Market fragmentation and price impact *

Lewen Guo†
Pankaj K. Jain‡

December 26, 2022

Abstract

We investigate the effects of market fragmentation on price impact. Using a newly launched exchange as a quasi-natural experiment, we find that an exogenous increase in market fragmentation leads to a higher price impact of equity trading in the primary U.S. equity exchanges. Our IV estimates suggest a one-standard-deviation increase in market fragmentation of a stock will induce approximately 26.5 bps increases in NBBO price impact and much more significant increases in each *exchange-based* price impact for trading that stock. In addition, we also find the market depth at each existing lit exchange is negatively associated with the total order volume submitted to the new exchange. Our results are providing supportive evidence to the recent theories such as Chen and Duffie (2021) that market fragmentation decreases market depth at each exchange level, increases the aggressiveness of order submissions, and makes order book slope more inelastic thus leading to the increases in price impact under a multi-market setting.

Keywords: Market Fragmentation, Market Design, Price Impact, Order Book Slope

JEL Classification Numbers: D47, G12, G14

*First version: April 1, 2022. We thank Kelley Anderson, Yasuhiro Arikawa, Jeff Black, Allen Carrion, William Cheung, Jingchi Chen, Shinichi Hirota, Rasheek Irtisam, Thomas Marta(discussant), Joshua Mollner, Xinzhe Niu, Yusuke Osaki, Konstantin Sokolov, Yasuhiko Tanigawa, Robert Van Ness, Yoshiki Shimizu, Eduard Yelagin, Jiang Zhang and seminar participants at FMA Annual Meeting, Atlanta, 2022, University of Memphis, and Waseda University for their insightful suggestions. We thank our friends Lidong Cui and Xinzhe Niu for their kindly assistance in providing additional HPC accounts at the University of Memphis to help compute the data used in this paper. The paper is scheduled to present at AFA PhD Student Poster Session at the 2023 Annual Meeting

†Corresponding Author. Fogelman College of Business and Economics, Department of Finance, Insurance and Real Estate, University of Memphis, Emails: lguo5@memphis.edu; guolewen1994@gmail.com

‡Fogelman College of Business and Economics, Department of Finance, Insurance and Real Estate, University of Memphis.

1 Introduction

In the past decade, there are ongoing debates in the market design literature on whether financial assets should be traded in a centralized market where a single market clears all the transactions, or in a decentralized market where the same assets can be traded through separate-in-location but informational-connected-coexisting exchanges. The proponents of the "decentralized" market design advocate that market fragmentation is beneficial in two aspects. On the one hand, market fragmentation yields higher welfare as a result of the higher price informativeness and the increased allocation efficiency as market participants can infer more information on the intrinsic values of the assets from the multiple informational-connected prices across the exchanges (Malamud and Rostek, 2017; Wittwer, 2021). On the other hand, a fragmented market, intuitively, may also have smaller transaction costs and improved execution quality by facilitating the competition among the trading venues (O'Hara and Ye, 2011; Daures-Lescourret and Moinas, 2020; Cespa and Vives, 2022). The opponents of market fragmentation, however, concern that the gains from the competition may be offset by the costs associated with the increased number of trading venues. For example, market fragmentation may increase adverse selection costs by encouraging cross-venue arbitrage among traders with speed differentials (Pagnotta and Philippon, 2018; Lee, 2019; Malinova and Park, 2020; Baldauf and Mollner, 2021; Aquilina et al., 2022). Market fragmentation may also reduce the market depth at each trading venue, and therefore may possibly induce a higher price impact of trading (Malamud and Rostek, 2017; Chen and Duffie, 2021). In addition, the differences in fees structure across the proliferated trading venues may also give rise to inefficiency in execution quality (Colliard and Foucault, 2012).

In this paper, we shed light on the empirical question of whether market fragmentation is beneficial or detrimental to market participants in the U.S. equity market by exploiting the event of a newly launched exchange, the members exchange (MEMX). We posit that exploring this event adds two important insights to the literature. First, the quasi-natural setting of the launch of MEMX allows us to investigate the ***causal e ects*** of market fragmentation. As we show in Figure 1, the launch of MEMX induces exogenous market fragmentation. Our estimates suggest that the introduction of MEMX leads to a 1.66% increase in the level of market fragmentation for U.S. stocks. Second, our focus is on the introduction of a new lit exchange. Although numerous studies (Comerton-Forde and Putniņš, 2015; Kwan et al., 2015; Foley and Putniņš, 2016; Hatheway et al., 2017; Menkveld et al., 2017; Buti et al., 2017) have investigated the effects of dark pool trading on market quality, the impact of launching a new but important lit exchange which accounts for more than 4% of equity trading volume in the U.S. by the end of February 2022 remains surprisingly unexplored. From the market design perspective, it is crucial for regulators to evaluate the costs and the benefits of adding another new lit exchange to thus far fragmented U.S. equity market.

