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The Demise of the NYSE and Nasdaq: Market Quality in the Age of Market Fragmentation

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Abstract

U.S. equity exchanges have experienced a dramatic increase in competition from new entrants, resulting in the fragmentation of trading across venues. While market quality has generally improved over this period, we show most of the improvements have accrued to the largest stocks. We then show this bifurcation in market quality is related to the fragmentation of trading. Theoretically, more exchange competition should reduce trading costs, yet it may also increase adverse selection for liquidity providers, leading to higher spreads. We document evidence of both effects (fragmentation improves market quality for large stocks while small stocks experience relatively worse quality).

I. Introduction

U.S. equity markets have changed dramatically over the last two decades. In 2000, the New York Stock Exchange (NYSE) and Nasdaq accounted for approximately 95% of all U.S. equity trading volume. By 2016, they accounted for less than 30%. Over this time, the number of U.S. market centers available to trade at nearly tripled and with that, measures of market fragmentation more than doubled. Yet, despite the significance of these changes, there has been relatively little empirical research on the effects of exchange competition and the resulting fragmentation of trading across venues.

In this study, we provide novel evidence on the relation between exchange competition, trading behavior, and market quality. We start by documenting a

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striking fact: While liquidity has improved in U.S. equities over the last two decades, most of the improvements have accrued to the largest stocks (see Figure 1). In other words, improvements to liquidity have been distributed unequally across stocks: large companies have gotten much more liquid relative to small companies.

Theoretical models on exchange competition provide a potential explanation for this finding. When modeling the effect of exchange competition, the literature tends to highlight the trade-off between the positive effects that arise from increased competition and more trading against the negative network externalities that arise when liquidity is dispersed across different trading venues. If the negative network externalities dominate, then it is possible that liquidity providers will increase spreads and market quality will be worse. Otherwise, if the competitive effects dominate, market quality may improve. Ultimately, the net effect of these opposing forces is an empirical question.

Consistent with these theoretical channels, we find that the fragmentation of trading across market venues changes trading behavior and exerts heterogeneous effects on large and small stocks. In particular, we find that fragmentation is associated with smaller and more frequent trades, reduced 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), Rust and Hall (2003)). On the other hand, fragmentation is associated with very different effects for small stocks. For small stocks, fragmentation results in less trading, larger trades, increased spreads, and worse price efficiency. These effects are consistent with a variety of theoretical models in which exchange competition and fragmentation can lead to worse liquidity. For example, Baldauf and Mollner (2021) develop a model of fragmentation with imperfect competition between exchanges. They find that an increase in the number of trading venues leads to more arbitrage opportunities (because prices for the same asset may differ across venues); this results in additional risk for liquidity providers, who respond by increasing spreads.

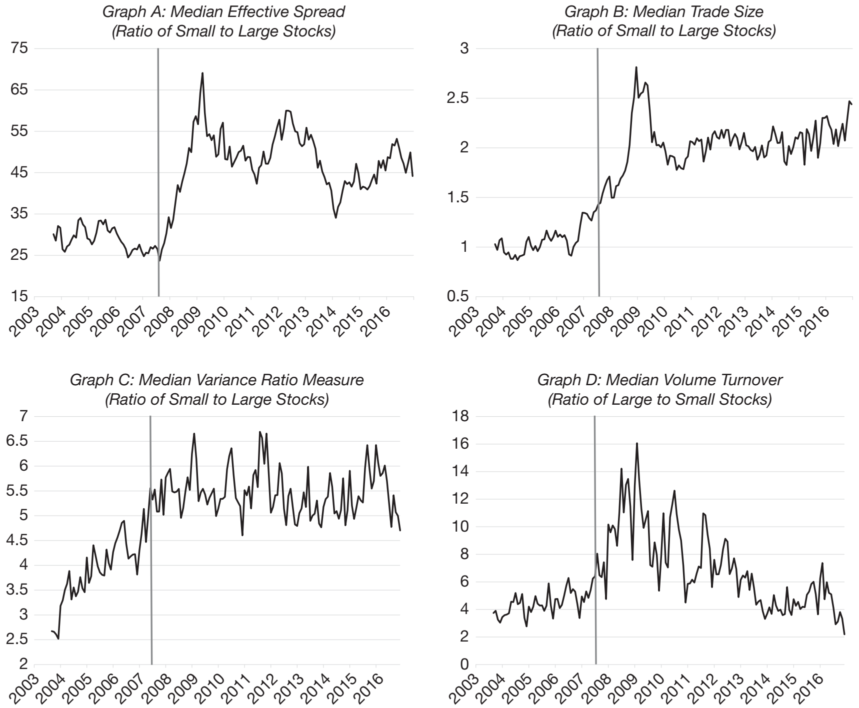
Our article document new evidence that the reduced transaction cost effect dominates for medium and large-capitalization stocks, leading to improvements in market quality, while the negative network externality effect dominates in small-capitalization stocks, leading to a reduction in trading and market quality. As a result, recent changes to market structure have benefited large companies more than small companies. These results have important implications; they suggest that market fragmentation may influence the ability of companies, especially small companies, to access capital markets.

Exchange competition in the United States began significantly increasing in the early 2000s with the rise of electronic trading platforms and accelerated after 2007 when the Securities and Exchange Commission (SEC) implemented Regulation National Market System (NMS). The stated goal of Regulation NMS was to increase "competition among individual markets and competition among individual orders" (Securities and Exchange Commission (2005)). Consistent with this, the regulation lead to a dramatic increase in market fragmentation. Yet, despite the

FIGURE 1

Changes in Market Quality: Small Stocks Relative to Large Stocks

Figure 1 displays a monthly time-series plot of liquidity and trading measures for small stocks relative to large stocks over the period of 2003 to 2016. Graph A displays the median of effective spread for the smallest quintile of stocks divided by the largest quintile of stocks. Graph B displays the median of trade size for the smallest quintile of stocks divided by the largest quintile of stocks. Graph C displays the median of price efficiency for the smallest quintile of stocks divided by the largest quintile of stocks, where price efficiency is the variance ratio measure. Graph D is the median of volume turnover for the largest quintile of stocks divided by the smallest quintile of stocks, where volume turnover is the number of shares transacted each day for each stock as a fraction of shares outstanding. The vertical gray line denotes the initial implementation of Regulation NMS on July 9, 2007.



significance of this change, there are relatively few articles examining Regulation NMS and the rise of market fragmentation.[1]

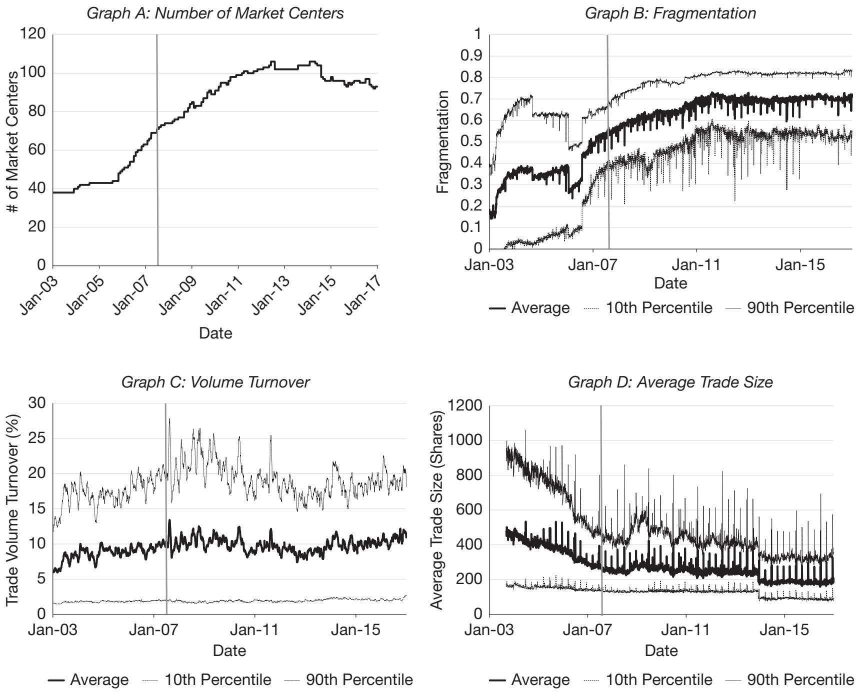
We start by examining whether the implementation of Regulation NMS in 2007 led to changes in market quality. Regulation NMS represented a modernization of the U.S. exchange framework, which, at the time, was facing disruption by newer electronic communication networks such as ARCA and Island. The regulation encouraged fragmentation by incentivizing and regulating competition among market centers. Using a difference-in-differences framework, we examine whether market quality changed after the start of NMS, relative to before NMS, for small versus large stocks. We find that it did. Specifically, we find that the rule change led smaller firms to experience lower turnover, larger trade sizes, greater spreads, and worse price efficiency relative to larger firms. To further explore these results, we

[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 below.

FIGURE 2

Trading Characteristics over Time

Figure 2 displays a time-series plot of the daily average, 10th percentile, and 90th percentile of trading characteristics. The sample contains data from 2003 to 2016. Graph A displays the number of market centers, defined as the sum of exchanges, electronic communications networks (ECNs), and alternative trading systems (ATSs) as reported by the SEC. Graph B displays fragmentation, measured as 1 minus the Herfindahl–Hirschman Index (HHI), where HHI measures the level of concentration of trading volume for each firm across the 18 trade reporting facilities in TAQ. Graph C displays volume turnover defined as the logarithm of daily trading volume divided by shares outstanding. Graph D contains the average trade size of an order, excluding trades from dark pools (TAQ exchange “D”). Observations outside 5-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 July 9, 2007.



also examine execution costs using a proprietary database of institutional investor trades. We find a small positive increase in realized execution costs for small stocks, relative to large stocks, after NMS. While this increase in execution cost is not statistically significant at the usual levels, the trading behavior of institutional investors helps explain the lack of significance. Specifically, we find that institutional investors responded to NMS by trading relatively less in small stocks, consistent with an increase in transaction costs in these assets.

