Relative Tick Size and the Trading Environment

Maureen O'Hara, Gideon Saar, and Zhuo Zhong*

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Abstract

This paper examines how the relative tick size influences market liquidity and the biodiversity of trader interactions. Using unique NYSE order-level data, we find that a larger relative tick size benefits High-Frequency Trading (HFT) firms that make markets on the NYSE: they leave orders in the book longer, trade more aggressively, and have higher profit margins. The effects of a larger relative tick size on the market are more complex. In a one-tick spread environment, a larger relative tick size results in greater depth and more volume; in a multi-tick environment, the opposite outcome prevails. The negative impact on depth and volume in the multi-tick environment is consistent with greater adverse selection coming from increased undercutting of limit orders by informed HFT market makers. Our work suggests why a one-size-fits-all spread policy is unlikely to be optimal, and we propose an alternative policy.

*Maureen O'Hara (mo19@cornell.edu) and Gideon Saar (gs25@cornell.edu) are from the Johnson Graduate School of Management, Cornell University, and Zhuo Zhong (zhuo.zhong@unimelb.edu.au) is from the Department of Finance, University of Melbourne. We thank Viral Acharya, Jim Angel, Bruno Biais, Simon Gervais, Michael Goldstein, Terrence Hendershott, Charles Jones, and Andrew Lo for helpful comments, as well as seminar participants at City University of Hong Kong, Princeton University, the University of Cambridge, FINRA's Economic Advisory Committee meeting, the Workshop on Microstructure Theory and Application (Cambridge), and the 2015 Center for International Finance and Regulation Conference. NYSE provided us with data and financial support for analyzing the data. All conclusions are those of the authors and do not represent the views of the NYSE.

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1. Introduction

There is resurgent interest in market structure issues in U.S. equity markets, and one area of particular focus is tick size.[1] Tick size refers to the smallest allowable increment between prices quoted by trading venues, and in the U.S. tick size is mandated to be one cent for all listed stocks with prices above $1.[2] That the minimum tick size could affect trading costs may seem obvious, at least for stocks in which the minimum is binding. What is less obvious is that tick size can have pervasive effects on market behavior, influencing, for example, traders' willingness to post limit orders, the interaction (and profitability) of different types of traders in the market, and even the dispersion of trading across venues. These influences, in turn, have led to practical concerns on a wide range of issues including whether a too small tick size may be inhibiting liquidity for IPO and small cap stocks (see Grant Thorton, 2012; SEC, 2013); whether the tick size regime may be affecting the prevalence of high frequency trading (Bartlett and McCrary ,2013; Yao and Ye, 2015); and whether the tick size may be inducing orders to move from exchanges to alternative trading venues (Buti, Consonni, Rindi, Werner, and Wen, 2014; Kwan, Masulis, and McInish, 2015; Gai, Yao and Ye, 2015). Common to these concerns is the question of whether a "one size fits all" tick policy is optimal for the U.S. markets.

In this research we use evidence from relative tick sizes to examine how differences in tick size affect the trading environment. Our research design exploits the fact that while the absolute tick size is fixed, the relative tick size (i.e., the tick size relative to the stock price)—which is the more relevant measure from an economic perspective—is not uniform across stocks, and can differ substantially depending upon stock price levels. By matching stocks with large relative tick sizes to a control sample of similar stocks with small relative tick sizes, we can isolate the specific effects of tick size on liquidity and the trading environment.[3]

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[1] The SEC, for example, has created a new Market Advisory Task Force to study market structure issues, and has announced a new pilot program to investigate allowing a larger tick increment for smaller, illiquid stocks.

[2] Reg NMS (National Market System) in 2001 mandated the minimum tick be set at one cent on all US exchanges. By contrast in Europe, stocks trade at different minimum tick sizes depending upon factors such as the stock price and trading volume.

[3] The reason that we do not investigate the tick size issue using penny stocks (i.e., around the price cutoff of one dollar where the tick size in the U.S. changes from $0.01 to $0.0001) is that such stocks typically have a very different investor clientele from the mixture of investors who are active in the overall market. As such, we are

Our analysis uses a unique dataset provided to us by the NYSE that includes all orders sent to the exchange. We observe both non-displayed and displayed orders, and the data allow us to categorize the traders behind the orders. We use these data to determine the nature of liquidity for stocks by constructing the order book and examining how it evolves with trading. In current "high-frequency" markets where trading algorithms reign, liquidity takes on many attributes, so our analysis looks at how a larger relative tick size affects a montage of liquidity measures.[4] Our data also allow us to investigate who is providing liquidity, or the "biodiversity" of the liquidity process. Liquidity today is often provided by computer algorithms, and in our analysis we can differentiate the specific roles played by high-frequency trading firms acting as market makers on the NYSE (henceforth, HFT market makers), institutional investors, quantitative traders, and individual traders.[5] We investigate how this liquidity provision process differs for large and small relative tick size stocks, with a focus on whether particular market participants are less likely to provide liquidity for stocks with larger relative tick sizes.

Our research produces a variety of intriguing results and we highlight two of them here. First, with a larger relative tick size, we find that HFT market makers' strategies are more aggressive: they leave limit orders in the book longer and they increase their undercutting of resting limit orders in the book, thereby improving prices. This results in liquidity being less "fleeting" than it is for smaller relative tick stocks. These aggressive strategies also help HFT market makers gain market share and they are more profitable. Our findings suggest that HFT market makers benefit in an environment with larger relative tick sizes.[6]

Second, we find that the impact of a larger relative tick on the market is more nuanced, and it depends greatly upon whether a stock's bid-ask spread is equal to a single tick or multiple

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unsure that results on how the tick size affects market outcomes or the biodiversity of trading can be generalized from penny stocks to the rest of the stocks in the market.

[4] For academic work on high-frequency traders, see Brogaard, Hendershott, and Riordan (2013), Carrion (2013), Chordia, Goyal, Lehmann, and Saar (2013), Hagströmer and Nordén (2013), Hasbrouck and Saar (2013), and Menkveld (2013).

[5] Our HFT market makers are the Designated Market Maker (DMM) and Supplementary Liquidity Providers (SLPs) operating on the NYSE. We give a detailed description regarding this type of traders in Section 2, where we discuss the uniqueness of our data.

[6] The empirical finding is the opposite of the predictions of Bartlett and McCreary (2013) who argue that high-frequency traders will fare worse in large tick environments.

ticks. In a one-tick spread environment, a larger relative tick size results in greater depth and more volume. In a multi-tick environment, the opposite outcome prevails, with lower depth and smaller volume. We argue that this divergence is due to informed HFT market makers submitting undercutting limit orders in the multi-tick environment. Specifically, we show that HFT market makers increase their use of undercutting orders relative to other trader types when the relative tick size is larger, and their orders have a greater permanent price impact than the undercutting orders of other trader types. The resulting adverse selection problem induces traders to scale back their limit order submissions, with consequent effects on depths and trades. This result underscores why a "one size fits all" tick policy is unlikely to be optimal. While we find little relation between percentage spreads or effective spreads and relative tick sizes, the market share of the primary listing market is affected by the relative tick size, consistent with trading in larger relative tick size stocks being diverted to venues in which sub-penny pricing can occur.[7]

As we discuss in the conclusions, our results are immediately applicable to the current debates regarding the optimality of a "one size fits all" tick policy across stocks. Our findings, added to those of other researchers (Bessembinder, Hao, and Zheng, 2015; Buti, Consonni, Rindi, Werner, and Wen, 2015), suggest that policy makers should be cautious with the adjustment of tick size. The upcoming SEC pilot to widen the tick size for less liquid stocks to five cents, as currently proposed, is not designed to look at how the economics of liquidity provision are affected by whether a stock trades in a one-tick or multi-tick spread environment . We propose an alternative tick size policy that we believe could improve liquidity provision and market quality.

Our research joins a large literature looking at the role of tick sizes in markets [see SEC (2012) for a recent review]. Harris (1994, 1996, 1997) highlights the role of tick size in influencing liquidity through its effects on order placement strategies, an issue addressed theoretically in Chordia and Subrahmanyam (1995), Seppi (1997), Anshuman and Kalay (1998), Cordella and Foucault (1999), Foucault, Kadan and Kandel (2005), Goettler, Parlour and Rajan (2005), Kadan (2006), and Buti et al (2015). Our results often support many of these

[7] Such an outcome is consistent with results of Bartlett and McCrary (2013) and Kwan, Masulis, and McInish (2015).

theoretical predictions, but in some areas conflict with such predictions perhaps due to the new high-frequency trading environment for stocks.

There is also extensive empirical research examining various market structure changes (both in the U.S. and in global markets) such as reducing tick sizes from eighths to sixteenths to decimals (see, e.g., Ahn, Cao, and Cho, 1996, Bacidore, 1997; Goldstein and Kavajecz, 2000; Jones and Lipson, 2001; Ronen and Weaver, 2001; Bacidore, Battalio, and Jennings, 2003; Bessembinder, 2003; Coughenour and Harris, 2004; Chakravarty, Panchapagesan, and Wood, 2005; Bollen and Busse, 2006) or changes in tick size when the stock price moves from one level to another (see Bessembinder, 2000). Other papers look at changes in the relative tick size around stock splits (e.g., Angel, 1997; Schultz, 2000). More recently, Bartlett and McCrary (2013), Kwan, Masulis and McInish (2015), Yao and Ye (2013), and Buti et al (2014) examine tick size issues in the context of sub-penny pricing and high-frequency trading. Our research provides a unique contribution by demonstrating how the tick size affects the behavior of specific market participants and the liquidity provision process in a high-frequency market setting. We are able to provide those insights by using NYSE data that allow a more detailed look at both the limit order book itself as well as how several trader types adapt their behavior to different relative tick sizes.

This paper is organized as follows. The next section sets out the empirical design of our study, discussing the sample, the data, our matched sample empirical methodology, and the conceptual framework behind our tests. Section 3 looks at the biodiversity of liquidity provision, focusing on the different roles played by institutions, quantitative traders, and HFT market makers and how their strategies change for stocks with larger relative tick sizes. In Section 4, we investigate the relationship between relative tick sizes and the state of liquidity in the market by analyzing depth, spreads, and volume. We also examine the impact of relative tick sizes on NYSE market share. In Section 5, we look at the profit margins of the HFT market makers. Section 6 discusses the implications of our research for the current debates surrounding tick size and the trading environment.

2. Empirical Design

To investigate the impact of different tick sizes on liquidity, an ideal design would compare stocks that are otherwise identical but have different mandated tick sizes. Unfortunately, for U.S. stocks this is infeasible because all non-penny stocks are traded with the same minimum one-cent price increment.[8] Nonetheless, as noted in the introduction, while the minimum absolute tick size is the same across stocks, the relative tick size—the dollar tick size divided by the price of the stock—is not. The relative tick measure is important because transactions costs for a portfolio manager are determined by the dollar quantity traded multiplied by the percentage costs (e.g., the percentage effective spread). Hence, transactions costs are driven by the relative tick size, not by the tick size in cents.[9] These transactions costs, paid by traders who demand liquidity, also constitute the profits of liquidity providers. Non-uniform relative tick sizes among U.S. stocks affect liquidity providers' strategies, and hence liquidity in the market as a whole. We discuss the relationships among the tick size, liquidity providers' strategies, and aggregate market liquidity in Section 2.4.

Our empirical investigation of how the trading environment differs for stocks with differing relative tick sizes is carried out by analyzing stocks with varying price levels. We use a matched sample approach whereby we match stocks based on attributes that affect liquidity but are not themselves affected by liquidity, such as industry and market capitalization, to essentially hold "everything else equal" and observe the effects of relative tick size differences across stocks.