[**Figure 1**]

A recent theory developed by Chen and Duffie (2021) has several predictions on the effects of the lit market fragmentation—the increase in the number of exchanges. In their model, both strategic traders and liquidity traders may alter their order submission strategies as the number of exchanges increases. For strategic traders, the option of order-splitting and the order flow shifting to the new lit exchange reduce the market depth on the existing lit exchanges. This option to split orders across different exchanges also reduces the inhibiting effect of price-impact avoidance on total order submission in the equilibrium of the market setting. In equilibrium, these inhibiting effects will encourage strategic traders to submit more aggressive orders as they seek to obtain optimal executions. Therefore, Chen and Duffie (2021) predicts while market fragmentation may increase (reduce) price impact (market depth) at each exchange level, the increased order aggressiveness may improve overall price efficiency.

We find that a higher market fragmentation level leads to an increase in the price impact of trading in the U.S. equity markets. Our results suggest if a stock i experienced a one-standard-deviation increase in market fragmentation due to the launch of MEMX, the price impact for trading that stock will increase by approximately 26.5 bps if the price impact is measured based on National Best Bid and Best Offer (NBBO). We also document similar effects of market fragmentation on price impact using our ***exchange-based*** price impact measure which captures the dynamic variations in price impact at each lit exchange level.[1] Consistent with the theoretical predictions from Malamud and Rostek (2017) and Chen and Duffie (2021), we find the launch of MEMX affects the price impact of other existing lit venues. Of all 13 existing lit exchanges, 11 exchanges that account for 96.43% of market shares exhibit positive effects of market fragmentation on price impact though the magnitude ranges from 40.8 bps to 3,090 bps. To access the economic significance of our results, we note that for a stock with a price of 49.59 USD and with a trading volume of 1.731 million shares per day, the estimated increase in transaction costs is about 24,550 USD if the stock experiences a 1.1% exogenous increase in market fragmentation. The costs resulting from the increased price impact would be larger if we measure the price impact exchange-wise using our exchange-based price impact measures. In contrast with the predictions from the exchange competition models (Daures-Lescourret and Moinas, 2020; Cespa and Vives, 2022) where they lean to the equilibrium that the competition among the exchanges will enhance the liquidity provision in the equity markets, the empirical results from our paper are supporting the predictions from (Chen and Duffie, 2021) that market fragmentation actually deteriorates a particular dimension of liquidity—price impact.

Our methodology to estimate the ***causal e ects*** is motivated by the staggered implementation of trading on MEMX for each individual stock around the early phase after the MEMX is launched.[2] At the individual stock level, the exogenous change in market fragmentation depends on whether the order flows of stock are shifted from other existing lit markets or in a

[1]To measure the price impact of trades, we follow Holden and Jacobsen (2014). Our modified version of *exchange-based* price impact captures the dynamic variations in liquidity on each local exchange. For stock i on each day t, we obtain 13 exchange-wise price impact observations. We also include the price impact based on NBBO quotes which is also calculated following Holden and Jacobsen (2014). The details are discussed in Section 3.4.2.

[2]See Figure 1.

more detectable way whether the stocks are actually traded on MEMX.[3] Therefore, our identification strategy builds upon an instrumental variable (IV) approach. To be more precise on our estimation method, we instrument the first-difference of market fragmentation (1-HHI) on the first-difference of whether a stock is traded on MEMX on a trading day around the launch of the MEMX. And in the second-stage, the instrumented variables are then regressed against the first-difference of price impact.

