Relative Tick Size and the Trading Environment

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Abstract

Recent proposals to raise the tick size on small stocks bring attention to the role played by market structure in shaping the trading environment and ultimately in capital formation. In this paper, we look at the how the relative tick size influences liquidity and the biodiversity of trader interactions in the market. Using unique order-level data from the NYSE, we find mixed evidence on whether a larger relative tick size enhances liquidity. Specifically, depth closer to market prices as well as fill rates of limit orders are higher with a larger relative tick size, but resiliency of depth at the best prices is lower and there is a shift to less displayed depth. We observe that high-frequency trading firms that operate as market makers on the NYSE take on a more prominent role in liquidity provision for stocks with larger relative tick sizes: spending more time at the quote, improving market-wide prices, and increasing their participation in trading. A larger relative tick size does not, however, seem to attract more overall trading volume from investors to the stocks, and we find that some volume shifts from the primary market to other (non-exchange) trading venues.

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1. Introduction

There are disquieting signs that all is not well in U.S. equity markets. The number of listed companies has fallen from more than 8,000 in 1997 to fewer than 5000 today.[1] Contributing to this decline is a precipitous fall in IPOs, with only 128 companies going public on U.S. markets in 2012, compared to 214 in 2007.[2] Equity market participation by US households, which peaked in 2007 at 65%, now stands at 52%, and equity market trading volume also remains below its 2007 level. By a variety of metrics, U.S. equity markets appear to be faltering. What is less clear is why this is the case. While a range of causes have been proposed, attention is increasingly turning to the role played by market structure.[3]

Proponents of a market structure explanation point to the role played by tick size, and its particular influence on the liquidity and trading environment for small, illiquid stocks. Tick size refers to the smallest allowable increment between prices that are quoted by trading venues, and in the U.S. tick size is mandated to be one cent for all listed stocks that are not "penny" stocks (whose prices are below $1).[4] That the minimum tick size can affect trading costs may seem obvious, at least for stocks in which the minimum is binding. What is less obvious is that the tick size can also affect other aspects of liquidity as well as the interaction of different types of traders in the market. With a penny tick, incentives to post limit orders are reduced (relative to the pre-decimalization regime) due to the enhanced ability of others to step in front of an order. For less actively traded stocks, this can lead to illiquidity if few orders are posted on the book. Moreover, the lower spreads that have followed decimalization have reduced profits to making

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[1] Data on listed companies and equity participation are from a speech by SEC Chair Mary Jo White on October 2nd, 2013, "Focusing on Fundamentals: The Path to Address Equity Market Structure.".

[2] See Renaissance Capital, US IPO Market 2012Annual Review. Taking a longer perspective is even more sobering. Weild and Kim (2012) note that in the interval 1991-1996, U.S. IPOs averaged 520 per year, and this average rose to 539 a year in 1996-2001.

[3] These other causes include Sarbanes-Oxley which raised the costs of being a public company, the Global Settlement which restricted the ability to subsidize analyst coverage using investment banking fees, the rise of alternative unlisted trading venues such as Second Market and Share Post which reduced the need to go public for start-up firms seeking liquidity, and even just cyclical factors perhaps exacerbated by the financial crisis.

[4] 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.

markets, which in turn can reduce incentives to provide analyst coverage for less active stocks.[5] With small stocks illiquid, and few investors aware of them in any case, the dearth of IPOs (and investors) may be at least partially due to a sub-optimal "one size fits all" tick size.

Would increasing the tick size for small stocks improve the situation? The SEC, Congress (in the recently passed JOBS Act), and a wide variety of industry and market groups have posed exactly this question.[6] But because U.S. non-"penny" stocks all have the same minimum tick size, proposals to answer this question generally involve implementing in the market pilot studies of different tick size regimes, a complex, costly, and time-consuming approach.[7] We believe there is a more direct way to address this issue, and in this paper 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 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, but 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.

Our analysis uses a unique dataset provided to us by the NYSE that includes all orders that arrive at 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 the 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 (such as spreads, depths, depth resiliency, cancellation and execution rates of limit orders, etc.).[8] Our data also allow us to investigate who is providing liquidity, or what is

[5] Weild and Kim (2012) argue that moving from eighths to decimals has cut compensation to market makers by 95% and this loss in trading profits is responsible for the subsequent fall in analyst coverage for new firms.
[6] See, for example, Security Traders Association of New York, Comment Letter to SEC, "Re: Tick Size Study Mandated by the Jumpstart Our Business Startups (JOBS) Act of 2012, August 7, 2012.
[7] Another potential issue with pilot studies is that they are typically of limited scope and duration, which can provide perverse incentives to some market participants hoping to game the pilot's outcome.
[8] 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).

known as the "biodiversity" of the liquidity process. Unlike in earlier times, liquidity today is often provided by computer algorithms deployed by high-frequency trading firms, and in our analysis we can differentiate the specific roles played by high-frequency trading firms acting as market makers (henceforth, HFT market makers), institutional investors, and quantitative traders. 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 size.

Our results provide new insights into liquidity provision in the high-frequency trading environment, and into the particular role played by the tick size in affecting liquidity. With respect to overall liquidity, there is little evidence that percentage spreads differ for stocks with large and small relative tick size, nor do we find differences in percentage effective spreads between our sample and control stocks. Thus, transaction costs do not seem to be related to the relative tick size. We find that larger relative tick size stocks have more depth in the book closer to market prices. Liquidity is also less "fleeting" in stocks with larger relative tick sizes, with lower order cancellation rates and higher execution rates, but depth at the top of the book is replenished more slowly and orders are more likely to be hidden. Overall, there is little evidence that a larger relative tick size substantially enhances stock liquidity.

What is perhaps more intriguing is that a larger relative tick size does change the "biodiversity" of the liquidity provision process. The greater depth close to market prices for stocks with larger relative tick size comes from all major trader types—institutions, quantitative traders, and HFT market makers—and they also spend more time at the quote. However, high-frequency trading firms acting as designated market makers (DMMs) and strategic liquidity providers (SLPs) take on a more prominent role in liquidity provision for stocks with larger relative tick sizes.[9] For these stocks, HFT market makers show the greatest difference between sample and control stocks in terms of percentage time spent at the quotes, and we also observe a greater propensity (relative to other trader types) to submit limit orders that either improve or match the NBBO. The bottom line from a biodiversity perspective is that HFT market makers

[9] We specifically investigate the activity of the high-frequency trading firms that serve as formal electronic market makers and have obligations to the exchange (i.e., DMMs and SLPs) rather than general activity by high-frequency trading firms.

participate more in trading both passively and actively for stocks with larger relative tick sizes (i.e., their market share in terms of dollar volume is higher).

Overall, our results suggest that simply raising the tick size may not be a panacea for the current market malaise. The arguments in support of a larger tick size for less actively-traded stocks stress the idea that this change in market structure would increase the compensation of market makers and bring about increased interest and trading by investors fueled by more analyst coverage (or broker promotion) of these stocks as well as by a deeper, more liquid market. The stated end goal appears to be more trading by investors. What we find is that while larger relative tick sizes attract more liquidity provision from HFT market makers, there is no evidence that their activity actually attracts greater investor trading volume to the stocks. Moreover, we find that the market share of the primary listing market is affected by tick size, consistent with trading in larger relative tick size stocks being diverted to venues in which sub-penny pricing can occur.[10] While our results are obtained by examining stocks trading on the NYSE, the very small size of many of our sample stocks suggests that these results may hold more generally across the market. We discuss these limitations, and the implications of our research for the current debates surrounding the tick size more fully in the paper.

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, Rindi, Wen, and Werner (2013). Our results often support many of these 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, for example, Ahn, Cao, and Cho (1996), Bacidore (1997), Goldstein and Kavajecz (2000), Jones and Lipson (2001), Ronen and Weaver (2001), Bacidore, Battalio, and

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

Jennings (2003), Bessembinder (2003), Chakravarty, Panchapagesan, and Wood (2005), and Bollen and Busse (2006)). Other papers looked at changes in the relative tick size around stock splits (e.g., Angel (1997), Schultz (2000)). More recently, several authors (Bartlett and McCrary (2013), Buti, Consonni, Rindi, and Werner (2013), Kwan, Masulis and McInish (2013), and Yao and Ye (2013)) have examined tick size issues in the context of sub-penny pricing and high-frequency trading. We believe 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. Lastly, as most stocks with the largest relative tick size are also small firms, our results highlight how important high-frequency traders that function as market makers are for liquidity provision in small firms.