2.1 Sample

Our sample period is May and June, 2012, and the universe of securities consists of all common domestic stocks listed on the NYSE. We form two groups with large relative tick sizes from among these stocks segmented by the stock price ranges \$5–\$10 and \$10–\$20 (where we use the stock price on the day before the sample period begins). Within each price range, we sort stocks

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[8] The investment environment (and hence the trading environment) of penny stocks may be sufficiently different from that of regular stocks (i.e., whose prices are consistently above \$1) to make generalizations from penny stocks difficult.

[9] The theoretical model in Buti et al (2015) shows that the effects on market quality and welfare of changing the relative tick size (i.e., changing the price holding the tick size in cents constant) are identical to those of changing the tick size in cents (except for the quoted spread).

by market capitalization and choose a stratified sample of 60 stocks in a uniform manner to represent the entire range of market capitalization. The first group (G1) is comprised of 60 stocks with prices between $5 and $10, and the second group (G2) is comprised of 60 stocks with prices from $10 and up to $20. We call stocks in G1 and G2 the "sample stocks."

Each stock in G1 and G2 is matched to a control stock with a small relative tick size, which means it has a higher price range (from $20 to $100), such that it is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization.[10] Our main goal in using industry and market capitalization is to control for investor interest in the stock. Stocks in different industries may be of interest to different sets of investors (and go through phases of heightened investor interest together). Similarly, larger stocks are more often mentioned in the news and have more investors holding their shares. Note that we cannot control for market factors such as volume, because the quantity of trading is directly determined by transactions costs, which could be influenced by the relative effective spread. Hence, in forming our controls, we only use variables that are fundamental to the security and the investor base rather than those that reflect the market environment. Having two groups with different levels of relative tick size allows us to evaluate the robustness of patterns in trading behavior across stocks.[11]

Table 1 presents summary statistics for the sample and control stocks. The mean price of sample stocks in G1 is $7.56 (versus $32.56 for the control stocks), and the mean price of sample stocks in G2 is $14.55 (versus $34.95 for the control stocks). Hence, the relative tick size of the sample stocks is roughly four times that of the control stocks in G1 and more than twice that of the control stocks in G2. The Table also shows that our size matching between the sample and control stocks (within the same industry) is excellent in G2 and good in G1.

[10] The market capitalization is taken from the end of the previous calendar year. The matching is done without replacement so that each sample stock has a unique control stock.

[11] An alternative procedure for creating the matched groups could have been to try and find a control stock that is exactly a certain multiple of relative tick size, e.g., five times, for each sample stock. This, however, would have had the unfortunate side effect of severely curtailing our ability to control for industry and market capitalization. In other words, we chose to have an exact control for industry at the stock level while controlling for the average price (or the average relative tick size) at the group level because one cannot implement a control for "an average" industry at the group level.

While the NYSE is the home to many large firms, there are many small and midcap firms listed on the exchange and they feature prominently in our size-stratified sample. In May, 2015, the SEC approved a proposed pilot program to increase the tick size of certain small and mid-cap stocks. The pilot defines candidates for an increase in tick size as those stocks satisfying two criteria: market capitalization less than $3 billion and average daily volume less than 1 million shares. It is interesting to note that there are 43 pairs of stocks (out of 60) in G1 for which both sample and control stocks satisfy the pilot definition, and similarly 39 pairs (out of 60) in G2. Thus, while our results relate specifically to the liquidity of larger relative tick size stocks, our study has implications for the outcomes market participants could expect to observe once the pilot is implemented.

2.2 Data

We use order-level data from the NYSE's DLE (Display Book Data Log Extractor) files. Display Book logs capture and timestamp all "events" within the Display Book application, which is the engine that handles trading on the NYSE. These events include orders and quotes, as well as a significant amount of inter- and intra-system messaging.[12] The files also include published quote messages from all other markets. These data sources, to the best of our knowledge, were not previously used in academic research. We use the data to reconstruct the limit order book at any point in time, examine patterns in order arrival, cancellation, and execution, and in general have a detailed look at the liquidity provision environment.

Of key interest is the "biodiversity" of liquidity provision and trading behavior and how it relates to the relative tick size. We associate each order with one of four mutually exclusive trader types. We use the Account Type field in the NYSE data to identify three "trader types": institutions (regular agency order flow), program traders and index arbitrageurs (for which we use the term "quantitative" order flow), and individuals (though limit order activity by individuals on the NYSE is negligible over our sample period and their market share of trading volume is less than 1%).[13]

[12] The NYSE further extracts messages from these log files into an EVENTS table that we use for the empirical analysis in this paper.

[13] The Account Type field was previously used in other research papers to identify individual investor trading (e.g., Kaniel, Saar, and Titman (2005)) or institutional trading (e.g., Boehmer and Kelley (2009)).

The last trader type is comprised of high-frequency traders (HFT) that function as market makers on the NYSE: the Designated Market Maker (DMM) and Supplementary Liquidity Providers (SLPs). Market making on the NYSE, which in the past was the purview of human "specialists," is now mostly carried out by high-frequency proprietary algorithms.[14] Each stock has only one DMM, but several SLPs may be active in the same stock (though not all stocks have active SLPs).[15] The activity of the DMM and SLPs corresponds well to the definition of high-frequency trading in the SEC Concept Release on Equity Market Structure (2010) and some of these firms have been mentioned in newspaper articles as major players in the HFT space. We note that this category consists of electronic market makers that have obligations to the exchange, and their trading strategies may be different from those of other HFT firms. We refer to them as HFT market makers to signify that these traders follow a rather specific subset of high-frequency trading strategies.[16]

We analyze the behavior of these trader types to obtain a finer picture of how a larger relative tick size affects the biodiversity in terms of placing orders in the book and executing trades.[17] We caution, however, that our four trader type designations may be noisy measures in that some trades may be misclassified. These designations also have a specific meaning in our research that may or may not correspond to the meaning of these labels elsewhere. For example, the "individuals" category represents only trading decisions made by the individual investors themselves, and not the trading decisions made on their behalf by private wealth mangers. The

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[14] While a human Designated Market Maker may intervene in trading, conversations with NYSE officials confirm to us that almost all DMM trading is currently done by algorithms. The DMM firms during our sample period are Barclays Capital Inc., Brendan E. Cryan & Co. LLC, Goldman Sachs & Co., J. Streicher &Co. LLC, KCG, and Virtu Financial Capital Markets LLC. The SLPs in NYSE securities are Barclays Capital, Inc., Citadel Securities LLC, HRT Financial LLC, Bank of America/Merrill, Octeg LLC, Tradebot Systems, Inc., Virtu Financial BD LLC, KCG, and Goldman Sachs &Co.

[15] DMMs have obligations to maintain a fair and orderly market in their stocks, and they need to quote at the NBBO a certain percentage of the time. Unlike the "specialists" they replaced, the DMM algorithms do not get an advance look at incoming order flow. Also unlike the specialists, they trade on parity with the public order flow and do not need to yield and let investors transact directly with one another. SLPs have significantly fewer responsibilities. They are only obligated to maintain a bid or an ask at the NBBO in each of their securities at least 10% of the trading day. To qualify for larger rebates when their quotes are executed (i.e., when they provide liquidity), they also need to trade above a certain threshold in terms of volume.

[16] One could also hypothesize that the strategy of the DMM will differ from the strategies of the SLPs because of the different level of obligations they have for the exchange. Our empirical analysis, however, suggests that the impact of the relative tick size on their activity is similar, and hence we put the DMM and the SLPs together in the HFT market makers' category.

[17] The residual category includes all other orders that arrive at the NYSE (e.g., non-agency order flow from member firms).

latter could appear in the "institutions" category. Also, proprietary trading may be present in more than one designation. These difficulties notwithstanding, the data are very accurate with respect to orders from HFT market makers (the DMMs and SLPs), and we expect classification errors in other categories to be relatively small.

Given that high-frequency trading is one of the developments we mention in the introduction driving the renewed interest in tick size, a particular strength of our study is that we can investigate the role some high-frequency traders play in the liquidity provision process. High-frequency traders in equity markets are heterogeneous, and often specialize in one or more strategies. An important and interesting type of high-frequency traders are the electronic market makers [see, Hagströmer and Nordén (2013) and Menkveld (2013)], and on the NYSE these HFTs include the DMMs (designated market makers) and SLPs (supplementary liquidity providers). Activity by high-frequency trading firms that do not make markets on the NYSE may appear as part of the "others" and "quantitative" categories, but we are unable to specifically identify it as such (in other words, we do not have exact identification of HFT strategies other than those of the DMM and SLPs).

We stress that while our data are of extremely high quality in terms of our ability to see activity on the NYSE, we do not have similar data on trading in NYSE stocks on other markets. For many stocks, there is significant trading on other exchanges and off-exchange venues and so we are seeing only a portion of the trading data. We have high-quality quotes from other exchanges in the NYSE dataset that allow us to compute the NBBO (from the perspective of the NYSE computer system) with a high degree of precision, and hence measures such as spreads or the relationship of NYSE order flow to market-wide prices are estimated precisely. Still, on some issues, such as the overall trader type mix in the market, we are only able to make an inference using NYSE orders.

2.3 Methodology

Our basic experimental design involves matched pairs consisting of a stock with a large relative tick size (in groups G1 and G2) and a stock with a small relative tick size that are matched by industry and market capitalization. For each variable of interest, say depth at the NBBO, we present the mean and median value of the variable for the sample stocks, the mean and median paired differences between the sample and control stocks, and tests (a *t*-test and a non-parametric Wilcoxon Signed-Rank test) against the two-sided hypothesis that the difference is zero.

Differences between the sample and control stocks in fundamental attributes of stocks other than industry and size could in principle confound the results. In particular, stocks that are held and traded by very different sets of investors may have dissimilarities in their trading environments that matching by industry and size may not capture. Similarly, volatility (or risk) is a fundamental attribute of a stock, and while it can be partially captured by industry and size, it is conceivable that we need to implement further controls.[18] Therefore, we also run regressions of the differences between the sample and control stocks on differences in two variables that describe the investor clientele and a volatility measure:

$$\Delta Y_i = \alpha + \beta_1 \Delta NumInv_i + \beta_2 \Delta PercInst_i + \beta_3 \Delta Volatility_i + \varepsilon_i \qquad (1)$$

where *i* indexes the matched pairs, *Y* stands for any of the variables we investigate, *NumInv* is the number of shareholders from COMPUSTAT, *PercInst* is the percent holdings by institutions taken from Thompson Reuters' dataset of 13F filings (supplemented, when needed, with information from Thompson One), and *Volatility* is the standard deviation of daily return in the two months prior to the beginning of the sample period. We report in the tables, alongside the mean and median differences as noted above, the coefficient α from equation (1) that gives the difference between the sample and control stocks after controlling for the right-hand-side variables, with a *p*-value against a two-sided hypothesis that the coefficient is equal to zero computed with White Heteroskedasticity-consistent standard errors.[19]

We investigate the relative tick size because we believe it is the more relevant concept from the perspective of trading costs, but there is one case in which the absolute tick size matters for the strategies of market participants: the one-tick spread. When the bid-ask spread is equal to one cent, traders cannot undercut each other and are forced to wait in the limit order queue to obtain execution or attempt to trade off the exchange. This may change their behavior in terms of

[18] We also looked at the price history of the sample stocks to see whether these are simply failing firms and therefore their low prices pick up idiosyncratic elements that are absent from the control stocks. However, we did not find statistically significant price differences between the sample and control stocks in the 3, 6, and 12 months prior to the sample period.

