The demise of the NYSE and NASDAQ: Market Quality in the Age of Market Fragmentation*

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ABSTRACT

We estimate the causal impact of market fragmentation. Theoretically, more exchange competition should reduce trading costs, however it may also generate negative network externalities which reduce market quality. We document evidence of both effects, however our results show differential impacts for large and small stocks. For large stocks, the former effect dominates and market quality is better. For small stocks, negative network externalities dominate and market quality is relatively worse. In response, we find that traders use inter-market sweep orders to avoid negative network externalities. Our results reconcile conflicting findings in the literature and show that fragmentation has dramatically changed U.S. markets.

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Keywords: Exchange competition, fragmentation, liquidity, market microstructure.

JEL Classification Numbers: G12, G14

I. Introduction

U.S. equity markets have changed dramatically over the last decade. Between 2004 and 2013, average trade sizes fell from 800 shares to 300 shares while daily trading volume increased from 7.9% of shares outstanding to 15.8% of shares outstanding. Moreover, the number of market centers available for trading nearly tripled and with that, measures of market fragmentation more than doubled (See Figure 1 and 2 for details). During this time, there were several significant changes to the operation of U.S. markets, including the rise of algorithmic and high-frequency trading and the implementation of Regulation NMS in 2007, which created a national market system and dramatically increased exchange competition.

While a number of papers have examined the impact of algorithmic and high-frequency trading (e.g., Hendershott, Jones, and Menkveld (2011), Hasbrouck and Saar (2013), Brogaard, Hendershott, and Riordan (2014)) relatively few papers have investigated the impact of regulation NMS and the resulting increase in market fragmentation.[1] Moreover, both the theoretical and empirical literature on market fragmentation provide mixed evidence on the relation between fragmentation, trading behavior, and market quality. Consequently, several important questions remain unanswered. Has fragmentation *caused* liquidity to change? If so, has fragmentation changed asset prices and trading behavior? Finally, is the effect of fragmentation homogeneous, or do some assets experience differential impacts from fragmentation?

In this study, we provide novel evidence on the *causal* impact of market fragmentation. In doing so, we also show that fragmentation changes trading behavior and it exerts heterogeneous effects on large and small stocks. In particular, we find that fragmentation causes reduced bid-ask spreads and better price efficiency for large stocks, consistent with theoretical models of market competition in which more competition and fragmentation lead to welfare improvements (e.g., Economides (1996), Hall and Rust (2003)). On the other

[1] O'Hara and Ye (2011) and Chung and Chuwonganant (2012) are two important exceptions. We discuss these papers and their relation to our findings in more detail in Section II.

hand, we find that fragmentation leads to very different effects for small stocks. For small stocks, fragmentation causes increased bid-ask spreads, worse price efficiency, and less trading. These effects are consistent with theoretical models in which exchange competition and fragmentation lead to negative network externalities which reduce liquidity. In particular, several models show that as trading fragments across exchanges, it becomes harder for individual traders to match with a counterparty on a given exchange, which further discourages trading thereby leading to reduced market quality (e.g., Pagano (1989b), Madhavan (1995), Madhavan (2000)). To date, there has been no consensus on the net impact of fragmentation; it is not clear whether the reduced transaction cost effect or the network externality effect dominate. Our findings present new evidence that the reduced transaction cost effect dominates for large stocks, leading to improvements in market quality, while the negative network externality effect dominates in small stocks, leading to a reduction in market quality.

Our work is closely related to two existing papers which empirically examine the impact of market fragmentation and regulation NMS. First, O'Hara and Ye (2011) examine effective spreads, realized spreads, execution speed, short-term volatility, and variance ratios using a matched sample approach for the period January 2, 2008 through January 30, 2008. They find that fragmentation is associated with lower spreads, faster execution, and prices that are closer to a random walk, however they also find some evidence of increased short-term volatility. They conclude that fragmentation does not harm market quality. On the other hand, Chung and Chuwonganant (2012) use a matched sample approach around the implementation of regulation NMS and document increases in quoted and effective spreads, slower execution, and reduced depth. They conclude that fragmentation hurts market quality. In this paper, we exploit the implementation of regulation NMS in a differences-in-difference framework and we use an instrumental variables analysis that examines the impact of fragmentation over a long time series. In doing so, we confirm and reconcile the seemingly contradictory results in O'Hara and Ye (2011) and Chung and Chuwonganant (2012) by showing that fragmentation exerts heterogeneous effects on large and small stocks.

We begin by examining the relation between fragmentation, market quality, and trading behavior using daily data from 1996 to 2014. We use a natural measure of fragmentation based on a Herfindahl-Hirschman Index (Hirschman (1964)) of trading volume across market centers. As shown in Panel C of Figure 2, it is clear that fragmentation has increased dramatically over the last decade. Our fragmentation measure, which can vary from 0 (no fragmentation) to 1 (high fragmentation), has more than doubled during our sample. Using ordinary least squares ("OLS") panel regressions we show that fragmentation is, on average, associated with improvements in bid-ask spreads and price efficiency, consistent with the evidence in O'Hara and Ye (2011). A one standard deviation increase in fragmentation is associated with a 2.2% reduction in bid-ask spreads and a 4% improvement in price efficiency.

However, the theory on fragmented markets predicts assets with thinner markets may be more adversely impacted by fragmentation. For example, in Pagano (1989a) traders endogenously choose whether to trade. As markets fragment and there are more trading locations, it becomes harder for each individual trader to find a counterparty. Thus, as markets become thinner, it is less likely that traders will participate which leads to a feedback effect that further hurts liquidity. Consistent with these models, we test whether fragmentation has different impacts on large (i.e., deep) assets and small (i.e., thin) assets.[2] We find that firms in different size deciles experience different effects from fragmentation. While fragmentation is associated with improvements in market quality for firms in the largest decile based on market capitalization (consistent with O'Hara and Ye (2011)), we find very different evidence for firms in the smallest deciles. For the smallest firms, a one standard deviation increase in fragmentation is associated with a 22.7% increase in bid-ask spreads and a 2.8% degradation in price efficiency. Accordingly, our results also support the conclusions of Chung and Chuwonganant (2012) who argue that fragmentation reduces market quality for some firms.

[2]Because liquidity is multi-dimensional, there are many possible ways of categorizing stocks into deeply traded and thinly traded; we use firm size (i.e., market capitalization) because of its simplicity and the fact that it is plausibly exogenous from other characteristics that lead to fragmentation. However, our results are robust to other ways of categorizing stocks into deeply vs. thinly traded. We also stress that we categorize stocks using ex-ante information to avoid the possibility of reverse causality (i.e., we measure market capitalization *before* fragmentation changes).

Of course, the OLS panel regressions discussed above are inherently limited and may be subject to several endogeneity concerns. First, while market fragmentation has changed over the last decade, so too have many other aspects of U.S. equity markets. For example, both algorithmic and high-frequency trading have increased dramatically over this period. As a consequence, any study on the impact of fragmentation, algorithmic trading, or high-frequency trading must worry about the possibility of an omitted variable bias. Second, OLS panel regressions are unable to establish causation. Thus, while our OLS regressions document a relation between market quality and fragmentation, it is unclear if fragmentation *caused* these changes.

Accordingly, we use two different sets of analyses to establish the *causal* impact of market competition and fragmentation. First, we use a difference-in-difference analysis that exploits the implementation of Regulation National Market System ("NMS") to identify the impact of fragmentation. Regulation NMS was implemented in 2007 to increase "competition among individual markets and competition among individual orders" (Securities and Exchange Commission (2007)). The regulation contained several provisions, but two provisions, in particular, stand out. The *Order Protection Rule* required trading centers to guarantee that trades were not executed at prices worse than the protected quotes available at other trading centers. The *Access Rule* ensured that market data, including quotations, were accessible across different market centers. Both measures went into effect for U.S. equities on August 20, 2007, leading to a significant increase in the ability of exchanges to compete for order flow. As with the OLS results discussed above, our difference-in-difference analysis finds that fragmentation causes reduced bid-ask spreads and better price efficiency for large stocks and increased bid-ask spreads, and less trading for small stocks.[3]

While our difference-in-difference analyses examine the causal impact of market fragmentation and exchange competition, they do so using data from a relatively short time period

[3]We discuss the precise details surrounding the implementation of regulation NMS later in the results section. NMS was briefly tested on a subsample of "pilot" stocks in July of 2007. It is also possible that some market centers implemented NMS prior to August 20, 2007, however, this would bias our difference-in-difference methodology against finding a result.

that spans April 1, 2007 through December 31, 2007. Thus, we also examine an instrumental variables analysis over the period 1999 to 2013 to establish the impact of fragmentation over a longer time period. Specifically, we use the number of market centers (i.e., trading venues) in the U.S. as an exogenous instrument to shock firm-level fragmentation. Our identifying assumption requires that the total number of U.S. markets available for equity trading is related to firm-level measures of market quality *only* through fragmentation. In other words, market centers do not open or close because of the characteristics of *individual* assets. Using the number of U.S. market centers as an instrument, we again confirm that fragmentation has a differential impact on large and small stocks. Consistent with our OLS and difference-in-difference results, the instrumental variables analyses show that market fragmentation leads to lower bid-ask spreads and better price efficiency for large stocks and worse bid-ask spreads and worse price efficiency for small stocks.

All of our results show that market fragmentation causes negative network externalities in small stocks. Thus, for small stocks, our findings suggest that more fragmentation makes it harder to access liquidity. This begs the question: as markets fragment, why would it become harder to access liquidity in small stocks? Indeed, the point of regulation NMS was to increase competition and thereby improve liquidity. The order protection rule provides a possible answer: regulation NMS only protects the *top* of the book at each market center. For small stocks, the top of the book might not provide enough depth, and as a consequence, trades might be routed to multiple market centers in order to access the desired quantity of shares. This could increase the time to execution and possibly allow other traders to pick-off the trade (e.g., Budish, Cramton, and Shim (2015)). In other words, for small stocks, regulation NMS might lead to increased execution risk, which would make traders less likely to trade (thereby generating negative network externalities). Consistent with this, we find that small stocks experience significantly more inter-market sweep orders when fragmentation is high. Inter-market sweep orders (ISO) allow traders to partially avoid the *Order Protection Rule* of regulation NMS so that they can immediately access a large-sized quotation with a price inferior to protected quotations at other trading venues (in a sense, avoiding market fragmentation). The results suggests that regulation NMS did create significant frictions that generate negative network externalities, especially for small stocks.

Overall, our results have important implications for academics, practitioners, and regulators. From an academic perspective, our paper contributes to the growing literature on market fragmentation by providing novel evidence on the causal impact of market fragmentation. In doing so, we reconcile several conflicting findings in the extant empirical literature. Moreover, we also provide novel evidence that market fragmentation causes investors to change their trading behavior and to use trading procedures that mitigate negative network externalities. From a practitioner perspective, our results provide the first evidence that market fragmentation exerts heterogeneous effects across stocks, which may lead to differences in execution risks and price efficiency. Finally, our research also has important policy implications. We show that Regulation NMS has *caused* changes in market quality; fragmentation has improved market quality for some assets, while damaging market quality in others. As such, our results suggest that regulators should consider the impact of future policy changes on individual assets which may be differentially impacted by market changes.

The rest of the paper proceeds as follows: Section II describes the theoretical mechanisms that relate market fragmentation, trading behavior, and asset prices and it discusses existing empirical findings. Section III describes the data and discusses the calculation of key variables. Section IV presents our analyses and findings. Section V concludes.

II. Theory and Extant Evidence

Our empirical analyses are motivated by the industrial organization literature on competition and network externalities. In what follows, we briefly describe the extant literature and its relation to our findings.

A.1 Theoretical Literature

Theoretical models of fragmentation typically compare the welfare losses that result from monopoly pricing to the welfare losses that result from negative network externalities. For example, Economides (1996) finds that the costs of negative network externalities are smaller than the costs of monopoly pricing power; thus, in his model fragmentation leads to improvements in welfare. Similarly, Hall and Rust (2003) examine equilibrium outcomes following an increase in the number of market makers who post quotes. As the number of publicly posted bid and ask prices increases, bid-ask spreads are reduced because more market makers are competing to post the best price. As a result, more people choose to trade and their model finds that increased competition leads to an improvement in equilibrium outcomes.

A number of models have explicitly examined the impact of fragmentation across trading venues. In Pagano (1989a), traders endogenously determine whether or not they want to participate in a market and their entry decision is related to market concentration. In concentrated markets, with many traders, the liquidity demands of one investor are more likely to be offset by the liquidity demands of other investors. In other words, concentrated trading makes it easier to find a counterparty which then impacts the trading decisions of traders, leading to a positive feedback cycle which boosts market quality. As a result, there is less price volatility from uninformed trading demand and thus, more traders participate and asset prices are higher. On the other hand, Pagano argues that when markets are fragmented and thin, price impact is higher and asset prices and trader participation are lower, leading to a negative network externality. Thus, Pagano (1989a) predicts that trades will naturally consolidate on the most liquid venue. In contrast, Madhavan (1995) shows that trader heterogeneity may prevent such consolidation. In his model, fragmentation can persist but it may lead to more volatility and worse price efficiency. Similarly, H. Mendelson (1987) also examines network externalities from fragmentation and finds that fragmentation can adversely impact price efficiency and volatility.

More recently, Parlour and Seppi (2003) develop a model of competition between exchanges and find that more fragmentation can increase or decrease the cost of liquidity. In other words, increased fragmentation can lead to either *more* or *less* liquidity. Interestingly, in our empirical tests we find that fragmentation leads to better liquidity for some firms, but worse liquidity for others. In addition, Pagnotta (2013) examines the impact of speed and fragmentation on asset prices. He shows that fragmentation can lead to improvements in liquidity while at the same time lowering asset prices because of changes in investor participation. Finally, Budish et al. (2015) discuss how liquidity provision is impaired by the potential for cross-market arbitrage opportunities in a multiple market framework. When an asset is traded on multiple (i.e., fragmented) markets, liquidity providers must worry about the possibility of having stale quotes which lead to different prices at different market centers for the same asset. As a consequence, they argue that high-frequency traders invest in speed in an attempt to pick off stale prices, which then causes liquidity providers to increase spreads.

In sum, the existing theoretical literature on fragmentation often trades-off two different forces: (1) the decrease in transaction costs that arise from increased competition and (2) the increase in negative externalities that arise from thin markets. In light of this, our results are largely consistent with extant theoretical predictions: for large stocks, with naturally deep markets, the former effect dominates while in small stocks, with naturally thin markets, the latter effect dominates.

A.2 Empirical Literature

Empirically, a number of papers have examined the impact of fragmentation, but relatively few papers have examined fragmentation following the implementation of regulation NMS in 2007. Prior to NMS, the fragmentation literature largely focused on the impact of competition between *market makers*, however, in the post-NMS world most of the increase in fragmentation has come from competition between *exchanges*.

