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The Causal Impact of Market Fragmentation on Liquidity

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ABSTRACT

We use the staggered implementation of regulation NMS and an instrumental variables analysis to establish the causal impact of market fragmentation. Theoretically, more exchange competition should lead to reduced transaction costs, however it may also lead to negative network externalities which reduce market quality. We document evidence of both effects, however our results show that fragmentation has a differential impact on large and small stocks. For large stocks, the former effect dominates and market quality, as measured by bid-ask spreads and price efficiency, is generally better. For small stocks, we find that negative network externalities dominate and liquidity and price efficiency are worse. Moreover, we find that higher fragmentation is associated with more uncertainty in liquidity which leads to changes in trading behavior. Overall, our results help reconcile conflicting findings in the literature and shed new light on the forces relating market fragmentation, trading behavior, and asset prices.

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 has increased from 7.9% of shares outstanding to 15.8% of shares outstanding. Moreover, the number of market centers available for trading has nearly tripled and with that, measures of market fragmentation have more than doubled (See Figure 1 and 2 for details). During this time, there have been several substantial 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? Is it possible to disentangle the impact of fragmentation from increased algorithmic and high-frequency trading? Is the impact of fragmentation the same for all stocks? Finally, has fragmentation changed trading behavior and prices?

In this study, we provide novel evidence on the *causal* impact of market fragmentation. In doing so, we also show that fragmentation 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)). On the other hand, we find that fragmentation leads to very different effects for

[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.

small stocks. For small stocks, fragmentation causes increased bid-ask spreads, worse price efficiency, and more variability in liquidity. These effects are consistent with models in which exchange competition and fragmentation lead to negative network externalities which reduces liquidity. In particular, several models note 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. In other words, 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 appear to 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 adopt several new techniques to examine the impact of fragmentation, and in doing so, we confirm and reconcile the seemingly contradictory results in O'Hara and Ye (2011) and Chung and Chuwonganant (2012).

We begin by examining the relation between fragmentation, market quality, and trading behavior using daily data from 2004 to 2013. We calculate a simple measure of fragmentation based on a Herfindahl index of trading volume across market centers. As shown in panel C of Figure 2, it is clear that market 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 OLS panel regressions, we show that fragmentation is 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, we then examine whether fragmentation exerts a heterogeneous impact on firms of different size. Specifically, we examine the impact of fragmentation for firms in different size deciles and we document significant differences across deciles. While fragmentation is associated with improvements in market quality for firms in the largest decile based on market capitalization, we find very different evidence for firms in the smallest deciles. Accordingly, our results also support the conclusions of Chung and Chuwonganant (2012) who argue that fragmentation reduces market quality for some firms.

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 novel sets of analyses to establish the *causal* impact of market competition and fragmentation. First, we use a difference-in-difference analysis that exploits the staggered implementation of regulation NMS to identify the true impact of fragmentation. Regulation NMS was implemented in 2007 to increase "competition among individual markets and competition among individual orders" (Securities and 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 all U.S. stocks on August 20, 2007.[2] However, the measures were tested on a pilot group of 250 stocks starting on July 9, 2007. We used this staggered implementation to identify the causal impact of market fragmentation using a difference-in-difference framework. As with the OLS results discussed above, we find that fragmentation causes reduced bid-ask spreads and better price efficiency for large stocks and increased bid-ask spreads, worse price efficiency, and more variability in liquidity for small stocks.

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 May 24, 2007 through October 1, 2007. Thus, we also examine an instrumental variables analysis over our entire 2004 to 2013 sample period to establish the impact of fragmentation over a longer time period. Specifically, we use the number of market centers in the U.S. as an exogenous instrument to shock firm-level fragmentation. We argue that the total number of U.S. market centers available for trading is exogenous from firm-level measures of market quality. 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 other 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 more variable liquidity for small stocks.

Overall, our results have important implications for academics, practitioners, and regu-

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

lators. From an academic perspective, our paper contributes to the growing literature on market fragmentation by establishing the *causal* impact of market fragmentation. In addition, we reconcile several conflicting findings in the extant empirical literature and provide new evidence on the theoretical mechanisms relating market fragmentation and liquidity. From a practitioner perspective, our results suggest that market fragmentation leads to significant heterogeneity across stocks, which leads 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. In doing so, our findings shed light on the market frictions that allow negative network externalities to exist. Moreover, we show that 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, instead of examining aggregate outcomes.

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 the 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. 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 will change consolidated depth, although the direction of this change is unclear. In other words, increased fragmentation can lead to either *more* or *less* consolidated depth. Interestingly, in our empirical tests we find that fragmentation leads to more depth for small firms but less depth for large firms. In a sense, our empirical findings show that assets exhibit considerably heterogeneity, and as a result, so too does the impact of fragmentation. 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 seem clear: 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, many 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 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.

Since the implementation of regulation NMS in 2007, only a few empirical papers have examined the impact of fragmentation. As discussed in the introduction, O'Hara and Ye (2011) and Chung and Chuwonganant (2012) examine the impact of fragmentation on market quality measures includes 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. 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. Finally, 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.

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 liquidity, we combine data from the Center for Research in Security Prices ("CRSP"), the New York Stock Exchange Trade and Quote database ("NYSE TAQ"), and the Securities and Exchange Commission ("SEC") over the period 2004 to 2013. The resulting sample contains approximately 8,000 unique assets and 16.5 million asset-days.

A. Construction of Variables

We obtain daily stock returns, trading volume, stock prices, and shares outstanding from CRSP. We include ordinary common shares in U.S. firms, American Depositary Receipts (ADRs), Real Estate Investment Trusts (REITs), and closed-end funds.[3]

From TAQ, we obtain information about trading volume and the top of the limit order book for up to 16 different trade reporting venues, representing the totality of visible liquidity 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 mean depth and best prevailing prices at every second over the trading day. We exclude the first and last five minutes of the trading day to avoid distortions caused by opening and closing auctions. Using the NBBO prices, we calculate the bid-ask spread at every second by taking the difference of the ask and bid price scaled by their midpoint. We also compute the

[3]While many studies limit their analyses to CRSP share codes 10 and 11 (ordinary common shares in U.S. firms), we include all share codes in order to examine the general impact of fragmentation on trading. In addition, we note that the pilot study for regulation NMS included many assets outside of CRSP share code 10 and 11. Thus, in order to use the NMS pilot experiment in our analyses, we include these assets in our sample.

consolidated depth at the NBBO, which indicates the number of shares a trader could access at the NBBO price. We then collapse the depth and bid-ask spread over the trading day to calculate the average depth, the variance of that depth, and the average bid-ask spread for the day.

In addition, we use the TAQ database to compute measures of fragmentation and average trade size. Measuring fragmentation is difficult due to the reporting standards of U.S. equity markets. TAQ, the most commonly used source for trade data, only lists consolidated trades which are attributed to one of sixteen different reporting venues. Many of the individual venues report their trades through one of these 16 market centers. Thus, even though there are currently almost one hundred different market centers, we can only measure differences in trading across the 16 venues reported in TAQ. In some of our analyses, we measure trade fragmentation using a Herfindahl Index of trade volume for every asset each day across these reporting venues. The Herfindahl Index captures the concentration of trade and ranges from zero to one. We subtract the Herfindahl Index value from one to get a measure of fragmentation, where zero indicates no fragmentation and one equals high fragmentation. 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 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. Moreover, in our analysis of the NMS pilot sample, we are able to examine the impact of fragmentation without using this measure.

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. We compile these reports to count the total number of venues available for equity trading every month. This number includes exchanges, electronic communication networks, and alternative trading systems.

Finally, in many of 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 52 weeks according to the model:

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

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

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

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

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.

B. Sample Properties

Figure 1 shows time-series plots of the daily mean values for several measures of market quality. All CRSP stocks are included in the figures; as such, they represent the true crosssectional average of tradeable securities in the U.S. marketplace. In panel A, the figure shows that bid-ask spreads have generally decreased, although they temporarily increased by a factor of three during the 2008 financial crisis. More interestingly, the figure shows that the variability of the bid-ask spread appears to have increased over time. In other words, while the mean has improved, the variance has gotten worse. The vertical gray line in each figure indicates the initial implementation of Regulation NMS and seems to align with the increased variation in bid-ask spreads. We also examine NBBO depth, which is the aggregated visible depth at the best prevailing bid or ask across all exchanges. Following the implementation of NMS, the figure shows a sharp drop in consolidated depth although eventually the average depth does recover. Finally, the last panel examines price delay, which steadily decreases following the implementation of regulation NMS. In other words, on average, prices have become more efficient over 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 has grown by about two and a half times and eventually topped out at over 100 before decreasing in the last year. Consistent with this, panel B plots the time-series of market fragmentation, measured as one minus the Herfindahl Index of trade volume across exchanges. From the figure, it is clear that fragmentation has increased with the number of market centers. In panel C, we plot volatility which, like bid-ask spreads, shows dramatic increases during the 2008 financial crisis. Interestingly, the figure suggests that volatility in non-crisis periods may be higher following NMS. Finally, panel D shows that average trade sizes have decreased dramatically. While this drop in trade size is likely due to many different factors, the figure suggests a sharp drop in average trade size following the implementation of regulation NMS. Of course, it is inherently difficult to draw any conclusions from time-series plots. Accordingly, in Section IV, we explore the relation between fragmentation, trading behavior, and liquidity in greater detail.

IV. Results

In the previous section, we showed that many aspects of U.S. equity markets have changed over the last decade. For example, average trade sizes have fallen, price delay has decreased, and volatility has increased. In this section, we explore the relation between fragmentation and these changes using three distinct sets of analyses.

A. The Relation between Fragmentation and Market Changes

We begin with OLS panel regression using daily data from 2006 to 2013. 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 compare the welfare losses that result from 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:

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

where $y_{i,t+1}$ is either the level of depth, the variance of depth, or the level of bid-ask spreads. Table II shows the coefficient estimates with T-statistics shown below in parentheses. We include firm-fixed effects in models (1), (5), and (9) to control for unobserved heterogeneity at the firm-level and we calculate T-statistics using standard errors clustered by firm and date. Because several of the variables are highly right skewed, we use the natural log of the level of depth, the variance of depth, and the bid-ask spread.