Our IV identification strategy distinguishes from the previous studies such as Degryse et al. (2015) and Gresse (2017) but is in the same spirit of Haslag and Ringgenberg (2021) where they use the level of the number of market centers as the instrument for the level of market fragmentation. We have two major differences. First, we calculate our fragmentation based on lit exchanges only. In DTAQ data, we are unable to calculate the market fragmentation within the dark pools where the trading volume are aggregated.[4] Second and more importantly, we estimate the model in a first-difference specification around the launch of the new exchange. The instrumental variables in most of our cases–the first-difference of whether a stock i is traded on MEMX on the trading day t–only have variations in the early phases after the launch of MEMX. This is important because whether a stock trades on MEMX is unlikely to be correlated with the unobserved characteristics that may affect the price impact at other existing lit exchanges in the second-stage regression. Therefore, our approach satisfies the exclusive restriction of IV method better. In addition, our instrument variable also has an economic interpretation as it only takes the values from the set of $\{-1, 0, 1\}$. In the first-stage regression, all of the coefficients are positively significant at the 1% level and they can be interpreted as the effects of adding one additional lit exchange on the stock-level of market fragmentation.

We validate our main results by conducting a set of robustness tests. Our robustness tests address several concerns with regard to the validity of our main results. Specifically, we consider: whether our results are robust by using the alternative measures of market fragmentation and price impact; whether there are any heterogeneous effects of market fragmentation on price impact across stocks; whether reverse causality and endogenous venue choice problem may bias our estimates; whether our results apply under the current market structure of trading—order routing and NMS Order Protection Rule; and the external validity using the introduction of another lit exchange. The results from these robustness tests are quantitatively similar to our main results. We summarize them in Table 4 and provide the details in Appendix A.

In addition to the robustness tests, we conduct a placebo test as follows: For trading days between October 29, 2020, and 20 days after the calendar days when stocks are first traded on MEMX, we generate Bernoulli random variables to replace the true indicators of whether a stock i is traded on MEMX. Then we use these generated variables to run our two-stage least

[3]The master file of DTAQ data has an indicator variable labeled as "TradedOnMEMX" which indicates whether a stock is traded on MEMX on a particular trading day after July 24, 2020.

[4]This means when calculating the measure of market fragmentation, we exclude the off-exchange trades in DTAQ trades files with PARTICIPANT IDs starting with "D", "S" and "W". We also exclude the trades that don't have the null timestamp for the column of "Trade Reporting Facility(TRF) Timestamp". This will not only exclude all the trades with "Exchange" as "D" but also exclude trades that are disseminated by FINRA Alternative Display Facility (ADF) or FINRA Trade Reporting Facility (TRF) which are trades executed off-exchange.

square regressions as we do in our main regressions. Not surprisingly, we find no significant results for ten different generated pseudo series suggesting that our estimated causal effects are unlikely driven by chance.

We next gauge the impact of order flow shifted to MEMX on the market depth of the other existing lit exchanges. When a new exchange is introduced, traders may split their limit orders to the new exchange aiming at obtaining better exposure to liquidity. Are the order flows migrated to MEMX when it is launched? To answer this question, we calculate 13 exchange-wise market depth defined as the time-weighted number of shares at best bid (ask) prices for each stock i and day t. For each stock-day around the launch of MEMX, we also obtain the total number of shares of all orders submitted to MEMX from SEC market structure files.[5] We find that higher order volume on MEMX is associated with decreased market depth for almost all the existing lit exchanges around the launch of MEMX. The negative correlations between order volume submitted to MEMX and market depth are stronger for primary exchanges such as NASDAQ, ARCA, NYSE, BZX, EDGX, and IEX than peripheral exchanges such as EDGA, BYX, BX, National, PSX, Chicago, and AMEX. The results are consistent with our conjectures and the theories that market depth is reduced with increased market fragmentation partly due to the shifting of order flows from existing exchanges to the new exchange MEMX.

Next, we discuss three potential order book-level mechanisms through which market fragmentation can lead to a higher price impact of trading. First, we test the changes in order aggressiveness around the introduction of MEMX. Empirical evidence from Griffiths et al. (2000) suggests that order aggressiveness is positively associated with the price impact. If the introduction of MEMX is associated with the increases in overall order aggressiveness, which is predicted by Chen and Duffie (2021), then the increased price impact that we observe can be attributed to the increased order aggressiveness due to the introduction of new lit exchange. To test this potential channel, we use NASDAQ TotalView-ITCH data to calculate the percentage of aggressive orders and unaggressive orders following the approach in Biais et al. (1995). We find the introduction of MEMX is associated with the increases in the proportion of the orders in the ***aggressive*** order types but is negatively associated with the proportion of the orders in the ***unaggressive*** types suggesting that the introduction of MEMX does increase overall order aggressiveness. Therefore, this channel could possibly explain the increased price impact that we observe when trading is more fragmented.