In one of the earliest papers to examine fragmentation, Hamilton (1979) examines the impact of off-board trading (i.e., the trading of NYSE-listed stocks on regional exchanges and the over-the-counter marketplace). He generally finds that off-board trading is associated with improvements in market quality, however, his setting does not account for the fact that traders endogenously choose where to trade. Several of the early fragmentation papers, including Hendershott and Jones (2005) and Bennett and Wei (2006), find that fragmentation hurts market quality. Specifically, Hendershott and Jones (2005) examine trading activity and price discovery in three ETFs following the decision of a large electronic communications network to stop displaying its order book for those assets. This change led to an increase in fragmentation between market makers and as a consequence, Hendershott and Jones find worse liquidity and price efficiency. Similarly, Bennett and Wei (2006) examine stocks which switched from being listed on the more fragmented NASDAQ to the less fragmented NYSE in 2002 and 2003. Their results also suggest that fragmentation has adverse impacts on liquidity and price efficiency.

While a number of papers examine fragmentation prior to the implementation of regulation NMS in 2007, Panels A and C of Figure 2 show that most of the market fragmentation in the U.S. has occurred over the last decade. Yet only a few empirical papers examine the impact of fragmentation following these recent market changes. As discussed in the introduction, O'Hara and Ye (2011) and Chung and Chuwonganant (2012) examine the impact of fragmentation after NMS by examining market quality measures including bid-ask spreads and execution speeds, however they document seemingly contradictory findings. O'Hara and Ye (2011) find fragmentation leads to improvements in market quality, while Chung and Chuwonganant (2012) find that fragmentation harms market quality. Degryse, de Jong, and Kervel (2015) examine the impact of both visible fragmentation and the proliferation of dark pool trading and they find that visible fragmentation is generally beneficial while dark pool trading can negatively impact liquidity. In a recent working paper, Baldauf and Mollner (2014) examine the impact of competition on the Australian stock exchange using detailed trade data. They estimate a model of imperfect competition and find evidence that welfare costs arising from increased adverse selection due to fragmentation are larger than welfare gains from increased competition. On net, they conclude that fragmentation leads to larger bid-ask spreads on the Australian exchange. In addition, Hatheway, Kwan, and Zheng (2013) show that segmentation by dark pools generally hurts overall market quality. Thus, while several papers suggest a cost to fragmentation, there is no clear consensus on the net impact.

Finally, several recent papers highlight the motivations for *why* fragmentation has increased since regulation NMS. One unique aspect of the U.S. equity markets is that the same asset is traded at many market centers, yet these market centers may be owned and operated by the same entity (e.g., BATS X and BATS Y). Chao, Yao, and Ye (2016) provide a model, with empirical support, that discrete pricing in stocks allows exchanges to set fees that create second-degree price discrimination which incentivizes the creation of more trading venues. Alternatively, Kwan, Masulis, and McInish (2014) point to the ability to use dark pools to bypass the time priority of markets. That is, when traders are sufficiently back in the trading queue they seek to trade elsewhere. These papers suggest that much of the dramatic rise in fragmentation is the product of the regulatory environment in which market centers operate.

Overall, the extant theoretical and empirical literature both suggest ambiguous impacts from fragmentation. As a result, the *net* effect of fragmented markets remains unknown.

III. Data

To investigate the impact of market fragmentation on market quality, we combine data from the Center for Research in Security Prices ("CRSP"), the New York Stock Exchange Trade and Quote database ("TAQ"), and the Securities and Exchange Commission ("SEC") over the period 1996 to 2014. The resulting sample contains approximately 12,000 unique assets and 20 million asset-days.

A. Construction of Variables

We obtain daily stock returns, trading volume, stock prices, and shares outstanding from CRSP. We constrain our sample to include only ordinary common shares in U.S. firms, share codes 10 and in 11 in CRSP. From TAQ, we obtain information about trading volume and the top of the limit order book for up to 17 different trade reporting facilities, representing the totality of visible liquidity at the top of the limit order book at any point in time. We then compile this data further to compute the national best bid and offer (NBBO) which represents the most competitive prices available on U.S. exchanges for each asset at each point in time. Because trading frequency differs by asset, we calculate the best prevailing prices at every second over the regular market hours of the trading day. Using the NBBO prices, we calculate the prevailing bid-ask spread at every second by taking the difference of the ask and bid price scaled by their midpoint. We also compute the consolidated depth at the NBBO, which indicates the number of shares a trader could hypothetically access at the NBBO price. We then collapse the depth and bid-ask spread over the trading day to calculate the average depth and bid-ask spread for the day.

In addition, we use the TAQ database to compute measures of fragmentation. Measuring fragmentation is challenging due to the reporting standards of U.S. equity markets. TAQ, the most commonly used source for trade data, lists consolidated trades which are attributed to one of 17 different reporting venues.[4] Many of the individual venues report their trades through one particular reporting venue, the trade reporting facility (TRF) set up by FINRA. In most of our analyses, we measure trade fragmentation using a Herfindahl-Hirschman of trade volume for every asset each day across these reporting venues. The Herfindahl-Hirschman Index captures the concentration of trade and ranges from zero to one. We subtract the Herfindahl-Hirschman Index value from one to get a measure of fragmen-

[4]Appendix A contains a table of the trade reporting venues in TAQ.

tation, where zero indicates no fragmentation and one equals high fragmentation.[5] Defining fragmentation this way allows us to gather a daily measure of the dispersion in trade across venues for every asset traded on U.S. public markets. As a result, we believe our variable is a close proxy for the true level of market fragmentation in each asset at each point in time.[6] Finally, we note that in our difference-in-difference analysis of regulation NMS we are able to examine the impact of fragmentation without using a measure of fragmentation; these results confirm the results we find using the Herfindahl-Hirschman Index of fragmentation.

In addition to CRSP and TAQ data, we also use SEC data to compute the number of active market centers in the U.S. at each point in time. In response to a Freedom of Information Act request, the SEC released a series of reports with the names of active market centers and the dates on which they became active or inactive. We compile these reports to count the total number of venues available for equity trading every day. This number includes exchanges, electronic communication networks, and alternative trading systems.[7]

Finally, in our analyses we examine the efficiency of prices using the Hou and Moskowitz (2005) measures of price delay. To calculate price delay, we first run regressions of each firm's return in week t on the contemporaneous market return and lagged market returns for the previous four weeks. Specifically, for each firm we run a rolling panel regression over the previous 100 weeks according to the model:

$$ret_{i,t} = \alpha + \beta_1^{i,t} r_{m,t} + \left(\sum_{j=1}^{4} \delta_j^{i,t} r_{m,t-j}\right) + \epsilon_{i,t} \tag{1}$$

[5] We note that this measure likely understates the true level of fragmentation since many marketplaces report to trade reporting facilities (TRFs). Nonetheless, much of the variation in our measure comes from the drastic reduction in market shares seen on the NYSE and NASDAQ exchanges. As such, our measure captures most of the variation in fragmentation that has occurred since regulation NMS was implemented.

[6] Our results are robust to an alternative measure of fragmentation proposed in O'Hara and Ye (2011): the ratio of a firm's listing exchange volume to its total volume. See Section VIII in the Appendix for the results using this alternative measure. These two measures of fragmentation have a correlation around 70%.

[7] We remove trading venues which are clearly non-equity trading venues (i.e., those which reference bonds, fixed income, options, etc., in their name). We do not differentiate between fragmentation across dark pools and "lit" markets. While this is an important issue, we focus on total fragmentation. See Kwan et al. (2014), among others, for a more complete discussion of the effects of light versus dark venue trading.

for each stock i in week t and where $r_{m,t}$ denotes the market return. The regression examines if systematic information is immediately impounded into a stock's price. If prices do not have a delay and information is immediately impounded then we expect each of the delta coefficients to equal zero. We then construct two delay variables which measure price delay:

$$Delay1_{i,t} = 1 - \frac{R^2_{[\delta_1=\delta_2=\delta_3=\delta_4=0]}}{R^2} \tag{2}$$

$$Delay2_{i,t} = \frac{\sum_{j=1}^{4} |\delta_j^{i,t}|}{\beta_1^{i,t} + \sum_{j=1}^{4} |\delta_j^{i,t}|} \tag{3}$$

The first measure ($Delay1$) captures the difference in explanatory power when lagged returns are included in the regression relative to the restricted model which only contains a contemporaneous relationship. The second measure ($Delay2$) depends on the size of the coefficients of the unconstrained regression. As expected, the two measures are highly correlated and we find similar results for the two measures in all of our analyses. For this reason, we include only $Delay1$ in our main results.

B. Sample Properties

Figure 1 shows time-series plots of the daily mean, 10^{th} percentile, and 90^{th} percentile for several measures of market quality. In Panel A, the figure shows that bid-ask spreads have generally decreased through time, although they temporarily increased by a factor of three during the 2008 financial crisis. More interestingly, it appears that the variability of the bid-ask spread has increased over time. In other words, while the mean has improved, the variance may have gotten worse. The vertical gray line in each figure indicates the initial implementation of Regulation NMS, while the dotted and dashed lines represent the 10th and 90th percentiles, respectively. Panel B contains the time-series of the Amihud (2002) illiquidity measure. Similar to bid-ask spreads we see a general decrease in the level of

Amihud illiquidity and a large, significant spike during the crisis. In Panel C we examine the distribution of price efficiency, as measured by $Delay1$, through time. $Delay1$ has generally drifted down through time, implying prices have slowly gotten more efficient across the entire distribution. Finally, the last panel examines intra-day volatility. Once again we see a large and significant spike during the crisis. The average and 10th percentile appear to have decreased significantly while the volatility of the 10th percentile may have actually increased through time.

In Figure 2, we examine several trading characteristics which have changed drastically over our sample period. One of the most dramatic examples of this is shown in Panel A of Figure 2, which examines the number of market centers available to trade U.S. equities. Over our sample, the number of market centers starts below 10 and peaks over 100 before decreasing in the last year. Consistent with the drastic increase in market centers, Panel B plots the time-series of market fragmentation, measured as one minus the Herfindahl-Hirschman Index of trade volume across exchanges. From the figure, it is clear that fragmentation has increased with the number of market centers. While there was always some fragmentation for most firms, there was a significant increase in fragmentation around 2003. Additionally, the rate of fragmentation increases significantly around the implementation of Regulation NMS before leveling off in the most recent years. In Panel C, we investigate average volume turnover through time; where turnover is defined as the log of daily trading volume expressed as a fraction of shares outstanding. The figure shows a steady increase in turnover across the entire distribution. Finally, Panel D shows the number of exchanges which have available depth at the NBBO. This TAQ-provided measure captures the level of competition amongst exchanges and shows that it has generally increased through time. Not surprisingly, the most dramatic increase occurs following the implementation of Regulation NMS, yet there has been a slight reduction in the most recent data. Table 1 provides the corresponding summary statistics for the variables shown in Figures 1 and 2. In Section IV, below, we explore the relation between fragmentation, trading behavior, and liquidity in greater detail.

IV. Results

The results in the previous section show that U.S. equity markets have changed in a number of ways over the last two decades. Notably, the number of market centers has increased dramatically leading to more fragmentation, trading volume has increased significantly, and measures of liquidity and price efficiency have both improved (on average). In this section, we explore the relation between fragmentation and these changes in market quality using three distinct sets of analyses: an OLS panel regression, a difference-in-difference regression, and an instrumental variables regression. These three analyses use different samples, with different identifying assumptions, yet we find similar results in all cases: fragmentation improves market quality for large stocks, while it leads to relatively worse market quality for small stocks.

A. The Relation between Fragmentation and Market Changes

We start our analysis using OLS panel regressions with daily data from 1996 to 2014. To the best of our knowledge, our paper is the first to analyze market fragmentation using a panel that covers the majority of the U.S. market over such a long sample period. Our tests are motivated by the industrial organization literature on competition and network externalities. As discussed in Section II, many extant theoretical models of fragmentation compare the welfare gains that result from a reduction in monopoly pricing to the welfare losses that result from negative network externalities. While the net impact of fragmentation is ambiguous, these models do suggest several possible effects. In particular, several models suggest that negative externalities will dominate and fragmentation will lead to increased volatility and worse price efficiency (e.g., Pagano (1989b), H. Mendelson (1987), Madhavan (1995)). On the other hand, Economides (1996) suggests that negative network externalities are smaller than the benefit of reduced transaction costs that come from increased exchange competition. Accordingly, we start by examining the relation between fragmentation and several measures of market quality using OLS panel regressions of the form:

$$y_{i,t+1} = \beta \text{Fragmentation}_{i,t} + \delta \text{Controls}_{i,t} + \varepsilon_{i,t+1} \tag{4}$$

where $y_{i,t+1}$ is either a measure of liquidity, price efficiency, or trading volume for asset i on day $t+1$ and *Controls* include market-to-book, leverage, return volatility over the previous 20 days, and the 20-day moving average of turnover. We include firm and day fixed effects in our fully specified models to account for any unobserved heterogeneity at the firm-level or macro-economic shocks that could affect the levels of outcome variables.

A key contribution of our analysis is to separate the effects of fragmentation for large and small firms. Motivated by the theory, and in particular the model presented by Pagano (1989a), we test whether fragmentation impacts small and large stocks differently. Specifically, the Pagano (1989a) model argues that traders endogenously determine whether or not they want to participate in a market and their entry decision is related to market concentration. In concentrated markets, with many traders, the liquidity demands of one investor are more likely to be offset by the liquidity demands of other investors. However, for thin markets, fragmentation makes it harder to find a counterparty and as a result, investor participation is lower, leading to a negative network externality.

We use each asset's ex-ante market capitalization, measured at $t-1$, as a proxy for the ease of finding a counter-party. In general, larger stocks tend to be held by more institutional investors and they tend to be more widely traded. As such, it is generally easier to find a counter-party in larger stocks.[8] Using market capitalization as a proxy for the ease of finding a counter-party, we then test whether fragmentation generates heterogeneous impacts for thin (i.e., small) and deep (i.e., large) stocks.

A.1 Liquidity Measures

[8]As discussed in the introduction, there are many possible ways of categorizing stocks into deeply traded and thinly traded, since liquidity is multi-dimensional. We use market capitalization because of its simplicity and the fact that it is plausibly exogenous from other characteristics that lead to fragmentation. However, our results are robust to other measures.

We start by examining the impact of fragmentation on two key liquidity variables: bid-ask spreads and the Amihud (2002) illiquidity measure. Across the entire sample, our results are consistent with the findings of O'Hara and Ye (2011): higher fragmentation is associated with improvements in liquidity, as measured by the level of Amihud and bid-ask spreads. However, as previously discussed, theory suggests that market fragmentation may exert heterogeneous impacts on different stocks.