The results in models (1) and (9) 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 NBBO depth and bid-ask spreads. However, motivated by models of negative network externalities, we theorize that market fragmentation may exert heterogeneous impacts on different stocks. In particular, in the model presented by Pagano (1989a), traders endogenously determine whether or not to participate in a market, and their entry decision is a function of market fragmentation. When markets are fragmented and thin, it is harder for a given trader to find a counterparty, which leads to less trading and even thinner markets (i.e., a negative network externality). Accordingly, we theorize 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.

To examine this theory, we augment the regression model to include several new terms. We add nine indicator variables, each of which equal one if a stock is in one of nine market capitalization deciles (we omit the first decile which contains the largest stocks, so large stocks 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.[4] Formally, we examine panel regressions of the form:

$$\begin{aligned} y_{i,t+1} = \alpha + \beta \text{Fragmentation}_{i,t} + \sum_{j=2}^{10} \gamma_j \text{Size Decile}_{i,j} + \delta \text{Controls} + \\ \sum_{k=2}^{10} \theta_k (\text{Size Decile}_{i,j} \times \text{Fragmentation}_{i,t}) + \varepsilon_{i,t+1}, \end{aligned} \tag{5}$$

where $y_{i,t+1}$ is either the level of depth, the variance of depth, or the level of bid-ask spreads. The results are shown in columns (3), (4), (7), (8), (11), and (12) of Table II. Interestingly, the results suggest that market fragmentation has significantly different effect for large and small assets. While market fragmentation is generally associated with reductions in bid-ask spreads, the interaction terms for deciles 5 through 10 (shown in columns (10) and (11)) suggest that bid-ask spreads are actually higher for small stocks. Similarly, the results show evidence of differential impact for small and large stocks on measures of depth. In other words, while fragmentation is associated with improved market quality for larges stocks, we find the opposite hold for small stocks.

Next, we examine whether fragmentation impacts asset prices. Theoretical models suggests that fragmentation impacts volatility and 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 variable. The results are shown in Table III. Again, we start by examining the general impact of fragmentation. The negative and statistically significant coefficient on $fragmentation$ in models (1), (2), (5), and (6) confirm the findings in O'Hara and Ye (2011): on average, fragmentation is associated with improved price efficiency (i.e, lower price delay). However, when we examine the results broken out by size deciles, we find evidence that price efficiency is worse for smaller firms. The positive coefficient on $SizeDecile$ for high deciles indicates that these

[4] 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.

firms have higher price delay. Moreover, the negative 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 large stocks. 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, we argue that negative market externalities act as a limit to arbitrage, preventing some investors from trading. Thus, firms with higher fragmentation have worse price efficiency.

Similarly, in Table IV we examine the relation between fragmentation and the volatility of stock returns. O'Hara and Ye (2011) document a positive relation between fragmentation and short-term volatility. Again, we confirm their findings: in columns (5) and (6), the positive and statistically significant coefficient on fragmentation indicates higher return volatility. However, once again, we also find evidence of differential impacts depending on market capitalization. In columns (7) and (8), the negative coefficients on the interaction terms for deciles 9 and 10 indicate that volatility increased less for small firms as fragmentation increased.

Overall, our results suggest that market fragmentation is associated with substantial variation in measures of market quality. 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 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, next we adopt a difference-in-difference approach that allows us to to control for possible confounding influences.

B. The Impact of the Regulation NMS Pilot

In this section, we use the staggered implementation of regulation NMS to provide novel evidence on the *causal* impact of fragmentation. We use a traditional difference-in-difference specification which compares the mean change in market quality measures for assets effected by fragmentation to the mean change for a group of assets not impacted by fragmentation. The model relies on the assumption of parallel trends in the outcome variables to establish the causal impact of fragmentation.[5] The nature of the specification in combination with the pseudo-random selection of firms to be included in the first phase of regulation NMS allows us to control for possible confounding influences. In doing so, we are the first to establish the causal impact of market fragmentation resulting from regulation NMS.[6]

Regulation NMS was implemented in 2007 to increase "competition among individual markets and competition among individual orders" (Securities and Commission (2007)). The regulation contained several provisions, but two provisions, in particular, stand out. The *Order Protection Rule* required trading centers to make sure that trades were not executed at prices that were worse than 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 all U.S. stocks on August 20, 2007.[7] However, the measures were tested on a pilot group of 250 stocks starting on July 9, 2007. The pilot include 100 NYSE assets, 100 NASDAQ assets, and 50 AMEX assets. As discussed in Section III, the pilot included more than just equities, so we include ADRs, ETFs, and REITs in our sample. We drop two assets that were involved in mergers around the NMS

[5]In unreported results, available from the authors upon request, we examine the parallel trends assumption for each of our difference-in-difference analyses. In all cases, the assumption appears valid.

[6]We note that Chung and Chuwonganant (2012) did examine market quality for pilot stocks around the implementation of regulation NMS. However, instead of using a traditional difference-in-difference approach, they use a matched sample. In particular, they examine the net change in market quality for pilot stocks relative to a matched sample of control stocks, before and after the implementation NMS. As discussed in Pearl (2009), the matched sample approach may actually increase bias due to the presence of dormant unobserved confounders.

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

implementation period, so our pilot group contains 248 assets.

We examine difference-in-difference regressions around the implementation of regulation NMS according to the model:

$$
\begin{aligned}
y_{i,t} = \alpha + \beta_1 \text{Period } 1_t + \beta_2 \text{Period } 2_t + \beta_3 \text{Pilot}_i + \beta_4 \text{Policy}_{i,t} + \\
\sum_{j=2}^{10} \gamma_j \text{Size Decile}_{i,j} + \sum_{k=2}^{10} \theta_k (\text{Policy}_{i,t} \times \text{Size Decile}_{i,k}) + \epsilon_{i,t},
\end{aligned}
\tag{6}
$$

where $y_{i,t}$ includes the same measures of market quality and trading examined in the OLS analyses above. The implementation of Regulation NMS occurred in two stages, so we structure the analysis to include three different periods. A pre-period, which measures the time before NMS was implemented for any assets, and two indicators variables that each equal one for phase 1 and phase 2 of the NMS implementation (we label these *Period* 1 and *Period* 2).

We also include *Pilot*, which is an indicator variable that equals one for the 248 assets included in the first phase of implementation; it allows us to control for any level differences between the initial pilot assets and all other assets. Finally, *Policy* is an indicator variable that equals one for an asset once it is officially subject to the rules of regulation NMS, and zero otherwise. We stress that our *Policy* variable encompasses the impact of regulation NMS turning-on for pilot assets and then, later, the impact of regulation NMS turning-on for all other assets. Thus, the *Policy* variable measures the causal impact of market fragmentation, controlling for possible confounding influences.

The results of the difference-in-difference analyses are shown in Tables V through VII, with T-statistics shown below the coefficient estimates in parentheses. We include firm-fixed effects in odd numbered models to control for unobserved heterogeneity at the firm-level and we calculate T-statistics using standard errors clustered by firm and date. Table V examines the causal impact of fragmentation on measures of depth and bid-ask spreads. In models (1), (3), and (5), we find that increased fragmentation, on average, led to decreases in the level and variance of depth. In contrast to Chung and Chuwonganant (2012), we find no statistically significant change in bid-ask spreads, however the sign on *Policy* in model (5) of Table V is positive, consistent with their finding that fragmentation led to increased bid-ask spreads, on average.

As before, we theorize 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. To examine this theory, we augment the difference-in-difference model to include indicator variables for nine different market capitalization deciles and we interact each indicator variable with our *Policy* variable. Our market capitalization deciles are defined one month prior to the experiment and each asset's decile assignment is held constant throughout the analysis. Thus, the interaction coefficients in Table V indicate the causal impact of fragmentation for assets with different market capitalizations.

Interestingly, the results suggest that the level and variance of depth, as well as the level of bid-ask spreads, are increasing in fragmentation for smaller assets. In other words, the results show that fragmentation exerts a differential impact on small assets. In particular, the positive coefficients on the interaction terms for small decile assets indicate substantial increases in bid-ask spreads for these assets.

We then examine whether fragmentation impacts price delay and volatility, as theorized in several extant models (e.g., H. Mendelson (1987), Madhavan (1995)). In Table VI, we examine a difference-in-difference specification using the Hou and Moskowitz (2005) measure of price delay as the dependent variable. In models (1) and (3), the positive and insignificant estimate on *Policy* suggests that delay did not change, on average, following the implementation of regulation NMS. However, when we condition on market capitalization in models (2) and (4) we find very different results. Here, the coefficient on *Policy* is negative and statistically significant, indicating that fragmentation causes improvements in price efficiency for the largest decile of assets. Moreover, the positive and significant estimates on the interactions terms suggest that fragmentation actually decreased price efficiency for smaller assets.

In Table VII, we further examine the relation between fragmentation and average trade size and volatility. Interestingly, we find that fragmentation caused significant changes in trading behavior. For large assets, fragmentation leads to smaller average trade sizes, while for small assets, we find the opposite. While this result might appear counterintuitive at first, it likely stems from the fact that depth dramatically decreased for large assets, as shown in Table V, leading to smaller trades. In model (4), we also find that increased fragmentation leads to increased volatility for small stocks, in general, although for the very smallest firms in decile 10, it leads to a reduction in volatility.

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 lower depth, smaller trade sizes, and improved price efficiency, while for small assets, fragmentation leads to higher depth, larger trade sizes, and significantly worse price efficiency. 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 May 24, 2007 through October 1, 2007. Thus, we next examine an instrumental variables analysis over our entire 2004 to 2013 sample period to establish the impact of fragmentation over a longer time period.