This paper is organized as follows. The next section sets out the empirical design of our study, discussing the sample, the data, and our methodology. Section 3 then looks at what happens to liquidity when relative tick sizes change. Using a matched sample approach, we characterize liquidity over a variety of dimensions for stocks with increasing levels of relative tick sizes and we test for significant differences related to tick size. In Section 4, we investigate who provides liquidity for our sample and control stocks, focusing on the different roles played by institutions, quantitative traders, and HFT market makers. Section 5 presents the impact of relative tick size on market share and volume, and 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. The investment environment (and hence the trading environment) for 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. Nonetheless, as noted in the introduction, while the minimum absolute tick size is constrained, the relative tick size—the dollar tick size divided by the price of the stock—is not. This latter 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.

In this research, we investigate how the trading environment differs for stocks with differing relative tick sizes 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 3 groups from among these stocks segmented by the stock price ranges: $1–$5, $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), which is comprised of 60 stocks with prices between $1 and $5, has the largest relative tick size. The second group (G2) is comprised of 60 stocks with prices from $5 and up to $10, and the third group (G3) is comprised of 60 stocks with prices from $10 and up to $20. We call stocks in G1, G2, and G3 the "sample stocks."

Each stock in G1, G2, and G3 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.[11] 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

[11] 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.

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 three groups with different levels of relative tick size allows us to evaluate the robustness of patterns in trading behavior across stocks.

While our matching procedure controls for industry and size, the size control may not be perfect because price and size are correlated in the cross-section of stocks. In particular, it is more difficult to find smaller control stocks in the price range $20 to $100 to match the smaller stocks in the price range $1 to $5. Therefore, we also analyze subgroups comprised of the largest 30 stocks in each group (denoted LG1, LG2, and LG3), and note in the text whether or not the patterns we observe in the overall sample appear to be driven by the larger stocks within each group (which are better matched on size). When the patterns are similar (both in terms of direction and statistical significance), it is more likely that these effects are driven by the relative tick size rather than by market capitalization.

Table 1 presents summary statistics for the sample and control stocks using information from CRSP and TAQ. Stocks with a larger relative tick size tend to be smaller. The mean market capitalization of G1 stocks is $297 million, while the mean size of G2 and G3 stocks are $851 million and $1.72 billion, respectively. The Table also shows that our size matching between the sample and control stocks (within the same industry) is excellent in G3, good in G2, and imperfect in G1. The summary statistics for LG3 and LG2 demonstrate excellent matching for the larger stocks, though for LG1 there clearly remains a size difference.

While the NYSE is the home to many large U.S. firms, there are many small and midcap firms listed on the exchange and they are featured prominently in our size-stratified sample. Out of the 60 stocks in G1 (the largest relative tick size group), 57 have market capitalization less than one billion dollars, while 46 of their control stocks are also under $1B. Out of the 60 stocks in G2, 48 are under $1B, with 45 of the control stocks also in this size category. Lastly 35 stocks out of 60 in G3 and 35 of the control stocks for G3 are under $1B. Thus, while our results relate specifically to the liquidity of larger relative tick size stocks, our study has implications for broader questions relating to the liquidity of small firms. This is especially relevant for the current discussion on changing the tick size, which appears to focus on the needs of smaller firms.

2.2 Data

We use order-level data from the NYSE to perform our analyses. The data source is 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. The NYSE further extracts messages from these log files (e.g., the EVENTS table) that enable a more efficient analysis of the order flow in each stock. 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. The data allow us to associate each order with one of four mutually exclusive trader types. We use the Account Type field in the NYSE data to identify three of the "trader types": institutions (regular agency order flow), individuals, and program traders and index arbitrageurs (for which we use the term "quantitative" order flow).[12] The last trader type is comprised of 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 deployed by several firms.[13] While a human Designated Market Maker may intervene in trading, almost all DMM trading is done by algorithms. Each stock has only one DMM, but several SLPs may be

[12] 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)).

[13] The DMM firms 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.

active in the same stock (though not all stocks have active SLPs).[14] We construct the high-frequency trading (HFT) "market makers" trader type by combining each stock's Designated Market Maker and Supplementary Liquidity Providers. 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.[15] We use these categorizations into 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, executing trades, and so on.

We have a residual category, "Others", which includes all other orders that arrive at the NYSE (e.g., non-agency order flow from member firms). 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 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). We expect classification errors in other categories to be relatively small.

As an important aside, these data also allow us to investigate the role some high-frequency traders play in the liquidity provision process. The population of high-frequency traders in equity markets is heterogeneous, with each firm specializing in one or more strategies. One of the most important and interesting type of high-frequency traders are the electronic market makers (see, Hagströmer and Nordén (2013) and Menkveld (2013)). The DMM and

[14] 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.

[15] NYSE data identifies DMM orders. We also received a list from the NYSE with Firm IDs for all the SLPs in each stock in our sample. By matching this list to the Firm ID in the NYSE data we were able to identify SLPs activity and add it to the DMM to create the "HFT market makers" trader type.

SLPs all belong to this specific category of HFT firms, and hence they allow us to investigate a representative set of high-frequency traders that follow this strategy. There may be additional high-frequency traders in the “others” and “quantitative” categories, but we are unable to specifically identify them as such.

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. Therefore, our order flow analysis uses data only from the NYSE. For many stocks, however, there is significant trading on other exchanges and off-exchange venues and so we are only seeing 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, G2, or G3) 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 BBO, we present the mean and median of the value of the variable for the sample stocks, the mean and median of the paired differences between the sample and control stocks, and tests (a *t*-test and a non-parametric Wilcoxon Signed-Rank) against the two-sided hypothesis that the difference is zero.

We acknowledge that there could be differences between the sample and control stocks in fundamental attributes of stocks other than industry and size that could in principle confound the results. In particular, we thought about two specific important attributes: investor clientele and volatility. Stocks that are held and traded by very different sets of investors may have dissimilarities in their trading environments that our 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.

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.

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., estimating mean-reversion parameters or duration models) is also done in the context of the relevant results in sections 3 and 4.

3. What happens to liquidity?

We begin our analysis of the relationship between relative tick size and liquidity by looking at quoted bid-ask spreads. Spreads have been 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 rise to bid-ask spreads (see O'Hara [1995]).[16] Exactly how spreads should change with tick size is unclear. Goettler, Parlour and Rajan's (2005) model of a

[16] 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.

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 effects on spreads (depending upon the number of dealers in the market), and Buti, Rindi, Wen, and Werner (2013) show that a smaller tick size would imply an increase in spread for illiquid stocks but a decrease in spread for liquid stocks.

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 2 shows the dollar spreads ($NYSEsprd and $NBBOsprd) while Panel B contains the percentage spreads (%NYSEsprd and %NBBOsprd), defined as the ask minus the bid divided by the midquote. 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: 3.3 cents in G3 (for $NYSEsprd) and 2.6 cents in G1 and G2. In percentage term, there is a larger difference across the sample stocks: 0.24%, 0.38%, and 1.11% for G3, G2, and G1, respectively, but overall these are rather small spreads. NBBO spreads are even a bit smaller, reflecting competition from other trading venues.

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, G2, and G3 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 results for percentage spreads, we indeed see a different picture. Only G1 stocks show a significant difference in the pairs *t*-tests, but even this significance disappears when we look at the coefficient on the intercept from the NBBO spread regression controlling for volatility and investor variables (the right-most two columns of the table). Hence, we find no evidence supporting a link between relative tick size and transaction costs in terms of quoted spreads.[17]

Panel C of Table 2 shows the percentage total price impact of an order, 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 midquote. This variable is also called the effective (half) spread in the market microstructure literature. Here as well, the regression coefficients in the right-most column show no statistically significant difference between the sample and control stocks, leading us to conclude that these measures of transaction 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 decimilazation.

While using the NBBO to compute spreads has the advantage that it reflects liquidity in the entire market across all trading venues, our NYSE data allow us to compute many more refined measures of liquidity by restricting our attention only to liquidity provision on the NYSE (the stocks' primary market). If the liquidity provision in stocks is subject to similar economic forces on the NYSE and on other trading venues, these measures would reflect, albeit imperfectly, liquidity provision in the market as a whole.

In Table 3 we look at depth in the limit order book close to market prices, which is arguably the more relevant depth. Goetler, Parlour, and Rajan (2005) predict that a smaller tick size would bring about less depth, while Buti, Rindi, Wen, and Werner (2013) predict that a smaller tick size should result in lower depth for illiquid stocks, with the opposite would be observed for liquid one. We use two depth measures: $DepthAt (time-weighted dollar depth at the NBBO) and $DepthUpto5₵ (time-weighted cumulative dollar depth up to 5 cents from the NBBO). We analyze "true" depth that includes both displayed and non-displayed orders on the NYSE book. Looking at depth up to 5 cents from the NBBO, we observe no statistically significant difference for G1 stocks, but significant differences between the sample and control stocks for both G2 and G3. For example, the mean depth of stocks with larger relative tick sizes

[17] 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.

is $127,598 higher than that of the matched stocks with smaller relative tick sizes in G2, and similarly $189,966 higher in G3.