While these results show there are differential effects from fragmentation, they do so using data from a very short time period around the implementation of Regulation NMS in 2007. To establish the external validity of these findings, we then examine ordinary least squares (OLS) panel regressions using a longer time series that spans the period of 2003 to 2016. Our analyses include day and firm fixed effects; as a result, they control for aggregate time series trends like changes in market quality that were unrelated to fragmentation. Consistent with theoretical predictions and the difference-in-differences analysis, the OLS panel regressions again find that market fragmentation changes trading behavior and market quality differentially for small versus large firms. We find that fragmentation is associated with improvements in market quality for firms in the largest size quintile (consistent with O'Hara and Ye (2011) who find that fragmentation is beneficial overall), but we find very different evidence for firms in the smallest quintile. For the smallest firms, a 1-standard-deviation increase in fragmentation is associated with a 2% to 6% increase in effective spreads and a 7% to 9% degradation in price efficiency.[2]

While each of our analyses rely on different assumptions, the consistency across the distinct samples and methodologies all points to the same interpretation. For small stocks, our analyses suggest that more fragmentation makes it relatively 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 in Regulation NMS provides a possible answer. The rule required trading centers to guarantee that trades were not executed at prices worse than the protected quotes available at other trading centers; however, it only protects the *top* of the book at each market center. This creates a friction which can play out through at least two nonmutually exclusive channels. First, as liquidity is dispersed and competition increases across market centers, market makers are exposed to increased "pick-off" risk (e.g., Budish, Cramton, and Shim (2015), Baldauf and Mollner (2021)). That is, market makers must worry that their quotes will become stale, especially in thinly traded stocks, allowing others to profit at their expense. To compensate for this risk, they will increase spreads. Thus, this channel suggests that spreads will increase more for smaller firms which ultimately makes those *demanding* liquidity worse off but those *supplying* liquidity indifferent. Second, 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. Thus, for small stocks, Regulation NMS might lead to increased "front-running" risk. That is, traders must worry that other, faster, traders will trade against them when they are trying to access liquidity on multiple venues. This channel would make traders less likely to trade, thereby generating negative network externalities which make other traders less likely to trade, ultimately hurting market quality.

We find evidence that supports both channels. First, we find direct evidence that additional fragmentation is associated with more instances of locked and crossed markets. Locked and crossed markets may indicate an arbitrage opportunity; they occur when the ask price on one market is less than or equal to the bid price on another market for the same stock. Put differently, they are indicative of stale quotes that can be picked off at the liquidity provider's expense. As such, these results link fragmentation to higher pick-off risk.

Pick-off risk is especially relevant for institutional investors who often break-up large orders into smaller pieces that are submitted to multiple venues. Therefore, we turn to a database of institutional trades to compare execution costs for liquidity

[2]While our main results demonstrate a *relative* degradation for small firms (i.e., small firms relative to large firms), we find overall level effects as well. That is, as the smallest firms are exposed to more fragmentation, there is less trading, higher effective spreads, and worse price efficiency overall.

suppliers versus liquidity demanders. When fragmentation is high, we find that institutions demanding liquidity pay significantly more than those providing liquidity. This is consistent with institutional liquidity providers widening spreads in response to the increased pick-off risk when providing passive liquidity. Furthermore, we find that liquidity demanders get worse execution and respond by trading less in smaller stocks.

We also find evidence of increased front-running risk. Regulation NMS created a new form of order called an inter-market sweep order (ISO) which allows traders to access shares at multiple market centers at the same time.[3] Thus, traders can use ISOs to limit their exposure to front-running. Consistent with the idea that fragmentation generates more front-running risk, we find that small stocks have significantly more ISOs when fragmentation is high. A 1-standard-deviation increase in fragmentation is associated with an 30% increase in ISOs. Taken together, our results suggest that Regulation NMS did create significant frictions that increase execution risk, especially for small stocks.

We run a number of robustness tests to establish the validity of our findings. For example, we examine different measures of liquidity and trading behavior. Moreover, in the Supplementary Material, we examine an instrumental variables analysis that relies on different identifying assumptions. Specifically, we use the opening and closing of market centers in the United States as an exogenous instrument to shock firm-level fragmentation. The results from the instrumental variables analysis confirm our main findings.

Overall, our findings show that the benefits of increased exchange competition were not universally distributed across firms. We find improvements to liquidity have been distributed unequally across stocks: Large companies have gotten much more liquid relative to small companies and in some cases, smaller companies are worse off in an absolute sense as a result of fragmentation. These findings highlight the complexity of market regulation and optimal market design. O'Hara (2007) notes that equity securities of small and large firms have very different characteristics, yet regulation often treats them the same, thereby creating rigidity in market structure that may generate outsized benefits to one group at the expense of another. Our findings provide evidence of such a situation. In the same vein, an Oct. 2017 report by the U.S. Department of Treasury supports our findings stating, "Treasury recognizes that one size may not fit all when it comes to trading venue regulation." Consistent with the policy implications of our results, the report recommends a change to Regulation NMS to allow less liquid stocks to trade on a smaller number of venues until a minimum threshold of liquidity is reached.

In summary, our article makes a number of contributions. First, we document a novel fact: Recent changes to capital market regulation have benefited large companies more than small companies. To the extent that equity markets are important to the allocation of capital in the economy, this suggests the regulation of financial markets has the potential to generate tangible and real effects on the economy. Indeed, we note that the rise of market fragmentation also correlates with a drop in

[3]ISOs allow traders to partially avoid the Order Protection Rule of Regulation NMS so that they can immediately access multiple venues to acquire a larger number of shares immediately at prices inferior to the current protected NBBO price.

initial public offerings (IPOs) by small companies (Gao, Ritter, and Zhu (2013)). Second, we provide some of the first evidence that fragmentation is associated with changes in trading behavior. We show it leads to more frequent and smaller trades, more locked–crossed markets, and increased usage of ISO trades, especially in small illiquid stocks. Finally, we provide novel evidence that these effects arise from both the "pick-off" risk and "front-running" channels.

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. 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.[4] Rust and Hall (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.

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

[4]See Boehmer and Boehmer (2003) and Foucault and Menkveld (2008) for different market structure models which yield similar predictions.

fragmentation leads to better liquidity for some firms, but worse liquidity for others. In addition, Pagnotta (2020) 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.

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 (HFTs) invest in speed in an attempt to pick-off stale prices, which then causes liquidity providers to increase spreads. If liquidity suppliers can increase spreads to compensate for this risk, then increases in pick-off risk should not significantly affect them, however, these increases are detrimental to those demanding liquidity, resulting in reduced trading by liquidity demanders and possibly less efficient prices.

The theoretical models have different baseline market structures but the competing forces tend to be the same; competition and negative network externalities represent the benefits and costs of a more fragmented market. To this end, in a recent article, Baldauf and Mollner (2021) examine the impact of competition between stock exchanges. They develop a model of imperfect competition which makes predictions that are context dependent. On the one hand, like many other models in the literature, they find that increased competition can reduce trading costs. However, they also find that an increase in the number of trading venues leads to more arbitrage opportunities; this increases pick-off risk for liquidity providers who respond by increasing spreads. While none of the existing models specifically predicts heterogeneous effects in small versus large stocks, Corollary 3 of their motivating model suggests that the benefits of fragmentation are greater when the arrival rate of investors is higher. Our tests on the differential impact of fragmentation are motivated, in part, by this prediction. The fact that smaller firms have lower turnover and less institutional trading suggest size is a good proxy for the arrival rate of investors.

B. Empirical Literature

Empirically, a number of articles have examined the impact of fragmentation, but few articles 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 articles 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 other early fragmentation articles find that fragmentation hurts market quality. Hendershott and Jones (2005) and Bennett and Wei (2006) use different empirical approaches from data in the early 2000s, and both articles find stocks subject to more fragmentation experience worse liquidity and price efficiency. While a number of articles examine fragmentation prior to the implementation of Regulation NMS in 2007, most of the market fragmentation in the United States has occurred over the last decade.

Our work is most closely related to two existing articles 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 of Jan. 2, 2008 through Jan. 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. While these articles represent an important first step examining the liquidity effects of fragmentation, our article differs in several key dimensions. Specifically, we are the first to show that fragmentation differentially affects liquidity in small stocks and we are the first to show that fragmentation significantly changes trading behavior and ISO usage. By doing so, we reconcile these conflicting findings in the literature. We note that the sample in Chung and Chuwonganant (2012) more heavily weights small stocks and we show that fragmentation leads to improved liquidity in medium and large-capitalization firms, but it has hurt liquidity and price efficiency in the smallest stocks.

C. Institutional Details and Empirical Predictions

In a frictionless world, theory suggests a truly national market system would 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. Regulation NMS suggests a source for the negative externality. In particular, Regulation NMS did not create a truly consolidated order book, as discussed in Mendelson, Peake, and Williams (1979) and Stoll (2006). In the current system, books are not consolidated and the trade-through rule requires trades to 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 an 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. 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.

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 1 dollar must be quoted in increments of 1 cent. Two recent articles have shown this rule leads to more fragmentation. Kwan, Masulis, and McInish (2015) 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, Yao, and Ye (2017) 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. Furthermore, Albuquerque, Song, and Yao (2020) find worse price efficiency and liquidity following increased minimum tick sizes.

Therefore, key frictions resulting from the implementation of Regulation NMS potentially yield two nonmutually exclusive explanations for our findings. First, theoretical models such as Budish et al. (2015) and Baldauf and Mollner (2021) suggest fragmentation exposes market makers to "pick-off risk," which generates the following prediction:

Pick-off risk prediction. As fragmentation increases, market makers widen spreads which harms those traders who are demanding liquidity.

Second, fragmentation may allow algorithmic traders to front-run orders because liquidity is now spread across multiple venues, which generates the following prediction:

Front-running risk prediction. As fragmentation increases, traders decrease their trading in stocks with higher front-running risk.

In our empirical analyses, we test these predictions to learn about the economic mechanism.

III. Data

To investigate the effect 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 SEC over the period of 2003 to 2016.

A. Construction of Variables

We obtain daily stock returns, trading volume, stock prices, and shares outstanding from CRSP. Our sample contains only ordinary common shares in U.S. firms (share codes 10 and 11 in CRSP). From TAQ, we obtain information

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about trading volume and the top of the limit order book for up to 18 different trade reporting facilities, representing the totality of visible liquidity at the top of the limit order book at any point in time. Using code adapted from Holden and Jacobsen (2014), we calculate common measures of spreads, trading activities, and price efficiency.

We focus on two measures of trading behavior: the average size of trades and trading intensity, as measured by volume turnover. In terms of market quality, we focus on the effective spread and price efficiency. Effective spreads have been shown to be a more relevant measure of liquidity in modern times (Goyenko, Holden, and Trzcinka (2009), Hendershott, Jones, and Menkveld (2011)). We winsorize all variables at the 0.005 level to ensure outliers do not influence the regression outcomes. Additionally, we log-transform all outcome variables to account for skewness.