[19] The pairs' tests and the regression are used in the analysis of almost all variables. We describe the variables themselves when each result is discussed. Exposition of additional methodologies (e.g., duration models) is also done in the context of the relevant results in sections 3, 4, and 5.

liquidity provision and can impact trading costs because it constrains the relative tick size for lower-priced stocks.

Panel B of Table 1 provides summary statistics on the percentage of time that the National Best Bid and Offer (NBBO) spread or the NYSE Best Bid and offer (BBO) spread are equal to exactly one tick. The average stock in G1 is constrained at one-tick NBBO spreads 62.5% of the time, and 47.6% of the time for the NYSE BBO. The numbers for G2 are also high: 50.7% (39.3%) of the time the NBBO (NYSE BBO) is equal to one tick. The dollar spreads of higher-priced stocks, however, tend to be larger. Hence, stocks that we use for control (in the price range $20 to $100) have larger spreads and hence tend to be less constrained by the one-tick spread. For example, the mean difference between sample and control stocks of the percentage of time their spreads are equal to one tick is both large and significant: 34.5% (NBBO) and 28.9% (NYSE BBO) in G2.

The fact that the sample and control stocks are not the same in terms of the percentage of time they face the one-tick constraint is important for the manner in which we analyze the results. Specifically, there is no difficulty in comparing the sample and control stocks within the one-tick environment, and similarly within the multi-tick environment. Therefore, the analysis in this paper is always conducted separately within each of these environments. Whenever the effects in the one-tick environment differ from those in the multi-tick environment, we present both sets of results and discuss the dissimilarity and its sources. If the effects are similar in both environments, however, there is no harm in combining them for the purpose of presentation and we do so to economize of the size of the tables. In such cases, we explicitly note in the text that the results are similar in both environments.

2.4 The Conceptual Framework

Before presenting the empirical results, it is useful to frame our analysis with a short discussion of the economic implications of having a minimum price increment (the "tick") in today's markets.[20] How does it affect the strategies of liquidity providers like HFT market makers? One

[20] There are several theoretical papers in which a non-zero minimum price increment is preferred by all traders or minimizes transactions costs. See, for example, Cordella and Foucault (1999), Foucault, Kadan, and Kandel (2005), and Seppi (1997). The impact of a larger or a smaller tick size on transactions costs can depend in these models on various attributes of the economic environment, such as the ratio of patient to impatient traders (Foucault, Kadan, and Kandel , 2005) or the number of dealers in the market (Kadan, 2006).

would expect liquidity providers to post limit orders such that the spread they quote, which is an integer multiple of the tick size, is sufficient to recover their out-of-pocket costs and return enough to cover their cost of capital. Fees and rebates that the liquidity provider earns should factor into the size of the spread, and there are also inventory control considerations that could make a particular HFT market maker willing at times to transact in a manner that yields negative profit if it means offsetting a particularly undesirable inventory position. Competition among professional liquidity providers in such a market would ensure that the spread is the smallest number of ticks that satisfy the above requirements.[21] A larger tick size should translate in this environment into greater profit for liquidity providers.[22]

The strategies of various traders could differ depending on whether the spread is equal to one tick or multiple ticks (though a larger tick size could also alter the mix between the one-tick and the multi-tick spread environments by increasing the likelihood of a one-tick environment). In a one-tick spread environment, a larger relative tick size means a larger wedge between the prices in which professional liquidity providers buy and sell shares, and hence increases their profits. Greater profits lead to intensified competition among them, but the opportunities for price competition are limited because liquidity providers cannot easily undercut existing orders in the book when the spread is equal to one tick. As such, they compete on other dimensions, such as submitting larger limit orders (more depth) and leaving orders longer on the book (lower cancellation rate). This results in a longer queue of limit orders at the best prices in the limit order book. Faster and more sophisticated traders, like HFT market makers, are in the best position to manage their place in the queue, cancelling and resubmitting as the environment changes, as well as moving orders across trading venues. Hence, their market share should increase in stocks with a larger relative tick size (Yao and Ye, 2015).[23]

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[21] See Boehmer, Li, and Saar (2015) for evidence that there are several underlying common strategies, including market making, with competing HFTs in each strategy in Canada. It is reasonable to assume that liquidity provision on the NYSE, in which the DMM and SLPs compete with each other as well as face competition from other HFT firms, is competitive enough to drive spreads down to the competitive level for most stocks.

[22] Anshuman and Kalay (1998) show in their model that a larger tick size benefits market makers, but at the same time causes liquidity traders with elastic demands to trade less due to the higher transaction costs. As such, there is an optimal tick size from the perspective of market makers in their model. See also the discussion in Angel (1997).

[23] If there are informed investors in the market, Glosten (1994) shows that traders in the front of the queue will earn positive profits while those in the back of the queue will break even. The HFT market makers' advantage in terms of speed and sophistication means that they more often can position themselves in the front of the queue, leading to

Having a longer queue at the top of the limit order book also means that more traders would choose to trade off the exchange to circumvent time priority of orders on the exchange. This effect is emphasized in several new papers analyzing the proliferation of crossing networks that enable traders to transact at the midpoint of the NBBO (see, for example, Bartlett and McCrary, 2013; Gai, Yao, and Ye, 2013; Kwan, Masulis, and McInish, 2015; Buti et al, 2014).

In a multiple-tick spread environment, the implications of a larger relative tick size are less clear. The main difference is that competition on price (or undercutting resting limit orders in the book) is now possible. If undercutting is done by uninformed traders, liquidity will be enhanced: traders with exogenous trading needs (e.g., portfolio rebalancing, inventory control) submit orders that narrow the spread and increase depth. On the other hand, if undercutting is done by informed traders, liquidity will suffer as the undercutting orders will impose adverse selection on resting limit orders in the book. Adverse selection arises in this case because informed traders will undercut only when it is profitable, leaving resting limit orders to execute when informed traders decide to refrain from undercutting (in which case the resting limit orders realize a truncated payoff distribution comprised mainly of losses). Such adverse selection will cause limit order providers to reduce the depth they supply with limit orders (see, for example, Kavajecz, 1998; Kavajecz, 1999; Charoenwong and Chung, 2000; Dupont, 2000).[24] The overall impact on depth would therefore depend on who is undercutting: it would increase (decrease) if stepping ahead is predominantly undertaken by uninformed (informed) traders.

3. Who provides liquidity?

The NYSE data we analyze give us the unique ability to look at the biodiversity of liquidity provision. We begin with the question of who provides liquidity, and how, if at all, this process differs for stocks with larger relative tick sizes. We look at this question from a variety of angles, all of which are meant to captures different dimensions of the concept of liquidity.

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greater profit with a larger relative tick size in a one-tick spread environment. We thank Bruno Biais for pointing this effect to us.

[24] While traders could also opt to post less competitive prices, or widen the spread, in response to increased adverse selection, this would increase the opportunity for undercutting by expanding the number of price points available for undercutting. As such, traders may prefer to maintain the same prices but decrease the size they quote in order to limit adverse-selection-induced losses.

3.1 Who is posting limit orders?

Liquidity provision on the New York Stock Exchange arises from the willingness of market participants to post limit orders. If changing tick sizes is a remedy for market illiquidity, then we would expect to find significant differences in market participants' order placement activities for stocks with different relative tick sizes. Of particular consequence are the dynamics of placing and cancelling limit orders, as well as the resulting executions of limit orders that rest in the book. Some market participants complain that depth is "fleeting" in that limit orders are cancelled very quickly. Harris (1996) claims that traders will allow their limit orders to stand for longer, and cancel them less often, when the relative tick size is larger. We begin our analysis of this issue with Figure 1, which depicts estimated distributions of time-to-cancellation (Panel A) and time-to-execution (Panel B) of limit order for the sample and control stocks in the two relative tick size categories. These distributions are estimated using the life-table method. For time-to-cancellation estimates, execution is assumed to be an exogenous censoring event, while for time-to-execution, cancellation is the censoring event.

Panel A shows that a significant portion of limit orders is cancelled very quickly and that, except at very short durations, time-to-cancellation is longer for stocks with larger relative tick sizes. In G1, for example, where the relative tick size of sample stocks is about four times that of the control stocks, 33.5% of limit orders in the sample stocks are cancelled within the first second compared to 41.9% for the control stocks. Within the first minute, 72.3% of the limit orders are cancelled for the sample stocks in G1 compared to 84.6% for the control stocks. This effect, which is consistent with the prediction from Harris (1996) that liquidity will be less "fleeting" in large tick stocks, is evident in both relative tick size categories, and the magnitude of the effect increases with the relative tick size difference between the sample and control stocks.[25]

Turning to execution rates, Goettler, Parlour, and Rajan (2005) predict that a smaller tick size would lead to shorter time to execution of limit orders. In the current age of trading

[25] This result is also consistent with Bacidore, Battalio, and Jennings (2003), who found an increase in the limit order cancellation rate after decimalization was implemented.

algorithms, the execution rate of limit orders is rather low. Still, we observe that execution is more likely for limit orders submitted in stocks with larger tick sizes, which contrasts with the theoretical prediction but is consistent with our finding of a longer time-to-cancellation: if limit orders remain in the book, the likelihood they execute goes up. Panel B of Figure 1 shows, for example, that 0.62% of limit orders are executed within a second for stocks with larger tick sizes in G1, compared to 0.39% for the control stocks. Similarly, 1.9% of the limit orders are executed within a minute in the sample stocks compared to 1.1% of the limit orders in the control stocks. Here as well, the effect seems to be increasing with tick size, and while the absolute magnitude of the execution probabilities is very small, the differences between the sample and control stocks are very visible in G1 and G2.

We use a more structured statistical methodology to study the cancellation and execution of limit orders by trader type. Specifically, we ask two questions: who is providing the liquidity more patiently by cancelling limit orders less often; and who is enjoying a higher execution rate of their limit orders. To analyze these limit order durations we use an accelerated failure model in which time-to-cancellation follows a Weibull distribution. The logarithm of time-to-cancellation is modeled as a linear function of an intercept, a dummy variable that takes the value 1 for the sample stocks, the distance of the limit price from the relevant side of the NBBO quote (i.e., bid for a limit buy order and ask for a limit sell order), same-side NYSE depth, and opposite-side NYSE depth. The inclusion of the last three covariates (all calculated at submission time of the limit order) is meant to control for the state of the market that can be relevant for the decision to cancel an order. We use a similar model to study the execution of limit orders. To aid in the interpretation of the results, we report a transformation that gives the percentage difference in the cancellation (or execution) rate of the limit orders.

Table 2 looks at three trader types: institutions, quantitative traders, and HFT market makers.[26] In general, HFT market makers exhibit the most difference between their strategies in stocks with larger and smaller relative tick sizes. These results are similar in the one-tick and

[26] The amount of individual investor activity on the NYSE is small relative to that of institutions, quantitative traders, and HFT market makers. This is especially the case when one looks at orders, as opposed to actual trades, because the more sophisticated trader types employ algorithms that cancel and resubmit orders frequently, and consequently the share of individual investors in the orders is negligible. Therefore, in analysis that involves orders we present only the results for institutions, quantitative traders, and HFT market makers.

multi-tick spread environments, so we present the overall results. For example, the mean cancellation rate of HFT market makers in large tick size stocks is smaller by 23.89% in G1 compared with 13.49% for institutions, and similarly we observe differences in the magnitude of the effects between HFT market makers and institutions in G2 (-18.48% versus -4.07%). The results for the quantitative traders often (though not always) appear to be in between those for institutions and HFT market makers, probably reflecting their heavier reliance on more sophisticated algorithms as well as the possible inclusion of high-frequency traders that are not the DMM and SLPs in this category.