The insignificant result for G1 is most likely driven by the imperfect matching on market capitalization. When we perform the same analysis for LG1, which is comprised of the largest 30 stocks in G1, the mean depth up to 5 cents from the NBBO is $55,695 higher for stocks with larger relative tick sizes, and the pairs *t*-test and Wilcoxon test (though not the regression coefficient) are statistically significant. It is important to note that even the stocks in LG1 are still rather small, and 27 out of the 30 stocks in this category have market capitalization less than $1 billion. These results suggest that stocks with a larger relative tick size have more depth in the book closer to market prices, a result consistent with Goetler, Parlour, and Rajan (2005) and with Buti, Rindi, Wen, and Werner (2013)'s prediction for illiquid stocks.[18] This enhanced depth potentially affords better execution to orders larger than the depth at the bid or ask prices.

Panel B of Table 3 looks at depth close to market prices and asks whether traders choose to expose their orders more in stocks with a larger relative tick size. Harris (1996, 1997) ties the tick size, which affects the cost of obtaining price priority, to risks from parasitic traders who use their knowledge about the pending interest in the book to the detriment of those submitting the resting limit orders. Traders can use multiple techniques to control the exposure of their orders, including cancelling and resubmitting orders more frequently (Boehmer, Saar, and Yu (2005)), which affects the ability of parasitic traders to interact with their orders, as well as submitting non-displayed limit orders, which may make it more difficult for parasitic traders to obtain a clear picture of the actual depth in the book.

The measure we present in Panel B of Table 3 is the percentage displayed depth in the NYSE book up to 5 cents from the best prices. We are able to compute this measure because we observe all orders that arrive at the NYSE, including non-displayed orders, but this is not a

[18] Buti, Consonni, Rindi, and Werner (2013) look at percentage spreads and book depth for NASDAQ stocks that trade around $1. Rule 612 of Reg NMS allows the tick size of stocks below $1 to go down from $0.01 to $0.0001. Like us, they find that a larger tick size is associated with greater depth. However, they document a larger percentage spread for stocks with a larger tick size, while differences in percentage spreads between the large and small relative tick size categories in our sample disappear when we control for volatility and investor variables. In addition to the difference in the set of control variables in the two studies, it could also be the case that the significant result in Buti et al. stems from the fact that the tick size for stocks above $1 is 100-times the tick size for stocks below $1, while we look at smaller differences (by a multiplier of 2, 4, or 10) between our sample and control stocks.

measure that a regular market participant could perfectly compute. We see that displayed depth constitutes more than 70% of the book for our sample stocks. Still, investors actually appear to display less depth in stocks with a larger relative tick size. The percentage displayed depth is 7.8% lower for stocks with a larger relative tick size in G1, 5.1% lower for stocks in G2, and 2.3% lower in G3, though the result for G3 is not statistically significant.[19] While the percentage difference appears small and the lack of significant result for G3 weakens the conclusions somewhat, we can say that a larger relative tick size does not entice traders to expose more liquidity closer to market prices. If at all, we find weak evidence in the other direction.

Our analysis of percentage quoted and effective spreads in Table 2 suggests that a larger relative tick size does not have an appreciable effect on transactions costs. Our results for depth up to 5 cents from the NBBO show that stocks with larger relative tick sizes have more depth in the book, which could lead to better execution for larger orders. However, we did not find that traders are willing to expose more of their orders when the relative tick size is larger, and hence market participants may not know that more depth is available.

In general, traders who want to execute a larger order in this age of computer trading algorithms often feed the order to an algorithm that chops it into smaller pieces and sends the pieces to the market over time. Hence, the dynamic nature of depth at the best bid or offer (BBO) becomes an important consideration. This issue has long been recognized in the market microstructure literature. Kyle (1985), for example, describes multiple dimensions of liquidity, among which is "resiliency." Resiliency is a dynamic concept that describes the speed at which a market attribute recovers from a shock. Foucault, Kadan, and Kandel (2005) argue that the resiliency of the market is larger when there is a non-zero tick size. Whether this is a general result relating tick size to resiliency of market depth (as opposed to just the spread) is unclear. We look at the resiliency of depth at the best prices to complement our static analysis of depth in Table 3. In particular, a more resilient depth at the NYSE BBO could be an important consideration for larger traders who use algorithms to trade their desired position change.[20]

[19] When we look at LG3 (the 30 largest stocks), the regression coefficient is negative and statistically significant (*p*-value=0.030).

[20] The algorithms that traders use in order to execute a desired position change for a portfolio manager are often called "agency algorithms." The goal of these algorithms is to minimize execution costs relative to a certain benchmark (e.g., VWAP, price at the beginning of the day, etc.). These are different from "proprietary algorithms"

Consider a mean-reversion model with long-run value θ and speed of adjustment κ, $\Delta L_t = \kappa(\theta - L_{t-1}) + \varepsilon_t$, where L_t is depth at the BBO at time t and ΔL_t is the change in depth from $t-1$ to t. We compute the time-weighted average depth at the NYSE BBO every minute during the trading day. We then estimate the mean reversion parameter κ from the following equation for each stock separately:

$$\Delta L_{i,t} = \alpha_i + \kappa_i L_{i,t-1} + \sum_{\tau=1}^{p} \gamma_{i,\tau} \Delta L_{i,t-\tau} + \varepsilon_{i,t}$$

where the constant $\alpha_i = \kappa_i \theta_i$, the interval t is measured in minutes, and we use p=20 lags of the change in depth as control variables (see Kempf, Mayston, and Yadav (2010)).[21]

Table 4 presents the results of the depth resiliency analysis. We show the cross-sectional attributes of the mean-reversion parameter κ separately for the bid and ask sides of the book as well as for total depth at the BBO. As expected, there is mean reversion (i.e., negative coefficients) for the sample stocks in all tick size categories, but the absolute magnitude is rather small (e.g., –0.034, –0.048, and –0.057 for the bid side in G1, G2, and G3, respectively). More importantly, mean reversion for the control stocks appears to be much more negative. For example, a mean difference of 0.081 for G1 on the bid side connotes that mean reversion for stocks with smaller relative tick sizes is faster (–0.150) compared to that of stocks with larger relative tick sizes (–0.034). The results are robust across the three tick size categories, and also after we control for investor variables and volatility in the regressions. This suggests that a larger tick size does not necessarily make depth more resilient in the sense that it replenishes faster, but rather the opposite, which could make it more difficult for larger traders who use agency algorithms to execute their trades.

Another angle with which to examine the dynamics of depth is to focus on the duration of cancellations and executions of orders. In particular, 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

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that are used by high-frequency trading firms to profit from the trading environment itself (see Hasbrouck and Saar (2013)).

[21] We also estimated the equation without lags of the dependent variable and the results were similar. In another test, we estimated this equation with visible depth (rather than total depth) as the dependent variable, and the results exhibited exactly the same patterns. Both analyses are available from the authors.

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) for the sample and control stocks in the three 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 of Figure 1 shows that a significant portion of the limit orders is cancelled very quickly (see also Hasbrouck and Saar (2009)). More importantly from our perspective, we observe that except at very short durations, time-to-cancellation is longer for stocks with larger relative tick sizes. In G2, 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 G2 compared to 84.6% for the control stocks that have smaller relative tick sizes. This effect, which is consistent with the prediction from Harris (1996), is evident in all three relative tick size categories, and the magnitude of the effect appears monotonically increasing with the relative tick size difference between the sample and control stocks.[22]

Turning to execution rates, the model in Goetler, Parlour, and Rajan (2005) predicts that a smaller tick size would lead to shorter time to execution of limit orders. In the current age of trading algorithms, the execution rate of limit orders is rather low. Still, we observe that execution is a more likely outcome for limit orders submitted in stocks with larger tick sizes, which contrasts with the theoretical prediction. 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 G2, 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, G2, and G3.

[22] 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.

We use two structured statistical methodologies to examine the cancellation and execution of limit orders. The first one is an accelerated failure model that assumes 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. The second methodology utilizes semi-parametric Cox regressions, where the logarithm of the hazard rate is modeled as a linear function of the same variables as in the Weibull model.

To aid in the interpretation of the results and make the models comparable, we report a transformation that gives the percentage difference in the cancellation (or execution) rate for both the Cox regressions and the Weibull model. Panel A of Table 5 presents the cross-sectional means (medians) of the percentage difference in cancellation and execution rates together with *p*-values from two-sided *t*-tests (Wilcoxon tests). The first line of the panel shows that the mean cancellation rate of limit orders in stocks with a larger relative tick size is 40.17%, 27.49%, or 17.43% lower than that of orders in stocks with a smaller relative tick size (in categories G1, G2, or G3, respectively) according to the Weibull model. Similarly, the Cox regressions in the second line show that the mean cancellation rate of stocks with a larger relative tick size is 34.61%, 24.12%, or 14.74% lower than the corresponding cancellation rates for the control stocks in G1, G2, or G3, respectively. These findings are highly statistically significant, and suggest that liquidity is less "fleeting" in stocks with larger relative tick sizes.