C. The Causal Impact of Fragmentation - Instrumental Variables Approach

In this section, we use the number of market centers in the U.S. as an exogenous instrument to shock firm-level fragmentation. We argue that the total number of U.S. market centers available for trading is exogenous from firm-level measures of market quality. In other words, the exclusion restriction for our analysis states that market centers impact the characteristics of individual assets *only* through their impact on fragmentation. Using the number of U.S. market centers as an instrument, we again confirm that fragmentation has a differential impact on large and small assets. Specifically, we examine two-stage least squares regressions (2SLS) of the form:

$$Fragmentation_{i,t} = \phi + \beta \text{Total Market Centers}_t + \gamma \text{Controls} + \nu_{i,t} \tag{7}$$

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

where $y_{i,t}$ includes the same measures of market quality and trading examined in the OLS and difference-in-difference analyses above. The first stage regression (equation (7)) uses time-series variation in the total number of U.S. market centers 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.[8]

The results of the 2SLS regressions are show in Tables VIII through X. While the 2SLS analyses examine a much longer time-series than the difference-in-difference analyses, in most models, the results confirm our earlier findings. In models (1), (3), and (5) of Table VIII, we find that higher fragmentation leads to lower values of the level and variance of depth and lower bid-ask spreads. However, once again, we also examine the results broken out by market capitalization deciles. As before, we find differential impacts for small and large assets. For large assets, depths and bid-ask spreads are lower when fragmentation is higher, but for small assets, the effect is reversed. In other words, small assets see increases in depth and bid-ask spreads when fragmentation is higher.

In Table IX, we again find that fragmentation leads to improvements in price efficiency, both unconditionally and for the largest firms. However, in contrast to our OLS and difference-in-difference results, the 2SLS results suggest the price efficiency has also im-

[8]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.

proved for smaller assets. The time-series plot in Panel D of Figure 1 suggests the reason. While delay did appear to increase around the implementation of regulation NMS, it has fallen considerably since. It is possible that the increase in market fragmentation that resulted from regulation NMS led to temporary disruptions in the marketplace which harmed price efficiency. However, in equilibrium, market participants should update their behavior in order to optimally respond to market changes and once this occurred, it appears that fragmentation led to improved price efficiency. The results show that conclusions based on short-time series may not necessarily reveal the entire impact of market changes.

Finally, in Table X, we examine trade sizes and volatility. Our results confirm the findings of the difference-in-difference analyses. In columns (1) and (2), we find that higher fragmentation leads to smaller trades sizes for large firms. Similarly, in columns (3) and (4), we find that fragmentation causes higher volatility for large assets, while for the smallest assets, we find some evidence of reduced volatility. The interaction coefficient is negative and statistically significant in model (3), although when we include time fixed effects in model (4) we find a positive effect. Nonetheless, the 2SLS instrumental variables analyses largely confirm the results of the OLS and difference-in-difference analyses. In general, fragmentation leads to lower bid ask spreads and depth for large assets, while it leads to higher bid-ask spreads and depth for small assets. Moreover, we confirm that price efficiency improves for large assets despite increased volatility.

D. Interpretation of Results

Our results have shown that fragmentation and regulation NMS lead to significant differences in liquidity and trading behavior. Moreover, we have documented evidence of heterogeneous impacts for different stocks, depending on their-ex-ante characteristics. For small stocks, increased fragmentation is more likely to result in thinner markets which could cause network externalities to outweigh the benefit of exchange competition and reduced transaction costs.

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 measuring the possible friction(s) 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 true consolidated order book, as discussed in M. Mendelson, Peake, and Jr. (1979). 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).

For example, imagine a world with two exchanges, A and B. Exchange A has a limit order at the top of the book willing to sell 400 shares at \$10.01 and exchange B has a limit order at the top of its book will to sell 100 shares at \$10.00. Imagine a trader places an order for 400 shares. In accordance with NMS, that trade will be routed to exchange B, since it has the "best price." Of course, B is only willing to provide 100 shares at that price, whereas A was willing to provide all 400 shares at \$10.01. In fact, it is possible that the total trade cost on B will actually exceed the cost of a trade on A. 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 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 have likely led to dramatic changes in trading behavior with respect to quoted depth and average trade sizes. Future research should continue to explore the nature of the network externailty in order to understand the friction(s) that generate it.

V. Conclusion

While a large literature has examined the impact of algorithmic and high frequency trading, less is known about the impact of recent 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 2006 to 2013, 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 turn to a difference-in-difference analysis which uses the staggered 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 our entire panel of data to conduct a comprehensive analysis of market fragmentation. We use the number of U.S. trading venues as an exogenous instrument for market fragmentation and we again confirm that market segmentation leads to better market quality, on average, for large stocks and worse market quality, on average, for small stocks.

While many extant theoretical and empirical papers on fragmentation have ambiguous conclusions, our results help reconcile these seemingly contradictory findings. 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. Our results show that for large stocks, with naturally deep markets, the former effect dominates while in small stocks, with naturally 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 average of market characteristics across all firms in CRSP. The bid-ask spread is defined 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. NBBO depth and prices are calculated from TAQ. We take the average for each second during regular market hours. We then take the variance and mean of these firm-seconds for each firm-day, excluding the first and last five minutes of trading. Delay is the Hou and Moskowitz (2005) measure of price efficiency. Observations outside 5 standard deviations of each variable are omitted. The vertical gray line denotes the initial implementation of Regulation NMS on July 9, 2007.

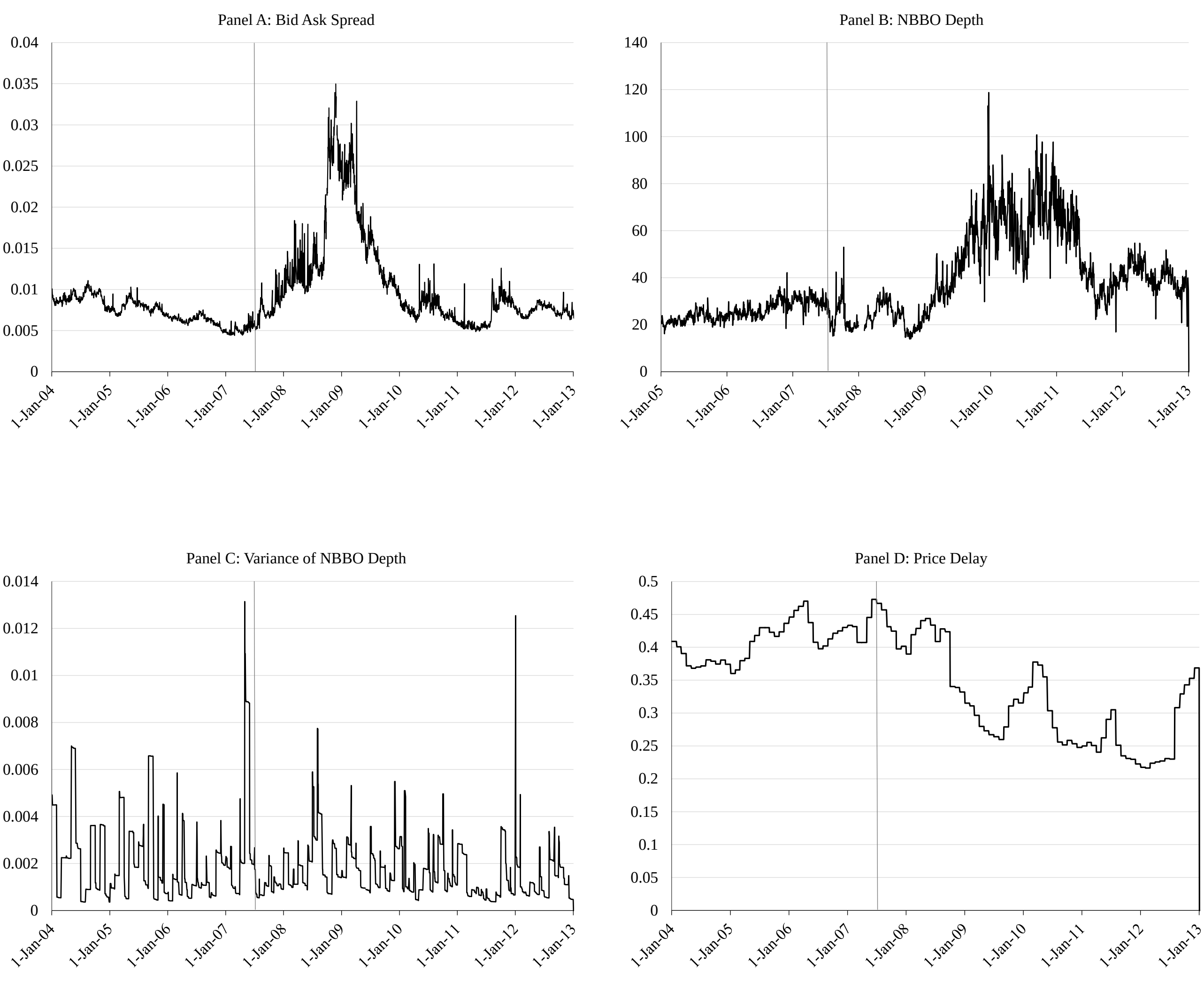

Figure 2. Trading Characteristics over Time

The figure displays a time-series plot of the daily average of trading characteristics across all firms in CRSP. The number of market centers is defined as the sum of exchanges, electronic communications networks (ECN), and alternative trading systems (ATS) as made available by the SEC. Volatility is the standard deviation of returns over the previous 22 days. Fragmentation is measured as one minus the Herfindahl-Hirschman Index (HHI), where HHI measures the level of concentration of trading volume for each firm across the 16 trade reporting facilities in TAQ. Observations outside 5 standard deviations of each variable are omitted. The vertical gray line denotes the initial implementation of Regulation NMS on July 9, 2007.