The change in strategies of HFT market makers means that limit orders are left longer on the book and result in a large increase in the mean execution rate of their orders: 523.9% in G1 and 482.2% in G2, compared with 99.6% and 110.8% for the institutions in G1 and G2, respectively. While the median execution rates point to a more modest increase, they also demonstrate a larger increase for HFT market makers relative to institutional investors. Overall, the prediction in Harris (1996) that a larger tick would enable traders to cancel limit orders less often is borne out by the data, and professional market makers are those best situated to take advantage of it and shift to somewhat more patient limit orders strategies that provide liquidity. As a result, they also enjoy a higher execution rate relative to other trader types.

3.2 Who is setting prices?

Another aspect of the quality of liquidity provision is the extent of competition among traders in submitting orders at the best prices. In Table 3 we study whether a larger relative tick size changes the incentives to compete in this manner by looking at who is submitting the limit orders at the NYSE BBO (in Panel A) or is improving the NYSE BBO (in Panel B). Panel A again shows overall results because we observe the same effects in the one-tick and multi-tick environments, while Panel B presents only the multi-tick environment because it is impossible to step ahead by submitting non-marketable limit orders when the spread is equal to one tick.

We see that the proportion of orders submitted at the NYSE best prices is higher in stocks with a larger tick size for HFT market makers and institutions (9.6% and 6.2% in G1, respectively), but the magnitude of the difference is greater for HFT market makers. The more striking picture emerges when we look at orders that improve the NYSE BBO. These orders show that HFT market makers compete more intently on liquidity provision in stocks with larger relative tick sizes. In fact, the proportion of limit orders that step ahead of the best prices increases significantly only for HFT market makers, while decreasing significantly for quantitative traders and possibly also for institutions (though the negative point estimates for the latter are not statistically different from zero).[27] The increase in market share of undercutting orders by HFT market makers is consistent with findings in Yao and Ye (2015) on HFT activity in NASDAQ stocks.

What is the impact on the market when some traders improve prices by undercutting resting limit orders in the book? In Section 2.4 we mentioned that if these traders are uninformed but have a greater need for immediacy, liquidity may be enhanced. On the other hand, if these traders are informed, their intensified activity may deter other traders from adding depth to the book because they will experience greater adverse selection. In other words, the informed traders undercut when it is advantageous for them, leaving resting limit orders in the book to execute only when it is less advantageous.

To examine whether the undercutting limit orders can be characterized as informed, we look at their permanent price impact. The permanent price impact (often computed in the literature for marketable orders) is usually defined as the change in price from the midquote prevailing at the time the order is submitted (as a representative price an instant before the order arrives) to a representative midquote after a certain interval of time. When the SEC rule on reporting execution quality statistics was implemented in 2001 (originally called 11ac1-5, now part of Rule 605 of Reg NMS), the common interval of time used in the literature to decompose the spread (into permanent and temporary components) was five minutes. In the era of high-frequency trading, the appropriate interval in our view should be much shorter, perhaps on the order of 5 seconds.

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[27] Harris and Panchapagesan (2005) find that specialists are more likely to step ahead of the limit order book when the relative tick size is small. When we conduct a similar analysis, we find that a smaller relative tick size makes institutions step ahead even more so than HFT market makers, which contributes to our finding in Table 3 that the share of HFT market makers in limit order submission at the top of the market is actually lower in stocks with smaller relative tick sizes. We suspect that changes in market structure since the 1990-1991 sample period in Harris and Panchapagesan's study are probably the reason behind the contrasting results. In particular, the privileged information about limit orders in the book that the NYSE specialist used to enjoy back in 1990-1991 no longer characterizes the new trading environment on the NYSE in which the DMM and the SLPs operate.

In Table 4 we present analysis in which we compute the percentage permanent price impact for an undercutting order as:

$$\text{Permanent Price Impact} = \frac{\left(\text{midquote}_{t+5\text{ seconds}} - \text{midquote}_t\right) I}{\text{midquote}}$$

where I = +1 for a buy limit order and I = −1 for a sell limit order, and average all such permanent price impacts for the undercutting orders of a trader type in a particular stock.[28] We find that the mean permanent price impact of an undercutting limit order of HFT market makers is over 60% larger than the mean permanent price impact of institutions and quantitative traders in G1 stocks (0.1086 versus 0.0663). In G2, the mean permanent price impact of HFT market maker orders is over 40% larger than the mean permanent price impact of institutions and quantitative traders. Furthermore, the permanent price impact of undercutting orders is greater in stocks with a larger relative tick size, and the biggest difference between sample and control stocks appears to be for the HFT market makers. These results suggest that HFT market makers are more informed when they step ahead of the book in that their orders generate a larger permanent price impact, and hence their intensified competition for liquidity provision may actually impose adverse selection on the market.

3.3 Who is executing trades?

If HFT market makers intensify their activity in large relative tick size stocks by canceling their limit orders less often and increasing their market share in orders at the top of the book, we expect that they end up trading more often. Their intensified activity in supplying liquidity could also spill over to demanding liquidity as HFT algorithms often use both limit and marketable orders to manage their inventory. The end result would be that HFT market makers gain a larger market share of trading than other trader types in the market.

This conjecture is confirmed by the evidence in Table 5. Because in this table we examine trading volume rather than limit order submission, we also include the results on individual investors. We observe that the only trader type that increases its market share of

[28] The results are similar in nature when we use 5 seconds, 60 seconds or 5 minutes as the interval of time between the prevailing and the subsequent midquotes.

trading in stocks with a larger relative tick size is HFT market makers.[29] In fact, HFT market makers grab between 5% and 6% additional market share in stocks with a larger relative tick size as a result of their more aggressive order strategies (in terms of less cancellations and more orders at and undercutting the best prices).[30]

3.4 Who is in the book?

We next examine who provides depth consistently to the limit order book. We analyze "true" depth that includes both displayed and non-displayed orders on the NYSE book. Panel A of Table 6 shows data on dollar depth by trader type for orders submitted at the NBBO, while Panel B gives similar data for cumulative depth up to 1% of the stock price from the NBBO.[31] Here we find a marked difference between the one-tick and the multi-tick spread environments, and so we present them separately. In the one-tick environment, we observe that all trader types appear to add depth to the NBBO in stocks with a large relative tick size. For example, HFT market makers add $7,667 ($7,450) depth at the NBBO for stocks with a large tick size in G1 (G2). However, in the multi-tick environment, all trader types appear to supply less depth at the NBBO. For example, institutions supply $3,147 less depth in stocks with a large relative tick size (G1), and quantitative traders supply $1,694 less depth.

When we look at cumulative depth near the best prices (up to 1%) in Panel B, the picture is similar, though only HFT market makers appear to significantly and consistently increase the amount of depth they add to the book in large relative tick size stocks (G1 and G2) in the one-tick environment. In the multi-tick environment, all trader types add less depth to books of stocks with a larger relative tick size.

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[29] Individuals, institutions, and quantitative traders do not seem to have a meaningful change in their market share, which means that increase in HFT market makers' market share comes mainly at the expense of our residual category of unclassified traders.

[30] Coughenour and Harris (2004) analyze the impact of decimalization and find that NYSE specialist participation rate in trading increased after the tick size was reduced. We believe that our contrasting result stems from the very different trading environment that prevails in today's equity markets in which most trading is done by algorithms and the NYSE DMM is also an HFT. Hagströmer and Nordén (2013) look at the impact of market making HFTs on volatility using an event study of tick size changes. The minimum tick size on NASDAQ-OMX Stockholm depends on the stock's price level, and they examine stocks that break through the price level boundaries between tick size categories. Like us, they find a greater market share for market making HFTs when the tick size is larger.

[31] Given the different price levels of the sample and control stocks, we use percentage price distance to ensure that cumulative depth is comparable across stocks. For each stock, we take the average price over the sample period and count the number of ticks in 1% of that price. We then accumulate depth from the NBBO up to that number of ticks. For example, we use 10 ticks above (and including) the ask price and similarly 10 ticks below (and including) the bid price for a $10 stock.

Why do traders add less depth to the books of stocks with a large relative tick size in the multi-tick environment? The key to understanding this result lies in our earlier results on limit order submission strategies. In particular, we find that HFT market makers undercut much more often than other trader types in stocks with a larger relative tick size, and we also documented that their undercutting orders have a larger permanent price impact than the orders of institutions and quantitative traders. These two findings combine to suggest that in a multi-tick environment, the undercutting by HFT market makers induces a greater adverse selection problem in stocks with a larger relative tick size. As we mention in Section 2.4., the natural response of traders to greater adverse selection is to provide less depth to the book. Institutions and quantitative traders understand that there is greater likelihood that their limit orders will execute at the wrong time, so they provide less liquidity. Even among HFT market makers (the DMM and the SLPs) there is intensified competition in undercutting the book, and the response is to limit potential losses by posting less depth in the multi-tick environment.

Overall, an interesting picture emerges of the biodiversity of liquidity provision. A larger relative tick size impacts the strategies of HFT market makers to a greater extent than the strategies of other market participants. In particular, HFT market makers cancel limit orders less often, and increase their market share of limit order submission at the top of the book. In fact, they are the only trader type that increases its market share in undercutting (or stepping ahead of) limit orders in the book. These aggressive strategies have two consequences. First, they increase the market share of HFT market makers in stocks with a larger relative tick size. Second, given our finding that their orders are more "informed" in that they have larger permanent price impacts, their undercutting orders impose greater adverse selection on the market in the multi-tick environment. This has implications for traders' willingness to supply depth, and we observe lower depth provided by all trader types in the multi-tick environment for stocks with a larger relative tick size. We next study how these trader strategies affect the state of liquidity in the market.

4. What happens to liquidity?

4.1 Depth

We begin our analysis of the relationship between relative tick size and the state of aggregate liquidity in the market by looking at depth in the limit order book close to market prices. Goettler, Parlour, and Rajan (2005) predict that a smaller tick size would bring about less depth, while Buti et al (2015) agree that a smaller tick size should result in lower book depth for illiquid stocks (which they define as stocks with an empty book), but argue that the opposite should occur for liquid stocks.[32] We use three depth measures in Table 7: $DepthAt (time-weighted dollar depth at the NBBO), $Depth5₵ (time-weighted cumulative dollar depth up to 5 cents from the NBBO), and $Depth1% (time-weighted cumulative dollar depth up to a distance from the NBBO equal to 1% of the stock price). As before, these depth measures include both displayed and non-displayed orders on the NYSE book.

Looking at the multi-tick environment, we observe the strong effect of increased adverse selection imposed by the HFT market makers' strategies: NBBO depth, as well as cumulative depth several ticks away from the best market prices, are all significantly lower for stocks with a larger relative tick size. For example, $DepthAt is $6,009 lower and $Depth1% is $330,802 lower on average in the books of stocks with a larger relative tick size in G2 (with similar magnitudes in G1). These differences are significant in all pairs test as well as the regressions in the last two columns of the table. Conversely, it appears that larger relative tick size stocks have more depth when they trade at a one-tick environment. This result is somewhat weaker in the sense that it is significant for all depth definitions and all statistical tests in G2, but only some of the tests are significant in G1.