We also examine institutional trade data from Ancerno for the year 2007 (around the implementation of Regulation NMS). We calculate two key measures following Anand, Irvine, Puckett, and Venkataraman (2013). First, we calculate a measure of institutional trading cost, execution shortfall, which is the volume-weighted average execution price of an order relative to the opening price in that stock each day. Formally, it is defined as in Anand et al. (2013):

$$\text{(1)} \qquad \text{EXECUTION\_SHORTFALL}(t) = D_I(t) \times \frac{P_I(t) - P_0(t)}{P_0(t)},$$

where $P_I(t)$ is the volume-weighted execution price of each order on day t, $P_0(t)$ is the opening price of the stock that day, and $D_I(t)$ is an indicator variable that takes the value of 1 for a buy order and -1 for a sell order.[5] Second, we calculate the TRADING_STYLE measure from Anand et al. (2013) which measures the relative percentage of volume an investor traded in the same direction as the stock's return on a given day. This measure takes the value -1 (liquidity supplying) or $+1$ (liquidity demanding), unless an institution is both buying and selling, in which case the measure takes the volume-weighted average of the values. Intuitively, institutions that are regularly trading in the same direction as returns are likely to be demanding liquidity, whereas those regularly trading in different directions are likely to be supplying liquidity. We calculate this measure for the last quarter of 2006, before the implementation of Regulation NMS, and use it to categorize investors into quintiles for the year 2007.[6]

In addition, we use the TAQ database to measure fragmentation, which 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 1 of 18 different reporting venues.[7] 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 Index of trade volume for every asset each day across these

[5]We remove observations that exceed CRSP volume for that trading day and winsorize execution shortfall at the 0.01 level to account for extreme outliers that are likely due to data errors.

[6]Anand et al. (2013) show TRADING_STYLE is highly persistent and lasts up to 1 year.

[7]Appendix A of the Supplementary Material contains a table of the trade reporting venues in TAQ.

reporting venues. We subtract the Herfindahl–Hirschman Index value from 1 to get a measure of fragmentation, where 0 indicates no fragmentation and 1 equals high fragmentation.[8] 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.[9]

Finally, we use TAQ to examine locked and crossed markets and the use of ISOs. We again adapt code from Holden and Jacobsen (2014) to calculate the national best bid and offer (NBBO) and we calculate the relative frequency of locked and crossed trades and quotes. For ISO orders, we run an algorithm to identify sequences of ISO orders that are part of a larger order to track the number of exchanges, the price movements, and the amount of volume taken from the original order (Table 1).

B. Empirical Design

Our goal is to understand the impact of fragmentation on trading behavior and market quality. Of course, 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 (e.g., Hendershott et al. (2011), Hasbrouck and Saar (2013)). In addition, it is possible that market fragmentation is an endogenous outcome of firm-level liquidity and trading. As such, we use two distinct analyses: a difference-in-differences regression and a panel regression with fixed effects.[10] These analyses use different samples, with different identifying assumptions, yet we find similar results.

1. Difference-in-Differences Around Regulation NMS

First, we use the implementation of Regulation NMS as a shock to market competition. As discussed in Section I, the implementation of Regulation NMS led to significant increases in fragmentation. The regulation contained several provisions and was implemented in 2 phases, the first on July 9, 2007 and the next on Aug. 20, 2007.[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

[8]We note that this measure likely understates the true level of fragmentation since many marketplaces report into 1 TRF. Nonetheless, much of the variation in our measure comes from the drastic reduction in market shares on the NYSE and Nasdaq exchanges. As such, our measure captures most of the variation in fragmentation over our sample.

[9]Our results are robust to an alternate measure of fragmentation proposed in O'Hara and Ye (2011): the ratio of a firm's listing exchange volume to its total volume. See Appendix D of the Supplementary Material for these results. We also note that our difference-in-differences analysis does not require the use of a fragmentation measure, yet our conclusions are similar.

[10]In the Supplementary Material, we also examine an instrumental variables regression.

[11]The first stage identified a set of "pilot" firms which were required to comply with the rule first. In untabulated results, we find that all firms experienced a significant increase in fragmentation around the initial implementation of Regulation NMS regardless of whether they were in the pilot group or not. The evidence suggests that many trading venues and traders implemented their technologies for all stocks (regardless of whether they were pilot stocks) on the first compliance date. We thank Terry Hendershott and Chester Spatt for helpful conversations on this point.

TABLE 1

Summary Statistics

Table 1 displays summary statistics. Panel A contains summary statistics for the sample constructed using daily data from Compustat, CRSP, and TAQ from 2003 to 2016. Panel B contains summary statistics for the institutional trading measures calculated using Ancerno data in 2007; for this data, the observation unit is the investor-stock-trade side-day. MARKET_CAP is the market capitalization, in thousands of U.S. dollars. FRAGMENTATION is measured as 1 minus the Herfindahl–Hirschman Index of trading volume across the exchanges provided in TAQ. log(MARKET_CENTERS) is the natural logarithm of available trading venues in the United States. TURNOVER is calculated as trading volume, scaled by shares outstanding. AVERAGE_TRADE_SIZE is the total volume traded divided by the number of trades. EFFECTIVE_SPREAD is the daily average of the signed transaction price difference from the midpoint as a percent, taken from WRDS DTAQ IID. VARIANCE_RATIO is the absolute difference of 1 and the ratio of 1-min returns to four times the 15-s return – also taken from WRDS DTAQ IID. VOLATILITY is return volatility over the previous 20 days. LEVERAGE is total long-term debt scaled by total assets. MTB is the market value of equity scaled by the book value. INVERSE_PRICE is the inverse of stock price. INTRADAY_VOLATILITY is the standard deviation of returns over 15-min intervals within the day. #_ISO_TRADES is a count of the number of Intermarket Sweep Orders (ISOs). ISO_TURNOVER is the number of shares traded using ISOs scaled by shares outstanding. ISO_#_EXCHANGES is the average number of exchanges that ISOs traded at during the day. ISO_%_DEPTH is the average of a ratio of ISO shares traded to number of available shares at the NBBO. ISO_PRICE_CHANGE is the average price change within each ISO trade over the trading day. OFF_LISTING_VOLUME_SHARE is the percentage of volume that is executed away from the stock's listing venue, as defined in O'Hara and Ye (2011). LOCK_CROSS is defined as the total number of locked and crossed NBBO quotes (this data is only for year 2007). EXECUTION_SHORTFALL is defined as the product of a trade sign indicator and the percent change of execution cost to open trading price. TURNOVER is volume divided by shares outstanding, measured in basis points. We create a Cartesian product of institution-firm-days to account for selection in trading. BUY_RATIO is defined as the buy volume divided by total volume. AVERAGE_SIZE is defined as total volume divided by the number of trades. TRADING_STYLE is the proportion of volume that trades in the same direction of the daily return for that stock-day. To account for skewness, we transform the following variables by taking the logarithm: EFFECTIVE_SPREAD, VARIANCE_RATIO, VOLATILITY, LEVERAGE, MTB, INVERSE_PRICE, INTRADAY_VOLATILITY, #_ISO_TRADES, ISO_#_EXCHANGES, ISO_%_DEPTH, and ISO_PRICE_CHANGE.

Variable	No. of obs.	Mean	Std. Dev.	1%	50%	99%
Panel A. CRSP and TAQ Variables						
MARKET_CAP (000s)	13,640,704	4,014,412	18,041,062	6,050	420,536	68,288,000
FRAGMENTATION	13,640,704	0.564	0.231	0.000	0.635	0.840
log(MARKET_CENTERS)	13,640,704	4.302	0.357	3.638	4.489	4.663
TURNOVER	13,640,699	0.85%	2.88%	0.00%	0.46%	6.12%
AVERAGE_TRADE_SIZE	12,615,211	297.797	341.290	64.600	191.820	2,000.000
log(EFFECTIVE_SPREAD)	12,561,450	−5.986	1.486	−8.551	−6.196	−2.311
log(VARIANCE_RATIO)	12,515,214	−1.229	1.031	−4.971	−0.867	−0.177
log(TURNOVER)	13,632,512	0.474	0.415	0.003	0.376	1.963
VOLATILITY	13,638,017	2.91%	2.39%	0.55%	2.30%	11.69%
LEVERAGE	12,997,419	0.171	0.171	0.000	0.137	0.669
MTB	12,594,754	7.605	0.977	5.285	7.527	10.418
INVERSE_PRICE	13,640,704	−2.562	1.258	−4.886	−2.752	0.916
INTRADAY_VOLATILITY	12,322,466	0.000	0.000	0.000	0.000	0.001
#_ISO_TRADES	7,724,483	5.783	2.360	0.000	6.078	10.145
ISO_TURNOVER	7,724,483	0.003	0.009	0.000	0.002	0.022
ISO_#_EXCHANGES	7,724,483	0.245	0.180	0.000	0.215	0.716
ISO_%_DEPTH	7,719,124	0.105	0.635	−1.997	0.125	1.907
ISO_PRICE_CHANGE	7,715,674	0.004	0.129	−0.086	−0.001	0.241
OFF_LISTING_VOLUME_SHARE	9,742,506	56.24%	27.41%	0.00%	59.65%	100.00%
LOCK_CROSS	1,008,954	226.010	705.178	0	19	4,105
Panel B. Ancerno Variables						
EXECUTION_SHORTFALL	2,721,423	2.40	130.11	−399.83	1.05	399.11
TURNOVER (bps)	96,797,251	30.25	1,019.70	0.00	0.00	120.35
BUY_RATIO	3,900,856	0.537	0.480	0.00	0.851	1.00
AVERAGE_SIZE	2,721,423	5,896.51	15,992.98	5.00	784.67	111,820.00
TRADING_STYLE	2,304,202	0.501	0.475	0.00	0.504	1.00

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. Moreover, Foley, Liu, and Jarnecic (2022) find that the Order Protection Rule induces additional fragmentation by creating incentives for brokers to allocate their liquidity provision to venues with less depth or competitive pricing.