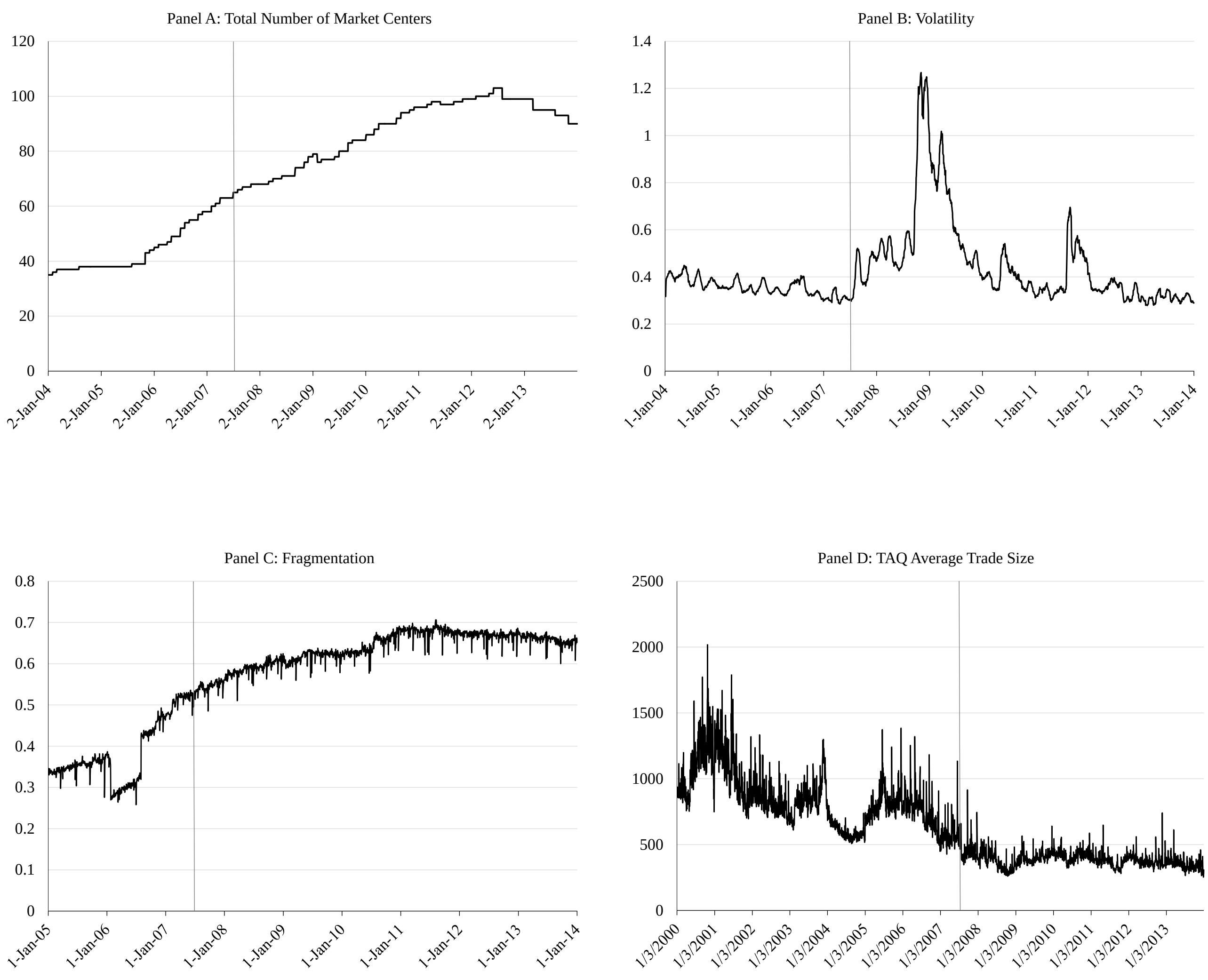

Table I
Summary Statistics

The table displays summary statistics four our sample, constructed using daily data from CRSP and TAQ from 2004 through 2013. Delay1 and Delay2 are calculated using Hou and Moskowitz (2005) over rolling 52 week windows. The level and variance of depth are obtained from TAQ data. We consolidate NBBO depth so that every second captures the average depth at that second. We then take the average and variance of these measures, excluding the first and last five minutes of the trading period. The bid-ask spread is calculated as the ask price less the bid price scaled by the midpoint for each asset and second. Volume percent is the total volume for a given month scaled by shares outstanding. Volatility is measured as the annualized standard deviation of returns over the previous 22 trading days. Fragmentation is measured as one minus the Herfindahl-Hirschman Index (HHI) of trading volume across the exchanges provided in TAQ.

Variable	Obs	Mean	Std. Dev.	P1	P50	P99
Market Cap	16723199	2736946	1.32e+07	3086.5	290131.5	4.52e+07
Delay1	7471839	.355	.286	.015	.263	.994
Delay2	7471839	.532	.189	.173	.513	.961
Small Volume (%)	7829686	.543	.232	.054	.568	.927
Variance of Depth	7906894	-10.326	2.145	-14.231	-10.59	-4.607
NBBO Depth	7071053	36.822	672.664	1.077	5.844	415.9
Bid-Ask Spread	16486872	-5.958	1.522	-8.867	-6.097	-2.226
Volume Percent	16321829	1.337	1.545	-3.19	1.462	5.045
Volatility	16708110	-1.136	.769	-3.132	-1.116	.628
Fragmentation	14678940	.567	.203	0	.622	.83

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

The table presents the results of an OLS panel regression examining the relation between depth, bid-ask spreads, and market fragmentation according to the model:

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

where $y_{i,t+1}$ is either the level of depth, the variance of depth, or the bid-ask spreads. We use the log-transform of the level of depth, the variance of depth, and the bid-ask spread to address skewness.. T-statistics are in parentheses calculated using standard errors clustered by firm and date. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) NBBO Depth	(2) NBBO Depth	(3) NBBO Depth	(4) NBBO Depth	(5) Depth Variance	(6) Depth Variance	(7) Depth Variance	(8) Depth Variance	(9) Bid-Ask Spread	(10) Bid-Ask Spread	(11) Bid-Ask Spread	(12) Bid-Ask Spread
Fragmentation	-0.8300***	-0.7692***	-0.9849***	-1.5228***	-0.1378***	-0.0597	-0.0365***	0.0773	-0.2407***	-0.1098***	-0.5887***	-0.8055***
	(-22.84)	*(-25.99)*	*(-8.77)*	*(-13.33)*	*(-3.10)*	*(-1.30)*	*(-3.23)*	*(1.24)*	*(-17.54)*	*(-13.44)*	*(-12.70)*	*(-19.35)*
Market Cap	-0.9964***	-1.1252***			-0.1708***	-0.2075***			-0.6632***	-0.5597***		
	(-76.90)	*(-82.79)*			*(-4.04)*	*(-3.85)*			*(-93.87)*	*(-106.72)*		
Volume (%)	-0.1793***	-0.1589***	-0.1790***	-0.1650***	0.0454***	0.0463***	0.0459***	0.0450***	-0.0836***	-0.1046***	-0.0841***	-0.1036***
	(-39.95)	*(-37.83)*	*(-40.15)*	*(-38.00)*	*(4.95)*	*(5.09)*	*(4.76)*	*(4.68)*	*(-35.02)*	*(-62.65)*	*(-29.53)*	*(-62.21)*
Size Decile 2			1.2651***	1.2497***			0.0080	0.0087			0.3868***	0.3741***
			(12.48)	*(12.41)*			*(0.99)*	*(1.02)*			*(10.69)*	*(11.31)*
Size Decile 3			1.6853***	1.6725***			-0.0030	-0.0047			0.6351***	0.6177***
			(15.15)	*(15.17)*			*(-0.47)*	*(-0.60)*			*(15.82)*	*(17.04)*
Size Decile 4			2.2522***	2.2522***			0.0133*	0.0091			0.9083***	0.8916***
			(19.36)	*(19.60)*			*(1.90)*	*(0.90)*			*(22.01)*	*(24.08)*
Size Decile 5			2.5475***	2.5368***			0.0338**	0.0274			1.1143***	1.0908***
			(19.98)	*(20.12)*			*(2.54)*	*(1.47)*			*(25.76)*	*(28.22)*
Size Decile 6			2.9756***	2.9052***			0.0717***	0.0781**			1.3311***	1.2828***
			(24.43)	*(24.10)*			*(2.94)*	*(2.39)*			*(29.78)*	*(32.42)*
Size Decile 7			3.5259***	3.3817***			0.1452***	0.1690***			1.5776***	1.4899***
			(29.25)	*(28.36)*			*(2.84)*	*(2.58)*			*(34.51)*	*(36.86)*
Size Decile 8			3.9683***	3.7388***			0.2219**	0.2636**			1.8335***	1.7070***
			(33.00)	*(31.64)*			*(2.01)*	*(2.08)*			*(39.33)*	*(42.00)*
Size Decile 9			4.4749***	4.1793***			0.3503*	0.4042*			2.1427***	1.9935***
			(36.81)	*(35.18)*			*(1.70)*	*(1.81)*			*(45.01)*	*(48.28)*
Size Decile 10			5.2021***	4.8232***			1.5671***	1.6338***			2.5375***	2.3545***
			(41.50)	*(39.55)*			*(3.03)*	*(2.99)*			*(50.74)*	*(54.40)*
Fragmentation*Decile2			-0.6296***	-0.6182***			0.0044	0.0039			-0.0379	-0.0111
			(-4.77)	*(-4.71)*			*(0.37)*	*(0.30)*			*(-0.79)*	*(-0.26)*
Fragmentation*Decile3			-0.2324*	-0.2420*			0.0359***	0.0400***			0.0773	0.1098**
			(-1.74)	*(-1.82)*			*(4.70)*	*(3.55)*			*(1.58)*	*(2.45)*
Fragmentation*Decile4			-0.1376	-0.1700			0.0247***	0.0326**			0.1203**	0.1648***
			(-1.00)	*(-1.24)*			*(2.90)*	*(2.17)*			*(2.51)*	*(3.73)*
Fragmentation*Decile5			0.2812*	0.2612*			-0.0053	0.0056			0.2256***	0.2892***
			(1.93)	*(1.80)*			*(-0.15)*	*(0.13)*			*(4.69)*	*(6.44)*
Fragmentation*Decile6			0.5790***	0.6296***			-0.0026	-0.0090			0.3054***	0.4190***
			(4.20)	*(4.55)*			*(-0.10)*	*(-0.24)*			*(6.18)*	*(9.19)*
Fragmentation*Decile7			0.6780***	0.8196***			-0.0742**	-0.1043*			0.4274***	0.6100***
			(5.26)	*(6.28)*			*(-2.17)*	*(-1.92)*			*(8.63)*	*(13.39)*
Fragmentation*Decile8			1.1544***	1.3934***			-0.0452	-0.1000			0.6290***	0.8793***
			(9.36)	*(11.17)*			*(-0.40)*	*(-0.80)*			*(12.73)*	*(19.72)*
Fragmentation*Decile9			1.3939***	1.6841***			-0.0410	-0.1080			0.7606***	1.0388***
			(11.39)	*(13.70)*			*(-0.15)*	*(-0.39)*			*(15.52)*	*(23.54)*
Fragmentation*Decile10			1.5519***	1.8964***			-1.1340**	-1.2102**			0.8156***	1.1201***
			(12.35)	*(15.13)*			*(-1.99)*	*(-2.02)*			*(16.16)*	*(24.91)*
Firm FE?	*YES*	*YES*	*NO*	*NO*	*YES*	*YES*	*NO*	*NO*	*YES*	*YES*	*NO*	*NO*
Quarter-Year FE?	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*
Observations	6,804,195	6,804,195	6,804,195	6,804,195	6,900,054	6,900,054	6,900,054	6,900,054	14,480,021	14,480,021	14,480,021	14,480,021
R-squared	0.227	0.261	0.210	0.229	0.003	0.003	0.004	0.005	0.231	0.300	0.126	0.279