The third and fourth lines of Panel A of Table 5 show the percentage difference in execution rate of limit orders between the sample and control stocks. The limit order execution analysis is done using the same Weibull model and Cox regressions as the analysis of cancellations. We see that the mean execution rate of limit orders in stocks with larger relative tick sizes is higher by 332.7%, 176.5%, or 189.8% than it is for stocks with smaller relative tick sizes in G1, G2, or G3, respectively, in the Weibull model (with similar numbers in the Cox regressions). The large percentage difference in mean execution rate is driven by the fact that the execution rate in general is very small, and the difference between the sample and control stocks is on the same order of magnitude as the execution rate itself.

The results of the duration models suggest that the dynamic liquidity provision environment for stocks with larger relative tick sizes could indeed be different from that of stocks with smaller relative tick sizes. If one considers lower cancellation rates and higher execution rates desirable, then these attributes can make the submission of limit orders in stocks with larger relative tick sizes more attractive to traders and hence may draw more liquidity provision.

Overall, we see a somewhat mixed picture when we look at the balance of the liquidity measures we investigate in this section. Although percentage spreads do not indicate a difference between stocks with larger or smaller relative tick sizes, depth closer to market prices is higher for stocks with larger relative tick sizes, and limit orders in these stocks have a lower cancellation rate and a higher execution rate. The larger depth and the duration results for limit orders portray a somewhat better environment in terms of liquidity. Still, we find that BBO depth is replenished slower in stocks with larger relative tick sizes, and a larger portion of their depth closer to market prices is non-displayed, which may heighten uncertainty about the amount of liquidity in the market.

4. Who provides liquidity?

Our analysis thus far has focused on characterizing the state of liquidity for stocks with differing relative tick sizes. Equally important to understand is who provides that liquidity, and how, if at all, this process differs for stocks with larger relative tick sizes. As noted earlier in the paper, liquidity provision on the New York Stock Exchange arises from the willingness of market participants to post limit orders. Because we are able to identify orders submitted by individuals, institutions, quantitative traders, and HFT market makers, our data provide a window from which to observe the "biodiversity" of the liquidity provision process. If changing tick sizes is a remedy for market illiquidity, then we would expect to find significant differences in these participants' order placement activities for stocks with different relative tick sizes.

The last set of tests in the previous section involved looking at cancellation rates and execution rates of limit orders. We saw a lower cancellation rate and a higher execution rate for limit orders in stocks with large relative tick sizes. Who is providing the liquidity more patiently by cancelling limit orders less often? Who is enjoying a higher execution rate of their limit orders? Panel B of Table 5 looks specifically at three trader types: institutions, quantitative traders, and HFT market makers.[23]

It is clear that HFT market makers exhibit the most difference between their strategies in stocks with larger and smaller relative tick sizes. For example, the mean cancellation rate of HFT market makers in large tick size stocks is smaller by 42.52% in G1 compared with 22.19% for institutions, and similarly we observe differences in the magnitude of the effects between HFT market makers and institutions in G2 (23.89% versus 13.49%) and G3 (18.48% versus 4.07%). The results for the quantitative traders 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 results in a large increase in the mean execution rate of their orders: 743.1% in G1, 523.9% in G2, and 482.2% in G3, compared with 294.5%, 99.6%, and 110.8% for the institutions in G1, G2, and G3, respectively. While the median execution rates point to a more modest increase, they also demonstrate a lager 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.

[23] The amount of individual investor trading 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 order flow, as opposed to actual trades, because the more sophisticated trader types employ algorithms that cancel and resubmit orders, and consequently the share of individual investors in the orders is negligible. Therefore, in some tables we present only the results for institutions, quantitative traders, and HFT market makers.

We next examine who provides depth close to market prices. 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 5 cents from the NBBO. What is clear from the data is that institutions, quantitative traders, and HFT market makers are all active providers of liquidity. Institutions and market makers play the most active roles, with quantitative traders submitting less dollar depth, particularly at the NBBO. The result in Table 2 that stocks with a larger relative tick size have more depth close to market prices seems to be driven by all three major trader types. The increasing depth pattern we observe (e.g., in Panel B) is strongest in G3, moderately strong in G2, and not statistically significant in G1. As our discussion of Table 2 stressed, the insignificant result in G1 may reflect the imperfect matching on market capitalization in this particular category (i.e., that the control stocks are larger than the sample stocks).[24]

The depth results in Table 6 are time-weighted, but the lower cancellation rates of all trader types in Table 5 would suggest that traders spend more time providing liquidity at the best prices. We can clarify who is actually standing ready to provide liquidity by looking at who is consistently at the inside quote. Table 7 shows this data for the three professional trader groups as well as for individuals. Individuals play a small to negligible role: even in G1, which is primarily comprised of small stocks with market capitalization below $1 billion, individuals are at the best bid or best offer on average only 5.12% of the time, and this number falls to 1.29% in G3. In general, we find that HFT market makers are at the inside quotes the most. This is consistent with Yao and Ye's (2013) finding that Nasdaq stocks with the lowest prices have the highest level of high frequency liquidity provision.[25] We also find that institutions and quantitative traders are more likely to be at the inside quote when the relative tick size is large. There are many reasons why this may occur. If sample stocks have lower trading volume, then orders at the BBO could simply be staying in the book longer waiting for a counterparty. Orders

[24] We see a marginally significant larger depth coming from HFT market makers in some of the tests when we restrict attention to LG1 (the 30 largest stocks in G1).

[25] Our result is thus at variance with Bartlett and McCray (2013) who use the frequency of BBO quote updates in the ITCH data to conclude that HFT activity is curtailed by a larger tick size. Our analysis has the advantage that we have a direct measure of HFT market maker activity rather than a proxy as in their paper. We note, though, that while our results are accurate for HFT market makers, they need not reflect the changes in strategies of other types of HFT traders.

for these larger relative tick size stocks may be more likely to execute elsewhere (in crossing networks, for example) and so orders left on the book at the NYSE stay longer at the BBO.[26]

Another aspect of the quality of liquidity provision is the extent of competition among traders in improving prices and submitting orders at the top of the market. 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 that improve the NBBO or are at the NBBO. Panel A of Table 8 gives market share data by trader type on limit order submissions ahead of the NBBO while Panel B gives market share data for limit orders at the NBBO. The behavior of institutions and quantitative traders shows little difference across our three tick size sample groups (both in terms of statistical significance and magnitude), but the competition from HFT market makers appears to intensify in stocks with larger relative tick sizes. For these stocks, HFT market makers take on an increasing share of limit order production. This result is strongest for limit orders that improve the NBBO and it is weaker for limit orders at the NBBO (where it is not significant for G1 and is marginally so for G3).

We now turn from looking at orders, which are indications of willingness to trade, to trading itself. If HFT market makers end up trading more passively by providing liquidity to other traders, then there need not be a change in the amount of trading they do, just a shift from active to passive trading. Alternatively, HFT market makers could increase their trading both on the passive and active sides as a result of the larger tick size, grabbing more of the total volume relative to other trader types.

We look at these two issues in Table 9 and Table 10. First, in Table 9 we look at the percent of volume of a trader type that represents "passive" liquidity supply (where a trader's limit orders are executed against incoming marketable orders). We measure this by the dollar volume in executed limit orders divided by the total dollar volume for a trader type. The changes appear rather small for all trader types. We observe that institutions and quantitative traders increase slightly their taking of liquidity with marketable orders (i.e., decrease liquidity supply). In the case of quantitative traders pursuing arbitrage strategies, this may reflect a desire for a

[26] Yet another explanation is that dollar spreads for stocks with larger relative tick sizes are so low that bettering the quote is difficult (or impossible if doing so would require sub-penny quoting), resulting in orders staying at the BBO.

faster execution if there are longer queues at each price point in stocks with larger relative tick sizes. Alternatively, the greater depth available near market prices may induce both these trader types to trade via market orders, thereby demanding rather than supplying liquidity. We do not find any significant change for either individuals or HFT market makers.

The results of Table 9—that there is no change in the passive liquidity provision ratio for HFT market makers—suggest that HFT market makers increase both their active and passive trading and hence it is possible that they take more of the market share of volume from other trader types in the market. This conjecture is confirmed by the evidence in Table 10. The numbers are not very large, but the market share in trading volume of HFT market makers in G3 goes up on average by 5.9% and in G2 by 5.5%, both statistically significant. The 3.1% increase in G1 is statistically significant in the pairs tests but not in the regression.[27] The rest of the changes are not statistically significant or not pervasive in the three relative tick-level groups.