To identify the effect of Regulation NMS on small versus large stocks, we use a difference-in-differences regression around the implementation of the regulation on

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July 9, 2007. We focus on a 12-month window centered around July 2007. Formally, the difference-in-differences regression is given by

$$y_{i,t} = \beta(\text{TREAT}_i \times \text{POST}_t) + \text{FE}_i + \text{FE}_t + \epsilon_{i,t}, \quad (2)$$

where $y_{i,t}$ is a measure of market quality for asset i on day t, TREAT is an indicator variable that takes the value 1 for firms in the smallest quintile of market capitalization at the beginning of 2007 (*prior* to the start of NMS), and 0 for firms in the largest quintile. POST is an indicator variable that equals one after the implementation of Regulation NMS on July 9, 2007. We include firm (FE_i) and day (FE_t) fixed effects in all specifications.

The difference-in-differences model in equation (2) compares: the expected value of treated firms *after* treatment minus the expected value of treated firms *before* treatment minus the expected value of control firms *after* treatment minus the expected value of control firms *before* treatment. Note that time-invariant firm-level characteristics drop out (any time-invariant firm characteristics, such as persistent differences in size, liquidity, etc., are accounted for by the regression). Put differently, it is okay if small stocks and large stocks had different characteristics prior to the implementation of Regulation NMS. The key identifying assumption is that market quality in small stocks would have *changed* in a manner similar to market quality in large stocks absent the implementation of Regulation NMS. To that end, Figure 1 displays event time graphs of market quality for small stocks relative to large stocks in event time around the start of Regulation NMS (shown by the gray vertical bar). In all 4 graphs, the ratio of small stock market quality to large stock market quality is shown as a relatively flat line prior to July 2007, and the line changes slope soon after Regulation NMS was implemented. Thus, the figure provides strong evidence that market quality in small stocks was evolving in a manner similar to large stocks prior to July 2007, but after the implementation of Regulation NMS large stocks started experiencing differential improvements in market quality.

While Figure 1 supports the parallel trends assumption, to help solidify our identifying assumptions, we use entropy balancing (Hainmueller (2012)). Entropy balancing re-weights the control firms (while leaving the treatment firms un-weighted) in order to recover the average treatment effect on treated firms and it has been used in a several recent articles in finance and economics (see, e.g., Hartzmark (2015)). We balance the treatment and control firms on the first three moments of overall and lit exchange fragmentation prior to the implementation of Regulation NMS. In other words, entropy balancing is similar to a matched-sample approach that is designed to balance the treatment and control groups so they are evolving in a similar fashion prior to treatment.

2. OLS Panel Regressions

We also examine OLS panel regressions with daily data from 2003 to 2016. While we find strong support for the identification assumptions underlying our difference-in-differences analyses, the OLS regressions allow us to examine the effects of fragmentation in a much longer time series and using different assumptions.

To the best of our knowledge, our article 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. Specifically, we examine the relation between fragmentation and several measures of market quality using OLS panel regressions of the form:

$$(3)\qquad y_{i,t+1} = \beta\text{FRAGMENTATION}_{i,t} + \delta\text{CONTROLS}_{i,t} + \text{FE}_i + \text{FE}_t + \epsilon_{i,t+1},$$

where $y_{i,t+1}$ is either a measure of trading behavior or market quality for asset i on day $t+1$. CONTROLS include MTB, LEVERAGE, PRICE_INVERSE, RETURN_VOLATILITY over the previous 20 days, and the 20-day moving average of turnover. We include firm (FE_i) and day (FE_t) fixed effects in the regressions 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. Hence, we examine regressions of the form:

$$(4)\qquad \begin{aligned} y_{i,t+1} = {} & \beta\text{FRAG}_{i,t} + \sum_{k\neq 3}\delta_k\text{SIZE\_QUINT}_k \\ & + \sum_{k\neq 3}\theta_k(\text{FRAG}\times\text{SIZE\_QUINT}_k) \\ & + \gamma\text{CONTROLS}_{i,t} + \text{FE}_i + \text{FE}_t + \varepsilon_{i,t+1}, \end{aligned}$$

where $\text{FRAG}_{i,t}$ is firm i's level of trade fragmentation on day t, SIZE_QUINT is the market capitalization quintile of firm i, FE_i represents firm fixed effects, FE_t represents day fixed effects, and the control variables are the same as the controls in equation (3). We use each asset's ex ante market capitalization, measured at $t-1$ and ranked into quintiles (SIZE_QUINT), as a proxy for the arrival rate of investors. 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.[12]

IV. Results

Figure 2 shows 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).

However, as previously discussed, Figure 1 suggests that these results are not homogeneous across firms. The figure displays changes in trading behavior and market quality for small stocks relative to large stocks. Strikingly, relative to small stocks, larger stocks experience significant improvement around the start of Regulation NMS. In this section, we explore the relation between fragmentation and market quality using two distinct analyses that use different samples with different

[12]We use market capitalization because of its simplicity and the fact that it is plausibly exogenous. However, our results are robust to other proxies (e.g., depth, volume, etc.).

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identifying assumptions. In Section IV.A, we examine a difference-in-differences regression around the implementation of Regulation NMS, while in Section IV.B, we examine OLS panel regressions using data from 2003 to 2016.

A. Difference-in-Differences Analysis Around Regulation NMS

1. Differential Impact of Regulation NMS

We begin our formal analysis by testing whether Regulation NMS had a significant, differential impact on trading behavior and market quality for small versus large firms.[13] We start by examining TAQ data from 2007 using our difference-in-differences specification, which is designed to estimate whether trading behavior and market quality change differently for small stocks, relative to large stocks, after the implementation of Regulation NMS. The results of the difference-in-differences regression are shown in Table 2.

We first examine whether fragmentation affects trading activity, as theorized in several extant models (e.g., Mendelson (1987), Madhavan (1995)). We find that it does. Several models also predict that fragmentation may be related to investor

TABLE 2

Difference-in-Differences: Regulation NMS and Market Quality

Table 2 displays results from a difference-in-difference regression with entropy balancing around the implementation of Regulation NMS of the form:

$$y_{i,t} = \alpha + \beta(\text{TREAT}_i \times \text{POST}_t) + \text{FE}_i + \text{FE}_t + \epsilon_{i,t},$$

where $y_{i,t}$ is a measure of market quality for asset i on day t, TREAT is an indicator variable that takes the value 1 for firms in the smallest quintile of market capitalization at the beginning of 2007 (*prior* to the start of NMS), and POST is an indicator variable that takes the value 1 after the implementation of Regulation NMS on July 9, 2007. We include firm (FE_i) and day (FE_t) fixed effects in all specifications. The sample is daily firm-level TAQ measures in the year 2007, approximately 6 months before and 6 months after the implementation of Regulation NMS. VOLUME_TURNOVER is daily volume scaled by the number of shares outstanding. AVERAGE_TRADE_SIZE, EFFECTIVE_SPREADS, and VARIANCE_RATIO are from the WRDS TAQ Millisecond Intraday Indicators database. All dependent variables are log-transformed to account for skewness. DIFFERENTIAL_EFFECT is the average differential treatment effect (TREAT × POST). The sample is restricted to quintiles 1 and 5 only, where firms are sorted into market capitalization quintiles on the first trading day of 2007. Firms are entropy balanced on the first three moments of the ex ante distribution of fragmentation (both overall and lit exchanges only). Standard errors clustered by firm and date are shown below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable			
	VOLUME_TURNOVER	AVERAGE_TRADE_SIZE	EFFECTIVE_SPREADS	VARIANCE_RATIO
Explanatory Variable	1	2	3	4
DIFFERENTIAL_ EFFECT (β)	−0.301***	0.119***	0.055*	0.068**
	(0.041)	(0.023)	(0.031)	(0.033)
CONSTANT (α)	0.818***	5.436***	−5.712***	−1.030***
	(0.010)	(0.006)	(0.008)	(0.008)
Firm FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
No. of obs.	370,721	370,721	370,202	368,616
R^2	0.628	0.691	0.928	0.640

[13] In Table E1 in Appendix E of the Supplementary Material, we show that market fragmentation increased significantly following the implementation of Regulation NMS. In the week following the implementation, fragmentation increased by almost 2%. Expanding the window to 6 months increases the effect to 7%, relative to the ex ante mean.

participation (e.g., Pagano (1989b), Pagnotta (2020)). Specifically, 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 lend support for these theories. In column 1 of Table 2, we find a coefficient of -0.301 which is significant at the 1% level. Thus, our results suggest small firms experienced a thirty percent relative drop in turnover following the implementation of Regulation NMS when compared to the largest firms. Column 2 shows that not only was there relatively less trading, but trading in smaller firms relied relatively more on larger trade sizes. This is consistent with the notion that traders were more willing to absorb higher costs to obtain the necessary liquidity as opposed to facing updated prices following smaller trades. In other words, the larger trade sizes are indicative of paying for immediacy to access liquidity on one market center, consistent with the predictions in Pagano (1989b).

We then examine market quality. Specifically, we test how the implementation of Regulation NMS impacted effective spreads and price efficiency for small versus large stocks. Column 3 shows that smaller firms experienced 5.5% higher effective spreads relative to large firms after the implementation of Regulation NMS compared to before NMS. Moreover, in column 4, the positive and statistically significant coefficient of 0.068 indicates that variance ratios in small stocks became 6.8% worse than large stocks after Regulation NMS. In other words, price efficiency in small stocks got relatively worse. Overall, all of these results point to the same conclusion: Over the course of a few months following the implementation of Regulation NMS, liquidity, turnover, and price efficiency significantly improved for large firms relative to small firms. The results are the first to show that the bifurcation in market quality in recent years is at least partially related to the fragmentation of trading.[14]

2. Regulation NMS and Institutional Trader Outcomes

While the results in Table 2 consistently point to the same conclusions, a handful of recent articles note that standard TAQ measures may not align with the reality of trading for institutions (e.g., Eaton, Irvine, and Liu (2021), Brugler, Comerton-Forde, and Hendershott (2021)). Accordingly, we next examine institutional trading data from Ancerno in 2007 to test how trading costs and behavior changed in response to the implementation of Regulation NMS. However, we note that for our setting, there are some drawbacks to the Ancerno data. For example, in the TAQ data, we observe daily liquidity measures for all firm and dates, but Ancerno data only contains information when an institution in the database trades a stock. Because the database contains only a subset of institutional investors, and these investors trade more in large stocks, the data does not have many observations for small stocks, which could give our tests poor power.