To examine this, we add nine indicator variables, each of which takes the value one if a stock is in one of nine market capitalization deciles (we omit the sixth decile, so median-sized firms represent the base case). In addition, we also add nine interaction terms which measure the product of market fragmentation and each of the nine market capitalization deciles.[9] Formally, we examine panel regressions of the form:

$$\begin{aligned} y_{i,t+1} = \beta \text{Fragmentation}_{i,t} + \sum_{j \neq 6} \gamma_j \text{Size Decile}_{i,j} + \sum_{k \neq 6} \theta_k (\text{Size Decile}_{i,k} \times \text{Fragmentation}_{i,t}) \\ + \delta \text{Controls}_{i,t} + \varepsilon_{i,t+1}, \end{aligned} \tag{5}$$

where $y_{i,t+1}$ is either the level of bid-ask spreads or the Amihud measure for asset i on day $t+1$. The results are shown in Table II with standard errors, clustered by firm and date, shown below the coefficient estimates. Columns (1) and (4) show the results for the entire sample, while columns (2), (3), (5), and (6) show the results broken out by size decile. Interestingly, the results suggest that market fragmentation has a significantly different effect for large and small assets. While market fragmentation is generally associated with reductions in bid-ask spreads and Amihud illiquidity, the interaction terms for deciles 1 through 10 show evidence of significant heterogeneity across firms. For example, in column (6) the

[9] We use indicator variables to measure the impact of market capitalization, instead of including market capitalization directly in the regression, for two reasons. First, our specification allows us to include market capitalization without taking a stance on the parametric form of the relation between market capitalization and our dependent variables. Second, by including indicator variables, we can measure the impact of market fragmentation separately for firms in individual size categories.

statistically significant coefficient of 0.7851 suggests that bid-ask spreads are increasing in fragmentation for small stocks (decile 1). For small stocks, a one standard deviation increase in fragmentation results in a 10% increase in bid-ask spreads. In contrast, for large stocks the statistically significant coefficient of -0.2688 implies that a one standard deviation increase in fragmentation results in a -19% decrease in bid-ask spreads. Similarly, the results show evidence of a differential impact for small and large stocks on the Amihud measure, however, the results suggest the Amihud price impact measure, on average, actually *decreased* for the smallest stocks. At first glance, this seems to suggest that fragmentation has a benefit for small stocks, however another possible interpretation exists: fragmentation makes it harder to execute large trades in small stocks. As a result, consistent with the model in Pagano (1989a), traders endogenously choose to stop trading in this stock, which means there are few large trades and thus, very little evidence of price impact. Later in the paper, we explore these effects in greater detail.

A.2 Price Efficiency and Trading Behavior

Next, we examine whether fragmentation impacts asset prices. Theoretical models suggest that fragmentation impacts price efficiency (H. Mendelson (1987), Madhavan (1995)). Accordingly, we re-run the OLS regressions shown in equations (4) and (5), using the Hou and Moskowitz (2005) measure of price delay as the dependent variables. The results are shown in Table III with standard errors, clustered by firm and date, shown below the coefficient estimates. Again, we start by examining the average impact of fragmentation on market quality. The statistically significant coefficient of -0.0154 on $fragmentation$ in model (1) confirm the findings in O'Hara and Ye (2011): on average, fragmentation is associated with improved price efficiency (i.e, lower price delay). A one standard deviation increase in fragmentation is associated with an approximately 7% reduction in price delay. However, when we examine the results broken out by size deciles in models (2) and (3), we find evidence that more fragmentation is associated with worse price efficiency for smaller firms. Moreover, the positive coefficient on the interaction terms for these deciles suggest that fragmentation did not improve efficiency in these stocks in the same manner that it did for the median stock. The results are consistent with models in which limited stock market participation causes prices to incorporate information more slowly (e.g., Merton (1987), Basak and Cuoco (1998)). In our setting, negative network externalities act as a limit to arbitrage, preventing some investors from trading. Thus, firms with higher fragmentation experience worse price efficiency. Interestingly, the results in Table III show that larger firms also have a positive and significant interaction coefficient. While this result may seem surprising, we note that the mean delay for large firms was quite small prior to the dramatic increase in fragmentation and therefore large firms had little room for improvement. In other words, the prices of large firms were already highly efficient, so as fragmentation increases over the sample period it is not surprising that it leads to relatively less improvement for large stocks, as compared to the median firm.[10]

In addition, in Table III we also examine volume turnover. The theoretical literature on fragmentation predicts that fragmentation in thin assets will tend to decrease market participation. The results are shown in models (4), (5), and (6). The positive and statistically significant coefficient on $fragmentation$ in model (4) shows that, on average, fragmentation is associated with a greater amount of trading. Here, a one standard deviation increase in fragmentation is associated with a 10% increase in turnover. However, as we differentiate these effects across size deciles in models (5) and (6), it is clear that this effect is concentrated in the largest firms. The negative and statistically significant interaction terms in models (5) and (6) suggest there is less trading for small assets. The results are consistent with theoretical predictions: when markets are thinly traded and fragmentation increases, investors choose not to trade. Thus, for thin assets, increased fragmentation is associated with reduced investor participation.

While our results generally confirm the findings in O'Hara and Ye (2011), our sample covers substantially more assets over a much longer time period. Moreover, we provide new

[10]Another possibility for the U-shaped effect in price delay may be that increased HFT activity decreases incentives to acquire information (See Gider et al. 2016).

evidence that the relation between fragmentation and measures of market quality varies substantially by market capitalization. Of course, we note that the recent increase in market fragmentation coincides with many other changes to U.S. equity markets, including the rise of algorithmic and high-frequency trading. In addition, it is possible that market fragmentation is an endogenous outcome of firm-level liquidity and trading. As a consequence, our OLS regression results may be subject to endogeneity biases. Accordingly, we adopt two approaches, a difference-in-difference regression and an instrumental variables regression, that allow us to address these possible confounding influences.

B. The Impact of the Regulation NMS

In this section, we use the implementation of regulation NMS to provide novel evidence on the *causal* impact of fragmentation. As discussed in Section III.B, the implementation of regulation NMS led to significant increases in market fragmentation. Regulation NMS was implemented in 2007 to increase "competition among individual markets and competition among individual orders" (Securities and Exchange Commission (2007)). The regulation went into effect for all U.S. stocks on August 20, 2007 and it contained several provisions.[11] The *Order Protection Rule* requires trading centers to make sure that trades are not executed at prices that are worse than protected quotes available at other trading centers. The *Access Rule* ensured that market data, including quotations, were accessible across different market centers. Almost by definition these rules resulted in increased fragmentation, since they require a trade to be re-routed to an alternative trading venue if the original venue does not have the best bid or ask price. Hence, in this section we use the implementation of Regulation NMS as a natural shock to fragmentation. Motivated by the theoretical prediction that fragmentation may exert heterogeneous effects for different assets, we again test whether smaller (thin) firms react differently to increased fragmentation (e.g., Pagano (1989a)).

To capture the differential effects of fragmentation, we use a set up similar to the OLS

[11] It is possible that some market centers implemented features of Regulation NMS for all stocks prior to August 20, 2007, however, this would bias our difference-in-difference methodology against finding a result.

regressions discussed in the previous sub-section. Specifically, we use indicator variables to test for the differential effects of fragmentation before and after implementation of Regulation NMS. Theory predicts that thinly traded stocks may be negatively affected by negative network externalities when exposed to increases in fragmentation, so the decile indicators allows us to test for different treatment effects for different groups of stocks. We focus on a four-month window on either side of the implementation of Regulation NMS to allow the regulation take effect, while also attempting to avoid any confounding effects of the 2008 Financial Crisis. Formally, we examine a dynamic difference-in-difference regressions around the implementation of Regulation NMS according to the model:

$$\begin{aligned} y_{i,t} = &\sum_{\tau=-4}^{4} \beta_\tau \text{Month}_\tau + \sum_{\tau=-4}^{4} \sum_{k \neq 5} \delta_{k,\tau} (\text{Month}_\tau \times \text{Size Decile}_{k,t=-6}) \\ &+ \sum_{k \neq 5} \gamma_k \text{Size Decile}_{k,t=-6} + \text{FE}_i + \text{FE}_t + \epsilon_{i,t}, \end{aligned} \tag{6}$$

where $y_{i,t}$ includes the same daily measures of market quality and trading examined in the prior OLS analyses, FE_i is a firm fixed effect, and FE_t is a day fixed effect.[12] *Size Decile* is an indicator variable which takes a value of one if the firm is in a given size decile. Firms are sorted on size as of February 1, 2007 (i.e., before regulation NMS is implemented) and *Size Decile* 6, median-sized firms, is the omitted group. *Month* is an indicator variable that takes a value of one for a given month, and the omitted indicator is the month prior to the implementation of regulation NMS (July 2007).

Traditionally, difference-in-difference regressions contain an indicator variable which takes the value one during the treatment period, and zero otherwise. In our setup, the month indicator variables are a more flexible version of the treatment period indicator variable. This dynamic approach allows us to examine, month by month, whether the treatment effects are concentrated in the treatment period, as expected, or whether they occur prior to

[12] The daily fixed effects remove common variation which helps isolate the differential effect. Therefore the interpretation of the coefficients is the incremental effect as compared to the median firm.

treatment. Thus, the dynamic difference-in-difference specification allows us to examine the identifying assumptions in greater detail. In addition, difference-in-difference regressions in a finance setting typically contain an indicator variable that takes the value one for treatment stocks, and zero otherwise. Because regulation NMS was implemented for all stocks, we do not have a treatment indicator variable; instead, we use the size decile indicator variables to test for heterogeneous treatment effects across different firms. As a result, we stress that our difference-in-difference regression is not designed to causally identify the average effect of regulation NMS across *all* firms; our identifying assumptions are designed to test for heterogeneous effects across *different* firms.[13]

The identification of the model relies on the assumption of parallel trends in the outcome variables to establish the causal impact of fragmentation. Importantly, we include firm fixed effects, so time-invariant level differences between the stocks do not compromise the identification. In our setting, the parallel trends assumption states that, in the absence of Regulation NMS, the average change in outcome variables for large stocks would have been equal to the average change in outcome variables for small stocks. Our dynamic difference-in-difference specification allows us to provide evidence supporting the identifying assumptions. Specifically, if we find no statistically significant treatment difference between large and small stocks before the implementation of Regulation NMS, then this would support the parallel trends assumption.

In addition, we also note that in this setup, control variables are only necessary if there are *time-varying* variables that differentially affect treatment. In other words, if the parallel trends assumption holds, then the average change in outcome variables for small and large

[13]Regulation NMS did include a pilot experiment which implemented the regulation on a subset of firms, potentially allowing for a traditional difference-in-difference analysis with separate treatment and control firms. However, the selection of treatment firms in the pilot experiment was not random. The pilot study creators chose 100 stocks from NYSE, 100 stocks from NASDAQ, and 50 stocks from AMEX. As a result of the large number of NASDAQ and AMEX stocks chosen, smaller stocks were over-represented in the sample. Chung and Chuwonganant (2012) examine market quality for pilot stocks around the implementation of regulation NMS. However, because of the non-random selection of treatment firms, they use a matched sample difference-in-difference which may actually increase bias due to the presence of dormant unobserved confounders (Pearl (2009)). They find that fragmentations leads to worse market quality which is consistent with our results on small stocks (since their sample heavily weights small stocks).

stocks should not be related to other firm-specific characteristics. In our main specification, we run the difference-in-difference model without control variables, however, our results are qualitatively unchanged if we include control variables. In particular, in unreported results available upon request, we control for turnover, inverse of price, and return as in O'Hara and Ye (2011). The controls are designed to capture any time-varying differences within firms that could explain the dependent variables. The fact that our treatment coefficients do not change when controls are added provides additional evidence in support of the identifying assumptions (Roberts and Whited (2012)).

B.1 Liquidity Measures

The results of the difference-in-difference analyses are shown in Figure 3 and Table IV. To understand the differential impact of fragmentation on market quality, Figure 3 plots the dynamic treatment effects (i.e., the coefficients on the interaction between the $Month$ and *Size Decile* variables). For simplicity, we plot only the coefficients for size deciles 1 and 10, but the general patterns are consistent across all of the size deciles in that the results become more attenuated as they approach the median-sized decile. The figure displays the mean treatment effect in each month: the triangle represents the mean for decile 1 assets and the circle represents the mean for decile 10 assets, while the lines represent 95% confidence intervals. As discussed above, the parallel trends assumption implies that the treatment effect for decile 1 and decile 10 should not be statistically different prior to the implementation of Regulation NMS. In general, the parallel trends assumption appears to hold: prior to month t, the triangle and the circle are typically very close, but starting at period t they tend to move apart.

As before, theory suggests that market fragmentation may actually harm smaller stocks that are, ex-ante, more likely to have thin markets. For these assets, increased fragmentation is more likely to result in thinner markets which could cause the network externality to outweigh the benefit of exchange competition and reduced transaction costs. Panel A of Figure 3 shows the dynamic treatment coefficients for the Amihud (2002) measure (and the coefficients with standard errors clustered by firm and date are shown in Table IV). The coefficients prior to the implementation of Regulation NMS are not different from each other, satisfying the parallel trends identifying assumption. After the implementation, it is clear that the largest assets experience significantly improved liquidity relative to the smallest assets. Similarly, Panel B shows the results for bid-ask spreads. Again, we see that the small assets experienced significantly greater spreads following the implementation of NMS, while the large assets experienced reduced spreads.

Interestingly, the results suggest that the liquidity for smaller assets is relatively worse following the implementation of Regulation NMS, while the largest assets generally saw improved liquidity. In other words, the results show that Regulation NMS exerts a differential impact on small assets, consistent with our OLS results.

B.2 Price Efficiency and Trading Behavior

We next examine whether fragmentation impacts price efficiency and trading activity, as theorized in several extant models (e.g., H. Mendelson (1987), Madhavan (1995)). In Panel C of 3 and model (3) of Table IV, we examine the difference-in-difference specification using the Hou and Moskowitz (2005) measure of price delay as the dependent variable. Here, the coefficients following the implementation of Regulation NMS are actually negative for both small and large firms, indicating that fragmentation causes improvements in price efficiency for the largest and smallest decile of assets. While our OLS results in Table III also found that fragmentation was associated with lower price delay, on average, in that analysis we found the results were relatively worse for the smallest and largest assets. Here, after accounting for the potentially endogeneity of fragmentation, we find that fragmentation generally causes improvements in price efficiency, consistent with the findings of O'Hara and Ye (2011).

Finally, in Panel D of 3 and model (4) of Table IV, we examine the relation between fragmentation and market participation, as measured by the log of volume turnover. Several models predict that fragmentation may be related to investor participation (e.g., Pagano (1989b), Pagnotta (2013)). Thus, if fragmentation leads to negative network externalities, we would expect to see relatively less trading in the smallest assets after the implementation of Regulation NMS. The results show exactly that. In the months prior to Regulation NMS, small assets generally had slightly higher turnover than large assets, but following NMS the pattern sharply reverses. In the implementation month (t), the results show a dramatic drop in turnover for the smallest assets, relative to the largest assets. However, the results also suggest a caveat. For turnover, Figure 3 provides some evidence of a possible pre-trend for the smallest firms. In other words, it appears that turnover was slightly decreasing in the smallest assets prior to NMS, indicating a possible violation of the parallel trends assumption. While the pre-trend appears economically small, the fact that difference-in-difference regressions require a small time-window around the implementation event makes it difficult to understand long-term trends in outcome variables. Accordingly, in the next section, we use an instrumental variables analysis over the period 1999 to 2013 to establish the impact of fragmentation over a longer time period.