Our second possible channel that may explain the higher price impact of equity trading after the introduction of MEMX for more fragmented stocks is the changes in the slopes of the limit order book around the introduction of MEMX. As predicted by Chen and Duffie (2021)'s model and also in our simplified version of his model shown in Figure 2 in the next section, the slope of the (inverse) demand schedule will become less steep and more inelastic in the fragmented markets compared with the centralized market. If the launch of MEMX decreases the steepness of the slopes in the limit order book for each local exchange, the price impact will be larger for executing the same quantities that walk the book. By constructing two stock-

[5] See https://www.sec.gov/opa/data/market-structure/market-structure-data-security-and-exchange.html.

day level measures of order book slopes based on Kalay et al. (2004) and Næs and Skjeltorp (2006), we test the changes in order book slopes around the introduction of MEMX. We find the slopes become less steep and more inelastic after the introduction of MEMX and thus support the channel that the changes in the slopes of the limit order book around the launch of new exchange also contribute to the observed increasing price impact in a more fragmented market.

Our third channel considers the liquidity supply and demand dynamics around the launch of MEMX. We conjecture that strategic traders will take advantage of the advent of MEMX and split orders from existing lit exchanges to the new exchange in order to gain optimal execution as predicted by the mechanical channel of Chen and Duffie (2021)'s model. Thus, on the liquidity-supplying side, we should observe a reduction in market depth following the launch of MEMX. While from the liquidity-demanding side, the liquidity traders who demand liquidity and submit marketable orders are not affected much by fragmentation.[6] Therefore, we should also find relatively small or insignificant changes in trade sizes compared with the changes in market depth following the introduction of MEMX. With a relatively larger trade size of liquidity trades (market orders) compared with the size of market depth (unmarketable limit orders) when trading becomes more fragmented, it is more likely that trades will exhaust the depth of the order book and move the price dramatically. Thus, the price impact will increase mechanically at each existing exchange.[7]

To verify our conjectures, we investigate the liquidity supply and demand dynamics for primary exchanges using market depth at best bid prices as the proxy for liquidity supply and trade sizes as well as trade sizes of Intermarket Sweep Order (ISO) trades as the proxies for liquidity demand.[8] From the liquidity-supplying side perspective, we document sharp decreases in market depth for major exchanges immediately after the introduction of MEMX. For instance, the market depth decreases about 9.33%, 5.15%, 8.67%, 2.33%, and 4.35% within 20 days after the launch of MEMX for NASDAQ, ARCA, NYSE, BZX, and EDGX–the five primary exchanges which comprise 81.88% dollar volume for all of the lit exchanges–respectively. In contrast, we find different results on the liquidity-demanding side. First, we find trade sizes remain relatively unchanged around the launch of MEMX for these major exchanges discussed above. Second, we find that despite some exchanges experiencing significant decreases in the trade sizes of ISO trades, their magnitudes are small compared with the decreases in the supply side–market depth at the bid. Our findings suggest it is the asymmetric impacts on the liquidity demand and supply due to the launch of a new lit exchange that induces a higher price impact

[6]In Chen and Duffie (2021)'s model, "liquidity traders" submit aggregated market orders at each lit exchange. The quantities (trade sizes) are exogenous random variables, independently and identically distributed across exchanges and periods.

[7]See Figure 2. The market depth at exchange A in case 1 is 200 shares, and there will be a 50% of reduction after the introduction of new exchange B if the trader decides to evenly split the orders. However, if the trade sizes of the exogenous trade (σ_Q) only reduce from 300 to 250, then the price impact will increase from 0.3 in case 1 to 0.5 in case 2 for that trade.

[8]ISO is an order that automatically executes in a designated market center even if there exists better price at other venues (Chakravarty et al., 2012). We believe the ISO trades, which can be identified in our data, are a good proxy for the liquidity trades to a specific exchange as discussed in the model of Chen and Duffie (2021). In Chen and Duffie (2021)'s model, they argue that the liquidity trades are i.i.d across liquidity traders. Liquidity traders collectively submit exogenous quantities to a specific exchange.

of trading.