[14]Because we cannot test quintiles individually in the difference-in-differences empirical strategy, we run a simple first difference regression for each quintile individually. We find that turnover statistically increases for the top 3 size quartiles, average trade size declines in a monotonic fashion, effective spreads increase and the largest impact is in small stocks, and variance ratios improve for all stocks with the smallest improvement for small stocks. However, these analyses do not include time fixed effects and such, they should be interpreted with caution as they may not account for correlated macroeconomic changes.

TABLE 3

Difference-in-Differences: Regulation NMS and Institutional Trading Measures

Table 3 displays results from a difference-in-difference regression with entropy balancing around the implementation of Regulation NMS of the form:

$$y_{i,t,j,s} = \alpha + \beta(\text{TREAT}_i \times \text{POST}_t) + \text{FE}_i + \text{FE}_t + \epsilon_{i,t,j,s},$$

where $y_{i,t,j,s}$ is a measure of institutional trading for asset i on day t by investor j in trade direction s, TREAT is an indicator variable that takes the value 1 for firms in the smallest quintile of market capitalization at the beginning of 2007 (*prior* to the start of NMS), and POST is an indicator variable that takes the value 1 after the implementation of Regulation NMS on July 9, 2007. We include firm (FE_i) and day (FE_t) fixed effects in all specifications, and investor, trade direction, or investor-firm fixed effects as indicated at the bottom of the table. The sample is daily firm-level measures in the year 2007, approximately 6 months before and 6 months after the implementation of Regulation NMS. Institutional trading data is from Ancerno. EXECUTION_SHORTFALL is defined as the product of a trade sign indicator and the percent change of execution cost to open trading price. TURNOVER is calculated as volume divided by shares outstanding, measured in basis points. For TURNOVER, we create a Cartesian product of institution-firm-days to account for selection in trading. BUY_RATIO is defined as the buy volume divided by total volume. AVERAGE_TRADE SIZE is defined as total volume divided by the number of trades. TRADING_STYLE is the proportion of volume that trades in the same direction of the daily return for that stock-day. DIFFERENTIAL_EFFECT is the average differential treatment effect (TREAT × POST). The sample is restricted to quintiles 1 and 5 only, where firms are sorted into market capitalization quintiles on the first trading day of 2007. Firms are entropy balanced on the first three moments of the ex ante distribution of fragmentation (both overall and lit exchanges only). Standard errors clustered by firm and date are shown below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable				
	EXECUTION_ SHORTFALL	TURNOVER	BUY_RATIO	AVERAGE_ TRADE SIZE	TRADING_STYLE
Explanatory Variable	1	2	3	4	5
DIFFERENTIAL_EFFECT (β)	2.464	−5.731***	−0.114***	0.025	0.038**
	(4.657)	(2.106)	(0.021)	(0.050)	(0.018)
CONSTANT (α)	2.371***	19.908***	0.519	6.289***	0.002
	(0.012)	(0.504)	(0.000)	(0.000)	(0.000)
Firm FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Investor FE	Yes	No	No	Yes	Yes
Trade direction FE	Yes	No	No	Yes	Yes
Investor-firm FE	No	Yes	Yes	No	No
No. of obs.	2,721,362	96,797,251	2,290,283	2,721,362	2,721,362
R^2	0.016	0.058	0.320	0.210	0.001

Using the Ancerno data, we again examine difference-in-differences regressions around the implementation of Regulation NMS. The results are shown in Table 3. Consistent with the TAQ measures, column 1 shows that smaller firms experience an increase in execution shortfall of 2.46 basis points following the implementation of Regulation NMS. In other words, it is consistent with the idea that realized trading costs increased for small stocks, relative to large stocks. Moreover, this finding holds when using multiple fixed effects, which control for average execution of the investor as well as the side of the trade. However, while the direction of the result is consistent with our main findings, these results are not significantly significant at the usual levels. As discussed above, one issue with the Ancerno data is that institutional investors tend to trade less in smaller stocks, which may adversely affect the power of this test. Indeed, firms in the smallest quintile represent only 0.76% of all Ancerno observations. Moreover, if fragmentation differentially impacts small firms, institutional investors may respond by further decreasing their trading in these stocks.

Therefore, we next test where institutional trading behavior can help explain the lack of statistical significance for execution shortfall. In particular, column 2 examines the level of institutional trading in each stock when fragmentation increases. The negative and statistically significant coefficient of −5.731 indicates that institutions reduce their trading in smaller firms by approximately 19% after the implementation of Regulation NMS, relative to the average level of turnover.[15] The result is consistent with an increase in trading costs for these firms (as a result of higher execution costs, investors trade less in these stocks). Moreover, because the Ancerno data includes the direction of each trade, we can also examine the Buy Ratio which is defined as buy volume divided by total investor-firm-day volume. The negative and statistically significant result in column 3 indicates that institutions are selling relatively more small stocks, and buying fewer of them, in response to increased fragmentation. Finally, we explore whether institutional investors changed their trading styles. Column 4 examines average trade size for the smallest quintiles of firms while column 5 examines whether institutions are supplying or demanding liquidity. While the result in column 4 is not statistically significant, the positive and statistically significant estimate in column 5 indicates that institutions are approximately 3.8% more likely to demand liquidity for small stocks, compared to large stocks, after the implementation of Regulation NMS. Recall from Section III.A that trading style is the percentage of trading volume that was trading in the same direction of the return that day. In that sense, the result suggests that institutions have a relatively harder time accessing liquidity in smaller stocks after Regulation NMS, and respond by being more aggressive in their trading of smaller firms.

Overall, the results in this section are clear: The implementation of Regulation NMS, which increased exchange competition, is associated with relatively worse market quality for smaller stocks, and this led to a change in trading behavior by institutional investors.

B. OLS Panel Analysis

The results in the previous section suggest that increased intermarket competition resulting from Regulation NMS led to differential changes in trading behavior and market quality. However, these tests examine narrow windows of time around the implementation of Regulation NMS and thus may not fully capture the long-run impacts of fragmentation. Accordingly, we next examine OLS panel regressions with daily data from 2003 to 2016.

1. Overall Effects of Fragmentation

The results of the panel regressions using firm and day fixed effects are shown in Tables 4 and 5 with standard errors, clustered by firm and date, shown below the coefficient estimates. We begin our OLS analysis by investigating the average relation between fragmentation, trading behavior, and market quality across all firms. The base results are shown in the odd numbered columns in Table 4. In the even columns, we show results after controlling for market capitalization quintiles. Focusing on model 1 of Table 4, the statistically significant estimate on fragmentation indicates that fragmentation is, on average, associated with greater volume turnover. In column 3, the statistically significant estimate implies the average trade

[15]Note: For this specification, we build a database that has an observation for all firms and dates regardless of whether or not a trade was observed (we code turnover as 0 if no trade was observed) so the number of observations is significantly larger than other specifications.

TABLE 4

Panel Regression of Market Quality and Fragmentation

Table 4 displays results from an OLS panel regression of the form:

$$y_{i,t+1} = \alpha + \beta \text{FRAGMENTATION}_{i,t} + \sum_{k \neq 3} \delta_k \text{SIZE}_k + \text{FE}_i + \text{FE}_t + \text{CONTROLS}_{i,t} + \epsilon_{i,t+1},$$

where $y_{i,t+1}$ is either VOLUME_TURNOVER, AVERAGE_TRADE_SIZE, EFFECTIVE_SPREAD, or VARIANCE_RATIO. The sample is daily firm-level TAQ variables from 2003 to 2016. FRAGMENTATION is measured as 1 minus the Herfindahl–Hirschman Index of trading volume across the exchanges provided in TAQ. The variables QUINTILE_1 through QUINTILE_5 are indicator variables that take the value 1 if a firm is ranked in a particular quintile when sorted by market capitalization, and 0 otherwise. QUINTILE_1 contains firms with the smallest market capitalization. Firms are sorted into market capitalization quintiles on day $t-1$. Control variables are discussed in Section IV. All models include firm and day fixed effects. All dependent variables are log-transformed to account for skewness. Standard errors clustered by firm and date are shown below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable							
	TURNOVER	TURNOVER	AVERAGE_ TRADE_SIZE	AVERAGE_ TRADE_SIZE	EFFECTIVE_ SPREAD	EFFECTIVE_ SPREAD	VARIANCE_ RATIO	VARIANCE_ RATIO
Explanatory Variable	1	2	3	4	5	6	7	8
FRAGMENTATION	0.301***	0.235***	−0.507***	−0.426***	−0.502***	0.015	−0.408***	−0.160***
	(0.006)	(0.006)	(0.012)	(0.010)	(0.021)	(0.013)	(0.013)	(0.010)
QUINTILE_1		−0.150***		0.002		0.562***		0.140***
		(0.008)		(0.010)		(0.019)		(0.010)
QUINTILE_2		−0.093***		−0.013**		0.260***		0.152***
		(0.005)		(0.005)		(0.010)		(0.006)
QUINTILE_4		0.062***		0.110***		−0.177***		−0.282***
		(0.005)		(0.005)		(0.010)		(0.008)
QUINTILE_5		0.045***		0.240***		−0.333***		−0.511***
		(0.009)		(0.009)		(0.018)		(0.014)
RETURN_ VOLATILITY		4.346***		−0.146***		6.653***		0.691***
		(0.122)		(0.051)		(0.202)		(0.060)
LEVERAGE		0.103***		−0.085***		0.057*		−0.066***
		(0.018)		(0.021)		(0.033)		(0.025)
MTB		0.007***		0.043***		0.030***		0.007**
		(0.003)		(0.003)		(0.005)		(0.003)
INVERSE_ PRICE		−0.054***		0.348***		0.346***		0.076***
		(0.004)		(0.005)		(0.010)		(0.005)
VOLUME_ TURNOVER				0.079***		−0.354***		−0.234***
				(0.003)		(0.005)		(0.004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	13,632,509	12,463,452	12,612,251	11,513,827	12,561,437	11,467,882	12,515,113	11,428,364
R^2	0.474	0.528	0.527	0.587	0.813	0.877	0.491	0.520

size decreased significantly in response to increased fragmentation (the coefficient of −0.507 indicates a 1-standard-deviation increase in fragmentation decreases the average trade size by 10%, or approximately 30 shares).

In terms of market quality, we again examine effective spreads and price efficiency. The panel regressions in model 5 of Table 4 suggest fragmentation led to lower spreads, on average. However, in column 6, when we control for variables like market capitalization and turnover, the estimate becomes insignificant. Finally, column 7 examines the variance ratio. The statistically significant estimate of −0.408 indicates that a 1-standard-deviation in fragmentation leads to a 3% improvement in price efficiency, on average. Overall, the results in Table 4 are largely consistent with O'Hara and Ye (2011).