Overall, the results in this section establish novel evidence on the causal impact of market fragmentation. We find that for large assets, fragmentation leads to better liquidity and improved price efficiency while for small assets, fragmentation leads to lower liquidity. While our difference-in-difference analyses do establish the causal impact of market fragmentation and exchange competition, they do so using data from a relatively short time period that spans April 1, 2007 through December 31, 2007. Accordingly, in the next section we use an instrumental variables analysis which allows us to examine long-term effects.

C. The Causal Impact of Fragmentation - Instrumental Variables Approach

In this section, we use the log of the number of market centers in the U.S. as an exogenous instrument to shock firm-level fragmentation. The identifying assumption is that trading locations do not open or close because of the characteristics of individual assets. In other words, the exclusion restriction for our instrumental variables analysis states that the number of market centers impacts the characteristics of individual assets *only through* its impact on fragmentation. Specifically, we examine two-stage least squares regressions (2SLS) of the form:

$$Fragmentation_{i,t} = \phi + \eta(\#\ \text{Markets})_t + \text{Controls}_{i,t} + \nu_{i,t} \tag{7}$$

$$y_{i,t+1} = \alpha + \beta \widehat{\text{Fragmentation}}_{i,t} + \text{Controls}_{i,t} + \varepsilon_{i,t+1}, \tag{8}$$

where $y_{i,t+1}$ is either a measure of liquidity, price efficiency, or trading volume for asset i on day $t+1$ and *Controls* include market-to-book, leverage, return volatility over the previous 20 days, and the 20-day moving average of turnover. The first stage regression (equation (7)) uses time-series variation in the log of the total number of U.S. market centers ($\#\ Markets$) to predict fragmentation in each asset, while the second stage regression (equation (8)) uses the fitted value of fragmentation as the key variable of interest.[14]

Once again, we test for heterogeneous impacts from fragmentation using size deciles. Specifically, we augment the 2SLS model to include size deciles, and interactions between the size deciles and the fitted value of fragmentation according to the model:[15]

$$\text{Fragmentation}_{i,t} = \phi + \eta(\#\ \text{Markets}_t) + \sum_{k \neq 6} \gamma_k \text{Size}_k + \sum_{k \neq 6} \mu_k (\#\ \text{Markets}_t \times \text{Size}_k) + \text{Controls}_{i,t} + \nu_{i,t} \tag{9}$$

$$y_{i,t+1} = \alpha + \beta \widehat{\text{Fragmentation}}_{i,t} + \sum_{k \neq 6} \delta_k \text{Size}_k + \sum_{k \neq 6} \theta_k (\widehat{\text{Frag}} \times \text{Size}_k) + \text{Controls}_{i,t} + \varepsilon_{i,t+1} \tag{10}$$

Formally, there are two requirements for a variable to be a valid instrument in a two-stage least squares regression: (1) the relevance condition and (2) the exclusion restriction. First, our instrument, the log of the total number of U.S. market centers, must be sufficiently correlated with firm-level fragmentation. Second, the exclusion restriction requires the number

[14] Using an augmented Dickey-Fuller test, we strongly reject the null of a unit root for our instrument. In other words, the log of the total number of U.S. market centers is stationary. The natural log transform also lends a natural interpretation in this setting in that it implies a decreasing marginal impact from each new market center (i.e., each additional market center that is opened has a smaller impact). We also provide additional support for the 2SLS analysis in Appendix C which displays reduced form results.

[15] We instrument the interaction of fragmentation and size decile by the interaction of the log of market centers and size decile as discussed in Wooldridge (2010).

of market centers to be uncorrelated with the true error of the endogenous data generating process. Simply put, the number of market centers must be correlated with fragmentation at the firm level, but must only affect the outcome variables through fragmentation. While the exclusion restriction is inherently untestable, the relevance condition is testable: accordingly, in unreported results (available upon request) we examine the first-stage regression to test the relevance assumption for our instrument. As expected, the number of trading venues has a strong positive relation with the level of fragmentation and thus, we easily reject the null of a weak instrument problem.

C.1 Liquidity Measures

The results of the 2SLS regressions are shown in Tables V and VI. In models (1) through (3) we examine the relation between the Amihud (2002) measure and fragmentation, while in models (4) through (6) we examine bid-ask spreads. In general, the 2SLS results suggest improvements in bid-ask spreads, but there is some evidence of deterioration in the Amihud measure. In model (1) of Table V we find that fragmentation is generally associated with higher price impact, as measured by the Amihud measure. Moreover, in models (2) and (3) we again find that small firms appear to be hurt by fragmentation, when compared to the median firm. However, while several of the coefficients in models (2) and (3) suggest that the Amihud illiquidity measure has improved for many firms, the 2SLS results suggest fragmentation did not improve illiquidity in the largest firms (in contrast to our OLS and difference-in-difference results).

In model (4) we again find that higher fragmentation leads to lower values of bid-ask spreads, confirming the findings in O'Hara and Ye (2011) and the findings in our OLS and difference-in-difference regressions. As before, we find differential impacts for small and large assets. For large assets, bid-ask spreads are lower when fragmentation is higher, but for small assets, the effect is reversed. Specifically, for size decile 1 (i.e., small) firms the statistically significant coefficient of 1.0646 in model (6) implies that a one standard deviation increase in fragmentation is associated with a 37% increase in bid-ask spreads relative to the median firm. However, we find that large firms (i.e., decile 10) experience similar effects to the median firm. For these firms, a one standard deviation increase in fragmentation is associated with a dramatic 60% reduction in bid-ask spreads. Overall, the results are largely consistent with our other results: fragmentation generally leads to liquidity improvements for most firms, however, for the smallest firms, fragmentation leads to worse price impact and higher bid-ask spreads.

C.2 Price Efficiency and Trading Behavior

As before, we also examine the impact of fragmentation on price efficiency and trading behavior. In Table VI, we again find that fragmentation leads to improvements in price efficiency, on average. Moreover, consistent with the OLS results in Table III, we find that fragmentation causes price efficiency to be improve less for the smallest firms. In model (3), the statistically significant coefficient of 0.2760 on decile 1 assets implies that a one standard deviation increases in fragmentation is associated with a 12% increase in price delay relative to the median firm, as measured by the Hou and Moskowitz (2005) measure. Moreover, the coefficients on size decile 10 (i.e., large firms) also imply relatively less improvement in price efficiency, consistent with our OLS results. As discussed in Section A, this result is perhaps not surprising. The prices of large firms were already highly efficient, so as fragmentation increases over our sample period it leads to *relatively* less improvement for large stocks, when they are compared to the median firm.

Finally, in columns (4) through (6) of Table VI, we focus on trading activity. Consistent with theory, we find that higher fragmentation is associated with less trading in small firms, but relatively more trading for large firms. In other words, the results support the idea that traders endogenously *choose* to trade. For large stocks, fragmentation leads to better liquidity, and as a result, more trading. In contrast, for small stocks, fragmentation makes it harder for trades to execute and as a result, traders respond by trading less. Overall, the results point to the same conclusion: fragmentation leads to increased liquidity, price efficiency, and trading activity for large assets, while it leads to the opposite result for small assets.

D. Discussion

D.1 Frictions

Our results show that fragmentation and Regulation NMS lead to significant differences in liquidity and trading behavior. Moreover, we document evidence of heterogeneous impacts for different stocks, depending on their ex-ante characteristics. For large stocks, fragmentation generally results in better market quality, consistent with the findings of O'Hara and Ye (2011). For small stocks, increased fragmentation is generally associated with worse liquidity and less trading, consistent with the findings of Chung and Chuwonganant (2012). The results suggest that fragmentation results in thinner markets for small stocks which cause negative network externalities to outweigh the benefits of exchange competition.

Nonetheless, in a frictionless world, we would still expect a truly national market system to be weakly better for all stocks, including small ones. Thus, the fact that market quality degrades for small stocks with more fragmentation suggests the existence of at least one friction which generates a negative network externality. While identifying all possible frictions is beyond the scope of the current paper, we note that Regulation NMS suggests a source for the negative externality. In particular, Regulation NMS does not create a truly consolidated order book, as discussed in M. Mendelson, Peake, and Jr. (1979) and Stoll (2006). In the current system, books are not consolidated, but trades must be routed to another venue if a better trade is available. However, the trade-through rule measures whether or not another venue is "better" only by examining price (i.e., it does not consider quantity).

Stoll (2006) provides a simple example. Imagine a world with two exchanges, A and B. Exchange A is willing to buy 600 shares at \$20.01, which is the top of its book, and 300 shares at \$20.00. At the same time, exchange B has an order at the top of its book to buy 300 shares at \$19.99. Now imagine a trader places an order to sell 900 shares. The trader's best outcome would occur if the entire order were executed on exchange A. However, because Regulation NMS protects only the top of the book at each location, the trade would be obligated to execute 600 shares on exchange A and 300 shares on exchange B. Thus, the specific rules underlying Regulation NMS may in fact be the friction that generates negative network externalities. Put another way, instead of having a consolidated limited order book, Regulation NMS relies on the price-time priority rule and the trade-through rule as a way to generate some competition between trading venues. But, since neither of these rules account for quantities, they generate new execution risks and costs which may deter trading, especially in stocks that do not have depth at the top of the book.

Moreover, recent evidence also suggests that the *Order Protection Rule* in Regulation NMS may give rise to high-frequency traders who attempt to "pick-off" orders as they are routed to different market centers. For example, Budish et al. (2015) discuss how liquidity provision is impaired by the potential for cross-market arbitrage opportunities in a multiple market framework. They show, theoretically and empirically, that when an asset is traded on multiple (i.e., fragmented) markets, high-frequency traders overinvest in speed and liquidity providers must thereby increase spreads to incorporate the increased cost of being picked off at stale prices. Thus, the risk of having an order picked-off by high-frequency traders may also deter trading in small stocks, further increasing the negative network externality.

Finally, we note that another key provision of Regulation NMS is the minimum tick size rule. This rule requires that all shares with a price above one dollar must be quoted in increments of one cent. Two recent papers have shown this rule leads to more fragmentation. Kwan et al. (2014) find that dark pools can bypass traditional limit order queues and therefore offer slightly better pricing. This induces trading to move off the exchange and results in additional fragmentation. Similarly, Chao et al. (2016) provide a model where the minimum tick size induces second-degree price discrimination that can encourage more exchanges and hence more fragmentation. The authors then use ETF stock splits to show that an increase in relative tick size leads to additional fragmentation. Overall, both the *Order Protection Rule* and the minimum tick size rule create key frictions that may hinder the stated goal of Regulation NMS: to create a true national market system.

D.2 Inter-market Sweep Orders

If Regulation NMS does result in frictions that lead to negative network externalities, then in equilibrium we would expect traders to alter their behavior to mitigate the impact of these market frictions. In particular, we would expect traders to respond by strategically gathering liquidity in an attempt to mitigate negative network externalities. In practice, traders can use inter-market sweep orders (ISO) to avoid the frictions created by Regulation NMS. ISOs are special orders which are split across multiple market centers simultaneously and may execute at a directed market center even though it is not at the NBBO, essentially creating an exemption to the order protection rule. Chakravarty, Jain, Upson, and Wood (2012) show that these orders are used quite extensively, representing almost half of the total orders following the implementation in 2007. If Regulation NMS did create frictions that generate negative network externalities, we would expect to see more ISO trading in assets which were most impacted. Accordingly, in Table VII we regress ISO volume on fragmentation in both panel and IV regressions.[16] We consistently find that smaller firms tend to use more ISO volume when exposed to more fragmentation.[17] For example, in model (6), the interaction coefficients are positive and statistically significant for the four smallest deciles, but not for the other deciles. This suggests that traders attempt to mitigate negative network externalities by using more ISO orders for small (thin) assets. Therefore, while we cannot decisively pinpoint the exact friction(s) which are responsible for the negative network externalities we document, the increased use of ISO trades for small firms suggests that Regulation NMS did create these externalities because it did not create a true consolidated limit order book.

[16]We use raw ISO volume (i.e., not scaled by shares outstanding) to facilitate interpretation. However, we include firm fixed effects in all models and adjust for stock spits, buybacks, etc. We are unable to conduct our difference-in-difference tests with ISOs because these order types were introduced in response to Regulation NMS. As such, at the time of our difference-in-difference analysis, there is not sufficient data on ISOs.

[17]We control for institutional ownership because ISOs are more likely to be used by institutional investors.

D.3 Alternatives

Using three distinct set of analyses, our results consistently show that small firms are adversely affected by increased fragmentation, while larger firms tend to experience improved market quality from the increased competition. Of course, it remains possible that some other omitted variable is jointly driving both fragmentation and our market quality measures. For example, in 2003 the Global Analyst Research Settlement may have played a role in reducing market quality for small firms.[18] Global settlement made it costly for analysts to follow smaller firms, incentivizing brokerage firms to drop coverage of small firms over time. An artifact of decreased analyst coverage could possibly lead to less institutional investors and therefore relatively less trade in small firms. This reduction in trading of small firms would therefore be consistent with these small firms experiencing worse market quality due to a reduction in analysts. While it is likely that Global settlement impacted small firms differently than large firms, we note that our difference-in-difference analysis explicitly shows a change around the implementation of Regulation NMS, which occurred several years *after* the 2003 Global Analyst Research Settlement. Similarly, our IV analysis explicitly shows that small firms react differently as fragmentation changes. Finally, we note that our analyses are unchanged if we include the number of analysts as a control variable. As such, we believe our results are not likely driven by alternative explanations like Global settlement.

Finally, we are careful to note that our results do not contain any welfare implications about Regulation NMS. In other words, our results do not say that Regulation NMS was, on net, good or bad. Rather, our results suggest that fragmentation improves market quality for some assets, but leads to negative market externalities for other assets. Future research should continue to explore the nature of the network externality in order to further understand the friction(s) that generate it.

[18] We thank Maureen O'Hara for pointing out this alternative.

V. Conclusion

While a large literature has examined the impact of algorithmic and high frequency trading, less is known about the impact of recent increases in market fragmentation. We present three distinct sets of analyses to examine the impact of fragmentation and we find that market fragmentation leads to significant changes in market quality and trading.

First, using OLS panel regressions over the period 1996 to 2014, we show that fragmentation is generally associated with improvements in bid-ask spreads and price efficiency, confirming the findings in O'Hara and Ye (2011). However, we then provide novel evidence that the relation between fragmentation and market quality is dramatically different for stocks in different size deciles. In particular, we show that fragmentation is associated with reduced bid-ask spreads and better price efficiency for large stocks, while it is associated with increased bid-ask spreads and worse price efficiency for small stocks.

Of course, we note that OLS regressions may be subject to endogeneity biases. Accordingly, we examine a difference-in-difference analysis which uses the implementation of Regulation NMS to identify the causal impact of market fragmentation. Consistent with the OLS results, we find that fragmentation *causes* reduced bid-ask spreads and better price efficiency for large stocks, while it *causes* increased bid-ask spreads and worse price efficiency for small stocks. Finally, we use an instrumental variables analysis that uses the panel of data from 1999-2013 to conduct a comprehensive analysis of market fragmentation. We use the log of the number of U.S. trading venues as an exogenous instrument for market fragmentation and we again confirm that market fragmentation leads to better market quality, on average, for large stocks and worse market quality, on average, for small stocks.