The unconditional results for depth are a mixture of the one-tick and multi-tick environments and depend on the time spent in each environment. Given that the effects of a larger relative tick size differ between the one-tick and multi-tick environments, it is no surprise that in Table 7 we see a somewhat mixed picture for overall depth. For example, $DepthAt shows no significant differences in G1, while some tests are significant in G2. We see more depth in stocks with a larger relative tick size when we consider the $Depth5₵ measure, but less depth when we look at $Depth1% (though the result for G2 is not statistically significant). Therefore, the only clear results we observe for depth are when we condition on whether the

[32] BBO depth in their model, however, would decrease for all stocks when the relative tick size decreases.

spread is tick-constrained or not. Theoretical papers that provide predictions on the relationship between tick size and depth (e.g., Goettler, Parlour, and Rajan, 2005; Buti et al, 2015), however, do not differentiate the one-tick and the multi-tick environments and hence do not provide implications against which we could benchmark our results.[33]

4.2 Volume

As mentioned in the introduction, the arguments in support of a larger tick size for less actively-traded stocks stress the idea that this change would bring about increased trading by investors. The channels could be via increased liquidity (which we test in this paper) or increased analyst coverage and broker promotion (which we do not test in this paper). Regardless of channel, if this argument is valid, we should find that sample stocks with larger relative tick sizes have more volume than the control stocks. Panel A of Table 8 shows this is not the case: five out of the six statistical tests for overall daily volume differences between smaller and larger relative tick size stocks (three different tests for each of the two relative tick size groups) are not significant at the 5% level. While the analysis we present in the table is conducted on volume during the continuous trading session (from the Thomson Reuters Tick History database), the result is identical (five insignificant tests out of six) when we use total volume from CRSP that includes the opening auctions.

The reason to look at volume during the continuous trading session is that we can get additional insights by looking separately at the one-tick versus multi-tick environments. In a multi-tick environment, there is significantly less trading volume in stocks with a larger relative tick size. In other words, the adverse selection imposed by HFT market makers from increased undercutting of limit orders in the book translates into both lower depth and lower volume. On the other hand, the aggressive strategies by HFT market makers that cancel orders less frequently, increase order submission at the best prices, and post more depth in the book have the opposite effect in the one-tick environment: they generate more trading volume. Hence, the insignificant overall volume result masks two conditional results that go in opposite directions.

[33] We note that the models in Goettler, Parlour, and Rajan (2005) and Buti et al (2015) do not have differential information among traders. Therefore, even if one were to separate the one-tick and multi-tick environments in these models, they may not give rise to the adverse selection effects driven by the HFT market makers' increased use of undercutting limit orders in the multi-tick environment.

The execution of orders (i.e., volume) necessitates that incoming marketable orders are able to find depth in the book, which drives the similarity we observe in the conditional patterns of depth and volume.

While a larger relative tick size may not affect total volume, it can play a role in redistributing it among trading venues in the fragmented marketplace. The current U.S. equity market consists of a plethora of trading venues, some of which predominantly trade in penny increments (e.g., the NYSE) while others are able to execute trades at sub-penny increments (e.g., alternative trading systems such as crossing networks). Panel B of Table 8 shows that a larger relative tick size reduces the NYSE market share of trading. The reduction in total market share ranges from 6.5% in G1 to 3% in G2, but all differences are statistically significant. These results, which echo those in Bartlett and McCray (2013), Buti et al (2014), and Kwan, Masulis, and McInish (2015), suggest that a tick size change without a reform in rules on whether trades can execute in sub-pennies may turn into an exercise in shifting order flow among trading venues rather than an increase in total investor trading.

We also see that the reduction in NYSE market share is much greater in the one-tick environment: 21.2% (G1) and 15.6% (G2). This result makes sense: when the queue is longer on the NYSE because limit orders cannot improve on the best prices in the one-tick environment, traders send limit orders to other venues, including those that execute within the spread. While we do not have direct information about volume that executes on crossing networks, we can look at volume reported by Alternative Display Facilities (ADFs) that were set up to report off-exchange volume, mostly from dark pools and over-the-counter trading by dealers. Panel C of Table 8 shows that indeed the market share of ADFs increases the most in the one-tick environment (by 13% in G1 and 7.1% in G2) for stocks with a larger relative tick size.[34]

4.3 Spreads

The last set of liquidity measures we study is computed from prices (either quoted or transacted). Quoted spreads are extensively used as a measure of liquidity in the market microstructure literature, and there are many models in which frictions create impediments to liquidity and give

[34] We note that the overall increase in market share of ADFs for stocks with a larger relative tick size is smaller than the decrease in the NYSE market share of trading these stocks, suggesting that part of the decrease in NYSE market share is driven by order flow moving to other exchanges perhaps to gain time priority.

rise to bid-ask spreads [see O'Hara (1995)].[35] Exactly how spreads should change with tick size is unclear. Goettler, Parlour and Rajan's (2005) model of a dynamic limit order market predicts that a market with a smaller tick size should have smaller quoted spreads, while Kadan (2006) argues that a change in tick size will have an ambiguous effect on spreads (depending upon the number of dealers in the market). Buti et al (2015) show that a smaller relative tick size would imply an increase in spreads, though the percentage spread prediction depends on the liquidity of the stock (which they define as empty versus full initial state of the limit order book in the model).

We calculate time-weighted quoted spreads in two ways: (i) "true" NYSE spreads based on all orders in the book (including both displayed and non-displayed orders, as well as orders for fewer than 100 shares), and (ii) NBBO spreads (based on published quotes from the NYSE and all the other markets). Panel A of Table 9 shows the dollar spreads while Panel B contains the percentage spreads, defined as the ask minus the bid divided by the mid-quote. The percentage spreads can be viewed as the round-trip transaction costs of a portfolio manager who attempts to trade a small dollar position. What is immediately apparent from the table is that dollar spreads for a size-stratified sample of NYSE stocks these days are very small: 2.6 cents in G1 (for $NYSEsprd) and 3.3 cents in G2. NBBO spreads are even a bit smaller, reflecting competition from other trading venues.[36]

The influence of the relative tick size on spreads differs depending on whether one looks at dollar or percentage spreads. Dollar spreads for stocks with a larger relative tick size appear to be reliably smaller. It is conceivable that the smaller spreads for G1 and G2 sample stocks are driven by the lower prices of these stocks, though the relationship between dollar spreads and stock prices is not strong in our sample. One motivation for paying more attention to percentage spreads than to dollar spreads is that percentage spreads can be viewed as adjusting for the different price level of the sample and control stocks by construction. When we examine the

[35] While strictly speaking the spread is only a measure of liquidity for relatively small marketable orders (Easley and O'Hara, 1987), it is important to recognize that the economic frictions driving illiquidity also create the spread, and hence spreads are a proxy for the presence of these economic frictions and therefore relevant for the discussion of liquidity in general.
[36] We do not condition the spread analysis on being in a one-tick versus a multi-tick spread environment because the two environments are defined in terms of the size of the spread (one tick versus multiple ticks) and hence the implications for the spread size would be trivial.

results for percentage spreads, we indeed see a different picture: 11 out of the 12 statistical tests (two spread measures x two groups x three statistical tests per measure/group) are not statistically different from zero at the 5% significance level. Hence, we find no evidence supporting a link between relative tick size and transactions costs in terms of percentage quoted spreads.[37]

Panel C of Table 9 shows the percentage effective (half) spreads, defined as price minus the mid-quote for marketable buy orders or mid-quote minus price for marketable sell orders, divided by the mid-quote. The percentage effective spread is a measure of the total price impact of marketable orders. Here as well, the regression coefficients in the right-most columns show no statistically significant difference between the sample and control stocks, strongly suggesting that these measures of transactions costs also do not seem to be related to the relative tick size. This result is consistent with Bacidore, Battalio, and Jennings (2003) and Bessembinder (2003) who found that percentage effective spreads did not significantly change for NYSE stocks (in the former) or Nasdaq stocks (in the latter) following decimalization.[38]

In summary, we find that the relative tick size does not have a material effect on liquidity: results for depth are mixed depending on the measure, volume differences are insignificant, and percentage spreads differences are insignificant. The deeper insights require conditioning on whether the spread is constrained to one tick or not, which strongly affects the strategies of the HFT market makers. When these fast and sophisticated traders are able to undercut (other trader types and each other) in a multi-tick environment, the increase in adverse selection imposed by the undercutting translates into worsened liquidity: less depth and lower volume. When the spread is constrained to one tick, the more aggressive strategies employed by HFT market makers result in better liquidity: more depth and higher volume. It is important to understand the nature of the conditional results when thinking about tick size regulation that can impact the mix between the one-tick and multi-tick environments. We return to this issue in the conclusions.

[37] Our result is consistent with Bourghelle and Declerck's (2004) finding of no effect on quoted spreads following a change in tick size on Euronext Paris.

[38] Buti et al (2015) look at the relations between relative tick size and both spreads and percentage spreads for U.S. stocks. They find that smaller relative tick size stocks have wider quoted spreads and narrower percentage quoted spreads, which is consistent with the prediction of their model for illiquid stocks.

5. What about profits?

Why would HFT market makers change their strategies to trade more often in stocks with larger relative tick sizes? One potential explanation is profitability – they simply make more money trading those stocks. While their larger market share result is suggestive of greater profitability, our unique data enables us to provide more direct evidence of the HFT market makers' profit margins on trading.

At the outset, however, we offer a caution on computations that have to do with HFT profits. The current market structure in the U.S. is highly fragmented, and the same firms that operate as the DMM and the SLPs on the NYSE trade the same stocks on other venues such as other exchanges or dark pools. Since our data comes from the NYSE systems, our picture of the HFT market makers' overall profits could be unreliable. For example, positions that are entered into on the NYSE can be reversed on another trading venue. Hence, even if the HFT firm actually ends every day with a zero inventory, we may observe an end-of-day imbalance. Carrion (2013) shows that assumptions on how to value such end-of-day inventory imbalances (as well as other assumptions made when computing overall profits) can greatly affect the conclusions drawn from the analysis even if one has perfect data from a single trading venue.[39]

Therefore, we pursue a different approach that focuses on evaluating the traders' (unit) profit margins on trades (or shares traded) rather than their overall profits. We treat the HFT market makers trader type as comprising of a single trader. This assumption is completely accurate in some stocks (where no SLPs are active and hence only the DMM trades), while in other stocks this is an approximation because both the DMM and SLPs are active. In those other stocks, the approximation relies on the reasonable assumption that trading strategies of HFT market makers are highly correlated with each other. In general, looking at profit margins from trading is most meaningful for a market participant whose strategies are solely based on frequent trading in its role as an intermediary, as opposed to investors who hold the security for portfolio considerations. Since the other trader types (institutions, quantitative traders, and individuals) may contain many participants with an investing, rather than trading, horizon, and since the

[39] See also the discussion in Chordia, Goyal, Lehmann, and Saar (2013).

strategies of market participants within each of these other trader types need not be highly correlated, we conduct the profit margin analysis only for the HFT market makers.

We analyze two measures: profit margin per trade and profit margin per share traded. For each stock, we sum every day the cash inflows from all sell trades (shares traded) of the HFT market makers, subtract from it the sum of cash outflows from all their buy trades (shares traded), and divide by the number of their trades (shares traded). The daily average over the sample period of each measure is our estimate of the profit margins per trade (shares traded) of the stock.[40] We then carry out cross-sectional pairs' tests and regressions as in the other tables to evaluate the differences in profit margins between the sample and control stocks.

Table 10 presents the results. The profit margins per trade of HFT market makers in stocks with the largest relative tick sizes (G1) are \$0.86 greater on average than their profit margins in the control stocks. This difference is highly significant in the pairs' tests as well as in the regression analysis. The difference in profit margins for G2 stocks is smaller (\$0.36), but is still significant in the Wilcoxon pairs' test and the regression (though not in the t-test). Generally, the per-share profit margins show a similar pattern (though for G2 the regression coefficient is also insignificant). The overall picture we observe is that stocks with larger relative tick sizes afford the HFT market makers higher profit margins on trades.