5. Where does trading go?

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). If this argument is valid, *ceterus paribus* we should find that sample stocks with larger relative tick sizes have more volume than the control stocks. Panel A of Table 11 shows this is not the case. We work with three definitions of volume: ContVolume is average daily dollar volume during the continuous trading session (9:30am-4:00pm) on the NYSE, TotVolume adds to ContVolume the opening and closing NYSE auctions, , and MktWideVol is average daily dollar volume in the entire market (not just on the NYSE). The first two measures are computed using our NYSE dataset, and hence they include trades that do not print on the tape, like odd-lot trades. The second measure is taken from the CRSP database (daily share volume multiplied by closing price).

[27] 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.

Looking at the regression coefficients in the right most columns of Panel A, there are no statistically significant changes in NYSE volume (once we control for volatility and investor variables) in G3 and G2. The lower volume in G1 sample stocks likely represents insufficient adjustment for market capitalization in this group. Market-wide volume from CRSP for our sample stocks is significantly smaller in G1, not statistically different from the control stocks in G2, and marginally larger in G3. Hopes that raising the tick size will induce greater trading volume are thus not supported by our data; there is no convincing evidence that volume is higher in stocks with larger relative tick sizes.

While tick size may not affect total volume consistently, it can play a role in redistributing it among trading venues in our fragmented markets. The current fragmented U.S. equity market consists of a plethora of trading venues that mostly trade at prices with penny increments (e.g., exchanges such as the NYSE), while others (e.g., alternative trading systems such as crossing networks) are able to execute trades at sub-penny increments (see Buti, Rindi, Wen, and Werner (2013)). Panel B of Table 11 shows that a larger tick size reduces the NYSE market share of trading. The reduction in total market share ranges from 3.07% in G3 to 11.41% in G1, but all changes are statistically significant.[28] These results, which echo those in Bartlett and McCray (2013) and Kwan, Masulis, and McInish (2013), 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.

6. The tick size debate

Mary Jo White, Chairman of the SEC, recently called for increased "focus on fundamentals" to guide decisions regarding "what—if anything—is to be changed in our market structure."[29] Our empirical analysis of relative tick size effects focuses on one such fundamental structure issue, and in this concluding section we discuss the implications of our results for the current debate regarding raising minimum tick sizes for small firms.

[28] This also explains the small difference between the NYSE and market-wide volume results in Panel A of Table 11: while the market-wide volume number for our sample stocks in G3 is larger somewhat from that of the control stocks (and marginally significant), the differences for the NYSE volume measures are not statistically different from zero.
[29] See White (2013).

Advocates of raising the tick size stress the linkage from tick size to market maker profits. Two avenues are suggested for how these profits would then drive additional investor trading. First, more profitable market making could lead to an increase in liquidity provision for the stocks, which would attract additional volume from investors who are willing to trade liquid stocks but shy away from illiquid ones. Second, the higher profitability of market making operations at sell-side firms could lead to greater analyst coverage, enhanced promotion by brokers, and increased willingness of companies to go public. In particular, the argument is that the fall in tick sizes to decimals has both reduced incentives to post limit orders and dramatically reduced compensation to market making in those stocks. The resulting illiquidity has made such stocks unattractive to investors and, combined with the fall in analyst coverage of small firms, also made listing new stocks unattractive to issuers. Raising the minimum tick size addresses these concerns by improving the trading environment for small stocks.

Our analysis essentially follows the first linkage above (tick size to liquidity to volume) by looking at the trading environment for stocks with different relative tick sizes. In our analysis, stocks in our G1 sample face relative tick sizes that are approximately 10 times larger than those of the control stocks, G2 face relative tick sizes that are 4 times larger, and G3 stocks face relative ticks that are 2 times larger. Because our analysis controls for other factors that also affect liquidity (e.g., market capitalization, industry, investor clientele, and volatility), we can extract the effects of tick size on liquidity and the liquidity provision process.

Does a larger relative tick size increase liquidity? We find little evidence of this. Percentage spreads are not significantly different between sample and control stocks, and transactions costs, as captured by the total price impact of a trade, also do not appear to be statistically related to tick size differences. We do find that stocks with larger relative tick sizes have more depth in the book closer to market prices, in large part because institutions, quantitative traders, and especially HFT market makers actively contribute to depth at the quote and their orders spend more time at the quote when the tick size is larger. But this depth replenishes slowly after trades and orders are more likely to be hidden, so accessing or even discerning this available depth may be difficult for the market. In general, though, the lower cancellation rate of limit orders and the higher execution rates when the relative tick size is larger could be viewed as improving at least some aspects of the trading environment.

Does a larger relative tick size increase market maker participation in the trading process? Here our results are more positive in that we do find greater involvement by designated market makers (DMMs) and supplementary liquidity providers (SLPs) for stocks with larger relative tick sizes. The greater market share of these high-frequency traders in larger relative tick size stocks is consistent with their earning higher profits from market making activities. But there is no evidence that this increased market making induces other traders to the market as we find no significant effects on volume relating to tick size. What does appear to happen is that some trading volume for larger relative tick size stocks shifts to other trading venues, perhaps due to the ability of venues such as crossing networks to provide sub-penny pricing. Raising the tick size for small stocks may enrich market makers, but it is not clear that it will lead to significantly more investor trading.

Will a larger tick size lead to greater analyst coverage? Possibly, but there are reasons to question this outcome. Our research shows that high-frequency traders play a larger role in liquidity provision for large relative tick size stocks. But many of these high-frequency trading firms are not in the business of providing equity research, so the cross-subsidization of such services by increased market making profits is chimerical. Certainly, the fact that we found no positive effect of a larger relative tick size on volume also raises doubt concerning whether such a subsidy for analyst coverage is able to attract more investor interest.

Would increasing the tick size for small stocks improve U.S. equity markets? Our empirical evidence suggests the answer is no. As with all research, however, our research has limitations and it is important to be cognizant of these when evaluating policy proposals. Our empirical methodology carefully controls for other factors affecting liquidity, but for the very smallest firms it is difficult to find perfect matching firms. Drawing inferences for even smaller stocks (e.g., stocks with market capitalization below $50 million or even $100 million) for example, is more problematic. Our analysis also uses trading data from listed stocks on the NYSE. To the extent that trading of those stocks is different in other venues, our results may not capture entirely the liquidity provision process. The NYSE also features designated market makers, in contrast to the purely voluntary provision of liquidity in other market settings, though some of the same high-frequency trading firms that make a market on the NYSE most likely make markets on other trading venues as well, and are also active in NASDAQ-listed stocks. Still, it would be interesting see how the liquidity provision process differs across market settings, but that analysis will await the availability of better data.

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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 3 groups from among these stocks segmented by the stock price ranges: $1–$5, $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), which is comprised of 60 stocks with prices between $1 and $5, has the largest relative tick size. The second group (G2) is comprised of 60 stocks with prices from $5 and up to $10, and the third group (G3) is comprised of 60 stocks with prices from $10 and up to $20. We call stocks in G1, G2, and G3 the “sample stocks.” Each stock in G1, G2, and G3 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. The table presents market capitalization and price summary statistics for both sample and control stocks obtained from the CRSP and TAQ databases. We provide summary statistics for G1, G2, and G3, as well as for subgroups comprised of the largest 30 stocks in each group (in terms of market capitalization), denoted LG1, LG2, and LG3.