2. Heterogeneous Effects of Fragmentation

Motivated by the previously discussed theoretical literature, we next examine whether fragmentation affects asset prices and trading behavior differently for

TABLE 5

Panel Regression of the Differential Effects of Fragmentation on Market Quality

Table 5 displays the results of an OLS panel regression of the form:

$$y_{i,t+1} = \alpha + \beta \text{FRAGMENTATION}_{i,t} + \sum_{k \neq 3} \delta_k \text{SIZE}_k + \sum_{k \neq 3} \theta_k (\text{FRAGMENTATION} \times \text{SIZE}_k) + \text{FE}_i + \text{FE}_t + \text{CONTROLS}_{i,t} + \epsilon_{i,t+1},$$

where $y_{i,t+1}$ is either VOLUME_TURNOVER, AVERAGE_TRADE_SIZE, EFFECTIVE_SPREAD, or VARIANCE_RATIO. The sample is daily firm-level variables from 2003 to 2016. FRAGMENTATION is measured as 1 minus the Herfindahl–Hirschman Index of trading volume across the exchanges provided in TAQ. The variables QUINTILE_1 through QUINTILE_5 are indicator variables that take the value 1 if a firm is ranked in a particular quintile when sorted by market capitalization, and 0 otherwise. QUINTILE_1 contains firms with the smallest market capitalization. Firms are sorted into market capitalization quintiles on day $t-1$. Control variables are discussed in Section IV. All models include firm and day fixed effects. All dependent variables are log-transformed to account for skewness. Standard errors clustered by firm and date are shown below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable							
	TURNOVER	TURNOVER	AVERAGE_ TRADE_SIZE	AVERAGE_ TRADE_SIZE	EFFECTIVE_ SPREAD	EFFECTIVE_ SPREAD	VARIANCE_ RATIO	VARIANCE_ RATIO
Explanatory Variable	1	2	3	4	5	6	7	8
FRAGMENTATION	0.251***	0.218***	−0.444***	−0.435***	−0.310***	−0.012	−0.404***	−0.236***
	(0.011)	(0.011)	(0.017)	(0.016)	(0.031)	(0.028)	(0.020)	(0.019)
FRAG × QUINTILE_1	−0.044***	−0.065***	0.552***	0.440***	0.271***	0.084***	0.395***	0.342***
	(0.012)	(0.012)	(0.022)	(0.019)	(0.035)	(0.032)	(0.021)	(0.019)
FRAG × QUINTILE_2	−0.035***	−0.035***	0.204***	0.155***	−0.085***	−0.133***	0.277***	0.277***
	(0.011)	(0.011)	(0.020)	(0.018)	(0.033)	(0.031)	(0.020)	(0.019)
FRAG × QUINTILE_4	0.075***	0.068***	−0.217***	−0.145***	−0.035	0.064**	−0.393***	−0.366***
	(0.014)	(0.013)	(0.020)	(0.018)	(0.033)	(0.031)	(0.027)	(0.025)
FRAG × QUINTILE_5	0.145***	0.135***	−0.718***	−0.585***	−0.197***	0.081*	−0.148***	−0.049
	(0.015)	(0.015)	(0.027)	(0.025)	(0.044)	(0.042)	(0.035)	(0.034)
QUINTILE_1	−0.142***	−0.128***	0.188***	−0.173***	1.198***	0.519***	0.157***	−0.022
	(0.009)	(0.009)	(0.016)	(0.015)	(0.027)	(0.028)	(0.014)	(0.014)
QUINTILE_2	−0.092***	−0.078***	0.075***	−0.081***	0.674***	0.332***	0.110***	0.000
	(0.007)	(0.007)	(0.014)	(0.013)	(0.023)	(0.022)	(0.013)	(0.013)
QUINTILE_4	0.033***	0.025***	0.043***	0.178***	−0.479***	−0.216***	−0.121***	−0.055***
	(0.010)	(0.009)	(0.014)	(0.013)	(0.024)	(0.022)	(0.019)	(0.018)
QUINTILE_5	−0.012	−0.032**	0.294***	0.585***	−0.801***	−0.383***	−0.543***	−0.482***
	(0.013)	(0.013)	(0.020)	(0.018)	(0.035)	(0.032)	(0.027)	(0.026)
RETURN_ VOLATILITY		4.352***		−0.282***		6.661***		0.625***
		(0.122)		(0.049)		(0.202)		(0.058)
LEVERAGE		0.098***		−0.064***		0.054		−0.055**
		(0.018)		(0.019)		(0.034)		(0.024)
MTB		0.007**		0.045***		0.030***		0.008**
		(0.003)		(0.003)		(0.005)		(0.003)
INVERSE_PRICE		−0.049***		0.324***		0.348***		0.064***
		(0.004)		(0.005)		(0.010)		(0.005)
VOLUME_ TURNOVER				0.086***		−0.354***		−0.232***
				(0.002)		(0.005)		(0.004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	13,632,509	12,463,452	12,612,251	11,513,827	12,561,437	11,467,882	12,515,113	11,428,364
R^2	0.483	0.529	0.559	0.597	0.849	0.878	0.510	0.522

smaller firms. Again, we find it does. The results are shown in Table 5. Consistent with theory, we find that higher fragmentation is associated with less trading in small firms, but relatively more trading for large firms in columns 1 and 2. In terms of economic magnitudes, the coefficient of −0.065 on FRAG × QUINTILE_1 indicates the smallest firms reduce trading on a relative basis by an additional 3.2% in response to a 1-standard-deviation increase in fragmentation. In other words, the results support the idea that traders in small firms trade less in response to increased fragmentation, as compared to the median firm. These results present the first evidence that market fragmentation is responsible for at least some of the differential changes in market quality that have affected small stocks in recent years.

Moreover, we find that fragmentation not only affects the intensity of trading but also *how* traders choose to trade. The coefficients of −0.718 and −0.585 on FRAG × QUINTILE_5 in columns 3 and 4 show that average trade size decreased significantly for the largest firms. However, for the smallest firms fragmentation leads to relatively larger trade sizes. Fragmented markets imply liquidity is more dispersed which, in turn, requires that traders split orders across market centers in order to capture more liquidity. For large stocks, we find strong evidence of this. However, if some market centers have high execution risk due to low trading volume, traders may prefer instead to submit large costly orders at one market center. Our results suggest this effect dominates for small stocks.

Next, we turn our attention to market quality measures. When we test for heterogeneous effects on effective spreads, in models 5 and 6, we find that small firms appear to be hurt by fragmentation, when compared to the median firm. For large assets, effective spreads are lower when fragmentation is higher, but for smaller assets, the effect is reversed. Specifically, for FRAG × QUINTILE_1 (i.e., small firms) the statistically significant coefficient of 0.084 in model 6 implies that a 1-standard-deviation increase in fragmentation is associated with a 2% increase in effective spreads relative to the median firm. Nevertheless, we find that in response to increased fragmentation large firms (i.e., quintile 5) experience slightly higher spreads as compared to the median firm. While this result may seem surprising, it intuitively makes sense when incorporating the fact that effective spreads are essentially bounded at 0. The liquidity of large firms was already high, 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.

Moreover, we find that fragmentation is associated with worse price efficiency for the smallest firms. In model 7, the statistically significant coefficient of 0.342 on FRAG × QUINTILE_1 implies that a 1-standard-deviation increase in fragmentation leads to a 7.9% deterioration in price efficiency relative to the median firm, as measured by the variance ratio measure. Moreover, the coefficients on quintile 5 (i.e., large firms) imply only slight improvements in price efficiency, and the results in column 8 are not statistically significant.

3. Absolute Effects of Fragmentation

So far, our results show that fragmentation generated different effects for small firms *relative* to large firms, consistent with the theoretical predictions of exchange competition. However, policy implications may depend on whether the increase in fragmentation resulted in *absolute* changes in market quality for the smallest firms. To examine this, in Table B1 in the Supplementary Material, we provide the total effect of fragmentation for each of the included quintiles. Specifically, we calculate the linear combination of the average effect of fragmentation (from omitted quintile 3) and the differential response for each corresponding quintile. The table shows results of a test of this combination of coefficients against the null hypothesis of no effect.

The results from Table B1 in the Supplementary Material indicate that the effects of fragmentation had a modest *absolute* effect on trading behavior, but had a significant impact on market quality. In fact, fragmentation not only leads to a *relative* effect but also a statistically significant *absolute* increase of 1.7% in spreads for the smallest firms. Moreover, in terms of price efficiency, we find that the *absolute* effect of fragmentation results in 2.4% worse price efficiency for the smallest firms. These results call into question whether small and illiquid firms should be subject to the same market structure as those of their larger counterparts.

Overall, the OLS results are largely consistent with the difference-in-differences results. Fragmentation generally leads to improvements in liquidity and price efficiency, especially for larger firms. However, for the smallest firms, fragmentation leads to worse liquidity (both in a relative and an absolute sense).

C. Economic Mechanism

The fact that small firms experience both a relative and absolute negative response to fragmentation suggests that negative network externalities play an important role in understanding the underlying mechanism(s) behind our results. In this section, we use the two predictions derived in Section II.C to learn more about the mechanism underlying our results. First, we examine whether fragmentation results in more pick-off risk by examining locked and crossed markets and by using Ancerno data to understand if those supplying liquidity or those demanding liquidity are worse off. Second, we use the fact that ISO orders are specifically meant to deal with front-running risk to examine whether trading in smaller firms is associated with higher risk of front-running.

1. Pick-Off Risk

Our first test looks at the frequency of locked and crossed markets for a stock around the implementation of Regulation NMS. Locked and crossed markets occur when the ask price on one market is less than or equal to the bid price on another market for the same stock (Holden and Jacobsen (2014)). Such situations may signal the existence of an arbitrage opportunity – stale quotes on one market center can be picked off at the liquidity provider's expense. In columns 1 and 2 of Table 6, the positive and statistically significant estimates on FRAGMENTATION indicate that fragmentation is associated with an increase in such arbitrage opportunities. Moreover, columns 3 and 4 show this relation is present for both the largest and smallest quintiles of firms. Overall, the results are consistent with the idea that fragmentation increases the risk that liquidity provider's quotes will be picked-off.[16]

Next, we again explore the Ancerno institutional trading data. The data allow us to compare execution quality for those supplying liquidity to those demanding liquidity. Specifically, we examine execution shortfall to see which types of traders bear the costs of fragmentation. Both the "pick-off" and "front-running" mechanisms predict that those demanding liquidity will be worse off as fragmentation increases. However, the "pick-off risk" channel uniquely predicts that market makers should increase spreads (to compensate for increased pick-off risk). To test these ideas, we run panel regressions using data in 2007 with firm-day, institution-day, and firm-side fixed effects. The analysis examines whether fragmentation directly affected execution shortfall for liquidity suppliers and liquidity demanders. All specifications control for average execution by institution and stock.