Collectively, these channels point towards that the introduction of a new exchange may alter the current structure of the limit order book which may induce unexpected consequences on the market liquidity, especially in a multi-market setting.

Related literature. We contribute to the literature by providing empirical evidence to recent theoretical papers deliberated on market designs (Malamud and Rostek, 2017; Bernales et al., 2018; Pagnotta and Philippon, 2018; Lee, 2019; Üslü, 2019; Bernales et al., 2020; Daures-Lescourret and Moinas, 2020; Baldauf and Mollner, 2021; Chen and Duffie, 2021; Rostek and Yoon, 2021; Wittwer, 2021; Aquilina et al., 2022; Cespa and Vives, 2022).[9] While economists debate theoretically on whether markets should be designed to be centralized and fragmented, empirical evidence on this aspect is elusive given the intricate causes and consequences of market fragmentation.[10] Our paper helps to improve the understanding of this elusive concept using an exogenous shock in market fragmentation arising from the launch of a new lit exchange. This is important because as shown by Babus and Parlatore (2021), market fragmentation may be endogenously determined by investors' disagreement on the values of the underlying assets.[11]

Specifically, our paper tests the theoretical model proposed by the work of Chen and Duffie (2021) where they predict lit market fragmentation will induce lower market depth, higher price impact, and order aggressiveness. Our paper provides supportive evidence for their model. Previous studies (Battalio, 1997; Comerton-Forde and Putniņš, 2015; Kwan et al., 2015; Foley and Putniņš, 2016; Hatheway et al., 2017; Menkveld et al., 2017; Buti et al., 2017; Saint-Jean, 2021) have extensively focused on the effects of increased fragmentation arising from the off-exchange dark pool or broker-dealer's trading on market quality, while our focus is exclusively on the impact of establishing a new lit market which is relatively unexplored in the literature.[12] In this context, we are among the first to provide the empirical evidence that increasing one additional lit exchange leads to a higher price impact of ***other existing*** lit exchanges. Thus, our paper illustrates the consequences of launching a new lit exchange which is crucial to regulators.

[9]An earlier strand of literature investigates the effects of multi-market trading on trading volume, price formation, price informativeness and the correlation between the cross-exchange trading volume (Mendelson, 1987; Chowdhry and Nanda, 1991; Stoll, 2001; Baruch et al., 2007).

[10]Among the abovementioned theoretical literature, Pagnotta and Philippon (2018), Bernales et al. (2018), Daures-Lescourret and Moinas (2020), Baldauf and Mollner (2021) and Cespa and Vives (2022) along with earlier studies such as Hamilton (1979), Parlour and Seppi (2003) and Rust and Hall (2003) study the impact of fragmentation using an exchange-based or an agent-based (imperfect) competition model. In contrast, Lee (2019) and Aquilina et al. (2022) investigate the impact of fragmentation from the speed differential perspective. Empirical studies also show contradictory conclusions with regard to how market fragmentation affects market quality. For example, the earlier empirical work by O'Hara and Ye (2011) finds that more fragmented stocks have lower transaction costs and faster execution speeds. While later studies by Gresse (2017) and Haslag and Ringgenberg (2021) observe a dichotomy between the impacts of market fragmentation on small stocks and the impacts on large stocks. They find market fragmentation is detrimental to the liquidity of small stocks.

[11]Also, liquidity and fragmentation may be co-determined, with not only fragmentation impacting liquidity but also liquidity determining fragmentation. Liquid stocks are more likely to be traded at multiple exchanges than illiquid stocks as traders could shred their parent orders not just into smaller child orders (Obizhaeva and Wang, 2013) but also submit the child orders across exchanges to gain a reduction in transaction costs (Menkveld et al., 2017).

[12]The only one exception is De Fontnouvelle et al. (2003) in which they documented effective and quoted bid–ask spreads decrease significantly after some equity options have changed from a single exclusive listing exchange to multiple listings in August 1999.

While our paper is not testing all the consequences[13] that may occur when markets switch from centralized to fragmented, but at least we partially support the conclusions that fragmentation does induce a larger price impact in equity trading, mechanically.