		G1		G2		G3	
		Sample	Control	Sample	Control	Sample	Control
Market Cap	Mean	296,683	920,265	850,993	999,223	1,721,834	1,784,106
(in $1,000)	Median	161,406	660,939	446,563	660,939	805,484	850,813
Price ($)	Mean	3.04	32.69	7.56	32.56	14.55	34.95
	Median	3.36	26.63	7.70	27.44	14.45	30.99
Num. of Stocks		60	60	60	60	60	60
		LG1		LG2		LG3	
		Sample	Control	Sample	Control	Sample	Control
Market Cap	Mean	513,014	1,173,952	1,454,551	1,478,727	2,979,728	3,011,730
(in $1,000)	Median	375,097	767,420	847,381	933,527	1,843,035	1,842,058
Price ($)	Mean	3.36	34.84	7.81	34.21	14.78	37.88
	Median	3.59	28.36	8.02	29.18	14.77	35.52
Num. of Stocks		30	30	30	30	30	30

Table 2

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, G2, or G3). 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 Heterskedasticity-consistent standard errors. G1 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $1 and $5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between $5 and $10 ($10 and $20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	$NBBOsprd	0.022	0.013	-0.058	-0.037	<0.001	<0.001	-0.052	<0.001
	$NYSEsprd	0.026	0.030	-0.066	-0.035	<0.001	<0.001	-0.049	0.002
G2 (larger relative tick size)	$NBBOsprd	0.023	0.014	-0.060	-0.033	<0.001	<0.001	-0.063	<0.001
	$NYSEsprd	0.026	0.017	-0.068	-0.040	<0.001	<0.001	-0.070	<0.001
G3 (large relative tick size)	$NBBOsprd	0.027	0.019	-0.041	-0.026	<0.001	<0.001	-0.043	<0.001
	$NYSEsprd	0.033	0.022	-0.047	-0.028	<0.001	<0.001	-0.049	<0.001

Panel B: Percentage Quoted Spreads

Group	Variable	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	%NBBOsprd	0.90%	0.51%	0.63%	0.27%	<0.001	<0.001	0.002	0.331
	%NYSEsprd	1.11%	0.66%	0.80%	0.48%	<0.001	<0.001	0.004	0.052
G2 (larger relative tick size)	%NBBOsprd	0.33%	0.21%	0.06%	0.02%	0.209	0.067	0.0003	0.528
	%NYSEsprd	0.38%	0.24%	0.07%	0.04%	0.081	0.037	0.0005	0.312
G3 (large relative tick size)	%NBBOsprd	0.20%	0.16%	-0.008%	-0.01%	0.728	0.317	-0.0002	0.447
	%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-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	0.38%	0.21%	0.29%	0.16%	<0.001	<0.001	0.0013	0.122
G2 (larger relative tick size)	0.12%	0.07%	0.03%	0.02%	0.048	0.004	0.0003	0.216
G3 (large relative tick size)	0.07%	0.05%	0.00%	0.00%	0.872	0.273	-0.00004	0.630

Table 3
Depth

This table presents analysis of NYSE depth close to the best bid and ask prices in the market. In Panel A, 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 and cumulative NYSE depth up to 5 cents from the National Best Bid and Offer (NBBO) is denoted by $DepthUpto5₵. In Panel B, we present the cross-sectional mean and median of percentage displayed depth in the NYSE book (displayed time-weighted depth over total time-weighted depth), where the depth measure we use is cumulative depth up to 5 cents from the best bid and ask prices. 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, G2, or G3). 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 Heterskedasticity-consistent standard errors. G1 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $1 and $5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between $5 and $10 ($10 and $20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, respectively. LG1, LG2, and LG3 are subgroups comprised of the largest 30 stocks in each group, G1, G2, and G3, respectively, in terms of market capitalization. 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: Time-Weighted Dollar NYSE Depth

Group	Variable	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	$DepthAt	12,691	5,215	-6,068	-4,002	0.309	0.084	849.11	0.92
	$DepthUpto5₵	77,990	25,388	-22,061	-5,985	0.537	0.332	12,586.74	0.81
G2 (larger relative tick size)	$DepthAt	25,857	10,319	6,643	457	0.334	0.605	9,123.40	0.31
	$DepthUpto5₵	228,844	97,021	127,598	39,919	0.012	<0.001	145,179.15	0.03
G3 (large relative tick size)	$DepthAt	28,604	10,177	12,259	532	0.006	0.068	11,820.83	0.01
	$DepthUpto5₵	327,665	110,932	189,966	49,144	<0.001	<0.001	182,862.05	0.00
LG1 (30 largest stocks in G1)	$DepthAt	21,878	14,189	9,078	3,119	0.015	0.038	11,102.22	0.07
	$DepthUpto5₵	138,355	74,167	55,695	13,839	0.043	0.033	52,972.35	0.25
LG2 (30 largest stocks in G2)	$DepthAt	44,113	18,232	19,587	4,759	0.142	0.004	31,103.56	0.09
	$DepthUpto5₵	405,538	254,271	248,909	203,132	0.012	<0.001	301,104.50	0.03
LG3 (30 largest stocks in G3)	$DepthAt	48,022	28,364	26,492	11,655	0.002	<0.001	28,962.33	0.00
	$DepthUpto5₵	592,244	351,724	355,851	239,206	<0.001	<0.001	357,389.00	0.00

Panel B: Percentage Displayed Depth in the Book Up to 5 Cents from Market Prices

Group	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	71.7%	75.0%	-7.8%	-6.3%	0.005	0.009	-0.111	0.008
G2 (larger relative tick size)	73.9%	74.6%	-5.1%	-4.6%	0.019	0.010	-0.058	0.041
G3 (large relative tick size)	78.0%	80.6%	-2.3%	-1.3%	0.337	0.300	-0.025	0.306

Table 4
Depth Resilience

This table presents analysis of depth resilience at the NYSE best bid and/or offer prices (BBO). Consider a mean-reversion model with long-run value θ and speed of adjustment κ, $\Delta L_t = \kappa(\theta - L_{t-1}) + \varepsilon_t$, where L_t is depth at the BBO at time *t* and ΔL_t is the change in depth from *t-1* to *t*. We compute the time-weighted average depth at the NYSE BBO every minute during the trading day. We then estimate the mean reversion parameter κ from the following equation for each stock separately:

$$\Delta L_{i,t} = \alpha_i + \kappa_i L_{i,t-1} + \sum_{\tau=1}^{p} \gamma_{i,\tau} \Delta L_{i,t-\tau} + \varepsilon_{i,t}$$

where the constant $\alpha_i = \kappa_i \theta_i$, the interval *t* is measured in minutes, and we use *p*=20 lags of the change in depth as control variables. We present the cross-sectional attributes of the mean-reversion parameter κ separately for the bid and ask sides of the book as well as for total depth at the BBO. MnDiff and MdDiff refer to the mean and median differences, respectively, between the sample and control stocks in each relative tick size category (G1, G2, or G3). 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 Heterskedasticity-consistent standard errors. G1 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $1 and $5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between $5 and $10 ($10 and $20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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	Mean-Reversion	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1	Bid Side	-0.034	-0.032	0.081	0.082	<.001	<.001	0.080	<.001
(largest relative	Ask Side	-0.040	-0.038	0.081	0.075	<.001	<.001	0.091	<.001
tick size)	All Depth at BBO	-0.027	-0.025	0.071	0.069	<.001	<.001	0.078	<.001
G2	Bid Side	-0.048	-0.042	0.070	0.070	<.001	<.001	0.071	<.001
(larger relative	Ask Side	-0.044	-0.040	0.081	0.070	<.001	<.001	0.086	<.001
tick size)	All Depth at BBO	-0.021	-0.027	0.078	0.076	<.001	<.001	0.084	<.001
G3	Bid Side	-0.057	-0.068	0.061	0.052	<.001	<.001	0.059	<.001
(large relative	Ask Side	-0.059	-0.063	0.079	0.068	<.001	<.001	0.082	<.001
tick size)	All Depth at BBO	-0.030	-0.042	0.071	0.065	<.001	<.001	0.071	0.001

Table 5

Duration Analysis

This table presents duration analysis of limit order cancellation and execution using two different methodologies. The first one is 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. The second methodology utilizes semi-parametric Cox regressions, where the logarithm of the hazard rate of is modeled as a linear function with the same variables as in the Weibull model. To aid in the interpretation of the results and make the models comparable, we report a transformation that gives the percentage difference in the cancellation (or execution) rate for both the Cox regressions and the Weibull model. Panel A reports the cross-sectional means (medians) of the percent difference in the cancellation or execution rate together with *p*-values from two-sided *t*-tests (Wilcoxon tests) for each relative tick size category separately (G1, G2, or G3). Panel B reports 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 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $1 and $5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between $5 and $10 ($10 and $20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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: Percentage Difference in Cancellation and Execution Rates

	G1		G2		G3	
	Mean	Median	Mean	Median	Mean	Median
%ΔCancellation Rate	-40.17%	-52.64%	-27.49%	-41.36%	-17.43%	-26.71%
(Weibull Model)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.002)	(<0.001)
%ΔCancellation Rate	-34.61%	-44.45%	-24.12%	-31.43%	-14.74%	-21.66%
(Cox Regressions)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(<0.001)
%ΔExecution Rate	332.7%	144.3%	176.5%	100.3%	189.8%	67.8%
(Weibull Model)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.008)	(<0.001)
%ΔExecution Rate	357.5%	147.8%	187.8%	105.8%	197.2%	69.9%
(Cox Regressions)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.007)	(<0.001)

Panel B: Cancellation and Execution Rates by Trader Type (Weibull Model)