[16]The results are robust to alternate specifications; we find similar results when using intraday volatility as an alternate measure of pick-off risk. See Tables B2 and C4 in the Supplementary Material.

TABLE 6

Panel Regression of Locked–Crossed Markets and Fragmentation

Table 6 displays results from an OLS panel regression of the form:

$$\text{LOCK\_CROSS}_{i,t+1} = \alpha + \beta \text{FRAGMENTATION}_{i,t} + \sum_{k \neq 3} \delta_k \text{SIZE}_k + \text{FE}_i + \text{FE}_t + \text{CONTROLS}_{i,t} + \epsilon_{i,t+1}.$$

The dependent variable, LOCK_CROSS, is defined as the total number of locked and crossed NBBO quotes for each stock and day. FRAGMENTATION is measured as 1 minus the Herfindahl–Hirschman Index of trading volume across the exchanges provided in TAQ. The variables QUINTILE_1 through QUINTILE_5 are indicator variables that take the value 1 if a firm is ranked in a particular quintile when sorted by market capitalization, and 0 otherwise. QUINTILE_1 takes the value 1 for firms with the smallest market capitalization, while QUINTILE_5 is an indicator variable that take the value 1 for firms with the highest market capitalization. Firms are sorted into market capitalization quintiles on day $t-1$. Control variables are discussed in Section IV. All models include firm and day fixed effects. Standard errors clustered by firm and date are shown below the estimates. Models 1 and 2 examine the entire sample of firms, while model 3 examines only firms in the smallest quintile of market capitalization and model 4 examines only firms in the largest quintile of market capitalization. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: LOCK_CROSS			
Explanatory Variables	1	2	3	4
FRAGMENTATION	169.158***	136.033***	2.208***	1,496.253***
	(21.055)	(20.201)	(0.647)	(180.330)
VOLUME_TURNOVER		241.728	151.227***	4,264.334***
		(158.755)	(41.311)	(1,436.852)
RETURN_VOLATILITY		−548.218	−9.568	−2,081.628
		(361.098)	(13.826)	(1,672.269)
LEVERAGE		18.651	−1.508	238.916***
		(20.171)	(4.641)	(76.373)
MTB		130.462***	−6.216	508.015***
		(24.401)	(3.941)	(70.672)
PRICE_INVERSE		104.151***	4.872***	513.112***
		(9.351)	(0.937)	(51.113)
QUINTILE_1		−83.002***		
		(15.564)		
QUINTILE_2		−47.840***		
		(8.636)		
QUINTILE_4		50.603***		
		(12.685)		
QUINTILE_5		90.544***		
		(32.048)		
Subsample	No	No	Smallest	Largest
Day FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
No. of obs.	1,008,950	931,149	171,683	213,237
R^2	0.667	0.674	0.058	0.683

The results are shown Table 7. In column 1, Trading Style 1 designates liquidity suppliers while Trading Style 5 designates liquidity demanders. The positive coefficient estimate of 9.35 on FRAGMENTATION × TRADING_STYLE_5 indicates that liquidity demanders pay significantly *more* after the implementation of Regulation NMS, relative to the median trading style firms. While none of the level effects are statistically significant at the usual levels, we do find that the difference between liquidity suppliers and demanders is statistically significant in response to fragmentation. Columns 2 and 3 repeat this analysis but subset on the smallest and largest firms by market capitalization.[17] Consistent with previous analyses, in

[17]In column 2, we have to change the fixed from Firm × Date to Firm × Week because there is insufficient trading to allow such tight fixed effects. This is a limitation of the Ancerno data where trading in the smallest quintile of firms is more sparse.

TABLE 7

Panel Regression of Execution Shortfall and Fragmentation

Table 7 displays results from an OLS panel regression of the form:

$$\text{SHORTFALL}_{i,t+1} = \alpha + \beta \text{FRAGMENTATION}_{i,t} + \sum_{k \neq 3} (\text{FRAG}_{i,t} \times \delta_k \text{STYLE}_k) + \text{FE}_i + \text{FE}_t + \text{CONTROLS}_{i,t} + \epsilon_{i,t+1}.$$

The dependent variable, EXECUTION_SHORTFALL, is defined at the institution-firm-trade direction-day level as the product of a trade direction indicator and the percent change of execution cost to open trading price as in Anand et al. (2013). The sample uses institutional trading data from Ancerno in 2007. FRAGMENTATION is measured as 1 minus the Herfindahl–Hirschman Index of trading volume across the exchanges provided in TAQ. TRADING_STYLE indicates whether an investor is a liquidity supplier or demander and is calculated as the average trading style for the institution in Dec. 2006. "Liquidity Demander" is the top quintile of average trading style while "Liquidity Supplier" represents the bottom quintile of average trading style. Control variables are discussed in Section IV. Fixed effects are indicated at the bottom of the table. Standard errors clustered by firm and date are shown below the estimates. Model 1 examines the entire sample of firms, model 2 examines only firms in the smallest quintile of market capitalization, model 3 examines only firms in the largest quintile of market capitalization, model 4 examines only "Liquidity Demanders," and model 5 examines only "Liquidity Suppliers." ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: EXECUTION_SHORTFALL				
Explanatory Variables	1	2	3	4	5
FRAGMENTATION	−3.091	−28.112	−14.189	7.822	−7.972**
	(27.222)	(24.201)	(41.255)	(6.443)	(3.860)
FRAGMENTATION × TRADING_STYLE_1	−2.284	15.418	−7.387		
	(8.081)	(45.007)	(9.180)		
FRAGMENTATION × TRADING_STYLE_2	−4.466	7.436	−5.528		
	(7.025)	(33.704)	(7.716)		
FRAGMENTATION × TRADING_STYLE_4	3.472	32.636	0.623		
	(5.615)	(30.660)	(5.918)		
FRAGMENTATION × TRADING_STYLE_5	9.350	122.821**	11.921		
	(11.637)	(59.569)	(11.634)		
RETURN_VOLATILITY				500.309***	−225.114***
				(105.795)	(68.564)
LEVERAGE				−18.466	−18.283
				(30.678)	(20.198)
MTB				−5.148	−2.590
				(4.631)	(3.503)
INSTITUTIONAL_OWNERSHIP				−6.697	−8.895
				(11.385)	(8.843)
PRICE_INVERSE				5.000	5.685
				(4.620)	(3.660)
VOLUME_TURNOVER				−7.466***	−0.213
				(2.385)	(1.429)
CONSTANT	3.989	7.900	11.635	89.981**	53.974**
	(15.857)	(6.972)	(24.859)	(37.793)	(23.864)
Subsample	No	Smallest	Largest	Liq. Demander	Liq. Supplier
Firm × Date FE	Yes	No	Yes	No	No
Firm × Week FE	No	Yes	No	No	No
Institution FE	Yes	Yes	Yes	Yes	Yes
Firm × Side FE	Yes	Yes	Yes	Yes	Yes
Day FE	No	No	No	Yes	Yes
No. of obs.	4,195,042	16,298	2,681,745	219,205	421,442
R^2	0.186	0.386	0.101	0.079	0.061

column 2, we find that liquidity demanders in the smallest firms experience relatively worse execution. In fact, a 1-standard-deviation increase in fragmentation yields a 28 basis point increase in execution shortfall for liquidity demanders trading in the smallest quintile of firms. The largest firms exhibit a similar pattern but there is no statistical significance. Column 4 examines a subset composed of just liquidity demanders: the positive coefficient of 7.822 suggests liquidity demanders are worse off in light of increased fragmentation, but the coefficient is not statistically significant. Column 5 examines a subset composed of just liquidity suppliers: the negative and statistically significant coefficient of −7.972 shows execution shortfall for liquidity suppliers *improves* by 1.8 basis points with a 1-standard-deviation increase in fragmentation.

Overall, these estimates are consistent with the pick-off risk channel: liquidity demanders receive worse execution costs, while liquidity suppliers receive higher spreads. Even more, comparing the size of the coefficients in columns 4 and 5 suggests that these effects offset, consistent with liquidity suppliers increasing spreads to compensate for the increased risk they bear.

2. Front-Running Risk

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 ISO to avoid some frictions created by Regulation NMS. ISOs are special order types 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 frequently, representing almost half of the total orders following the implementation in 2007. If Regulation NMS did create frictions that generate risks of front-running (the "front-running" prediction), we would expect to see more ISO trading in assets that were most impacted.

Accordingly, in Table 8 we present the first evidence on the relation between fragmentation and ISO use. We regress the number of ISO orders and ISO volume on fragmentation using OLS panel regressions with data from 2007 to 2016.[18]

In columns 1 and 2, we consistently find that smaller stocks tend to have fewer ISO orders – consistent with a decrease in trading, yet they use ISOs disproportionately more when they do trade. Comparing the amount of ISO trades in column 2 to ISO turnover in column 4, the discrepancy in trades against turnover suggests that for larger orders, ISOs become more attractive for smaller stocks, consistent with the idea that traders are using these orders to collect liquidity when it is highly fragmented across market centers.

ISOs are unique in that they are flagged in the TAQ database, originate from a single order, yet are executed potentially across multiple exchanges. In order to further understand the mechanism behind the relation between fragmentation and ISOs, we create an algorithm to match the individual ISO trades to the originating order. Our algorithm takes advantage of the strict rules regulating this order type, the TRF locations on TAQ, and the millisecond times the orders are executed.

Once we have aggregated the individual "child" orders to the "parent" order, in columns 5–1 of Table 8 we investigate the aggressiveness of ISO orders by looking at the number of exchanges at which they are executed, the percentage of NBBO depth acquired, and the price change as compared to the NBBO at the time the ISO

[18]We are unable to conduct our difference-in-differences regressions with ISOs because these order types were introduced in conjunction with the implementation of Regulation NMS in 2007. As such, there is no data on ISO trades prior to 2007. Nevertheless, our instrumental variables regressions show similar results. See Table C5 in the Supplementary Material.

