp25	-0.649***	-0.645***
P-Value	(0.000)	(0.000)
logp50	-0.688***	-0.679***
P-Value	(0.000)	(0.000)
logp75	-0.517***	-0.678***
P-Value	(0.000)	(0.000)
logp90	0.028	-0.188**
P-Value	(0.765)	(0.044)
logp95	0.139	-0.045
P-Value	(0.138)	(0.634)
logp99	0.180*	0.086
P-Value	(0.053)	(0.358)

Table 9: Impact of Change in Tick Size Constraints on Speed Competition of Liquidity Making and Taker/maker Market Share

This table studies the effect of change in the tick size contains on HFT market making and on the market share of the taker/maker market. We use stock splitting event as an exogenous shock to the change of tick size constraints. We examine all firms that declared a two-for-one, three-for-one, or four-for-one stock split between January 2010 and November 2011 in the CRSP universe. Each of our pre- and post-event windows is comprised of the 30 trading days immediately before the stock-splitting date, and 30 trading days immediately after the stock-splitting date, including the splitting date. We excluded stocks that split more than once during the sample period. We employ the diff-in-diff regression to study the relationship. The specification for column 1-5 is

$$Speed_{it} = \alpha + \beta_1 treatment_i + \beta_2 after_t + \beta_3 treatment_i * after_t + e_{it}$$

where the proxies of the HFT market making speed is the 1st, 5th 10th, 25th and 50th percentile of the resubmission speed of a limit order subsequent to an order execution. $Treatment_i$ is equal to 1 for stocks that split and 0 for the matched sample, after_t equal to 1 after the splitting day for stock i and 0 before the stock split.

The specification for column 6 is

$$Edgeratio_{it} = \alpha + \beta_1 treatment_i + \beta_2 after_t + \beta_3 treatment_i * after_t + e_{it}$$

where $Edgeratio_{it}$ is the volume of EDGA relative to the volume of EDGA plus EDGX. Standard errors are in parentheses, and ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) logp1	(2) logp5	(3) logp10	(4) logp25	(5) logp50	(6) edga_x
after	0.0237	0.0262	0.0669	0.108	0.00836	-0.0167
	(0.0710)	(0.0716)	(0.0755)	(0.0834)	(0.0799)	(0.0118)
pilot	-0.0232	-0.0166	-0.0892	-0.184**	-0.200**	-0.0477***
	(0.0699)	(0.0706)	(0.0744)	(0.0821)	(0.0787)	(0.0117)
pilot_after	-0.195**	-0.228**	-0.210**	-0.211*	-0.293***	0.0732***
	(0.0991)	(0.100)	(0.105)	(0.116)	(0.112)	(0.0166)
Constant	-7.810***	-7.096***	-6.536***	-4.504***	-0.951***	0.310***
	(0.0500)	(0.0505)	(0.0532)	(0.0588)	(0.0564)	(0.00826)
Observations	9,169	9,169	9,169	9,169	9,169	6,556
R-squared	0.001	0.002	0.002	0.003	0.006	0.004

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Market Share in Volume in the Taker/Maker Market with Respect to High Frequency Liquidity Provision

This figure shows relationship between the market share in trading volume in Direct Edge A and high-frequency liquidity provision in NASDAQ. The sample includes 117 stocks in the NASDAQ high-frequency data in Oct 2010. We first calculate the average percentage of BBO depth provided by high frequency traders for each stock, and then sort the stocks into five quintiles based on the percentage. Stocks in quintile 1 exhibit the lowest percentage of the BBO depth provided by high frequency traders, and stocks in quintile 5 exhibits the highest percentage of BBO depth provided by high frequency traders. For each stock in the quintile, we find the average percentage of the EDGA trading volume relative to the total volume of EDGA and EDGX, and we equally weigh the stocks in each quintile.