	G1		G2		G3	
	Mean	Median	Mean	Median	Mean	Median
Institutions	-22.19%	-41.26%	-13.49%	-18.84%	-4.07%	-13.59%
(%ΔCancellation Rate)	(0.044)	(<0.001)	(0.012)	(0.002)	(0.474)	(0.116)
Quantitative	-42.52%	-41.97%	-21.21%	-26.02%	-12.81%	-9.83%
(%ΔCancellation Rate)	(0.044)	(<0.001)	(0.012)	(0.002)	(0.474)	(0.116)
HFT Market Makers	-38.08%	-57.52%	-23.89%	-40.41%	-18.48%	-35.41%
(%ΔCancellation Rate)	(<0.001)	(<0.001)	(0.005)	(<0.001)	(0.035)	(<0.001)
Institutions	294.5%	153.5%	99.6%	84.3%	110.8%	40.8%
(%ΔExecution Rate)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Quantitative	418.1%	232.9%	185.8%	111.5%	156.1%	77.9%
(%ΔCancellation Rate)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
HFT Market Makers	743.1%	165.8%	523.9%	141.9%	482.2%	128.4%
(%ΔExecution Rate)	(0.003)	(<0.001)	(0.001)	(<0.001)	(<0.001)	(<0.001)

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, G2, or G3). 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 Heterskedasticity-consistent standard errors. G1 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between \$1 and \$5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between \$5 and \$10 (\$10 and \$20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	Institutions	5,878	2,590	-5,052	-1,587	0.271	0.358	-143.90	0.98
	Quantitative	1,670	752	-1,174	-1,479	<0.001	<0.001	-793.80	0.08
	HFT Mkt Makers	3,711	469	1,304	-791	0.141	0.114	-1,996.23	0.13
G2 (larger relative tick size)	Institutions	10,535	4,529	219	269	0.952	0.440	773.49	0.87
	Quantitative	3,895	2,151	989	-591	0.113	0.290	1,034.35	0.21
	HFT Mkt Makers	9,062	1,819	6,369	-45	0.015	0.098	7,958.33	0.02
G3 (large relative tick size)	Institutions	11,656	4,037	4,630	339	0.010	0.159	4,553.97	0.01
	Quantitative	4,241	2,500	1,041	54	0.033	0.427	896.89	0.05
	HFT Mkt Makers	10,157	1,901	6,256	527	0.006	0.006	6,044.50	0.01

Panel B: Dollar Depth up to 5 cents from the NBBO by Trader Type

Group	Trader Type	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	Institutions	28,397	11,307	-29,880	-1,384	0.305	0.471	-2,722.87	0.95
	Quantitative	11,853	5,411	-1,156	-3,885	0.570	0.109	1,495.35	0.62
	HFT Mkt Mkrs	17,751	2,775	6,078	-1,950	0.226	0.103	7,468.48	0.32
G2 (larger relative tick size)	Institutions	84,801	33,196	32,611	7,143	0.198	0.001	37,422.70	0.26
	Quantitative	36,726	33,475	23,284	17,402	<0.001	<0.001	23,212.76	0.00
	HFT Mkt Mkrs	47,308	6,664	36,670	1,064	0.010	0.062	43,151.46	0.02
G3 (large relative tick size)	Institutions	132,098	36,316	76,486	14,121	<0.001	<0.001	71,880.22	0.00
	Quantitative	46,928	34,287	28,855	17,891	<0.001	<0.001	28,546.34	0.00
	HFT Mkt Mkrs	63,600	10,622	38,332	3,460	0.003	0.019	36,607.23	0.01

Table 7

Presence of Each Trader Type at the Best Prices on the NYSE

This table presents results on presence of each trader type at the NYSE best bid or offer prices. In particular, we compute the fraction of the time that limit orders of each trader type are either at the best bid or the best ask prices (or both) on the NYSE. The trader types we consider in this table are: individual investors, 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 percentage of time at the NYSE best prices 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, G2, or G3). 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 Heterskedasticity-consistent standard errors. G1 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $1 and $5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between $5 and $10 ($10 and $20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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-test)	p(W-test)	Coef.	p-value
G1	Individuals	5.12%	3.36%	4.36%	2.80%	<0.001	<0.001	0.046	<0.001
(largest	Institutions	79.45%	81.21%	18.06%	19.43%	<0.001	<0.001	0.216	<0.001
relative	Quantitative	72.26%	83.08%	20.46%	26.96%	<0.001	<0.001	0.271	<0.001
tick size)	HFT Mkt Mkrs	82.89%	85.99%	29.93%	33.28%	<0.001	<0.001	0.304	<0.001
G2	Individuals	2.46%	1.53%	1.77%	1.06%	<0.001	<0.001	0.013	0.037
(larger	Institutions	77.40%	75.70%	15.78%	17.44%	<0.001	<0.001	0.158	<0.001
relative	Quantitative	75.14%	79.04%	24.16%	24.57%	<0.001	<0.001	0.236	<0.001
tick size)	HFT Mkt Mkrs	83.11%	89.76%	29.48%	32.48%	<0.001	<0.001	0.345	<0.001
G3	Individuals	1.29%	0.81%	0.58%	0.38%	0.012	0.001	0.058	0.015
(large	Institutions	75.27%	71.68%	10.70%	8.88%	<0.001	<0.001	0.109	<0.001
relative	Quantitative	71.65%	70.17%	19.02%	19.51%	<0.001	<0.001	0.190	<0.001
tick size)	HFT Mkt Mkrs	78.90%	82.51%	23.44%	25.75%	<0.001	<0.001	0.234	<0.001

Table 8
Limit Order Submission by Trader Type

This table presents results on the share of each trader type in limit order submission at the top of the market. Panel A provides information about limit orders that improve the National Best Bid or Offer (NBBO) and therefore that step ahead of the best market prices. For each trader type, we compute the ratio of its limit orders that improve the NBBO to all limit orders that improve the NBBO (by all trader types). Similarly, Panel B provides information about the share of each trader type in the category of limit orders that are submitted at the NBBO. 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, G2, or G3). 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 Heterskedasticity-consistent standard errors. G1 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between \$1 and \$5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between \$5 and \$10 (\$10 and \$20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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 Ahead of the NBBO

Group	Trader Type	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	Institutions	35.1%	31.4%	3.3%	2.8%	0.292	0.362	0.040	0.391
	Quantitative	14.8%	14.7%	6.5%	6.3%	<.001	<.001	0.069	0.002
	HFT Mkt Makers	36.0%	33.6%	16.5%	11.2%	<.001	<.001	0.137	0.004
G2 (larger relative tick size)	Institutions	36.5%	28.0%	5.8%	-0.03%	0.027	0.227	0.073	0.035
	Quantitative	12.0%	10.6%	3.6%	2.0%	0.001	0.002	0.020	0.123
	HFT Mkt Makers	29.1%	25.8%	9.1%	8.5%	0.001	0.001	0.097	0.005
G3 (large relative tick size)	Institutions	35.3%	30.0%	3.7%	0.5%	0.179	0.422	0.039	0.167
	Quantitative	9.4%	9.3%	1.4%	0.7%	0.097	0.175	0.015	0.048
	HFT Mkt Makers	28.1%	22.5%	6.7%	7.5%	0.006	0.007	0.062	0.010

Panel B: Proportion of Limit Orders Submitted at the NBBO

Group	Trader Type	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	Institutions	17.6%	14.9%	0.5%	1.6%	0.725	0.466	0.013	0.566
	Quantitative	17.6%	17.2%	-2.8%	-4.2%	0.133	0.016	-0.095	<.001
	HFT Mkt Makers	32.0%	31.1%	6.3%	3.6%	0.018	0.026	0.022	0.548
G2 (larger relative tick size)	Institutions	19.8%	18.9%	3.4%	2.4%	0.035	0.049	0.036	0.081
	Quantitative	17.6%	17.6%	-1.4%	-2.7%	0.361	0.077	-0.024	0.219
	HFT Mkt Makers	34.4%	37.0%	7.2%	6.2%	0.002	0.003	0.101	<.001
G3 (large relative tick size)	Institutions	21.4%	16.8%	2.4%	0.7%	0.200	0.307	0.025	0.176
	Quantitative	18.1%	19.6%	0.6%	-1.7%	0.675	0.822	0.008	0.550
	HFT Mkt Makers	34.5%	32.9%	4.4%	2.3%	0.063	0.082	0.043	0.060