TABLE 8

Panel Regression of Intermarket Sweep Orders and Fragmentation

Table 8 displays the results of a panel regression of inter-market sweep order (ISO) volume on fragmentation, according to the model:

$$y_{i,t+1} = \alpha + \beta \text{FRAGMENTATION}_{i,t} + \sum_{k\neq 3} \delta_k \text{SIZE}_k + \sum_{k\neq 3} \theta_k (\text{FRAG} \times \text{SIZE}_k) + \text{CONTROLS}_{i,t} + \epsilon_{i,t+1},$$

where $y_{i,t+1}$ measures the use of ISO trades in the TAQ database using daily firm-level data from 2007 to 2016. #_ISO_TRADES is defined as the number of ISO trades, grouped together by the "parent" order. ISO_TURNOVER is the natural logarithm of the volume of ISO trades scaled by shares outstanding. #_EXCHANGES is the number of exchanges at which the ISO was executed on, averaged across the day. %_DEPTH is the number of shares executed by the ISO order scaled by the depth at the NBBO prior to the ISO order, then averaged across the day. PRICE_CHANGE is the total price change comparing the "worst" price of the ISO as compared to the NBBO prior to execution, then averaged across the day. When PRICE_CHANGE is higher, the ISO pushed prices further from the NBBO to the detriment of the trader. FRAGMENTATION is measured as 1 minus the Herfindahl–Hirschman Index of trading volume across the exchanges provided in TAQ. The variables QUINTILE_1 through QUINTILE_5 are indicator variables that take the value 1 if a firm is ranked in a particular quintile when sorted by market capitalization, and 0 otherwise. QUINTILE_1 takes the value 1 for firms with the smallest market capitalization, while QUINTILE_5 is an indicator variable that take the value 1 for firms with the highest market capitalization. Firms are sorted into market capitalization quintiles on day $t-1$. Control variables are discussed in Section IV. All models include firm and day fixed effects. Standard errors clustered by firm and date are shown below the estimates. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable									
	#_ISO_TRADES		ISO_TURNOVER		#_EXCHANGES		%_DEPTH		PRICE_CHANGE	
Explanatory Variables	1	2	3	4	5	6	7	8	9	10
FRAGMENTATION	0.924***	0.974***	0.616***	0.473***	0.041***	0.052***	0.096***	−0.088***	−0.000	−0.007
	(0.017)	(0.043)	(0.012)	(0.032)	(0.002)	(0.005)	(0.007)	(0.016)	(0.002)	(0.005)
FRAG × QUINTILE_1		−0.353***		0.091**		−0.070***		0.381***		0.006
		(0.049)		(0.038)		(0.006)		(0.020)		(0.006)
FRAG × QUINTILE_2		0.149***		0.229***		−0.074***		0.003		0.003
		(0.048)		(0.035)		(0.006)		(0.020)		(0.005)
FRAG × QUINTILE_4		0.213***		0.078**		0.152***		0.101***		0.010
		(0.054)		(0.038)		(0.008)		(0.024)		(0.009)
FRAG × QUINTILE_5		0.823***		0.635***		0.535***		0.175***		0.063***
		(0.090)		(0.073)		(0.016)		(0.041)		(0.021)
QUINTILE_1	−0.938***	−0.753***	−0.135***	−0.209***	−0.015***	0.023***	0.214***	−0.010	0.006	0.002
	(0.029)	(0.042)	(0.013)	(0.029)	(0.003)	(0.005)	(0.013)	(0.018)	(0.004)	(0.005)
QUINTILE_2	−0.421***	−0.519***	−0.102***	−0.254***	−0.005**	0.040***	0.077***	0.070***	0.003	0.000
	(0.015)	(0.035)	(0.007)	(0.025)	(0.002)	(0.004)	(0.007)	(0.014)	(0.002)	(0.004)
QUINTILE_4	0.299***	0.154***	0.050***	0.001	0.008***	−0.097***	0.033***	−0.037**	−0.001	−0.008
	(0.014)	(0.041)	(0.008)	(0.029)	(0.002)	(0.006)	(0.007)	(0.018)	(0.002)	(0.007)
QUINTILE_5	0.561***	−0.035	0.081***	−0.381***	0.018***	−0.371***	0.118***	−0.007	−0.002	−0.048***
	(0.023)	(0.070)	(0.012)	(0.057)	(0.003)	(0.012)	(0.012)	(0.032)	(0.004)	(0.016)
VOLUME_ TURNOVER	0.974***	0.975***	1.018***	1.018***	0.038***	0.039***	0.030***	0.030***	0.001	0.001
	(0.007)	(0.007)	(0.005)	(0.005)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
RETURN_ VOLATILITY	−2.337***	−2.346***	−1.546***	−1.550***	−0.047***	−0.053***	1.684***	1.681***	−0.081***	−0.082***
	(0.132)	(0.133)	(0.097)	(0.097)	(0.016)	(0.014)	(0.087)	(0.087)	(0.016)	(0.016)
LEVERAGE	−0.061	−0.073	0.110***	0.103***	0.066***	0.058***	0.033	0.033	−0.023**	−0.024***
	(0.048)	(0.048)	(0.024)	(0.024)	(0.008)	(0.007)	(0.026)	(0.026)	(0.009)	(0.009)
MTB	0.038***	0.041***	−0.033***	−0.032***	−0.004***	−0.002**	0.029***	0.028***	0.002	0.002
	(0.008)	(0.008)	(0.004)	(0.004)	(0.001)	(0.001)	(0.004)	(0.004)	(0.001)	(0.001)
PRICE_INVERSE	0.024*	0.035***	−0.076***	−0.072***	0.002	0.008***	−0.062***	−0.064***	−0.000	0.000
	(0.014)	(0.014)	(0.006)	(0.006)	(0.002)	(0.002)	(0.009)	(0.009)	(0.002)	(0.002)
CONSTANT	3.222***	3.191***	−1.992***	−1.889***	0.168***	0.159***	−0.529***	−0.405***	0.004	0.009
	(0.052)	(0.057)	(0.030)	(0.039)	(0.007)	(0.007)	(0.025)	(0.027)	(0.010)	(0.010)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	7,219,652	7,219,652	7,219,652	7,219,652	7,219,652	7,219,652	7,214,636	7,214,636	7,210,699	7,210,699
R^2	0.910	0.911	0.699	0.699	0.672	0.682	0.169	0.170	0.521	0.521

was initiated. In general, the results in columns 5, 7, and 9 of Table 8 suggest that fragmentation results in ISOs using a greater number of exchanges, taking a larger percentage of NBBO depth, yet have little impact of pushing prices away from the NBBO. When looking at the heterogeneous impacts of fragmentation, column 6 finds that the smallest firms use fewer exchanges with ISOs but take a significantly greater portion of the available depth (column 8). Hence, for the smallest firms, ISO usage appears to be more aggressive than the median firms' usage, yet the price impact also appears muted. Given the previous results, we conclude that ISOs can help alleviate the negative network externalities arising from fragmentation, but they are not able to totally overcome them.

3. Alternative Explanations and Robustness

Using a set of distinct analyses, our results consistently show that small firms are adversely affected by increased fragmentation, while larger firms tend to experience improved market quality. Of course, it remains possible that some other omitted variable is jointly driving both fragmentation and our market quality measures.

For example, it is possible that designated market makers may have previously subsidized liquidity in smaller, less liquid stocks, using their trading profits in large firms.[19] As exchange competition increased, they may have become less willing to provide this subsidy. This may have been particularly relevant at a large consolidated exchanges like NYSE, while the market makers at Nasdaq may be less sensitive to this fragmentation effect. Hence, we re-run the same analyses on subsets of NYSE-listed and Nasdaq-listed firms to see if there are any notable differences. We find similar effects for both Nasdaq-listed and NYSE-listed firms. Thus, while this change may have affected market quality, it does not explain away the effects of fragmentation.[20]

In addition, we perform a number of robustness tests to support our main findings. Appendix C of the Supplementary Material confirms our results are robust to an instrumental variables approach using the number of market centers available to trade as an instrument for fragmentation. Appendix F of the Supplementary Material confirms our results hold when using an alternative measure of fragmentation. Additionally, in unreported tests, we find that our results are robust to using alternative liquidity or market quality measures as well as using different proxies for firm-level liquidity instead of market capitalization.

V. Conclusion

To date, there has been relatively little research on the impact of recent changes to the structure of equity trading. While market quality has generally improved over the last decade, we show strong evidence that recent improvements to liquidity have been unequally shared across stocks. Large stocks have benefited much more than small stocks. We then examine the mechanism underlying these changes. We examine two distinct analyses and samples to understand the impact of fragmentation. Across a variety of analyses, samples, and outcome variables, we consistently find that fragmentation is associated with more trading and better market quality for large stocks, but these benefits do not accrue to small stocks. In fact, small firms tend to experience worse market quality when faced with increases in fragmentation.

[19]We thank Gideon Saar for this suggestion.

[20]It is also possible that other proximate events, like the 2003 Global Analyst Research Settlement, could have changed liquidity in smaller stocks. However, our results are unchanged if we include the number of analysts or institutional ownership as control variables.

Consistent with theoretical models of exchange competition, we find that these effects change trading behavior. In response to more fragmentation, trading frequency decreases significantly for smaller firms as compared to larger firms. Motivated by the theoretical predictions of Budish et al. (2015), Foucault (1999), and Baldauf and Mollner (2021), we test whether frictions in the implementation of Regulation NMS lead to more pick-off risk and front-running risk. We find evidence that fragmentation directly increases pick-off risk. Using institutional trading data, we also find that fragmentation may increase front-running risk. Furthermore, we find the use of ISOs helps alleviate some of the costs associated with fragmentation, but not all of them. Overall, our results show that market design affects trading behavior and as a result, market quality.

As a final thought, we note that the rise in fragmentation, and the subsequent decline in market quality for small stocks, correlates strongly with the drop in IPOs by small companies (e.g., Gao et al. (2013)). Our results suggest that regulators should be cautious about the implementation of "one size fits all" policies. In their 2017 report, the U.S. Department of Treasury suggested that a one size fits all approach to the regulation of trading venues may not be optimal. Our results suggest that small firms may actually be worse off as a result of Regulation NMS. Future research should continue to explore how the design of equity markets effects the allocation of capital in the economy.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109022001545.

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