Interestingly, the mean and median per trade profit margins (in the first two columns of the table) are negative in G1 and G2. This likely reflects two attributes of the current equity market environment. First, the make-take fee structure provides a cash rebate for executed limit orders at the same time that marketable orders pay a fee. This arrangement benefits HFT market makers and can offset negative profits on liquidity-providing trades (Brogaard, Hendershott, and Riordan, 2014). Second, these HFT market makers are likely active across a number of trading venues, and their strategies are profitable overall even if one segment of the strategy (the portion that we observe on the NYSE) need not be profitable.

The result we document, that stocks with larger relative tick sizes yield HFT market makers higher profit margins on the NYSE, likely reflects a difference in the overall profit margins of the HFT market makers in these stocks across all trading venues. However, an

[40] Note that while the analysis of profit margins does not alleviate the problem that we only observe trading on the NYSE, it sidesteps the need to value the overnight inventory.

alternative interpretation could be that higher profit margins on the NYSE are offset by lower profit margins on other trading venues (that we cannot observe). If the relationship between profit margins on the NYSE and profit margins on other trading venues differs between our sample and control stocks, the results we obtain on the difference between larger and smaller relative tick size stocks would not generalize to the overall profitability of these HFT market makers. We have no evidence to support this alternative interpretation, and our data do not enable us to look at the HFT market makers' profit on other trading venues. As such, we are more comfortable with the interpretation that the result we document reflects differences in the HFT market makers' overall profit margins, though the alternative interpretation cannot be ruled out unequivocally.[41]

6. Conclusions

Mary Jo White, Chairman of the SEC, recently called for a need "to rethink some of the assumptions that underlie today's market structure," and in particular questioned whether today's markets should retain a "one-size-fits-all structure."[42] Tick size policy is one such fundamental market structure issue, and in this concluding section we discuss the implications of our results for the current debates regarding the role of tick size in affecting U.S. equity market quality.

For some of these debates our results provide clear answers. We find, for example, that a larger relative tick size is beneficial to HFT market makers. The larger tick size increases profit margins on trades and HFT market makers end up trading more aggressively. Our results suggest that increasing minimum tick sizes will result in high-frequency trading firms playing an even larger role in these stocks. We also found supporting evidence that a larger tick size induces trading to gravitate from the primary market to other non-exchange trading venues. This has been an area of concern to some who feel that markets are already too fragmented, and our results suggest that raising the tick size for some firms would contribute to this tendency.

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[41] We note that our findings on the NYSE market share appear somewhat less consistent with the alternative interpretation according to which the HFT market makers' profit margins increase on the NYSE but decrease on other trading venues. If this were the case, we would expect HFT market makers to shift trading to the NYSE and help the exchange gain market share in stocks with larger relative tick sizes. What we find, however, is the opposite result: the market share of the NYSE in trading these stocks is actually lower, not higher.

[42] See White (2013).

Can varying the minimum tick size improve market quality? Our results suggest that it can, but that both the goals of doing so and its implementation are crucial. In particular, we find that overall percentage spreads are not lower, and overall volume is not higher for stocks with a larger relative tick size. To the extent that raising the tick size is intended to induce more investors to trade these stocks, then this policy may not succeed. Similarly, if the hope is to lower transactions costs then again this is unlikely to occur. But as we discussed, it is crucial not to overlook the role played by a firm's normal spread environment. For stocks trading with a spread of one-tick (i.e. the stock has a one cent spread), increasing the tick should lead to greater depth and higher volume, both features suggestive of higher market quality. For stocks trading with a multi-tick spread, the opposite occurs with lower depth and smaller volume. Simply raising tick sizes for broad classes of stocks is unlikely to be optimal.

Recently, the SEC announced a pilot program to investigate the effects of raising the tick size to 0.05 for small, illiquid stocks. The SEC will run a controlled field experiment, changing the absolute tick size for matched set of sample stocks. Interestingly, the majority of our sample firms meet the eligibility requirements for inclusion into the pilot , with 43 pairs out of 60 in G1 and 39 pairs out of 60 in G2 satisfying the SEC criteria. We reran our analysis using only these eligible pairs and found essentially unchanged results. Hence, our findings here are directly applicable to the proposed pilot. Of particular importance, our research underscores the necessity of the SEC evaluating the empirical results of the pilot conditional on whether sample firms trade in a one-tick or a multi-tick environment.

Overall, our research suggests that a one-size-fits-all tick policy may no longer be optimal for U.S. equity markets. While our research here has looked at the effects of larger relative tick sizes, for many actively traded firms a smaller tick size may actually be better suited to their trading environment. In particular, one way to interpret our results is that the optimal minimum tick size is one that approximates a stock's normal (unconstrained) spread level. From this perspective, the minimum tick might be better set for active stocks at half a cent or even lower, while for inactive stocks at 5 cents or higher. With the advent of technology, adjusting the minimum tick to a stock's trading environment, perhaps by linking it to the stock's average spread level (say over the previous 12 months), seems a notion worth pursuing.

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Table 1
Summary Statistics

Our sample period is May and June, 2012, and the universe of securities consists of all common domestic stocks listed on the NYSE. We form 2 groups from among these stocks segmented by the stock price ranges: \$5–\$10, and \$10–\$20 (where we use the stock price on the day before the sample period begins). Within each price range, we sort stocks by market capitalization and choose a stratified sample of 60 stocks in a uniform manner to represent the entire range of market capitalization. The first group (G1) is comprised of 60 stocks with prices between \$5 and \$10, and the second group (G2) is comprised of 60 stocks with prices from \$10 and up to \$20. We call stocks in G1 and G2 the "sample stocks." Each stock in G1 and G2 is then matched to a control stock with a higher price range (from \$20 to \$100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization as of the end of the previous calendar year. Panel A provides price and market capitalization summary statistics for both sample and control stocks from the CRSP and TAQ databases. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets. Panel B uses the NYSE data to compare the percentage of time that the bid-ask spread (either the NBBO or the NYSE BBO) for the sample and control stocks is equal exactly one tick. We present the cross-sectional mean and median of the percentage of time at one-tick spreads for the sample stocks, as well as mean and median differences between the matched pairs of sample and control stocks in each relative tick size category (G1 or G2). We provide *p*-values for two-sided pairs *t*-test and Wilcoxon singed-rank test against the hypothesis of zero difference. The two right-most columns of the table contain the intercept and *p*-value from a regression of the paired differences in the variable presented on paired differences between the sample and control stocks in volatility and investor clientele variables (the number of investors and the percentage of institutional holdings). The *p*-value for the regression coefficient is computed using White Heteroskedasticity-consistent standard errors.

Panel A: Summary Statistics for the Sample and Control Stocks

		G1		G2	
		Sample	Control	Sample	Control
Market Cap (in \$1,000)	Mean	850,993	999,223	1,721,834	1,784,106
	Median	446,563	660,939	805,484	850,813
Price (\$)	Mean	7.56	32.56	14.55	34.95
	Median	7.70	27.44	14.45	30.99
Num. of Stocks		60	60	60	60

Panel B: Percentage of Time at 1-Tick Spreads

Group	Variable	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-value
G1 (largest rel. tick size)	1tickNBBO	62.5%	72.7%	50.2%	48.8%	<.001	<.001	0.492	<.001
	1tickBBO	47.6%	49.1%	40.4%	40.2%	<.001	<.001	0.393	<.001
G2 (large rel. tick size)	1tickNBBO	50.7%	46.6%	34.5%	29.7%	<.001	<.001	0.349	<.001
	1tickBBO	39.3%	30.7%	28.9%	21.5%	<.001	<.001	0.292	<.001

Table 2

Duration Analysis by Trader Type

This table presents duration analysis of limit order cancellation and execution. We use an accelerated failure model that assumes time-to-cancellation (or time-to-execution) follows a Weibull distribution. The logarithm of time-to-cancellation (or time-to-execution) is modeled as a linear function of an intercept, a dummy variable that takes the value 1 for the sample stocks, the distance of the limit price from the relevant side of the NBBO quote (i.e., bid for a limit buy order and ask for a limit sell order), same-side NYSE depth, and opposite-side NYSE depth. To aid in the interpretation of the results, we report a transformation that gives the percentage difference in the cancellation (or execution) rate. We report the percent differences in cancellation and execution rates estimated using the Weibull Model separately for limit orders submitted by institutions (regular agency order flow), quantitative traders (program traders and index arbitrageurs), and HFT market makers (high-frequency trading firms that act as market makers on the NYSE, either as the Designated Market Maker or as Supplementary Liquidity Providers). G1(G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between \$5 and \$10 (\$10 and \$20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range (\$20 to \$100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The estimates are based on all limit orders that arrived in each stock during the two-month sample period: May and June, 2012. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets.

	G1		G2	
	Mean	Median	Mean	Median
Institutions	-13.49%	-18.84%	-4.07%	-13.59%
(%ΔCancellation Rate)	(0.012)	(0.006)	(0.474)	(0.052)
Quantitative	-21.21%	-26.02%	-12.81%	-9.83%
(%ΔCancellation Rate)	(<.001)	(<.001)	(<.001)	(0.003)
HFT Market Makers	-23.89%	-40.41%	-18.48%	-35.41%
(%ΔCancellation Rate)	(0.005)	(<.001)	(0.035)	(<.001)
Institutions	99.6%	84.3%	110.8%	40.8%
(%ΔExecution Rate)	(<.001)	(<.001)	(<.001)	(<.001)
Quantitative	185.8%	111.5%	156.1%	77.9%
(%ΔExecution Rate)	(<.001)	(<.001)	(<.001)	(0.001)
HFT Market Makers	523.9%	141.9%	482.2%	128.4%
(%ΔExecution Rate)	(0.001)	(<.001)	(<.001)	(<.001)

Table 3

Limit Order Submission by Trader Type

This table presents results on the share of each trader type in limit order submission at the best NYSE bid and ask prices. Panel A provides information about the share of each trader type in the category of limit orders that are submitted at the best prices. Panel B provides information about limit orders that improve (or undercut) the best NYSE prices (only at times at which the spread consists of multiple ticks). For each trader type, we compute the ratio of its limit orders that step ahead of the best prices to all limit orders that improve the best prices (by all trader types). The trader types we consider in this table are: institutions (regular agency order flow), quantitative traders (program traders and index arbitrageurs), and HFT market makers (high-frequency trading firms that act as market makers on the NYSE, either as the Designated Market Maker or as Supplementary Liquidity Providers). We present the cross-sectional mean and median of the limit order submission measure for the sample stocks, as well as mean and median differences between the matched pairs of sample and control stocks in each relative tick size category (G1 or G2). We provide *p*-values for two-sided pairs *t*-test and Wilcoxon singed-rank test against the hypothesis of zero difference. The two right-most columns of the table contain the intercept and *p*-value from a regression of the paired differences in the variable presented on paired differences between the sample and control stocks in volatility and investor clientele variables (the number of investors and the percentage of institutional holdings). The *p*-value for the regression coefficient is computed using White Heteroskedasticity-consistent standard errors. G1 (G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $5 and $10 ($10 and $20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range ($20 to $100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The two-month sample period is comprised of May and June, 2012. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets.