Table III
OLS Regression of Price Delay on Fragmentation

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

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

where $y_{i,t+1}$ is *Price Delay* as in Hou and Moskowitz (2005). T-statistics are in parentheses calculated using standard errors clustered by firm and date. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**Delay1**	**Delay1**	**Delay1**	**Delay1**	**Delay2**	**Delay2**	**Delay2**	**Delay2**
Fragmentation	-0.2036***	0.0023	-0.2108***	0.0507***	-0.1578***	-0.0108***	-0.1901***	-0.0199*
	(-31.00)	*(0.45)*	*(-16.31)*	*(3.63)*	*(-33.02)*	*(-3.23)*	*(-18.03)*	*(-1.96)*
Market Cap	-0.0062**	-0.0453***			-0.0006	-0.0274***		
	(-2.38)	*(-17.65)*			*(-0.35)*	*(-16.76)*		
Bid-Ask Spread	0.0132***	0.0071***	0.0076***	0.0082***	0.0142***	0.0058***	0.0110***	0.0066***
	(15.45)	*(11.13)*	*(8.06)*	*(12.68)*	*(23.16)*	*(14.43)*	*(17.02)*	*(15.89)*
Volume (%)	0.0065***	0.0011	0.0071***	0.0026***	0.0073***	0.0017***	0.0071***	0.0024***
	(7.24)	*(1.43)*	*(8.16)*	*(3.49)*	*(12.08)*	*(3.75)*	*(11.98)*	*(5.14)*
Size Decile 2			-0.0074	0.0009			-0.0149	-0.0090
			(-0.58)	*(0.08)*			*(-1.54)*	*(-0.99)*
Size Decile 3			-0.0102	-0.0050			-0.0274**	-0.0229**
			(-0.70)	*(-0.37)*			*(-2.51)*	*(-2.26)*
Size Decile 4			-0.0061	-0.0041			-0.0284**	-0.0262**
			(-0.41)	*(-0.29)*			*(-2.48)*	*(-2.47)*
Size Decile 5			0.0515***	0.0605***			-0.0008	0.0059
			(2.99)	*(3.67)*			*(-0.07)*	*(0.51)*
Size Decile 6			0.0650***	0.1015***			-0.0054	0.0227**
			(3.76)	*(6.13)*			*(-0.44)*	*(1.99)*
Size Decile 7			0.1083***	0.1769***			0.0054	0.0575***
			(6.06)	*(10.35)*			*(0.44)*	*(4.98)*
Size Decile 8			0.0703***	0.1771***			-0.0202	0.0608***
			(3.99)	*(10.46)*			*(-1.63)*	*(5.29)*
Size Decile 9			0.0739***	0.2091***			-0.0195	0.0829***
			(4.24)	*(12.34)*			*(-1.58)*	*(7.19)*
Size Decile 10			0.0983***	0.2668***			-0.0124	0.1167***
			(5.19)	*(14.74)*			*(-0.94)*	*(9.49)*
Fragmentation*Decile2			0.0011	-0.0072			0.0088	0.0067
			(0.06)	*(-0.44)*			*(0.66)*	*(0.54)*
Fragmentation*Decile3			-0.0076	-0.0073			0.0116	0.0178
			(-0.39)	*(-0.40)*			*(0.79)*	*(1.32)*
Fragmentation*Decile4			-0.0037	0.0000			0.0165	0.0292**
			(-0.19)	*(0.00)*			*(1.10)*	*(2.13)*
Fragmentation*Decile5			-0.0784***	-0.0861***			-0.0167	-0.0089
			(-3.55)	*(-4.08)*			*(-1.07)*	*(-0.61)*
Fragmentation*Decile6			-0.0637***	-0.1041***			0.0068	-0.0078
			(-2.99)	*(-5.05)*			*(0.46)*	*(-0.55)*
Fragmentation*Decile7			-0.0797***	-0.1589***			0.0137	-0.0276**
			(-3.73)	*(-7.63)*			*(0.94)*	*(-2.01)*
Fragmentation*Decile8			0.0432**	-0.0845***			0.0835***	0.0091
			(2.31)	*(-4.48)*			*(6.35)*	*(0.72)*
Fragmentation*Decile9			0.1141***	-0.0360**			0.1188***	0.0309**
			(6.65)	*(-2.03)*			*(9.55)*	*(2.55)*
Fragmentation*Decile10			0.1381***	-0.0337*			0.1346***	0.0317**
			(7.43)	*(-1.81)*			*(10.18)*	*(2.46)*
Firm FE?	*YES*	*YES*	*NO*	*NO*	*YES*	*YES*	*NO*	*NO*
Quarter-Year FE?	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*
Observations	6,307,939	6,307,939	6,307,939	6,307,939	6,307,939	6,307,939	6,307,939	6,307,939
R-squared	0.034	0.127	0.044	0.134	0.046	0.161	0.052	0.164

Table IV
OLS Regression of Trade Size and Volatility on Fragmentation

The table presents the results of an OLS panel regression of trade size and volatility on market fragmentation according to the model:

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

where $y_{i,t+1}$ is either average trade size from TAQ or annualized volatility, calculated as the standard deviation of daily returns over the previous 21 days. T-statistics are in parentheses calculated using standard errors clustered by firm and date. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Small Volume	(2) Small Volume	(3) Small Volume	(4) Small Volume	(5) Volatility	(6) Volatility	(7) Volatility	(8) Volatility
Fragmentation	0.5010***	0.2173***	0.6623***	0.4142***	0.3850***	0.1211***	0.5969***	0.0840***
	(71.19)	*(50.22)*	*(49.00)*	*(39.88)*	*(29.53)*	*(19.83)*	*(23.21)*	*(3.85)*
Market Cap	0.0694***	0.0957***			-0.2012***	-0.1222***		
	(41.33)	*(52.99)*			*(-39.80)*	*(-39.37)*		
Bid-Ask Spread	-0.0037***	-0.0124***	-0.0177***	-0.0289***	0.1684***	0.0873***	0.2298***	0.0994***
	(-5.47)	*(-22.71)*	*(-23.97)*	*(-39.45)*	*(42.90)*	*(70.25)*	*(42.22)*	*(75.75)*
Volume (%)	-0.0111***	-0.0117***	-0.0104***	-0.0118***	0.1126***	0.0934***	0.1179***	0.0949***
	(-17.59)	*(-24.19)*	*(-17.90)*	*(-23.83)*	*(57.55)*	*(74.00)*	*(60.25)*	*(75.06)*
Size Decile 2			0.0287***	0.0614***			0.0213	0.0518***
			(2.70)	*(6.35)*			*(1.19)*	*(2.74)*
Size Decile 3			0.1097***	0.1446***			0.0699***	0.1270***
			(9.80)	*(14.00)*			*(3.38)*	*(6.08)*
Size Decile 4			0.1507***	0.1868***			0.0651***	0.1564***
			(12.93)	*(17.45)*			*(2.91)*	*(7.14)*
Size Decile 5			0.2231***	0.2525***			0.0824***	0.1859***
			(18.58)	*(23.08)*			*(3.50)*	*(8.26)*
Size Decile 6			0.2460***	0.2627***			0.1396***	0.2399***
			(21.69)	*(25.66)*			*(5.78)*	*(10.61)*
Size Decile 7			0.2265***	0.2191***			0.1662***	0.2516***
			(21.60)	*(23.58)*			*(6.65)*	*(10.80)*
Size Decile 8			0.2284***	0.1956***			0.2913***	0.3648***
			(23.62)	*(22.68)*			*(11.21)*	*(15.19)*
Size Decile 9			0.2296***	0.1748***			0.4106***	0.4882***
			(28.07)	*(23.92)*			*(15.64)*	*(20.35)*
Size Decile 10							0.5169***	0.6044***
							(19.13)	*(24.74)*
Fragmentation*Decile2			0.0433***	0.0046			-0.0239	0.0140
			(2.76)	*(0.34)*			*(-1.02)*	*(0.57)*
Fragmentation*Decile3			-0.0590***	-0.0895***			-0.0566**	0.0108
			(-3.62)	*(-6.43)*			*(-2.23)*	*(0.41)*
Fragmentation*Decile4			-0.1241***	-0.1425***			-0.0193	0.0712***
			(-7.31)	*(-9.80)*			*(-0.73)*	*(2.65)*
Fragmentation*Decile5			-0.2557***	-0.2551***			-0.0183	0.1189***
			(-14.47)	*(-16.88)*			*(-0.67)*	*(4.44)*
Fragmentation*Decile6			-0.3346***	-0.3098***			-0.0961***	0.1084***
			(-19.75)	*(-21.95)*			*(-3.53)*	*(4.17)*
Fragmentation*Decile7			-0.3659***	-0.3029***			-0.1750***	0.1212***
			(-22.41)	*(-22.60)*			*(-6.20)*	*(4.67)*
Fragmentation*Decile8			-0.4596***	-0.3547***			-0.3977***	-0.0013
			(-29.33)	*(-27.89)*			*(-13.16)*	*(-0.05)*
Fragmentation*Decile9			-0.5400***	-0.4037***			-0.5187***	-0.0544**
			(-37.33)	*(-34.35)*			*(-17.52)*	*(-2.10)*
Fragmentation*Decile10							-0.5612***	-0.0378
							(-18.73)	*(-1.49)*
Firm FE?	*YES*	*YES*	*NO*	*NO*	*YES*	*YES*	*NO*	*NO*
Quarter-Year FE?	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*
Observations	6,622,621	6,622,621	6,622,621	6,622,621	14,475,479	14,475,479	14,475,479	14,475,479
R-squared	0.355	0.519	0.384	0.499	0.228	0.415	0.195	0.411