While many theoretical and empirical papers on fragmentation have ambiguous conclusions, our results help reconcile these seemingly contradictory findings. The existing theoretical literature on fragmentation often discusses two forces: (1) the decrease in transaction costs that arise from increased competition and (2) the increase in negative externalities that arise from thin markets. Our results show that for large stocks, with deep markets, the former effect dominates while in small stocks, with thin markets, the latter effect dominates. Accordingly, our results show *how* the predictions of theoretical models of fragmentation apply to real world assets. In the process, we confirm and reconcile the seemingly contradictory findings of O'Hara and Ye (2011) and Chung and Chuwonganant (2012).

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Figure 1. Market Characteristics over Time

The figure displays a time-series plot of the daily mean, $10th$ percentile, and $90th$ percentile of market characteristics across firms in our sample. Panel A displays the bid-ask spread, calculated as the difference between the bid and ask of the national best bid and offer (NBBO) scaled by the midpoint of the bid and ask. Panel B displays the Amihud (2002) illiquidity measured, calculated at the daily level as the absolute return per dollar traded. Panel C displays price efficiency, calculated as the Hou and Moskowitz (2005) $Delay1$ measure of price efficiency. Panel D displays volatility, calculated as the intraday return volatility over 15 minute periods. Observations outside five standard deviations of each variable are omitted to reduce the impact of outliers. Bid-ask spread, Amihud illiquidity, and intraday volatility are log-transformed to reduce skewness. The vertical gray line denotes the initial implementation of Regulation NMS on August 20, 2007.

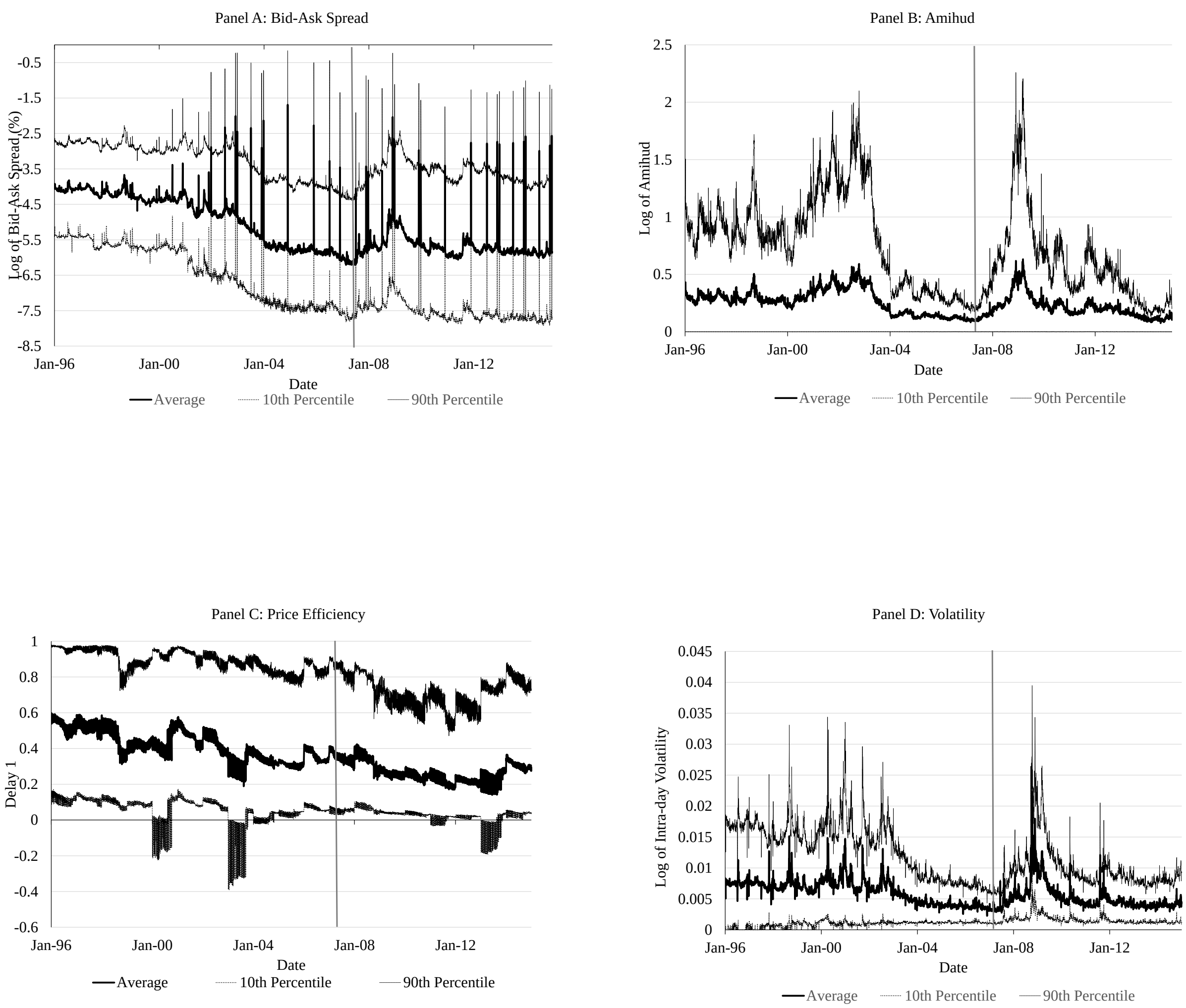


Figure 2. Trading Characteristics over Time

The figure displays a time-series plot of the daily average, $10th$ percentile, and $90th$ percentile of trading characteristics. Panel A displays the number of market centers, defined as the sum of exchanges, electronic communications networks (ECN), and alternative trading systems (ATS) as reported by the SEC. Panel B displays fragmentation, measured as one minus the Herfindahl-Hirschman Index (HHI), where HHI measures the level of concentration of trading volume for each firm across the 17 trade reporting facilities in TAQ. Panel C displays volume turnover defined as the log of daily trading volume divided by shares outstanding. Panel D contains a TAQ provided measure of the number of exchanges which have depth posted at the NBBO. Observations outside five standard deviations of each variable are omitted to reduce the impact of outliers. The vertical gray line denotes the initial implementation of Regulation NMS on August 20, 2007.

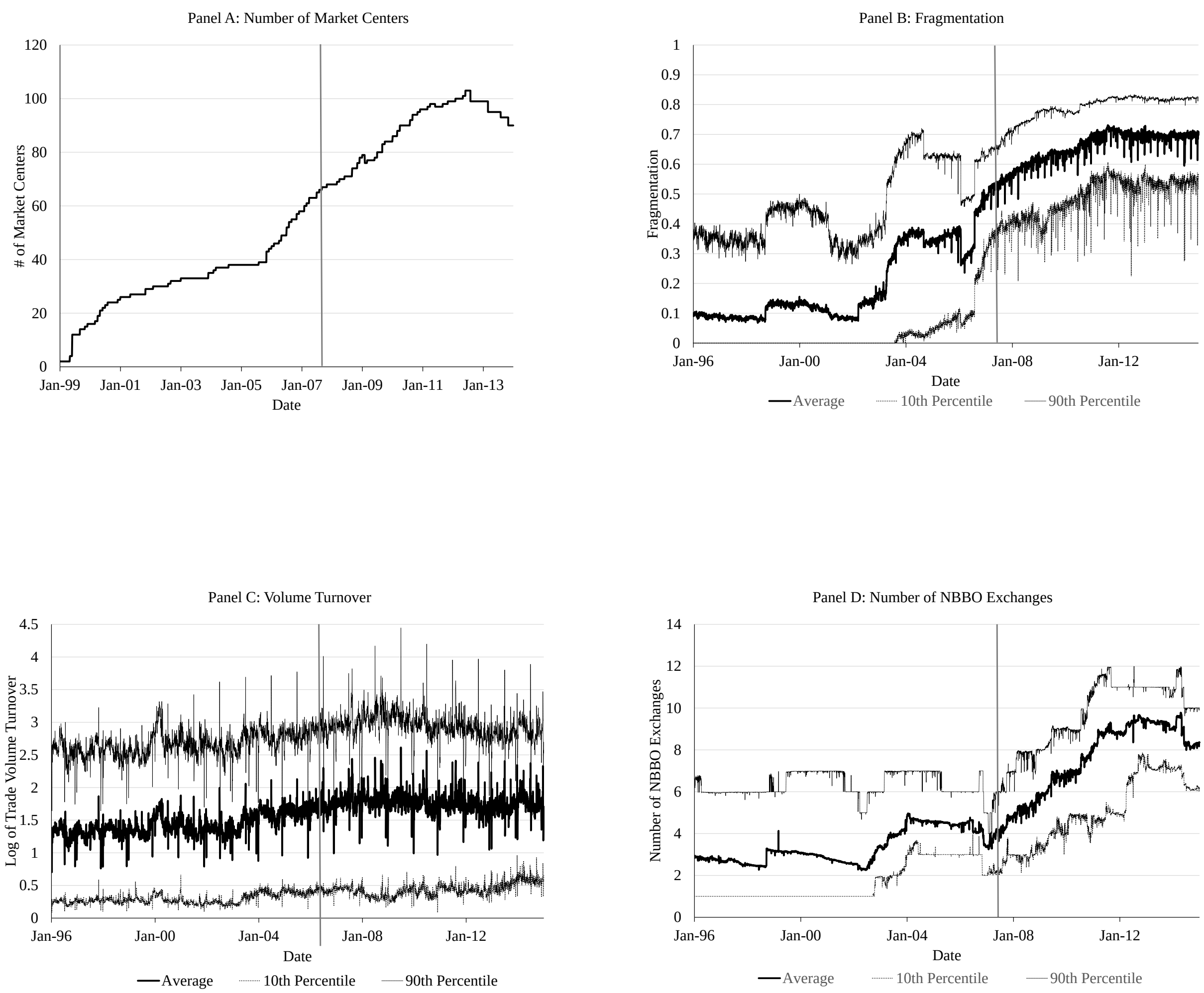
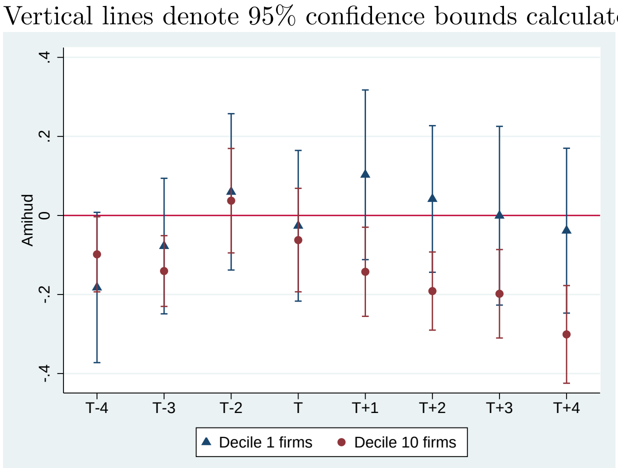


Figure 3. Regulation NMS Difference-in-Difference

The figure presents the results of a difference-in-difference regression around the implementation of Regulation NMS according to the model:

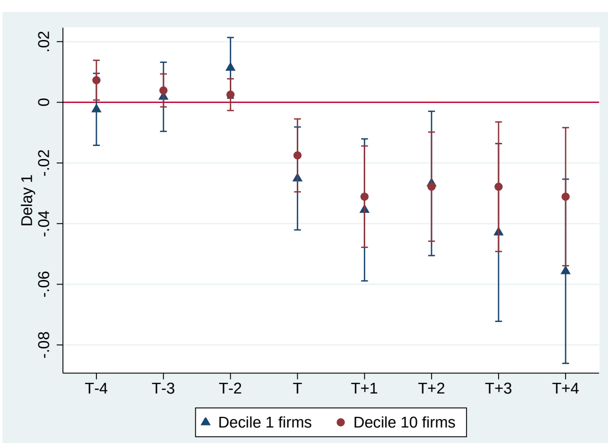
$$
\begin{aligned}
y_{i,t} = &\sum_{\tau=-4}^{4} \beta_\tau \text{Month}_\tau + \sum_{\tau=-4}^{4} \sum_{k \neq 6} \delta_{k,\tau} (\text{Month}_\tau \times \text{Size Decile}_{k,t=-6}) \\
&+ \sum_{k \neq 6} \gamma_k \text{Size Decile}_{k,t=-6} + \text{FE}_i + \text{FE}_t + \epsilon_{i,t},
\end{aligned}
$$

where $y_{i,t}$ is a measure of market quality, FE_i is a firm fixed effect, FE_t is a day fixed effect, *Size Decile* is an indicator where decile 10 is the largest firms, and *Month* is an indicator variable which takes the value of one for a given month. The plotted coefficients are the interactions between *Size Deciles* 1 and 10 and the month indicator variables. *Size Decile* 6, the median firms, and $Month_{t-1}$ are omitted to avoid collinearity. Firms are sorted into market capitalization deciles one month prior to the experiment. Panels (a)-(d) plot the monthly treatment effect for Decile 1 (small) versus Decile 10 (large) firms on Amihud illiquidity, Bid-Ask spread, Hou and Moskowitz (2005) price delay, and volume turnover respectively. In each panel, the "triangle" represents the mean for Decile 1 firms, while the "circle" represents the mean for Decile 10 firms. Vertical lines denote 95% confidence bounds calculated using standard errors clustered by firm and date.

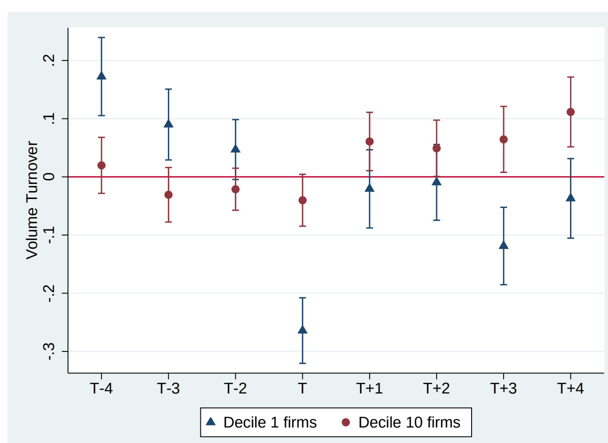


(a) Amihud

(b) Bid-Ask Spread



(c) Delay 1



(d) Volume

Table I
Summary Statistics

The table displays summary statistics for our sample, constructed using daily data from CRSP and TAQ from 1996 through 2014. *Market Cap* is the market capitalization, in thousands of U.S. dollars. *Delay*1 and *Delay*2 are the Hou and Moskowitz (2005) measures calculated over rolling 100 week windows. *Fragmentation* is measured as one minus the Herfindahl-Hirschman Index of trading volume across the exchanges provided in TAQ. $Bid - Ask\ Spread$ is the difference between the ask and bid of the national best bid and offer (NBBO) scaled by the midpoint for each asset. *Amihud* is the Amihud (2002) illiquidity measure. *Volatility* is measured as the intraday return volatility over 15-minute intervals. *Turnover* is the log of trading volume as a fraction of shares outstanding. *NBBO Exchanges* is the number of different exchanges posting liquidity at the NBBO, as provided by TAQ. We measure $Bid - Ask\ Spread$ and the number of *NBBO Exchanges* as the average of these measures over the entire trading day for each asset.