Empirically, we contribute to the growing literature investigating how market fragmentation affects market quality. A bunch of empirical papers (Foucault and Menkveld, 2008; O'Hara and Ye, 2011; Degryse et al., 2015; Boneva et al., 2016; Gresse, 2017; Hatheway et al., 2017; Upson and Van Ness, 2017; Malinova and Park, 2020; Haslag and Ringgenberg, 2021) examine the effects of market fragmentation on market liquidity, market efficiency, and market quality under various settings. Especially, our paper examines the determinants of price impact—an important but less studied dimension of liquidity—in a multi-market setting. Thus, our paper complements previous empirical studies and provides additional evidence on the determinants of price impact (Dufour and Engle, 2000; Chiyachantana et al., 2004; Cont et al., 2014; Chiyachantana et al., 2017; Malinova and Park, 2020) by testing a unique mechanical channel—the effects from launching a new lit exchange.

Our paper is closely related to two contemporary studies and we complement them in various ways. Malinova and Park (2020) investigates the price impact of split trades arising from order-splitting activities across multiple exchanges in Canada. Using a proprietary trader-level dataset, they find that the increased price impact for the split trades is accrued to a group of fourteen faster traders. Their findings suggest these faster traders are more informative and in a multi-market setting they can react faster to stale quotes. Therefore, trades from this type of trader are generally more informed and thus have a larger price impact. Our paper focuses on a more general mechanical channel—the change in price impact originating from launching a new exchange which affects all existing stocks traded on the U.S. lit exchanges rather than a small subsample of the stocks. Therefore, our paper provides additional insights into the determinants of price impact in the multi-market setting complementing the work of Malinova and Park (2020). Another notable empirical work by Haslag and Ringgenberg (2021) investigates the variations in liquidity provision from 2003 to 2016 where the implementation of Regulation National Market System (NMS) rule 611 during this period requires orders to receive best execution prices across all exchanges thus inducing market fragmentation. They show that the improved liquidity is associated with the increased market fragmentation during this period but most of the improvements in liquidity are accrued to large stocks. Our paper has two major differences compared with Haslag and Ringgenberg (2021). First, we focus on a short-term period after the introduction of MEMX—the event that induces exogenous market fragmentation. Second, Haslag and Ringgenberg (2021) are extensively focused on market quality measures such as turnover ratio, effective spread, trade size as well as variance ratio. Our paper complements their work by exploring a relatively unexplored but important aspect of market liquidity—price impact—at each lit exchange level.

Finally, we contribute to empirical market microstructure literature by proposing ***exchange-based*** measures of price impact and market depth using public big datasets. These new

[13]For example, price informativeness and welfare effects. See Bernales et al. (2020) for details.

exchange-wise measures capture the variations of some key market microstructure variables at each local exchange level. To our best knowledge, this is novel to empirical market microstructure literature. Our proposed measures should have growing importance as recent studies such as Irtisam and Sokolov (2021), and Shkilko et al. (2021) are examining the market quality of the U.S. markets at each exchange level. Our exchange-based measures can serve as the benchmark metrics for the research investigating market quality at the exchange level. In addition, computing these variables require the usage of High-Performance Computing (HPC) facilities which allow us to conduct computing-extensive tasks, in our case, merging quotes files and trades files at each exchange level.[14] As discussed in a recent survey paper by Goldstein et al. (2021), future finance research may involve intensive interactions with big data. Therefore, our paper is also contributing to this strand of literature.

2 Institutional Details and Hypotheses Development

This section discusses the institutional details of the new lit exchange MEMX (Section 2.1) and our hypotheses development (Section 2.2) based on Chen and Duffie (2021). We illustrate some stylized facts about the new exchange and the growing importance of this new exchange. We summarize the major predictions based on Chen and Duffie (2021).

2.1 Institutional details of MEMX

Supported by large financial institutions such as BlackRock and Fidelity, MEMX was initially launched with seven pilot symbols on September 21, 2020. After one month of testing period and completion of the U.S. stock exchange rollout, MEMX started to trade all NMS symbols on October 29, 2020. Being one of the fastest-growing exchanges in the U.S., the market share of MEMX has steadily increased over time.[15] By the end of April 2022, the trading volume of MEMX ranks 6th across all lit exchanges in the U.S, and the market shares of MEMX has reached 6.4%. In addition, quotes from MEMX appear, on average, 36.2% of the time in NBBO files following NASDAQ (65.0%), ARCA (42.9%), and NYSE (39.2%). There are 1,650 tickers that are mainly quoted by MEMX.[16] MEMX had 49 active member firms (institutions) with 55% of volume executed as principal and 45% executed on an agency or riskless principal basis in April 2022.