Table V

Regulation NMS Experiment - Depth and Bid-Ask Spreads

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

$$y_{i,t} = \alpha + \beta_1 \text{Period } 1_t + \beta_2 \text{Period } 2_t + \beta_3 \text{Pilot}_i + \beta_4 \text{Policy}_{i,t} + \sum_{j=2}^{10} \gamma_j \text{Size Decile}_{i,j} + \sum_{k=2}^{10} \text{Policy}_{i,t} \times \text{Size Decile}_{i,k}$$

The implementation of Regulation NMS occurred in two stages, so we include a pre-period and two dummies for the following two stages of implementation, Period 1 and Period 2. Pilot is a dummy which accounts for any level differences between the initial pilot firms and all other firms. Policy is a dummy for when a firm is officially subject to the rules of the regulation. Firms are sorted into market capitalization deciles one month prior to the experiment and then interacted with the policy variable to capture the differential effect of exchange competition on firms with potential costs and benefits of fragmentation. Depth and Bid-ask spreads are calculated using TAQ. T-statistics are in parentheses calculated using standard errors clustered by firm and date. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) NBBO Depth	(2) NBBO Depth	(3) Var(NBBO Depth)	(4) Var(NBBO Depth)	(5) Bid-Ask Spread	(6) Bid-Ask Spread
Period 1	-0.1466***	-0.1485***	-0.2467***	-0.2597***	0.1880***	0.1811***
	(-24.8486)	(-26.5249)	(-16.1963)	(-17.3819)	(47.9292)	(51.6399)
Period 2	-0.1886***	-0.2059***	-0.1856***	-0.2661***	0.2255***	0.2070***
	(-9.8066)	(-10.8573)	(-3.5893)	(-5.1590)	(13.5883)	(12.9523)
Pilot	0.7263***	0.4539***	-0.6017***	0.2376**	-0.6359***	-0.0252
	(8.8767)	(5.5489)	(-4.4741)	(2.2052)	(-8.5662)	(-0.7543)
Policy	-0.0576***	-0.0996***	-0.0730	-0.2274***	0.0134	-0.0096
	(-3.2752)	(-4.5347)	(-1.5038)	(-3.8859)	(0.8539)	(-0.5475)
Size Decile 2		-0.5721***		0.0602		0.3099***
		(-8.6588)		(0.7040)		(15.3698)
Size Decile 3		-0.6666***		0.2000**		0.5121***
		(-9.5829)		(2.2437)		(24.1489)
Size Decile 4		-0.8414***		0.3430***		0.7289***
		(-12.2055)		(3.8126)		(34.8845)
Size Decile 5		-0.9628***		0.6094***		1.0105***
		(-14.3711)		(6.8187)		(45.2348)
Size Decile 6		-1.1464***		1.1698***		1.2650***
		(-17.9391)		(13.1681)		(51.6000)
Size Decile 7		-1.1951***		2.2068***		1.7095***
		(-16.9830)		(23.2678)		(61.3971)
Size Decile 8		-1.0506***		3.1565***		2.0786***
		(-14.4517)		(31.3077)		(67.4328)
Size Decile 9		-1.0776***		3.7126***		2.5108***
		(-15.0934)		(39.1557)		(71.1351)
Size Decile 10		-0.8067***		4.3925***		2.6462***
		(-9.3306)		(40.8182)		(53.1393)
Policy × Decile 2		0.0578*		0.0955		0.0293*
		(1.8954)		(1.6335)		(1.9388)
Policy × Decile 3		-0.0183		0.0345		0.0316**
		(-0.7088)		(0.6274)		(2.2118)
Policy × Decile 4		0.0397		0.1361**		0.0078
		(1.4283)		(2.3460)		(0.5428)
Policy × Decile 5		0.0603**		0.2708***		0.0232
		(2.0192)		(4.2897)		(1.5642)
Policy × Decile 6		0.0734***		0.3508***		0.0176
		(2.9487)		(6.2781)		(1.2078)
Policy × Decile 7		0.1295***		0.3086***		0.0686***
		(4.3657)		(4.7902)		(4.3350)
Policy × Decile 8		0.0964***		0.3988***		0.0421**
		(3.2205)		(6.2588)		(2.5604)
Policy × Decile 9		0.1616***		0.4038***		0.0430***
		(5.2048)		(5.8359)		(2.5884)
Policy × Decile 10		0.1400***		0.4566***		0.0150
		(3.1466)		(4.5969)		(0.8068)
Constant	2.7938***	3.5801***	-10.3309***	-11.5820***	-6.0759***	-7.3725***
	(160.4074)	(69.4818)	(-320.2398)	(-183.5179)	(-449.2951)	(-515.0192)
Observations	337,390	329,400	330,687	324,370	607,479	590,181
R-squared	0.0243	0.1286	0.0068	0.4854	0.0123	0.4629

Table VI
Regulation NMS Experiment - Price Delay

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

$$y_{i,t} = \alpha + \beta_1 \text{Period } 1_t + \beta_2 \text{Period } 2_t + \beta_3 \text{Pilot}_i + \beta_4 \text{Policy}_{i,t} + \sum_{j=2}^{10} \gamma_j \text{Size Decile}_{i,j} + \sum_{k=2}^{10} \text{Policy}_{i,t} \times \text{Size Decile}_{i,k}$$

The implementation of Regulation NMS occurred in two stages, so we include a pre-period and two dummies for the following two stages of implementation, Period 1 and Period 2. Pilot is a dummy which accounts for any level differences between the initial pilot firms and all other firms. Policy is a dummy for when a firm is officially subject to the rules of the regulation. Firms are sorted into market capitalization deciles one month prior to the experiment and then interacted with the policy variable to capture the differential effect of exchange competition on firms with potential costs and benefits of fragmentation. Delay is calculated as in Hou and Moskowitz (2005). T-statistics are in parentheses calculated using standard errors clustered by firm and date. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) Delay1	(2) Delay1	(3) Delay2	(4) Delay2
Period1	-0.0052**	-0.0054**	0.0156***	0.0155***
	(-2.3474)	(-2.4585)	(11.1713)	(11.1684)
Period2	-0.0332***	-0.0389***	0.0077	0.0044
	(-4.5080)	(-5.2253)	(1.5823)	(0.8848)
Pilot	-0.0833***	0.0157	-0.0559***	0.0039
	(-4.2108)	(0.9139)	(-4.6029)	(0.3590)
Policy	0.0059	-0.0288***	0.0042	-0.0187***
	(0.9863)	(-3.2572)	(1.0269)	(-3.1534)
Size Decile 2		0.0410***		0.0285***
		(3.0204)		(3.1737)
Size Decile 3		0.0382***		0.0372***
		(2.7793)		(4.0883)
Size Decile 4		0.0532***		0.0427***
		(3.7402)		(4.6067)
Size Decile 5		0.1063***		0.0794***
		(6.7785)		(8.0927)
Size Decile 6		0.1742***		0.1182***
		(10.9155)		(11.8046)
Size Decile 7		0.3569***		0.2123***
		(22.1047)		(21.3877)
Size Decile 8		0.4042***		0.2408***
		(25.8909)		(24.7962)
Size Decile 9		0.4494***		0.2614***
		(28.7418)		(26.4001)
Size Decile 10		0.4810***		0.2816***
		(27.6782)		(24.8767)
Policy × Decile 2		0.0355***		0.0294***
		(2.9230)		(3.7424)
Policy × Decile 3		0.0443***		0.0287***
		(3.5032)		(3.5152)
Policy × Decile 4		0.0767***		0.0515***
		(5.8976)		(6.1567)
Policy × Decile 5		0.0747***		0.0480***
		(5.3219)		(5.5269)
Policy × Decile 6		0.0483***		0.0307***
		(3.1479)		(3.3745)
Policy × Decile 7		0.0292*		0.0195**
		(1.8992)		(2.1487)
Policy × Decile 8		0.0216		0.0085
		(1.3853)		(0.9193)
Policy × Decile 9		0.0295*		0.0149*
		(1.9146)		(1.6533)
Policy × Decile 10		0.0428**		0.0254**
		(2.2662)		(2.1710)
Constant	0.4709***	0.3036***	0.6085***	0.5029***
	(94.9400)	(31.4378)	(200.2662)	(78.6343)
Observations	304,652	304,652	304,652	304,652
R-squared	0.0048	0.3324	0.0053	0.2918

Table VII
Regulation NMS Experiment - Trade Size and Volatility

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

$$y_{i,t} = \alpha + \beta_1 \text{Period } 1_t + \beta_2 \text{Period } 2_t + \beta_3 \text{Pilot}_i + \beta_4 \text{Policy}_{i,t} + \sum_{j=2}^{10} \gamma_j \text{Size Decile}_{i,j} + \sum_{k=2}^{10} \text{Policy}_{i,t} \times \text{Size Decile}_{i,k}$$