Table 9

Trading as a Liquidity Supplier

This table looks at liquidity provision of each trader type by focusing on actual trades in which the trader type supplied liquidity. By supplying liquidity we mean that the trader submitted the limit order that resided in the book and that was executed by an incoming marketable order. If each trader can execute a desired position change either by submitting marketable orders or having its limit orders executed, our measure is the dollar volume in limit orders that were executed divided by the total dollar volume for a trader type. The trader types we consider in this table are: individual investors, 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 percentage of volume in which the trader type supplied rather than demanded liquidity 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, G2, or G3). 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 Heterskedasticity-consistent standard errors. G1 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $1 and $5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between $5 and $10 ($10 and $20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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-test)	p(W-test)	Coef.	p-value
G1	Individuals	63.4%	61.8%	-2.2%	0.1%	0.483	0.488	0.019	0.693
(largest	Institutions	42.8%	42.5%	-5.6%	-6.3%	<0.001	<0.001	-0.051	0.002
relative	Quantitative	45.0%	46.2%	-7.4%	-7.8%	<0.001	<0.001	-0.074	0.004
tick size)	HFT Mkt Mkrs	91.4%	93.8%	1.6%	0.7%	0.376	0.335	0.012	0.650
G2	Individuals	63.1%	65.5%	0.4%	-1.7%	0.900	0.949	0.015	0.718
(larger	Institutions	43.0%	43.3%	-5.2%	-5.5%	<0.001	<0.001	-0.055	<0.001
relative	Quantitative	49.7%	50.1%	-3.4%	-4.1%	0.017	0.001	-0.044	0.018
tick size)	HFT Mkt Mkrs	85.2%	89.5%	-3.1%	-1.1%	0.134	0.142	-0.035	0.204
G3	Individuals	61.8%	62.9%	-1.3%	1.8%	0.688	0.954	-0.018	0.555
(large	Institutions	44.8%	44.1%	-4.4%	-4.2%	<0.001	<0.001	-0.040	<0.001
relative	Quantitative	49.5%	49.6%	-2.9%	-1.6%	0.040	0.054	-0.034	0.010
tick size)	HFT Mkt Mkrs	83.2%	90.2%	-3.5%	-0.3%	0.132	0.203	-0.034	0.152

Table 10

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: 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, G2, or G3). 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 Heterskedasticity-consistent standard errors. G1 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $1 and $5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between $5 and $10 ($10 and $20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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-test)	p(W-test)	Coef.	p-value
G1	Individuals	2.6%	1.4%	2.1%	0.8%	0.000	<0.001	0.004	0.591
(largest	Institutions	52.8%	51.6%	6.5%	6.9%	0.000	<0.001	0.097	0.000
relative	Quantitative	20.2%	21.9%	-3.6%	-1.7%	0.017	0.056	-0.012	0.568
tick size)	HFT Mkt Mkrs	12.7%	12.2%	3.1%	3.0%	0.002	0.002	0.020	0.182
G2	Individuals	1.0%	0.5%	0.6%	0.1%	0.005	0.001	0.004	0.146
(larger	Institutions	47.8%	46.4%	1.1%	0.8%	0.371	0.647	0.009	0.551
relative	Quantitative	22.5%	23.5%	-1.0%	0.5%	0.348	0.988	-0.009	0.466
tick size)	HFT Mkt Mkrs	15.2%	14.8%	5.5%	4.6%	0.000	<0.001	0.066	0.000
G3	Individuals	0.5%	0.3%	0.1%	0.1%	0.627	0.296	0.001	0.603
(large	Institutions	45.8%	44.8%	0.6%	0.0%	0.620	0.766	0.003	0.786
relative	Quantitative	22.9%	23.7%	-0.4%	-1.1%	0.594	0.480	-0.003	0.737
tick size)	HFT Mkt Mkrs	16.0%	15.1%	5.9%	5.5%	0.000	<0.001	0.058	0.000

Table 11

Volume and Market Share

This table presents analysis of NYSE volume and market share. In Panel A, we present the cross-sectional mean and median of dollar NYSE volume. We use two measures: ContVolume is the daily average of dollar trading volume during the continuous trading session (from 9:30am to 4:00pm) on the NYSE, while TotVolume is the daily average of total NYSE dollar volume (that includes the opening and closing auctions). MktWideVol is the average daily dollar volume (share volume multiplied by the closing price) in the entire marketplace (not just the NYSE) from the CRSP database. In Panel B, we present the cross-sectional mean and median of NYSE volume market share. We provide two measures of market share: (i) ContMktShr is the daily average of the continuous trading volume from the NYSE dataset divided by the CRSP daily volume, and (ii) TotalMktShr is the daily average of the total trading volume (including opening and closing auctions) divided by CRSP daily volume. We note that the CRSP volume numbers include after-hours trading but do not include odd lots while our volume measures using the NYSE datasets do not include after-hours trading but include odd lots. Our results would not be biased if odd lots and after-hours trading are similar in nature for the sample and control stocks. 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, G2, or G3). 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 Heterskedasticity-consistent standard errors. G1 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $1 and $5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between $5 and $10 ($10 and $20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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: NYSE Dollar Volume

Group	Variable	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	ContVolume	373,247	106,817	-1,574,088	-842,340	<.001	<.001	-3,900,629	<0.001
	TotVolume	564,140	205,614	-1877,858	-921,306	<.001	<.001	-2,309,490	<0.001
	MktWideVol	2,723,692	641,140	-5,551,667	-2,384,327	<.001	<.001	-7,307,980	<0.001
G2 (larger relative tick size)	ContVolume	1,748,232	622,163	-271,573	-335,031	0.361	<.001	-902,663	0.250
	TotVolume	2,319,794	857,667	-220,456	-496,189	0.548	<.001	-470,051	0.330
	MktWideVol	11,661,286	2,468,717	2,968,296	-819,701	0.220	0.293	2,245,290	0.480
G3 (large relative tick size)	ContVolume	3,914,158	1,327,711	529,322	-6080	0.218	0.590	912,586	0.260
	TotVolume	4,814,452	1,766,860	522,366	-16,642	0.286	0.738	458,372	0.320
	MktWideVol	20,788,877	4,688,853	5,558,991	168,909	0.038	0.227	4,649,025	0.060

Panel B: NYSE Volume Market Share

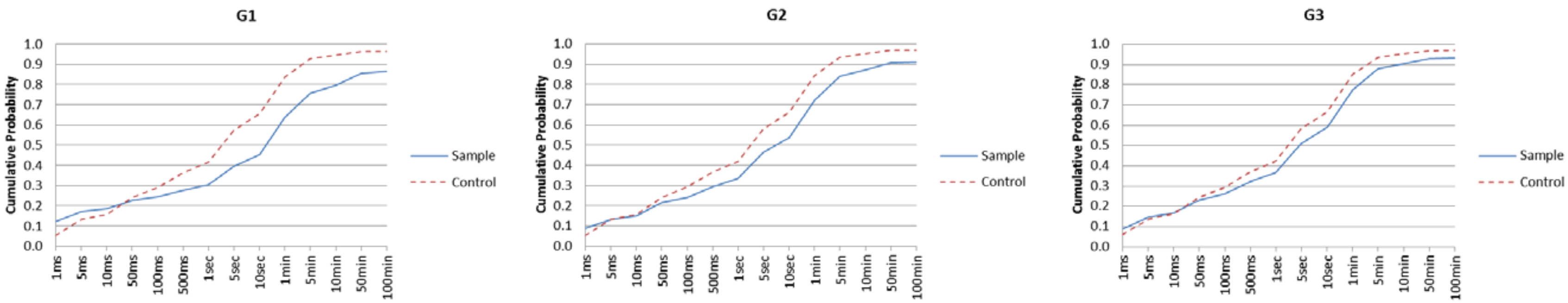
Group	Variable	Mean	Median	MnDiff	MdDiff	p(t-test)	p(W-test)	Coef.	p-value
G1 (largest relative tick size)	ContMktShr	15.66%	15.30%	-11.41%	-12.37%	<0.001	<0.001	-0.127	<0.001
	TotalMktShr	26.56%	26.68%	-9.71%	-9.62%	<0.001	<0.001	-0.090	<0.001
G2 (larger relative tick size)	ContMktShr	20.17%	19.38%	-6.03%	-6.50%	<0.001	<0.001	-0.065	<0.001
	TotalMktShr	29.49%	28.24%	-6.19%	-5.73%	<0.001	<0.001	-0.069	<0.001
G3 (large relative tick size)	ContMktShr	23.34%	23.18%	-2.76%	-2.62%	0.002	0.003	-0.025	0.004
	TotalMktShr	31.82%	30.67%	-3.07%	-2.70%	0.009	0.015	-0.028	0.018

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 three relative tick size categories (G1, G2, and G3). 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 sample stocks are a 60-stock stratified sample by market capitalization from among all common domestic NYSE stocks with prices between $1 and $5. G2 (G3) sample stocks are comprised of 60 stocks each similarly stratified by market capitalization from among the stocks with prices between $5 and $10 ($10 and $20). Each stock in G1, G2, and G3 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 10, 4, or 2 times that of the sample stocks in G1, G2, or G3, 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



Panel B: Distribution of Time-to-Execution