Variable	**Obs**	**Mean**	**Std Dev**	**1%**	**50%**	**99%**
Market Cap	20,785,033	3,063,313	15,200,000	4,606	280,139	54,100,000
Fragmentation	20,785,033	0.35	0.30	0.00	0.35	0.83
Delay 1	19,137,129	0.37	0.32	-0.13	0.28	1.00
Delay 2	19,137,129	0.54	0.20	0.15	0.52	0.98
Bid-Ask Spread	20,280,481	0.02	0.04	0.00	0.01	0.15
Amihud	20,769,274	3.23	275.96	0.00	0.01	34.68
Volatility (%)	20,588,196	0.57	0.59	0	0.38	3.02
Volume	20,785,033	735,193	4,960,260	200	82,007	10,500,000
NBBO Exchanges	20,280,481	4.8	3.0	1.0	4.6	11.2
Log(Turnover)	20,726,491	1.69	0.87	0.15	1.64	3.89
Log(Leverage)	19,816,340	0.18	0.17	0.0	0.14	0.66
Log(Market/Book)	19,252,965	7.62	1.00	5.31	7.54	10.56

Table II
OLS Regression of Amihud and Bid-Ask Spreads on Fragmentation

The table presents the results of an OLS panel regression examining the relation between liquidity measures and market fragmentation according to the model:

$$y_{i,t+1} = \alpha + \beta \text{Fragmentation}_{i,t} + \sum_{k \neq 6} \delta_k \text{Size Decile}_k + \sum_{k \neq 6} \gamma_k (\text{Frag}_{i,t} \times \text{Size Decile}_k) + \text{Controls}_{i,t} + \varepsilon_{i,t+1},$$

where $y_{i,t+1}$ is either the log of the Amihud (2002) illiquidity measure (models 1 through 3) or the log of the $Bid-Ask\ Spread$ (models 4 through 6) for asset i on day t. $Fragmentation$ is measured as one minus the Herfindahl-Hirschman Index of trading volume across venues. *Decile* 10 contains the largest firms while *Decile* 1 contains the smallest firms. Control variables are discussed in Section IV of the text, and we include firm and/or date fixed effects as indicated at the bottom of the table. Standard errors clustered by firm and date are shown in parentheses. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable=	**Amihud**	**Amihud**	**Amihud**	**Bid-Ask**	**Bid-Ask**	**Bid-Ask**
Fragmentation	-0.1934***	-0.0864***	-0.0580***	-0.3476***	-0.6548***	-0.4427***
	(0.01)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.02)*	*(0.02)*
Frag × Decile 1		-0.5514***	-0.4604***		0.9751***	0.7851***
		(0.03)	*(0.03)*		*(0.02)*	*(0.02)*
Frag × Decile 2		-0.3807***	-0.3201***		0.7488***	0.6428***
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Frag × Decile 3		-0.3277***	-0.2452***		0.4605***	0.4367***
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Frag × Decile 4		-0.2372***	-0.1657***		0.1814***	0.2016***
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Frag × Decile 5		-0.1050***	-0.0662***		0.0659***	0.0850***
		(0.01)	*(0.01)*		*(0.02)*	*(0.01)*
Frag × Decile 7		0.0635***	0.0344***		0.0116**	-0.0203**
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Frag × Decile 8		0.1001***	0.0639***		-0.0075***	-0.0714***
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Frag × Decile 9		0.1135***	0.0866***		-0.0193***	-0.1062***
		(0.01)	*(0.01)*		*(0.03)*	*(0.03)*
Frag × Decile 10		0.1128***	0.0791***		-0.2430***	-0.2688***
		(0.01)	*(0.01)*		*(0.03)*	*(0.04)*
Decile 1		1.1024***	0.8550***		1.2223***	1.1332***
		(0.01)	*(0.01)*		*(0.01)*	*(0.02)*
Decile 2		0.4955***	0.3630***		0.8873***	0.7821***
		(0.01)	*(0.01)*		*(0.01)*	*(0.01)*
Decile 3		0.2553***	0.1487***		0.6542***	0.5426***
		(0.01)	*(0.01)*		*(0.01)*	*(0.01)*
Decile 4		0.1198***	0.0502***		0.4416***	0.3567***
		(0.00)	*(0.00)*		*(0.01)*	*(0.01)*
Decile 5		0.0384***	0.0058***		0.2318***	0.1818***
		(0.00)	*(0.00)*		*(0.01)*	*(0.01)*
Decile 7		-0.0111***	0.0123***		-0.2594***	-0.2098***
		(0.00)	*(0.00)*		*(0.01)*	*(0.01)*
Decile 8		-0.0060***	0.0310***		-0.5463***	-0.4285***
		(0.00)	*(0.00)*		*(0.01)*	*(0.01)*
Decile 9		0.0032***	0.0506***		-0.8861***	-0.7068***
		(0.00)	*(0.00)*		*(0.01)*	*(0.01)*
Decile 10		0.0035***	0.0604***		-1.3822***	-1.0153***
		(0.00)	*(0.01)*		*(0.02)*	*(0.02)*
Firm FE?	YES	NO	YES	YES	NO	YES
Date FE?	YES	YES	YES	YES	YES	YES
Number of observations	19,053,701	19,053,741	19,053,701	18,600,274	18,600,310	18,600,274
R^2	0.418	0.401	0.448	0.875	0.869	0.897

Table III
OLS Regression of Price Efficiency and Trading Volume on Fragmentation

The table presents the results of an OLS panel regression of price delay on market fragmentation according to the model:

$$y_{i,t+1} = \alpha + \beta \text{Fragmentation}_{i,t} + \sum_{k \neq 6} \delta_k \text{Size Decile}_k + \sum_{k \neq 6} \gamma_k (\text{Frag}_{i,t} \times \text{Size Decile}_k) + \text{Controls}_{i,t} + \varepsilon_{i,t+1},$$

where $y_{i,t+1}$ is either *Price Delay* as in Hou and Moskowitz (2005) (models 1 through 3) or *Turnover* measured as the log of trading volume scaled by shares outstanding (models 4 through 6). *Fragmentation* is measured as one minus the Herfindahl-Hirschman Index of trading volume across venues. *Decile* 10 contains the largest firms while *Decile* 1 contains the smallest firms. Control variables are discussed in Section IV of the text, and we include firm and/or date fixed effects as indicated at the bottom of the table. Standard errors clustered by firm and date are shown in parentheses. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable=	**Delay 1**	**Delay 1**	**Delay 1**	**Turnover**	**Turnover**	**Turnover**
Fragmentation	-0.0154***	-0.1130***	-0.0880***	0.2941***	0.6256***	0.3280***
	(0.00)	*(0.01)*	*(0.01)*	*(0.01)*	*(0.03)*	*(0.02)*
Frag × Decile 1		0.1893***	0.1722***		-0.3453***	-0.0895***
		(0.01)	*(0.01)*		*(0.04)*	*(0.03)*
Frag × Decile 2		0.1395***	0.1451***		-0.4994***	-0.2791***
		(0.01)	*(0.01)*		*(0.04)*	*(0.03)*
Frag × Decile 3		0.0793***	0.0972***		-0.4046***	-0.2734***
		(0.01)	*(0.01)*		*(0.03)*	*(0.03)*
Frag × Decile 4		-0.0151	0.0205**		-0.2643***	-0.1461***
		(0.01)	*(0.01)*		*(0.03)*	*(0.02)*
Frag × Decile 5		-0.0414***	-0.0114		-0.1654***	-0.0821***
		(0.01)	*(0.01)*		*(0.03)*	*(0.02)*
Frag × Decile 7		0.0408***	0.0278***		0.0981***	0.0469**
		(0.01)	*(0.01)*		*(0.03)*	*(0.02)*
Frag × Decile 8		0.0831***	0.0700***		0.1840***	0.1625***
		(0.01)	*(0.01)*		*(0.04)*	*(0.03)*
Frag × Decile 9		0.1360***	0.1211***		0.2327***	0.2442***
		(0.01)	*(0.01)*		*(0.04)*	*(0.03)*
Frag × Decile 10		0.1962***	0.1767***		0.2340***	0.1887***
		(0.01)	*(0.01)*		*(0.04)*	*(0.04)*
Decile 1		0.2768***	0.2203***		-0.7985***	-0.9046***
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Decile 2		0.2194***	0.1547***		-0.5613***	-0.6174***
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Decile 3		0.1702***	0.1114***		-0.4208***	-0.4328***
		(0.01)	*(0.01)*		*(0.02)*	*(0.01)*
Decile 4		0.1144***	0.0732***		-0.2539***	-0.2757***
		(0.01)	*(0.01)*		*(0.02)*	*(0.01)*
Decile 5		0.0624***	0.0424***		-0.1151***	-0.1306***
		(0.00)	*(0.00)*		*(0.01)*	*(0.01)*
Decile 7		-0.0535***	-0.0450***		0.1182***	0.1170***
		(0.00)	*(0.00)*		*(0.01)*	*(0.01)*
Decile 8		-0.0996***	-0.0930***		0.2205***	0.2009***
		(0.01)	*(0.01)*		*(0.02)*	*(0.01)*
Decile 9		-0.1563***	-0.1485***		0.2606***	0.2440***
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Decile 10		-0.2175***	-0.2090***		0.2033***	0.2071***
		(0.01)	*(0.01)*		*(0.03)*	*(0.03)*
Firm FE?	YES	NO	YES	YES	NO	YES
Day FE?	YES	YES	YES	YES	YES	YES
Number of observations	17,746,655	17,746,744	17,746,655	19,062,962	19,063,004	19,062,962
R^2	0.474	0.390	0.490	0.677	0.392	0.683

Table IV
Difference-in-difference Estimate of Market Quality Around Regulation NMS

The table presents the results of a difference-in-difference regression according to the model:

$$y_{i,t} = \sum_{\tau=-4}^{4} \beta_\tau \text{Month}_\tau + \sum_{\tau=-4}^{4} \sum_{k\neq 6} \delta_{k,\tau}(\text{Month}_\tau \times \text{Size Decile}_k) + \sum_{k\neq 6} \gamma_k \text{Size Decile}_k + \text{FE}_i + \text{FE}_t + \epsilon_{i,t},$$

where $y_{i,t}$ is either the log of the Amihud (2002) illiquidity measure (model 1), the log of the $Bid - Ask$ $Spread$ (model 2), the Hou and Moskowitz (2005) $Delay1$ measure (model 3), or the log of $Turnover$ (model 4), FE_i is a firm fixed effect, FE_t is a day fixed effect, $Decile$ is an indicator variable which equals 1 when a firm is in that size decile, and zero otherwise and decile 10 is the largest firms, and $Month$ is an indicator variable which takes the value of one for a given month. $Size\ Decile$ 6, the median firms, and $Month_{t-1}$ are omitted to avoid collinearity and represent the base case. Standard errors clustered by firm and date are shown below the estimates. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable=	**Amihud**	**Bid-Ask**	**Delay 1**	**Turnover**
Decile 1, t-4	-0.1822*	0.0569*	-0.0023	0.1725***
	(0.10)	*(0.03)*	*(0.01)*	*(0.03)*
Decile 1, t-3	-0.0775	0.0216	0.0018	0.0899***
	(0.09)	*(0.03)*	*(0.01)*	*(0.03)*
Decile 1, t-2	0.0597	0.0492	0.0114**	0.0470*
	(0.10)	*(0.03)*	*(0.01)*	*(0.03)*
Decile 1, t=0	-0.0261	-0.0729**	-0.0251***	-0.2642***
	(0.10)	*(0.03)*	*(0.01)*	*(0.03)*
Decile 1, t+1	0.1029	-0.0203	-0.0355***	-0.0206
	(0.11)	*(0.03)*	*(0.01)*	*(0.03)*
Decile 1, t+2	0.0417	0.0615*	-0.0267**	-0.0095
	(0.09)	*(0.03)*	*(0.01)*	*(0.03)*
Decile 1, t+3	-0.0007	0.1213***	-0.0429***	-0.1188***
	(0.11)	*(0.04)*	*(0.01)*	*(0.03)*
Decile 1, t+4	-0.0385	0.2901***	-0.0557***	-0.0370
	(0.11)	*(0.05)*	*(0.02)*	*(0.03)*
Decile 10, t-4	-0.0983**	-0.0884	0.0073**	0.0198
	(0.05)	*(0.05)*	*(0.00)*	*(0.02)*
Decile 10, t-3	-0.1406***	-0.0432	0.0039	-0.0308
	(0.05)	*(0.05)*	*(0.00)*	*(0.02)*
Decile 10, t-2	0.0373	-0.0302	0.0025	-0.0213
	(0.07)	*(0.05)*	*(0.00)*	*(0.02)*
Decile 10, t=0	-0.0623	-0.1042**	-0.0175***	-0.0402*
	(0.07)	*(0.05)*	*(0.01)*	*(0.02)*
Decile 10, t+1	-0.1425**	-0.1661***	-0.0311***	0.0608**
	(0.06)	*(0.05)*	*(0.01)*	*(0.03)*
Decile 10, t+2	-0.1913***	-0.1645***	-0.0278***	0.0491**
	(0.05)	*(0.05)*	*(0.01)*	*(0.02)*
Decile 10, t+3	-0.1981***	-0.1520**	-0.0278**	0.0644**
	(0.06)	*(0.07)*	*(0.01)*	*(0.03)*
Decile 10, t+4	-0.3009***	-0.1572**	-0.0311***	0.1116***
	(0.06)	*(0.07)*	*(0.01)*	*(0.03)*
Firm FE?	YES	YES	YES	YES
Day FE?	YES	YES	YES	YES
Number of observations	627,556	641,491	611,500	641,497
R^2	0.843	0.892	0.698	0.887

Table V
Second Stage Estimates from 2SLS Regression of Amihud and Bid-Ask Spreads