The implementation of Regulation NMS occurred in two stages, so we include a pre-period and two dummies for the following two stages of implementation, Period 1 and Period 2. Pilot is a dummy which accounts for any level differences between the initial pilot firms and all other firms. Policy is a dummy for when a firm is officially subject to the rules of the regulation. Firms are sorted into market capitalization deciles one month prior to the experiment and then interacted with the policy variable to capture the differential effect of exchange competition on firms with potential costs and benefits of fragmentation. Volatility is the log-transformed variance of previous trading month returns. TAQ trade size is the average size of a trade on a given firm-day. T-statistics are in parentheses calculated using standard errors clustered by firm and date. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) TAQ Trade Size	(2) TAQ Trade Size	(3) Volatility	(4) Volatility
Period 1	-0.0451***	-0.0513***	0.1913***	0.1934***
	(-14.5016)	(-18.6234)	(42.7116)	(44.4704)
Period 2	-0.0505***	-0.0679***	0.3997***	0.4048***
	(-6.3237)	(-8.9900)	(17.2301)	(17.3623)
Treatment	-0.1205***	0.0213	0.0967***	0.1692***
	(-3.9156)	(0.8102)	(2.6693)	(5.2703)
Policy	-0.0043	-0.0279***	0.0243	-0.0157
	(-0.6329)	(-3.4596)	(1.0839)	(-0.6468)
Size Decile 2		-0.0772***		0.0753***
		(-3.8411)		(3.8046)
Size Decile 3		-0.0803***		0.1684***
		(-3.8617)		(8.0358)
Size Decile 4		-0.0678***		0.2096***
		(-3.1984)		(9.4309)
Size Decile 5		0.0020		0.2375***
		(0.0884)		(9.4974)
Size Decile 6		0.0487**		0.2237***
		(2.1364)		(8.3681)
Size Decile 7		0.2483***		0.1418***
		(10.3309)		(5.1627)
Size Decile 8		0.4066***		0.1748***
		(15.7094)		(6.0261)
Size Decile 9		0.4941***		0.2923***
		(20.4115)		(10.0200)
Size Decile 10		0.6414***		0.4595***
		(25.1598)		(14.4507)
Policy × Decile 2		0.0203**		0.0495***
		(2.3944)		(2.9728)
Policy × Decile 3		0.0046		0.0903***
		(0.6123)		(5.2440)
Policy × Decile 4		0.0256***		0.0918***
		(3.2230)		(5.1500)
Policy × Decile 5		0.0442***		0.1123***
		(5.4321)		(6.2332)
Policy × Decile 6		0.0450***		0.0533***
		(5.1659)		(3.0498)
Policy × Decile 7		0.0468***		0.0574***
		(4.2287)		(3.2619)
Policy × Decile 8		0.0424***		0.0123
		(3.1845)		(0.6530)
Policy × Decile 9		0.0639***		-0.0173
		(5.2248)		(-0.8936)
Policy × Decile 10		0.0343**		-0.0883***
		(2.2328)		(-4.7540)
Constant	5.7090***	5.5318***	-1.3979***	-1.5942***
	(847.5505)	(391.7619)	(-186.6557)	(-110.5701)
Observations	609,889	592,354	610,670	593,610
R-squared	0.0029	0.2131	0.0682	0.1003

Table VIII
2SLS Instrumental Variable Regression of Depth and Bid-Ask Spreads

The table presents the results of a two-stage least squares instrumental variables regression. We instrument the level of fragmentation using the total number of market centers in the U.S. at each point in time according to the model:

$$\text{First Stage: Fragmentation}_{i,t} = \phi + \beta \text{Total Market Centers}_t + \gamma \text{Controls} + \nu_{i,t}$$
$$\text{Second Stage: } y_{i,t+1} = \alpha + \beta \widehat{\text{Fragmentation}}_{i,t} + \delta \text{Controls} + \varepsilon_{i,t+1}$$

Firms are sorted into market capitalization deciles and then interacted with fragmentation in the first stage and we use the number of market centers × each market capitalization decile as additional instruments in the first stage. The bid-ask spread is defined 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. NBBO depth and prices are calculated from TAQ. We take the average for each second during regular market hours. We then take the variance and mean of these firm-seconds for each firm-day, excluding the first and last five minutes of trading. Depth, variance of depth, and bid-ask spreads are log-transformed to address skewness. Quarter-year fixed effects are included in the results of column (2), (4), and (6). T-statistics are in parentheses calculated using standard errors clustered by firm and date. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) NBBO Depth	(2) NBBO Depth	(3) Var(NBBO Depth)	(4) Var(NBBO Depth)	(5) Bid-Ask Spread	(6) Bid-Ask Spread
Fragmentation	-1.5701***	1.5441*	-0.0793***	0.3369	-1.4593***	-0.6216
	(-8.97)	*(1.91)*	*(-2.67)*	*(1.22)*	*(-20.38)*	*(-0.95)*
Bid-Ask Spread			0.0349***	0.0295***		
			(559.00)	*(103.85)*		
Volume (%)	-0.2598***	-0.4351***	0.0996***	0.0772***	-0.2274***	-0.2748***
	(-23.62)	*(-9.34)*	*(3.00)*	*(3.33)*	*(-61.08)*	*(-9.26)*
Size Decile 2	0.3106**	0.4045***	-0.0039	0.0078	0.3259***	0.3389***
	(2.47)	*(3.14)*	*(-0.28)*	*(0.53)*	*(6.55)*	*(8.18)*
Size Decile 3	0.2620**	0.1201	-0.0283*	-0.0489*	0.5922***	0.5290***
	(1.99)	*(0.86)*	*(-1.89)*	*(-1.78)*	*(11.69)*	*(7.62)*
Size Decile 4	0.3249**	-0.1597	-0.0116	-0.0771	0.8931***	0.7375***
	(2.42)	*(-0.85)*	*(-0.91)*	*(-1.40)*	*(17.13)*	*(5.43)*
Size Decile 5	0.3209**	-0.6200**	0.0140	-0.1130	1.1999***	0.9609***
	(2.25)	*(-2.15)*	*(1.12)*	*(-1.26)*	*(21.59)*	*(4.80)*
Size Decile 6	0.3278**	-0.7580**	0.0441**	-0.1033	1.2960***	1.0305***
	(2.28)	*(-2.36)*	*(2.02)*	*(-1.10)*	*(23.10)*	*(4.64)*
Size Decile 7	0.8921***	0.0499	0.1878***	0.0741	1.5002***	1.2722***
	(6.63)	*(0.19)*	*(3.10)*	*(1.28)*	*(26.31)*	*(6.82)*
Size Decile 8	0.8535***	0.2976	0.2589***	0.1816***	1.5271***	1.3446***
	(6.52)	*(1.46)*	*(2.91)*	*(3.06)*	*(25.19)*	*(8.72)*
Size Decile 9	1.3327***	0.9344***	0.3394*	0.2801*	1.7891***	1.6174***
	(10.19)	*(5.28)*	*(1.81)*	*(1.76)*	*(26.37)*	*(10.81)*
Size Decile 10	2.0702***	1.8041***	1.6527	1.6088	2.6887***	2.5419***
	(12.81)	*(9.99)*	*(1.51)*	*(1.50)*	*(32.47)*	*(16.77)*
Fragmentation*Decile2	-0.4773**	-0.5129**	0.0280	0.0244	0.1600**	0.1709**
	(-2.07)	*(-2.17)*	*(1.47)*	*(1.26)*	*(2.04)*	*(2.40)*
Fragmentation*Decile3	-0.2531	0.1323	0.0837***	0.1373**	0.1844**	0.3279**
	(-1.04)	*(0.49)*	*(3.06)*	*(2.26)*	*(2.28)*	*(2.29)*
Fragmentation*Decile4	0.1348	1.0534***	0.0961***	0.2213*	0.1630*	0.4572*
	(0.54)	*(3.00)*	*(2.97)*	*(1.94)*	*(1.95)*	*(1.78)*
Fragmentation*Decile5	0.8955***	2.5467***	0.1168***	0.3412*	0.1018	0.5411
	(3.41)	*(4.99)*	*(3.30)*	*(1.87)*	*(1.11)*	*(1.45)*
Fragmentation*Decile6	1.8689***	3.8329***	0.1475***	0.4161**	0.3981***	0.8963**
	(6.88)	*(6.58)*	*(4.22)*	*(2.00)*	*(4.28)*	*(2.12)*
Fragmentation*Decile7	2.0693***	3.7615***	0.0270	0.2583	0.5847***	1.0612***
	(8.13)	*(7.31)*	*(0.61)*	*(1.63)*	*(6.02)*	*(2.68)*
Fragmentation*Decile8	3.6471***	5.0770***	0.0773	0.2802**	1.3136***	1.7629***
	(14.75)	*(11.09)*	*(1.11)*	*(2.16)*	*(12.01)*	*(4.59)*
Fragmentation*Decile9	4.0137***	5.3993***	0.1645	0.3722	1.5544***	2.0588***
	(15.67)	*(11.86)*	*(0.58)*	*(1.61)*	*(11.71)*	*(4.72)*
Fragmentation*Decile10	4.0727***	5.4540***	-0.8108	-0.5828	0.3082	0.9826
	(12.33)	*(10.79)*	*(-0.38)*	*(-0.29)*	*(1.63)*	*(1.62)*
Intercept	-10.2340***	-12.4229***	-0.1516***	-0.4176*	-4.8927***	-5.8664***
	(-108.97)	*(-22.33)*	*(-2.89)*	*(-1.72)*	*(-1,674.02)*	*(-111.63)*
Quarter-Year FE?	*NO*	*YES*	*NO*	*YES*	*NO*	*YES*
Observations	6,804,195	6,804,195	6,900,055	6,900,055	14,480,023	14,480,023
R-squared	0.486	0.394	0.012	0.010	0.574	0.644