Panel A: Proportion of Limit Orders Submitted at the Best NYSE Prices

Group	Trader Type	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-value
G1 (largest)	Institutions	22.9%	20.8%	6.2%	5.0%	0.003	0.003	0.064	0.017
	Quantitative	14.7%	13.9%	1.3%	-0.6%	0.337	0.585	0.004	0.789
	HFT MM	32.6%	37.0%	9.6%	8.0%	<.001	<.001	0.128	<.001
G2 (large)	Institutions	23.0%	19.2%	4.0%	0.7%	0.036	0.136	0.041	0.037
	Quantitative	15.0%	14.5%	2.5%	1.2%	0.100	0.248	0.027	0.069
	HFT MM	32.9%	31.3%	6.3%	5.1%	0.016	0.031	0.062	0.015

Panel B: Proportion of Limit Orders Submitted Ahead of the Best NYSE Prices

Group	Trader Type	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-value
G1 (largest)	Institutions	38.4%	33.8%	-2.8%	-4.9%	0.370	0.227	-0.004	0.919
	Quantitative	10.2%	8.8%	-6.5%	-6.5%	<.001	<.001	-0.077	<.001
	HFT MM	39.0%	36.7%	9.7%	4.6%	0.004	0.008	0.089	0.034
G2 (large)	Institutions	40.6%	33.1%	-2.2%	-4.9%	0.509	0.39	-0.019	0.572
	Quantitative	11.2%	11.3%	-4.6%	-4.8%	<.001	<.001	-0.043	<.001
	HFT MM	36.0%	36.1%	7.1%	5.9%	0.035	0.037	0.064	0.055

Table 4

Permanent Price Impact of Undercutting Limit Orders

This table presents results on the percentage permanent price impact of limit orders that undercut the best NYSE prices. We compute the percentage permanent price impact for each limit order as:

$$\text{Permanent Price Impact} = \frac{\left(\text{midquote}_{t+5\text{seconds}} - \text{midquote}_{t}\right) I}{\text{midquote}}$$

where I = +1 for a buy limit order and I = –1 for a sell limit order, and average all such permanent price impacts for the undercutting orders of a trader type in a particular stock. We present the cross-sectional mean and median of the limit order submission measure for the sample stocks, as well as mean and median differences between the matched pairs of sample and control stocks in each relative tick size category (G1 or G2). We provide *p*-values for two-sided pairs *t*-test and Wilcoxon singed-rank test against the hypothesis of zero difference. The two right-most columns of the table contain the intercept and *p*-value from a regression of the paired differences in the variable presented on paired differences between the sample and control stocks in volatility and investor clientele variables (the number of investors and the percentage of institutional holdings). The *p*-value for the regression coefficient is computed using White Heteroskedasticity-consistent standard errors. G1 (G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $5 and $10 ($10 and $20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range ($20 to $100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The two-month sample period is comprised of May and June, 2012. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets.

Group	Trader Type	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-value
G1 (largest)	Institutions	0.0663	0.0667	0.0334	0.0318	<.001	<.001	0.0275	<.001
	Quantitative	0.0663	0.0670	0.0359	0.0332	<.001	<.001	0.0359	<.001
	HFT MM	0.1086	0.0880	0.0581	0.0526	<.001	<.001	0.0497	<.001
G2 (large)	Institutions	0.0437	0.0434	0.0164	0.0168	<.001	<.001	0.0155	<.001
	Quantitative	0.0451	0.0442	0.0175	0.0178	<.001	<.001	0.0167	<.001
	HFT MM	0.0638	0.0521	0.0201	0.0275	0.025	<.001	0.0192	0.034

Table 5

Trader Type Participation in Trading

This table presents the proportion of volume that comes from each trader type. The trader types we consider in this table are: individuals, institutions (regular agency order flow), quantitative traders (program traders and index arbitrageurs), and HFT market makers (high-frequency trading firms that act as market makers on the NYSE, either as the Designated Market Maker or as Supplementary Liquidity Providers). We present the cross-sectional mean and median of the proportion of volume of each trader type for the sample stocks, as well as mean and median differences between the matched pairs of sample and control stocks in each relative tick size category (G1 or G2). We provide *p*-values for two-sided pairs *t*-test and Wilcoxon singed-rank test against the hypothesis of zero difference. The two right-most columns of the table contain the intercept and *p*-value from a regression of the paired differences in the variable presented on paired differences between the sample and control stocks in volatility and investor clientele variables (the number of investors and the percentage of institutional holdings). The *p*-value for the regression coefficient is computed using White Heteroskedasticity-consistent standard errors. G1 (G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between \$5 and \$10 (\$10 and \$20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range (\$20 to \$100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The two-month sample period is comprised of May and June, 2012. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets.

Group	Trader Type	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-value
G1 (largest)	Individuals	1.0%	0.5%	0.6%	0.1%	0.005	0.001	0.004	0.146
	Institutions	47.8%	46.4%	1.1%	0.8%	0.373	0.641	0.009	0.549
	Quantitative	22.5%	23.5%	-1.0%	0.5%	0.348	0.988	-0.009	0.467
	HFT MM	15.2%	14.8%	5.5%	4.6%	<.001	<.001	0.066	<.001
G2 (large)	Individuals	0.6%	0.3%	0.1%	0.1%	0.627	0.296	0.001	0.603
	Institutions	45.8%	44.8%	0.6%	0.0%	0.618	0.766	0.003	0.784
	Quantitative	22.9%	23.7%	-0.4%	-1.1%	0.596	0.475	-0.003	0.739
	HFT MM	16.0%	15.1%	5.9%	5.5%	<.001	<.001	0.058	<.001

Table 6

Depth Contribution by Trader Type

This table presents analysis of the contribution to NYSE depth of different trader types: institutions (regular agency order flow), quantitative traders (program traders and index arbitrageurs), and HFT market makers (high-frequency trading firms that act as market makers on the NYSE, either as the Designated Market Maker or as Supplementary Liquidity Providers). In Panel A, we present the cross-sectional mean and median of time-weighted dollar NYSE depth that is contributed by each trader type at the National Best Bid or Offer (NBBO). The measure of depth we use represents "true" NYSE depth in that it includes both displayed and non-displayed shares on the book. In Panel B, we present the cross-sectional mean and median of cumulative time-weighted dollar NYSE depth up to 5 cents from the NBBO that is contributed by each trader type. MnDiff and MdDiff refer to the mean and median differences, respectively, between the matched pairs of sample and control stocks in each relative tick size category (G1 or G2). We provide *p*-values for two-sided pairs *t*-test and Wilcoxon singed-rank test against the hypothesis of zero difference. The two right-most columns of the table contain the intercept and *p*-value from a regression of the paired differences in the variable presented on paired differences between the sample and control stocks in volatility and investor clientele variables (the number of investors and the percentage of institutional holdings). The *p*-value for the regression coefficient is computed using White Heteroskedasticity-consistent standard errors. G1 (G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between \$5 and \$10 (\$10 and \$20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range (\$20 to \$100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The two-month sample period is comprised of May and June, 2012. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets.

Panel A: Dollar Depth at the NBBO by Trader Type

	Group	Trader Type	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-val.
One Tick	G1 (largest)	Institutions	10,287	4,051	1,416	2,225	0.730	<.001	1577.4	0.770
		Quantitative	3,704	1,906	2,564	1,024	<.001	<.001	2717.89	<.001
		HFT MM	8,814	1,371	7,667	651	0.005	<.001	9258.72	0.010
	G2 (large)	Institutions	11,600	3,615	7,051	1,948	0.001	<.001	7051.85	<.001
		Quantitative	3,701	1,850	2,382	1,075	<.001	<.001	2243.57	<.001
		HFT MM	9,544	1,396	7,450	974	0.002	<.001	7262.26	<.001
Multi Tick	G1 (largest)	Institutions	1,483	1,142	-3,147	-2,620	<.001	<.001	-3272.45	<.001
		Quantitative	618	656	-1,694	-1,602	<.001	<.001	-1787.62	<.001
		HFT MM	731	560	-1,225	-1,151	<.001	<.001	-1144.48	<.001
	G2 (large)	Institutions	2,115	1,864	-2,644	-2,233	<.001	<.001	-2578.17	<.001
		Quantitative	1,073	1,207	-1,303	-1,134	<.001	<.001	-1289.56	<.001
		HFT MM	1,133	979	-1,058	-912	<.001	<.001	-1074.09	<.001

Panel B: Dollar Depth up to 1% from the NBBO by Trader Type

	Group	Trader Type	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-val.
One Tick	G1 (largest)	Institutions	109,476	39,377	6,048	2,645	0.888	0.072	12518.05	0.830
		Quantitative	48,046	39,636	-10,342	-1,112	0.210	0.541	-10406.63	0.260
		HFT MM	56,796	6,326	45,756	2,789	0.005	<.001	52351.28	0.010
	G2 (large)	Institutions	213,273	71,824	100,379	27,779	<.001	<.001	100815.98	<.001
		Quantitative	110,480	90,095	13,745	13,661	0.361	0.046	16759.18	0.240
		HFT MM	84,380	8,978	45,633	3,549	0.004	0.001	46850.62	<.001
Multi Tick	G1 (largest)	Institutions	14,555	11,750	-104,976	-80,334	<.001	<.001	-113416.75	<.001
		Quantitative	14,855	10,320	-120,821	-76,919	<.001	<.001	-136580.48	<.001
		HFT MM	4,144	3,348	-18,293	-14,601	<.001	<.001	-20345.66	<.001
	G2 (large)	Institutions	48,246	38,807	-94,783	-65,567	<.001	<.001	-93612.88	<.001
		Quantitative	43,992	29,048	-151,361	-66,401	<.001	<.001	-149581.41	<.001
		HFT MM	8,689	6,687	-17,161	-14,948	<.001	<.001	-17008.09	<.001

Table 7
Depth

This table presents analysis of NYSE depth close to the best bid and ask prices in the market. We present the cross-sectional mean and median of "true" time-weighted dollar NYSE depth, which includes both displayed and non-displayed shares on the book. NYSE depth at the NBBO is denoted by $DepthAt, cumulative NYSE depth up to 5 cents from the National Best Bid and Offer (NBBO) is denoted by $Depth5ℂ, and cumulative NYSE depth up to the number of ticks that constitute 1% of the average price of the stock from the National Best Bid and Offer (NBBO) is denoted by $Depth1%. MnDiff and MdDiff refer to the mean and median differences, respectively, between the matched pairs of sample and control stocks in each relative tick size category (G1 or G2). We provide *p*-values for two-sided pairs *t*-test and Wilcoxon singed-rank test against the hypothesis of zero difference. The two right-most columns of the table contain the intercept and *p*-value from a regression of the paired differences in the variable presented on paired differences between the sample and control stocks in volatility and investor clientele variables (the number of investors and the percentage of institutional holdings). The *p*-value for the regression coefficient is computed using White Heteroskedasticity-consistent standard errors. G1 (G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $5 and $10 ($10 and $20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range ($20 to $100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The two-month sample period is comprised of May and June, 2012. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets.