We use the log of the total number of market centers in the U.S. at each point in time as an instrument according to the two-stage least squares model:

$$\text{Fragmentation}_{i,t} = \phi + \eta(\#\text{ Markets}_t) + \sum_{k\neq 6}\gamma_k \text{Size}_k + \sum_{k\neq 6}\mu_k(\#\text{ Markets}_t \times \text{Size}_k) + \text{Controls}_{i,t} + \nu_{i,t}$$
$$y_{i,t+1} = \alpha + \beta\widehat{\text{Fragmentation}}_{i,t} + \sum_{k\neq 6}\delta_k \text{Size}_k + \sum_{k\neq 6}\theta_k(\widehat{\text{Frag}} \times \text{Size}_k) + \text{Controls}_{i,t} + \varepsilon_{i,t+1},$$

where $y_{i,t+1}$ is either the log of the Amihud (2002) illiquidity measure (columns (1) through (3)) or the log of the $Bid - Ask\ Spread$ (columns (4) through (6)), and $Decile$ is an indicator variable which equals 1 when a firm is in that size decile, and zero otherwise and decile 10 is the largest firms. Control variables are discussed in Section IV of the text, and we include firm and/or date fixed effects as indicated at the bottom of the table. Firms are sorted into market capitalization deciles the period before the analysis begins and then interacted with fragmentation in the first stage and we use the log of the number of market centers × each market capitalization decile as additional instruments. Standard errors, clustered by firm and date, are shown below the estimates. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable=	**Amihud**	**Amihud**	**Amihud**	**Bid-Ask**	**Bid-Ask**	**Bid-Ask**
Fragmentation	0.7129***	0.0872***	0.4395***	-2.8294***	-2.1472***	-3.0560***
	(0.16)	*(0.01)*	*(0.14)*	*(0.49)*	*(0.05)*	*(0.49)*
Frag × Decile 1		0.4366***	0.5208***		1.3544***	1.0646***
		(0.08)	*(0.09)*		*(0.07)*	*(0.17)*
Frag × Decile 2		0.0499	0.1107**		1.0994***	0.8893***
		(0.03)	*(0.05)*		*(0.06)*	*(0.11)*
Frag × Decile 3		-0.1294***	-0.0997***		0.7413***	0.6365***
		(0.02)	*(0.03)*		*(0.05)*	*(0.07)*
Frag × Decile 4		-0.1583***	-0.1490***		0.3431***	0.2805***
		(0.01)	*(0.02)*		*(0.05)*	*(0.05)*
Frag × Decile 5		-0.0752***	-0.0713***		0.1177***	0.0838**
		(0.01)	*(0.01)*		*(0.04)*	*(0.03)*
Frag × Decile 7		0.0577***	0.0568***		0.0462	0.0234
		(0.01)	*(0.01)*		*(0.04)*	*(0.03)*
Frag × Decile 8		0.1139***	0.1092***		0.0578	0.0016
		(0.01)	*(0.01)*		*(0.05)*	*(0.05)*
Frag × Decile 9		0.1415***	0.1307***		0.0488	0.0122
		(0.01)	*(0.02)*		*(0.06)*	*(0.06)*
Frag × Decile 10		0.1033***	0.0932***		-0.1160*	-0.1085
		(0.01)	*(0.02)*		*(0.06)*	*(0.07)*
Decile 1		0.4897***	0.5324***		0.4539***	0.7943***
		(0.03)	*(0.03)*		*(0.03)*	*(0.04)*
Decile 2		0.1751***	0.1999***		0.3164***	0.5570***
		(0.02)	*(0.02)*		*(0.03)*	*(0.03)*
Decile 3		0.0630***	0.0814***		0.2365***	0.4005***
		(0.01)	*(0.01)*		*(0.02)*	*(0.03)*
Decile 4		0.0175**	0.0294***		0.1926***	0.3058***
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Decile 5		-0.0088*	-0.0041		0.1210***	0.1870***
		(0.00)	*(0.01)*		*(0.02)*	*(0.02)*
Decile 7		0.0227***	0.0197***		-0.1819***	-0.2395***
		(0.00)	*(0.01)*		*(0.02)*	*(0.02)*
Decile 8		0.0490***	0.0413***		-0.3433***	-0.4620***
		(0.01)	*(0.01)*		*(0.02)*	*(0.03)*
Decile 9		0.0846***	0.0710***		-0.5514***	-0.7461***
		(0.01)	*(0.01)*		*(0.03)*	*(0.04)*
Decile 10		0.1290***	0.1041***		-0.7167***	-1.0175***
		(0.01)	*(0.01)*		*(0.04)*	*(0.05)*
Firm FE?	YES	YES	YES	YES	YES	YES
Year FE?	YES	NO	YES	YES	NO	YES
Number of observations	14,328,805	14,328,805	14,328,805	14,292,406	14,292,406	14,292,406
R^2	0.414	0.453	0.436	0.799	0.810	0.799

Table VI
Second Stage Estimates from 2SLS Regression of Price Efficiency and Volume

We use the log of the total number of market centers in the U.S. at each point in time as an instrument according to the two-stage least squares model:

$$\text{Fragmentation}_{i,t} = \phi + \eta(\#\ \text{Markets}_t) + \sum_{k\neq 6}\gamma_k \text{Size}_k + \sum_{k\neq 6}\mu_k(\#\ \text{Markets}_t \times \text{Size}_k) + \text{Controls}_{i,t} + \nu_{i,t}$$

$$y_{i,t+1} = \alpha + \beta\widehat{\text{Fragmentation}}_{i,t} + \sum_{k\neq 6}\delta_k \text{Size}_k + \sum_{k\neq 6}\theta_k(\widehat{\text{Frag}} \times \text{Size}_k) + \text{Controls}_{i,t} + \varepsilon_{i,t+1},$$

where $y_{i,t+1}$ is either the Hou and Moskowitz (2005) measure of price delay (columns (1) through (3)) or the log of volume *Turnover* (columns (4) through (6)), and *Decile* is an indicator variable which equals 1 when a firm is in that size decile, and zero otherwise and decile 10 is the largest firms. Control variables are discussed in Section IV of the text, and we include firm and/or date fixed effects as indicated at the bottom of the table. Firms are sorted into market capitalization deciles the period before the analysis begins and then interacted with fragmentation in the first stage and we use the log of the number of market centers × each market capitalization decile as additional instruments. Standard errors, clustered by firm and date, are shown below the estimates. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable=	**Delay 1**	**Delay 1**	**Delay 1**	**Turnover**	**Turnover**	**Turnover**
Fragmentation	-0.1911	-0.4399***	-0.3409**	-2.5752***	0.9298***	-2.0520***
	(0.17)	*(0.01)*	*(0.16)*	*(0.48)*	*(0.04)*	*(0.44)*
Frag × Decile 1		0.2635***	0.2760***		-0.9949***	-2.0342***
		(0.03)	*(0.06)*		*(0.08)*	*(0.20)*
Frag × Decile 2		0.2789***	0.2895***		-0.9979***	-1.6861***
		(0.02)	*(0.04)*		*(0.06)*	*(0.14)*
Frag × Decile 3		0.2083***	0.2126***		-0.7569***	-1.1302***
		(0.02)	*(0.03)*		*(0.05)*	*(0.09)*
Frag × Decile 4		0.0600***	0.0606***		-0.3814***	-0.5242***
		(0.02)	*(0.02)*		*(0.04)*	*(0.06)*
Frag × Decile 5		-0.0179	-0.0175		-0.1870***	-0.2474***
		(0.01)	*(0.01)*		*(0.04)*	*(0.04)*
Frag × Decile 7		0.0580***	0.0584***		0.1330***	0.2195***
		(0.01)	*(0.01)*		*(0.04)*	*(0.04)*
Frag × Decile 8		0.1202***	0.1230***		0.2376***	0.4005***
		(0.02)	*(0.02)*		*(0.05)*	*(0.05)*
Frag × Decile 9		0.1798***	0.1793***		0.2768***	0.5112***
		(0.02)	*(0.02)*		*(0.05)*	*(0.06)*
Frag × Decile 10		0.2155***	0.2149***		0.1564***	0.4084***
		(0.02)	*(0.03)*		*(0.05)*	*(0.07)*
Decile 1		0.1626***	0.1820***		-0.3849***	-0.4169***
		(0.01)	*(0.02)*		*(0.04)*	*(0.05)*
Decile 2		0.0908***	0.1012***		-0.2328***	-0.2290***
		(0.01)	*(0.01)*		*(0.03)*	*(0.04)*
Decile 3		0.0591***	0.0661***		-0.1799***	-0.1863***
		(0.01)	*(0.01)*		*(0.02)*	*(0.03)*
Decile 4		0.0552***	0.0599***		-0.1484***	-0.1545***
		(0.01)	*(0.01)*		*(0.02)*	*(0.03)*
Decile 5		0.0471***	0.0494***		-0.0713***	-0.0602***
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Decile 7		-0.0640***	-0.0656***		0.0661***	0.0276
		(0.01)	*(0.01)*		*(0.02)*	*(0.02)*
Decile 8		-0.1235***	-0.1275***		0.1239***	0.0712**
		(0.01)	*(0.01)*		*(0.02)*	*(0.03)*
Decile 9		-0.1809***	-0.1865***		0.1502***	0.0917***
		(0.01)	*(0.01)*		*(0.03)*	*(0.04)*
Decile 10		-0.2232***	-0.2320***		0.1188***	0.0920**
		(0.01)	*(0.02)*		*(0.03)*	*(0.04)*
Firm FE?	YES	YES	YES	YES	YES	YES
Year FE?	YES	NO	YES	YES	NO	YES
Number of observations	13,527,260	13,527,260	13,527,260	14,336,187	14,336,187	14,336,187
R^2	0.452	0.431	0.453	0.452	0.682	0.431

Table VII
Intermarket Sweep Orders and Fragmentation

The table presents the results of OLS panel and two-stage instrumental variables regressions (IV) of intermarket sweep order (ISO) volume on fragmentation. For the IV regressions, we use the log of the total number of market centers in the U.S. at each point in time as an instrument according to the model:

$$\text{Fragmentation}_{i,t} = \phi + \eta(\#\ \text{Markets}_t) + \sum_{k \neq 6} \gamma_k \text{Size}_k + \sum_{k \neq 6} \mu_k (\#\ \text{Markets}_t \times \text{Size}_k) + \text{Controls}_{i,t} + \nu_{i,t}$$

$$y_{i,t+1} = \alpha + \beta \widehat{\text{Fragmentation}}_{i,t} + \sum_{k \neq 6} \delta_k \text{Size}_k + \sum_{k \neq 6} \theta_k (\widehat{\text{Frag}} \times \text{Size}_k) + \text{Controls}_{i,t} + \varepsilon_{i,t+1},$$

where $y_{i,t+1}$ is ISO trading volume from TAQ and *Decile* is an indicator variable which equals 1 when a firm is in that size decile, and zero otherwise and decile 10 is the largest firms. Control variables are discussed in Section IV of the text, and we include firm and/or date fixed effects as indicated at the bottom of the table. Firms are sorted into market capitalization deciles the period before the analysis begins and then interacted with fragmentation in the first stage and we use the log of the number of market centers × each market capitalization decile as additional instruments. Standard errors clustered by firm and date are shown below the estimates. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Model=	**OLS**	**OLS**	**IV**	**IV**	**IV**	**IV**
Fragmentation	45,326**	-144,952**	2,488,092***	61,874	54,818	2,502,635***
	(21,501)	*(61,031)*	*(464,896)*	*(188,866)*	*(91,219)*	*(547,516)*
Frag × Decile 1		223,708**			186,459*	719,056***
		(64,221)			*(103,523)*	*(207,977)*
Frag × Decile 2		209,944***			144,934	714,037***
		(62,504)			*(99,740)*	*(189,999)*
Frag × Decile 3		180,963***			74,171	487,017***
		(60,609)			*(98,530)*	*(160,247)*
Frag × Decile 4		110,063**			180,581	443,910**
		(55,165)			*(181,918)*	*(216,074)*
Frag × Decile 5		28,609			-81,765	103,710
		(64,334)			*(105,072)*	*(135,497)*
Frag × Decile 7		-102,655			-241,548	-458,091**
		(122,639)			*(161,513)*	*(182,112)*
Frag × Decile 8		225,876***			160,703	-282,614
		(75,634)			*(246,304)*	*(277,864)*
Frag × Decile 9		443,460***			518,806**	-74,954
		(107,879)			*(247,609)*	*(286,522)*
Frag × Decile 10		85,275			-699,411	-1,071,273
		(748,980)			*(1,254,619)*	*(1,290,267)*
Decile 1		-218,624***		-69,705***	-172,312***	-308,134***
		(38,389)		*(18,763)*	*(66,003)*	*(105,064)*
Decile 2		-200,037***		-70,027***	-155,549**	-382,597***
		(37,154)		*(14,364)*	*(65,661)*	*(104,421)*
Decile 3		-175,018***		-65,165***	-112,083*	-297,975***
		(36,142)		*(12,203)*	*(65,733)*	*(96,340)*
Decile 4		-124,021***		-56,810***	-170,396	-301,841**
		(33,128)		*(11,057)*	*(119,218)*	*(138,318)*
Decile 5		-53,993		-37,605***	14,775	-92,019
		(36,519)		*(8,412)*	*(65,448)*	*(85,492)*
Decile 7		121,360		57,442***	221,444*	357,213***
		(77,873)		*(11,017)*	*(113,711)*	*(126,981)*
Decile 8		28,976		183,501***	70,915	356,423*
		(55,615)		*(44,657)*	*(196,372)*	*(214,798)*
Decile 9		29,063		348,560***	-25,513	364,106
		(96,328)		*(85,378)*	*(219,358)*	*(240,741)*
Decile 10		368,397		419,371***	939,274	1,161,948
		(564,908)		*(117,427)*	*(941,360)*	*(961,974)*
Institutional Ownership		192,221***		96,103**	96,462**	17,804
		(59,189)		*(48,826)*	*(47,811)*	*(46,815)*
Firm FE?	YES	YES	YES	YES	YES	YES
Day FE?	YES	YES	NO	NO	NO	NO
Year FE?	NO	NO	YES	NO	NO	YES
Number of observations	12,201,505	11,565,376	10,564,038	10,363,861	10,363,861	10,363,861
R^2	0.593	0.603	0.606	0.618	0.617	0.607

VI. Appendix A - List of TAQ Reporting Facilities

Table A1
Market Centers in TAQ

The table displays the market centers contained in the NYSE TAQ database. The list is from the "Daily TAQ Client Specification" document version 2.0, dated 28 July 2014.