Table IX
2SLS Instrumental Variable Regression of Price Delay

The table presents the results of a two-stage least squares instrumental variables regression. We instrument the level of fragmentation using the total number of market centers in the U.S. at each point in time according to the model:

$$\text{First Stage: Fragmentation}_{i,t} = \phi + \beta\text{Total Market Centers}_t + \gamma\text{Controls} + \nu_{i,t}$$
$$\text{Second Stage: } y_{i,t+1} = \alpha + \beta\widehat{\text{Fragmentation}}_{i,t} + \delta\text{Controls} + \varepsilon_{i,t+1}$$

Firms are sorted into market capitalization deciles and then interacted with fragmentation in the first stage and we use the number of market centers × each market capitalization decile as additional instruments in the first stage. Delay is calculated as in Hou and Moskowitz (2005). The bid-ask spread is defined 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. We take the average for each second during regular market hours. We then take the variance and mean of these firm-seconds for each firm-day, excluding the first and last five minutes of trading. Depth, variance of depth, and bid-ask spreads are log-transformed to address skewness. Quarter-year fixed effects are included in the results of column (2), (4), and (6). T-statistics are in parentheses calculated using standard errors clustered by firm and date. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) Delay1	(2) Delay1	(3) Delay2	(4) Delay2
Fragmentation	-0.3222***	-0.5569***	-0.2914***	-0.4953***
	(-19.80)	*(-3.95)*	*(-21.36)*	*(-4.93)*
Bid-Ask Spread	0.0125***	0.0094***	0.0136***	0.0066***
	(11.93)	*(5.29)*	*(18.89)*	*(5.24)*
Volume (%)	0.0120***	0.0235***	0.0105***	0.0189***
	(9.12)	*(2.96)*	*(12.50)*	*(3.35)*
Size Decile 2	0.0244	0.0194	0.0056	0.0026
	(1.50)	*(1.12)*	*(0.46)*	*(0.20)*
Size Decile 3	0.0545***	0.0664***	0.0251**	0.0376***
	(3.15)	*(3.38)*	*(1.96)*	*(2.58)*
Size Decile 4	0.1003***	0.1410***	0.0590***	0.0970***
	(5.00)	*(4.31)*	*(4.01)*	*(4.07)*
Size Decile 5	0.2532***	0.3338***	0.1461***	0.2193***
	(10.31)	*(6.14)*	*(8.71)*	*(5.66)*
Size Decile 6	0.3897***	0.4833***	0.2134***	0.2975***
	(13.94)	*(7.79)*	*(11.63)*	*(6.79)*
Size Decile 7	0.5730***	0.6482***	0.2909***	0.3601***
	(21.67)	*(12.38)*	*(17.60)*	*(9.89)*
Size Decile 8	0.4920***	0.5448***	0.2401***	0.2896***
	(20.87)	*(13.72)*	*(16.34)*	*(10.58)*
Size Decile 9	0.4393***	0.4715***	0.2152***	0.2470***
	(18.73)	*(13.82)*	*(14.54)*	*(10.54)*
Size Decile 10	0.4147***	0.4380***	0.1883***	0.2143***
	(16.55)	*(13.65)*	*(11.60)*	*(9.82)*
Fragmentation*Decile2	-0.0367	-0.0346	-0.0104	-0.0082
	(-1.61)	*(-1.45)*	*(-0.58)*	*(-0.44)*
Fragmentation*Decile3	-0.0620**	-0.0887***	-0.0233	-0.0458*
	(-2.43)	*(-2.80)*	*(-1.17)*	*(-1.89)*
Fragmentation*Decile4	-0.1072***	-0.1775***	-0.0566**	-0.1155***
	(-3.58)	*(-3.31)*	*(-2.46)*	*(-2.93)*
Fragmentation*Decile5	-0.3113***	-0.4456***	-0.1654***	-0.2792***
	(-8.26)	*(-5.06)*	*(-6.22)*	*(-4.43)*
Fragmentation*Decile6	-0.4705***	-0.6294***	-0.2381***	-0.3699***
	(-10.54)	*(-6.09)*	*(-7.94)*	*(-5.05)*
Fragmentation*Decile7	-0.6527***	-0.7897***	-0.2981***	-0.4104***
	(-14.55)	*(-8.52)*	*(-10.54)*	*(-6.36)*
Fragmentation*Decile8	-0.3851***	-0.4999***	-0.1423***	-0.2299***
	(-8.94)	*(-6.27)*	*(-5.38)*	*(-4.17)*
Fragmentation*Decile9	-0.1795***	-0.2725***	-0.0458	-0.1092**
	(-3.84)	*(-3.44)*	*(-1.60)*	*(-2.00)*
Fragmentation*Decile10	-0.0269	-0.1184	0.0591*	-0.0015
	(-0.49)	*(-1.38)*	*(1.72)*	*(-0.03)*
Intercept	0.4758***	0.6996***	0.6957***	0.8414***
	(33.99)	*(8.05)*	*(65.45)*	*(13.63)*
Quarter-Year FE?		*YES*		*YES*
Observations	6,307,939	6,307,939	6,307,939	6,307,939
R-squared	0.317	0.259	0.281	0.206

Table X

2SLS Instrumental Variable Regression of Trade Size and Volatility

The table presents the results of a two-stage least squares instrumental variables regression. We instrument the level of fragmentation using the total number of market centers in the U.S. at each point in time according to the model:

$$\text{First Stage: Fragmentation}_{i,t} = \phi + \beta \text{Total Market Centers}_t + \gamma \text{Controls} + \nu_{i,t}$$
$$\text{Second Stage: } y_{i,t+1} = \alpha + \beta \widehat{\text{Fragmentation}}_{i,t} + \delta \text{Controls} + \varepsilon_{i,t+1}$$

Firms are sorted into market capitalization deciles and then interacted with fragmentation in the first stage and we use the number of market centers × each market capitalization decile as additional instruments in the first stage. Volatility is calculated as the annualized standard deviation of daily returns over the previous 21 days. The bid-ask spread is defined 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. We take the average for each second during regular market hours. We then take the variance and mean of these firm-seconds for each firm-day, excluding the first and last five minutes of trading. Depth, variance of depth, and bid-ask spreads are log-transformed to address skewness. Quarter-year fixed effects are included in the results of column (2), (4), and (6). T-statistics are in parentheses calculated using standard errors clustered by firm and date. ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively.

Variables	(1) Small Volume (%)	(2) Small Volume (%)	(3) Volatility	(4) Volatility
Fragmentation	0.8690***	-0.2864***	0.5818***	1.0736**
	(846.86)	*(-16.45)*	*(15.21)*	*(2.37)*
Bid-Ask Spread	-0.0342***	-0.0620***	0.3648***	0.2838***
	(-523.60)	*(-192.54)*	*(79.90)*	*(45.82)*
Volume (%)	-0.0404***	0.0137***	0.1555***	0.1041***
	(-609.47)	*(15.44)*	*(56.33)*	*(4.72)*
Size Decile 2	0.1213***	0.0704***	-0.1042***	-0.0710**
	(131.04)	*(53.20)*	*(-3.23)*	*(-2.13)*
Size Decile 3	0.1953***	0.2275***	-0.0345	-0.0347
	(194.38)	*(182.06)*	*(-0.95)*	*(-0.68)*
Size Decile 4	0.2093***	0.3754***	-0.0904**	-0.1344
	(183.72)	*(136.25)*	*(-2.29)*	*(-1.44)*
Size Decile 5	0.2223***	0.5657***	-0.0982**	-0.1791
	(164.44)	*(106.74)*	*(-2.14)*	*(-1.31)*
Size Decile 6	0.2572***	0.6596***	-0.1057**	-0.1994
	(184.75)	*(107.00)*	*(-2.31)*	*(-1.32)*
Size Decile 7	0.1481***	0.4702***	-0.2555***	-0.3040**
	(118.64)	*(94.40)*	*(-5.93)*	*(-2.45)*
Size Decile 8	0.1854***	0.4082***	-0.1463***	-0.1592
	(155.34)	*(114.84)*	*(-3.52)*	*(-1.59)*
Size Decile 9	0.2273***	0.3976***	-0.1068**	-0.0910
	(177.43)	*(133.04)*	*(-2.45)*	*(-0.96)*
Size Decile 10			0.2724***	0.3741***
			(5.63)	*(4.15)*
Fragmentation*Decile2	-0.0046***	0.0659***	0.0607	0.0854
	(-3.09)	*(32.41)*	*(1.13)*	*(1.54)*
Fragmentation*Decile3	-0.0789***	-0.1459***	-0.0641	0.0595
	(-48.41)	*(-68.55)*	*(-1.06)*	*(0.57)*
Fragmentation*Decile4	-0.1060***	-0.3676***	-0.0797	0.1536
	(-56.61)	*(-83.04)*	*(-1.24)*	*(0.84)*
Fragmentation*Decile5	-0.1640***	-0.6963***	-0.1968***	0.1393
	(-72.50)	*(-83.65)*	*(-2.62)*	*(0.53)*
Fragmentation*Decile6	-0.2880***	-0.9273***	-0.2694***	0.1364
	(-119.97)	*(-93.10)*	*(-3.50)*	*(0.46)*
Fragmentation*Decile7	-0.1946***	-0.7267***	-0.2233***	0.1799
	(-85.94)	*(-86.12)*	*(-2.93)*	*(0.64)*
Fragmentation*Decile8	-0.3600***	-0.7789***	-0.5130***	-0.0701
	(-153.62)	*(-112.54)*	*(-6.70)*	*(-0.26)*
Fragmentation*Decile9	-0.5317***	-0.9143***	-0.5670***	-0.0625
	(-198.07)	*(-132.89)*	*(-6.43)*	*(-0.20)*
Fragmentation*Decile10			-1.4812***	-0.9429**
			(-12.74)	*(-2.25)*
Intercept	-0.1518***	0.4007***	0.7564***	-0.3981
	(-248.23)	*(42.38)*	*(18.65)*	*(-1.17)*
Quarter-Year FE?	*NO*	*YES*	*NO*	*YES*
Observations	6,622,621	6,622,621	14,475,482	14,475,482
R-squared	0.402	0.194	0.261	0.345