	Group	Variable	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-val.
All	G1 (largest)	$DepthAt	25,863	10,318	6,654	461	0.334	0.61	9,137.83	0.31
		$Depth5ℂ	228,858	96,966	127,640	39,861	0.012	<.001	145,236.56	0.03
		$Depth1%	320,685	143,214	-157,339	-84,590	0.020	<.001	-167,377.23	0.06
	G2 (large)	$DepthAt	28,619	10,177	12,283	534	0.006	0.066	11,842.88	0.01
		$Depth5ℂ	327,929	110,889	190,167	49,157	<.001	<.001	183,038.87	0.00
		$Depth1%	625,042	358,234	-76,694	-7,881	0.172	0.27	-68,548.08	0.19
One Tick	G1 (largest)	$DepthAt	24,940	8,529	11,648	4,186	0.117	<.001	13,932.51	0.150
		$Depth5ℂ	221,207	79,839	151,013	54,069	0.005	<.001	169,758.56	0.020
		$Depth1%	307,690	127,192	83,316	7,997	0.276	0.030	105,845.34	0.290
	G2 (large)	$DepthAt	27,001	8,507	18,271	5,039	<.001	<.001	17,922.03	<.001
		$Depth5ℂ	312,437	80,569	216,767	53,486	<.001	<.001	210,416.52	<.001
		$Depth1%	565,521	243,873	238,710	76,092	0.001	<.001	244,763.79	<.001
Multi Tick	G1 (largest)	$DepthAt	3,431	3,240	-7,022	-6,368	<.001	<.001	-7,281.68	<.001
		$Depth5ℂ	27,086	23,622	-21,455	-12,145	<.001	<.001	-23,905.38	<.001
		$Depth1%	43,052	30,478	-287,132	-178,697	<.001	<.001	-323,969.80	<.001
	G2 (large)	$DepthAt	5,011	4,986	-6,009	-4,891	<.001	<.001	-5,917.02	<.001
		$Depth5ℂ	39,916	28,149	-16,031	-9,488	0.016	0.032	-15,872.12	0.020
		$Depth1%	122,183	96,304	-330,802	-151,055	<.001	<.001	-325,998.32	<.001

Table 8
Volume and Market Share

This table presents analysis of NYSE volume and market share as well as the market share of Alternative Display Facilities that report executions in dark pool and over-the-counter. In Panel A, we present the cross-sectional mean and median of dollar volume during the continuous trading session in all markets from the Thomson Reuters Tick History database. In Panel B, we present the cross-sectional mean and median of NYSE volume market share, while inn Panel C we present the market share of the Alternative Display Facilities. MnDiff and MdDiff refer to the mean and median differences, respectively, between the matched pairs of sample and control stocks in each relative tick size category (G1 or G2). We provide *p*-values for two-sided pairs *t*-test and Wilcoxon singed-rank test against the hypothesis of zero difference. The two right-most columns of the table contain the intercept and *p*-value from a regression of the paired differences in the variable presented on paired differences between the sample and control stocks in volatility and investor clientele variables (the number of investors and the percentage of institutional holdings). The *p*-value for the regression coefficient is computed using White Heteroskedasticity-consistent standard errors. G1 (G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $5 and $10 ($10 and $20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range ($20 to $100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The two-month sample period is comprised of May and June, 2012.

Panel A: Dollar Volume

		Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-val.
All	G1	9,950,210	1,945,526	2,519,563	-610,141	0.235	0.254	2,000,301	0.473
	G2	17,642,702	3,881,225	4,803,228	174,032	0.040	0.211	3,943,043	0.068
One Tick	G1	9,565,260	1,721,107	5,672,314	726,719	0.016	<.001	5,588,047	0.070
	G2	16,562,882	2,817,486	8,709,690	701,357	0.001	<.001	7,921,575	0.002
Multi Tick	G1	384,950	233,019	-3,152,751	-2,254,050	<.001	<.001	-3,587,746	<.001
	G2	1,079,821	744,293	-3,906,462	-1,704,736	<.001	<.001	-3,978,532	<.001

Panel B: NYSE Market Share

		Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-val.
All	G1	25.7%	24.7%	-6.5%	-6.5%	<.001	<.001	-0.074	<.001
	G2	28.7%	28.1%	-3.0%	-2.5%	0.005	0.010	-0.027	0.010
One Tick	G1	28.2%	26.8%	-21.2%	-17.0%	<.001	<.001	-0.242	<.001
	G2	34.3%	33.0%	-15.6%	-9.1%	<.001	<.001	-0.159	<.001
Multi Tick	G1	22.5%	19.6%	-7.1%	-9.0%	0.005	<.001	-0.068	0.036
	G2	23.8%	22.5%	-4.7%	-4.8%	<.001	<.001	-0.046	<.001

Panel C: Alternative Display Facilities Market Share

		Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-val.
All	G1	26.1%	26.7%	3.6%	4.2%	0.004	<.001	0.042	0.011
	G2	23.8%	23.2%	1.4%	1.3%	0.126	0.095	0.011	0.210
One Tick	G1	26.8%	26.9%	13.0%	13.1%	<.001	<.001	0.128	<.001
	G2	22.3%	22.9%	7.1%	7.6%	<.001	<.001	0.071	<.001
Multi Tick	G1	38.2%	38.6%	8.0%	9.7%	<.001	<.001	0.090	0.001
	G2	35.0%	34.1%	4.7%	4.0%	0.004	0.004	0.045	0.007

Table 9
Quoted and Effective Spreads

This table presents analysis of quoted and effective spreads. In Panel A, we present the cross-sectional mean and median of both National Best Bid and Offer (NBBO) time-weighted dollar quoted spreads ($NBBOsprd) and NYSE "true" time-weighted dollar quoted spreads ($NYSEsprd), which takes into account both displayed and non-displayed shares on the book. In Panel B, we present similar analysis of the percentage NBBO and NYSE quoted spreads, defined as the ask minus the bid divided by the relevant midquote (NBBO midquote for %NBBOsprd and NYSE midquote for %NYSEsprd). In Panel C, we present the average percentage effective (half) spread, defined as the difference between the trade price and the relevant side of the NBBO (price minus the midquote for marketable buy orders; midquote minus price for marketable sell orders), divided by the NBBO midquote. This variable can be thought of as the total price impact of a small marketable order. MnDiff and MdDiff refer to the mean and median differences, respectively, between the matched pairs of sample and control stocks in each relative tick size category (G1 or G2). We provide *p*-values for two-sided pairs *t*-test and Wilcoxon singed-rank test against the hypothesis of zero difference. The two right-most columns of the table contain the intercept and *p*-value from a regression of the paired differences in the variable presented on paired differences between the sample and control stocks in volatility and investor clientele variables (the number of investors and the percentage of institutional holdings). The *p*-value for the regression coefficient is computed using White Heteroskedasticity-consistent standard errors. G1 (G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $5 and $10 ($10 and $20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range ($20 to $100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The two-month sample period is comprised of May and June, 2012. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets.

Panel A: Dollar Quoted Spreads

Group	Variable	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-value
G1	$NBBOsprd	0.023	0.014	-0.060	-0.033	<.001	<.001	-0.063	<.001
(largest)	$NYSEsprd	0.026	0.017	-0.068	-0.040	<.001	<.001	-0.070	<.001
G2	$NBBOsprd	0.027	0.019	-0.041	-0.026	<.001	<.001	-0.043	<.001
(large)	$NYSEsprd	0.033	0.022	-0.047	-0.028	<.001	<.001	-0.049	<.001

Panel B: Percentage Quoted Spreads

Group	Variable	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-value
G1	%NBBOsprd	0.33%	0.21%	0.06%	0.02%	0.209	0.067	0.0003	0.528
(largest)	%NYSEsprd	0.38%	0.24%	0.07%	0.04%	0.081	0.037	0.0005	0.312
G2	%NBBOsprd	0.20%	0.16%	-0.008%	-0.01%	0.728	0.317	-0.0002	0.447
(large)	%NYSEsprd	0.24%	0.18%	-0.003%	-0.02%	0.925	0.254	-0.0001	0.675

Panel C: Percentage Effective (Half) Spreads

Group	Mean	Median	MnDiff	MdDiff	p(t)	p(W)	Coef.	p-value
G1 (largest)	0.12%	0.07%	0.03%	0.02%	0.048	0.004	0.0003	0.216
G2 (large)	0.07%	0.05%	0.00%	0.00%	0.872	0.273	-0.00004	0.630

Table 10

HFT Market Makers' Profit Margins per Trade and per Share-Traded

This table presents the average daily profit margins per trade and per share-traded of HFT market makers, which are high-frequency trading firms that act as market makers on the NYSE (either as the Designated Market Maker or as Supplementary Liquidity Providers). These profit margins measures are computed only from trading that occurs on the NYSE, and therefore do not reflect trading by the same HFT market makers in the same stocks on other markets. We present the cross-sectional mean and median of the two profit margins measures for the sample stocks, as well as mean and median differences between the matched pairs of sample and control stocks in each relative tick size category (G1 or G2). We provide *p*-values for two-sided pairs *t*-test and Wilcoxon singed-rank test against the hypothesis of zero difference. The two right-most columns of the table contain the intercept and *p*-value from a regression of the paired differences in the variable presented on paired differences between the sample and control stocks in volatility and investor clientele variables (the number of investors and the percentage of institutional holdings). The *p*-value for the regression coefficient is computed using White Heteroskedasticity-consistent standard errors. G1 (G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between \$5 and \$10 (\$10 and \$20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range (\$20 to \$100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The two-month sample period is comprised of May and June, 2012. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets.

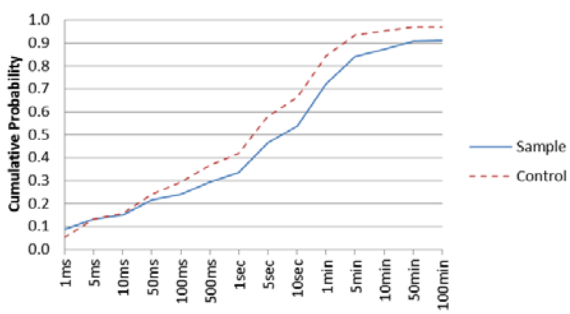
Group	Profit	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1	Per Trade	-0.0230	-0.0456	0.8570	0.7110	<.001	<.001	1.098	<.001
(largest)	Per Share	0.0000	-0.0002	0.0090	0.0070	0.001	<.001	0.012	0.001
G2	Per Trade	-0.1750	-0.0292	0.3610	0.2497	0.100	0.048	0.430	0.049
(large)	Per Share	-0.0020	-0.0003	0.0040	0.0032	0.151	0.044	0.004	0.103

Figure 1
Cancellation and Execution of Limit Orders

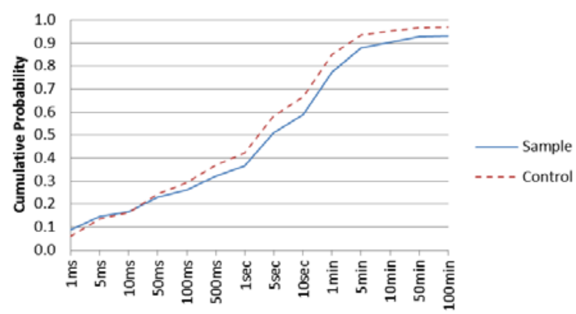
This figure presents estimated distribution functions for time-to-cancellation and time-to-execution for the sample and control stocks in the two relative tick size categories (G1 and G2). The functions are estimated using the life-table method. For time-to-cancellation estimates, execution is assumed to be an exogenous censoring event, while for time-to-execution, cancellation is the censoring event. G1 (G2) sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between \$5 and \$10 (\$10 and \$20). Each stock in G1 and G2 is matched without replacement to a control stock with a higher price range (\$20 to \$100) that is (i) in the same industry (using the Fama-French 10 industries classification), and (ii) closest to it in market capitalization. The relative tick size of the control stocks is on average approximately 4 and 2 times that of the sample stocks in G1 and G2, respectively. The estimates are based on all limit orders that arrived in each stock during the two-month sample period: May and June, 2012. We use order-level data from the NYSE: the exchange's EVENTS table, order and trade reports from the DLE files, as well as published quote messages from the NYSE and all other markets.

Panel A: Distribution of Time-to-Cancellation

G1

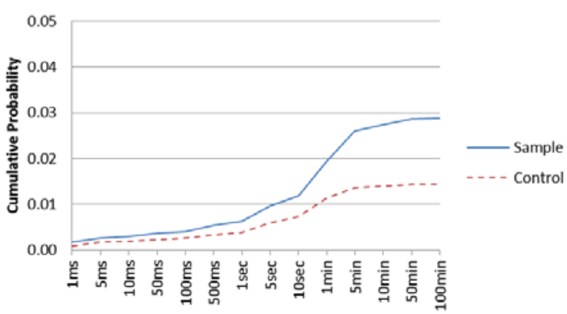


G2



Panel B: Distribution of Time-to-Execution

G1



G2