Code	Description
A	NYSE MKT Stock Exchange
B	NASDAQ OMX BX Stock Exchange
C	National Stock Exchange
D	FINRA
I	International Securities Exchange
J	Direct Edge A Stock Exchange
K	Direct Edge X Stock Exchange
M	Chicago Stock Exchange
N	New York Stock Exchange
P	NYSE Arca SM
S	Consolidated Tape System
T	NASDAQ Stock Exchange
W	CBOE Stock Exchange
X	NASDAQ OMX PSX Stock Exchange
Y	BATS Y-Exchange
Z	BATS Exchange

VII. Appendix B - Reduced Form IV Results

Table B1
Reduced Form IV Results

The table presents the results of a reduced-form IV regression where we instrument for fragmentation using the log of the total number of market centers:

$$y_{i,t+1} = \alpha + \beta \# \widehat{\text{Markets}}_{i,t} + \sum_{k \neq 6} \delta_k \text{Size}_k + \sum_{k \neq 6} \theta_k (\# \text{ Markets} \times \text{Size}_k) + FE_i + FE_t + \text{Controls}_{i,t} + \varepsilon_{i,t+1},$$

where $y_{i,t}$ is either the log of the Amihud (2002) illiquidity measure (model 1), the log of the $Bid-Ask$ $Spread$ (model 2), the Hou and Moskowitz (2005) $Delay1$ measure (model 3), or the log of $Turnover$ (model 4), FE_i is a firm fixed effect, FE_t is a day fixed effect, $Size\ Decile$ is an indicator variable which equals 1 when a firm is in that size decile, and zero otherwise and decile 10 is the largest firms. Firms are sorted into market capitalization deciles and we use the log of $Total\ Market\ Centers \times$ each market capitalization decile as additional instruments. Standard errors clustered by firm and date are shown below the estimates. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable=	(1) Amihud	(2) Bid-Ask Spread	(3) Delay 1	(4) Turnover
Log(Market Centers)	-0.0105***	-0.1125***	-0.0356***	-0.1955***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*
Log(Mkt Centers) × Decile 1	0.1016***	0.4016***	0.0640***	-0.2116***
	(0.01)	*(0.02)*	*(0.01)*	*(0.01)*
Log(Mkt Centers) × Decile 2	0.0394***	0.3527***	0.0686***	-0.1696***
	(0.01)	*(0.01)*	*(0.00)*	*(0.01)*
Log(Mkt Centers) × Decile 3	0.0013	0.2582***	0.0525***	-0.0848***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*
Log(Mkt Centers) × Decile 4	-0.0222***	0.1204***	0.0178***	-0.0432***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*
Log(Mkt Centers) × Decile 5	-0.0080***	0.0494***	-0.0026	0.0399***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*
Log(Mkt Centers) × Decile 7	0.0082***	-0.0257***	0.0102***	0.0792***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*
Log(Mkt Centers) × Decile 8	0.0158***	-0.0670***	0.0243***	0.0993***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*
Log(Mkt Centers) × Decile 9	0.0216***	-0.0937***	0.0386***	0.0672***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*
Log(Mkt Centers) × Decile 10	0.0260***	-0.1126***	0.0450***	0.0121
	(0.00)	*(0.01)*	*(0.01)*	*(0.01)*
Decile 1	0.6809***	0.4588***	0.0028	-0.1977***
	(0.05)	*(0.07)*	*(0.02)*	*(0.06)*
Decile 2	0.3472***	0.1061*	-0.0760***	0.0652
	(0.03)	*(0.06)*	*(0.02)*	*(0.05)*
Decile 3	0.2312***	0.0533	-0.0672***	0.0754
	(0.02)	*(0.05)*	*(0.02)*	*(0.05)*
Decile 4	0.1805***	0.1825***	0.0063	-0.0371
	(0.01)	*(0.04)*	*(0.02)*	*(0.04)*
Decile 5	0.0616***	0.1229***	0.0443***	-0.0087
	(0.01)	*(0.03)*	*(0.01)*	*(0.03)*
Decile 7	-0.0501***	-0.1898***	-0.0693***	-0.0110
	(0.01)	*(0.03)*	*(0.01)*	*(0.03)*
Decile 8	-0.0934***	-0.3369***	-0.1462***	-0.0291
	(0.01)	*(0.03)*	*(0.02)*	*(0.04)*
Decile 9	-0.1274***	-0.5910***	-0.2241***	-0.0315
	(0.01)	*(0.04)*	*(0.02)*	*(0.05)*
Decile 10	-0.1561***	-0.8950***	-0.2654***	0.0459
	(0.01)	*(0.06)*	*(0.02)*	*(0.05)*
Firm FE?	YES	YES	YES	YES
Year FE?	YES	YES	YES	YES
Number of observations	15,524,237	15,486,087	14,541,418	14,336,187
R^2	0.435	0.840	0.456	0.703

VIII. Appendix C - Alternate Fragmentation Measure

Table C1

Alternative Measure of Fragmentation Results - Liquidity

The table presents the results of OLS panel and IV regressions using an alternative measure of fragmentation. Specifically, we use the percentage of volume traded off the listing exchange as proposed in O'Hara and Ye (2011). For the IV regressions, we instrument the level of fragmentation using the log of the total number of market centers in the U.S. at each point in time according to the model:

$$\text{Fragmentation}_{i,t} = \phi + \eta(\#\ \text{Markets}_t) + \sum_{k\neq 6} \gamma_k \text{Size}_k + \sum_{k\neq 6} \mu_k(\#\ \text{Markets}_t \times \text{Size}_k) + \text{Controls}_{i,t} + \nu_{i,t}$$

$$y_{i,t+1} = \alpha + \beta \widehat{\text{Fragmentation}}_{i,t} + \sum_{k\neq 6} \delta_k \text{Size}_k + \sum_{k\neq 6} \theta_k(\widehat{\text{Frag}} \times \text{Size}_k) + \text{Controls}_{i,t} + \varepsilon_{i,t+1},$$

where $y_{i,t+1}$ is either the log of the Amihud (2002) illiquidity measure (models 1 and 2) or the log of the $Bid-Ask\ Spread$ (models 3 and 4) for asset i on day t. Firms are sorted into market capitalization deciles and then interacted with fragmentation in the first stage and we use the log of $Total\ Market\ Centers \times$ each market capitalization decile as additional instruments. Size decile ten contains the largest firms. Additional variable coefficients are suppressed for brevity. Standard errors clustered by firm and date are shown below the estimates. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable=	**Amihud**	**Amihud**	**Bid-Ask Spread**	**Bid-Ask Spread**
Model=	OLS	IV	OLS	IV
Alt. Frag.	-0.0308***	0.7416***	-0.2719***	-3.5969***
	(0.01)	*(0.22)*	*(0.02)*	*(0.68)*
Alt. Frag × Decile 1	-0.1009***	0.6387***	0.6150***	2.1745***
	(0.02)	*(0.09)*	*(0.03)*	*(0.11)*
Alt. Frag × Decile 2	-0.0882***	0.2216***	0.4932***	1.8846***
	(0.01)	*(0.05)*	*(0.02)*	*(0.09)*
Alt. Frag × Decile 3	-0.0744***	-0.0202	0.3743***	1.4302***
	(0.01)	*(0.03)*	*(0.02)*	*(0.09)*
Alt. Frag × Decile 4	-0.0644***	-0.1055***	0.2160***	0.6392***
	(0.01)	*(0.02)*	*(0.02)*	*(0.08)*
Alt. Frag × Decile 5	-0.0232***	-0.0251	0.0906***	0.2016***
	(0.01)	*(0.02)*	*(0.02)*	*(0.06)*
Alt. Frag × Decile 7	0.0113**	0.0137	-0.0573***	-0.0052
	(0.00)	*(0.02)*	*(0.02)*	*(0.07)*
Alt. Frag × Decile 8	0.0143**	0.0211	-0.1344***	-0.0481
	(0.01)	*(0.02)*	*(0.02)*	*(0.09)*
Alt. Frag × Decile 9	0.0255***	-0.0284	-0.2120***	0.1940
	(0.01)	*(0.04)*	*(0.03)*	*(0.14)*
Alt. Frag × Decile 10	0.0355***	-0.0596	-0.3163***	0.3482*
	(0.01)	*(0.05)*	*(0.04)*	*(0.18)*
Decile 1	1.1303***	0.7032***	1.6802***	1.1160***
	(0.02)	*(0.05)*	*(0.02)*	*(0.07)*
Decile 2	0.5418***	0.3552***	1.1801***	0.7394***
	(0.01)	*(0.03)*	*(0.01)*	*(0.05)*
Decile 3	0.2684***	0.2158***	0.8255***	0.5401***
	(0.01)	*(0.02)*	*(0.01)*	*(0.04)*
Decile 4	0.1252***	0.1215***	0.5276***	0.4729***
	(0.00)	*(0.01)*	*(0.01)*	*(0.04)*
Decile 5	0.0438***	0.0287***	0.2670***	0.2950***
	(0.00)	*(0.01)*	*(0.01)*	*(0.03)*
Decile 7	-0.0260***	-0.0082	-0.2752***	-0.3577***
	(0.00)	*(0.01)*	*(0.01)*	*(0.04)*
Decile 8	-0.0427***	-0.0140	-0.5634***	-0.6965***
	(0.00)	*(0.02)*	*(0.01)*	*(0.06)*
Decile 9	-0.0572***	-0.0044	-0.8930***	-1.1581***
	(0.00)	*(0.02)*	*(0.01)*	*(0.08)*
Decile 10	-0.0706***	-0.0067	-1.2483***	-1.5848***
	(0.00)	*(0.03)*	*(0.02)*	*(0.10)*
Firm FE?	YES	YES	YES	YES
Day FE?	YES	NO	YES	NO
Year FE?	NO	YES	NO	YES
Number of observations	19,854,466	15,524,237	19,362,526	15,486,087
R^2	0.419	0.369	0.874	0.730

Table C2
Alternative Measure of Fragmentation Results - Price Efficiency and Turnover

The table presents the results of OLS panel and IV regressions using an alternative measure of fragmentation. Specifically, we use the percentage of volume traded off the listing exchange as proposed in O'Hara and Ye (2011). For the IV regressions, we instrument the level of fragmentation using the log of the total number of market centers in the U.S. at each point in time according to the model:

$$\text{Fragmentation}_{i,t} = \phi + \eta(\#\ \text{Markets}_t) + \sum_{k\neq 6} \gamma_k \text{Size}_k + \sum_{k\neq 6} \mu_k(\#\ \text{Markets}_t \times \text{Size}_k) + \text{Controls}_{i,t} + \nu_{i,t}$$

$$y_{i,t+1} = \alpha + \beta \widehat{\text{Fragmentation}}_{i,t} + \sum_{k\neq 6} \delta_k \text{Size}_k + \sum_{k\neq 6} \theta_k (\widehat{\text{Frag}} \times \text{Size}_k) + \text{Controls}_{i,t} + \varepsilon_{i,t+1},$$

where $y_{i,t+1}$ is either the Hou and Moskowitz (2005) $Delay1$ measure (models 1 and 2), $Delay2$ measure (models 3 and 4), or the log of $Turnover$ (models 5 and 6) for asset i on day t. Firms are sorted into market capitalization deciles and then interacted with fragmentation in the first stage and we use the log of $Total\ Market\ Centers$ $\times$ each market capitalization decile as additional instruments. Size decile ten contains the largest firms. Additional variable coefficients are suppressed for brevity. Standard errors clustered by firm and date are shown below the estimates. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable=	**Delay 1**	**Delay 1**	**Delay 2**	**Delay 2**	**Turnover**	**Turnover**
Model=	OLS	IV	OLS	IV	OLS	IV
Alt. Frag.	-0.0232***	-0.4384**	-0.0129***	-0.5186***	0.1728***	1.8692***
	(0.01)	*(0.20)*	*(0.00)*	*(0.14)*	*(5.46)*	*(10.14)*
Alt. Frag × Decile 1	0.0954***	0.3646***	0.0722***	0.2755***	-0.4075***	-2.2174***
	(0.01)	*(0.03)*	*(0.01)*	*(0.02)*	*(-9.28)*	*(-59.37)*
Alt. Frag × Decile 2	0.0841***	0.3700***	0.0658***	0.2826***	-0.4309***	-2.1070***
	(0.01)	*(0.03)*	*(0.01)*	*(0.02)*	*(-11.35)*	*(-58.26)*
Alt. Frag × Decile 3	0.0630***	0.2814***	0.0521***	0.2384***	-0.3558***	-1.5154***
	(0.01)	*(0.03)*	*(0.01)*	*(0.02)*	*(-10.01)*	*(-43.61)*
Alt. Frag × Decile 4	0.0315***	0.1027***	0.0279***	0.1039***	-0.1688***	-0.5547***
	(0.01)	*(0.02)*	*(0.01)*	*(0.02)*	*(-5.24)*	*(-23.42)*
Alt. Frag × Decile 5	0.0055	-0.0119	0.0101**	0.0094	-0.1092***	-0.2244***
	(0.01)	*(0.02)*	*(0.00)*	*(0.01)*	*(-4.41)*	*(-19.47)*
Alt. Frag × Decile 7	0.0191***	0.0703***	0.0003	0.0338**	0.0740***	0.0480***
	(0.01)	*(0.02)*	*(0.00)*	*(0.01)*	*(2.78)*	*(4.04)*
Alt. Frag × Decile 8	0.0442***	0.1536***	0.0056	0.0776***	0.2181***	0.0231
	(0.01)	*(0.03)*	*(0.01)*	*(0.02)*	*(6.03)*	*(1.50)*
Alt. Frag × Decile 9	0.0756***	0.2416***	0.0192***	0.1552***	0.2529***	-0.2399***
	(0.01)	*(0.04)*	*(0.01)*	*(0.03)*	*(6.11)*	*(-8.51)*
Alt. Frag × Decile 10	0.1133***	0.2825***	0.0427***	0.1988***	0.1360***	-0.6679***
	(0.01)	*(0.05)*	*(0.01)*	*(0.04)*	*(2.90)*	*(-16.58)*
Decile 1	0.2005***	0.0951***	0.1199***	0.0517***	-0.9286***	-0.1615***
	(0.01)	*(0.02)*	*(0.00)*	*(0.01)*	*(-30.75)*	*(-8.98)*
Decile 2	0.1455***	0.0326**	0.0867***	0.0116	-0.7531***	-0.1064***
	(0.01)	*(0.01)*	*(0.00)*	*(0.01)*	*(-32.37)*	*(-7.72)*
Decile 3	0.1047***	0.0232**	0.0616***	-0.0005	-0.5735***	-0.1968***
	(0.01)	*(0.01)*	*(0.00)*	*(0.01)*	*(-28.38)*	*(-17.84)*
Decile 4	0.0627***	0.0416***	0.0379***	0.0195**	-0.3696***	-0.3033***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*	*(-21.40)*	*(-33.85)*
Decile 5	0.0338***	0.0475***	0.0197***	0.0293***	-0.1575***	-0.1575***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*	*(-12.91)*	*(-25.37)*
Decile 7	-0.0383***	-0.0661***	-0.0216***	-0.0454***	0.1511***	0.1964***
	(0.00)	*(0.01)*	*(0.00)*	*(0.01)*	*(12.20)*	*(28.60)*
Decile 8	-0.0731***	-0.1268***	-0.0427***	-0.0877***	0.2840***	0.4113***
	(0.00)	*(0.02)*	*(0.00)*	*(0.01)*	*(14.60)*	*(35.35)*
Decile 9	-0.1132***	-0.1865***	-0.0701***	-0.1414***	0.3961***	0.6431***
	(0.01)	*(0.02)*	*(0.00)*	*(0.02)*	*(15.70)*	*(34.31)*
Decile 10	-0.1579***	-0.2206***	-0.1031***	-0.1770***	0.4186***	0.8161***
	(0.01)	*(0.03)*	*(0.00)*	*(0.02)*	*(12.19)*	*(34.39)*
Firm FE?	YES	YES	YES	YES	YES	YES
Day FE?	YES	NO	YES	NO	YES	NO
Year FE?	NO	YES	NO	YES	NO	YES
Number of observations	18,305,534	14,541,418	18,305,534	14,541,418	19,912,931	15,557,493
R^2	0.480	0.425	0.521	0.388	0.481	0.500