The rapid growth in trading volume may be attributed to the uniqueness of MEMX in three aspects–low access fees, diversified order types, and less internal competition. First, MEMX has very low access fees. For both professional and non-professional traders, access to real-time market data at the same low price of $0.01. As discussed by the CEO of MEMX, Jonathan

[14] We use the HPC at the University of Memphis to calculate the *exchange-based stock-day* measures. It takes approximately two months to complete the computing process using approximately one year of raw DTAQ data.

[15] See Figure C.1.

[16] 75% of NBBO quotes are from MEMX. Sources are from https://memx.com/exchange-highlights-robust-quote-performance-and-diverse-participation-across-order-types/, https://www.businesswire.com/news/home/20210921005373/en/MEMX-Reaches-Record-4-Market-Share-in-Year-One and https://memx.com/news/.

Kellner:"Our new fee schedule is an example of how we are working to improve upon the exchange experience for all participants. By introducing one low price for both professional and non-professional consumers, we hope to democratize access to our market data and minimize the friction for retail brokers associated with categorizing investors and how they are using stock exchange data." Second, MEMX has diversified order types including midpoint peg orders, limit reverse orders, and primary peg orders. The diversified order types offer traders with the flexibility to implement complex trading strategies. Third, MEMX also emerges as the largest independently operated exchange in the U.S. Irtisam and Sokolov (2021) discusses the ownership structure of the U.S. exchanges and the strategy that the peripheral exchange will employ to compete with the core exchange within the same group. In absence of this conflict, MEMX can adopt any effective strategy that may attract the order flows from other existing lit exchanges.

2.2 Hypotheses development

Our paper is directly testing the theory from Chen and Duffie (2021). They model the order submissions strategies and demand schedules in the context of trading in multiple exchanges with liquidity traders submitting exogenous market orders and strategic traders submitting limit orders (demand schedules) to multiple exchanges simultaneously. Conjecturing the order submission strategies of other traders, strategic traders maximize their expected discounted profits. In equilibrium, the price impact of all exchanges increases, and the depth at each exchange decreases with fragmentation as order volume is split across a greater number of trading venues. Figure 2 illustrates the simplified version of the mechanism proposed by Chen and Duffie (2021). We consider two scenarios: Case 1, the asset is traded on a centralized exchange. Case 2, the asset is traded on two exchanges. In the upper half of the figure, a trader submits limit orders from 19.0 to 20.0 with 200 shares at each price level forming a downward step-wise demand schedule (black solid line).[17] Suppose we assume that the expected size for an exogenous liquidity trade is 300 shares ($\sigma_Q = 300$) and the current market price is 20.0 (blue vertical line), a 300-shares market order will move the price from 20.0 to 19.7 provided the demand schedule is continuous rather than step-wise. In case 2, we consider the simplest case that the trader shreds the previous limit orders into two halves at each price level and submits orders to the two exchanges separately. In this case, the depth at each price level drops from 200 shares to 100 shares for exchange A. If a 250-shares market order arrives at exchange A, it will deplete the market depth at the best two bid prices driving the price down from 20.0 to 19.5, thus increasing the price impact of the trade in general.[18]

[Figure 2]

[17] The demand schedule is based on the information, for instance, σ_Q, that the trader obtains at the time he/she submits the limit orders. σ_Q is the expected exogenous liquidity trade size. See details in Section II of Chen and Duffie (2021).

[18] The 250-shares market order is just a simple example, the trade size of the exogenous market order will be important to determine the price impact.

In theory, the equilibrium demand schedules submitted by trades depend on each trader's maximization of his/her total expected discounted cash compensation received for executed orders, net of the present value of asset holding costs (Chen and Duffie, 2021). In our simplified version, we observe a change in both depth and the slope of the demand schedule if the asset is traded on multiple exchanges rather than on the centralized market. Suppose this trader alters his demand schedule ex-ante in both exchanges, the slope of the (inverse) demand schedule becomes less steep and the depth at each price level decreases compared to the centralized exchange. Consequently, the overall price impact of marketable orders increases in more fragmented markets.

Using the launch of a new stock exchange in the U.S.—the members exchange (MEMX) as a quasi-natural experiment, we directly investigate the impacts of fragmentation through a new lit exchange on the existing lit exchanges. We hypothesize that ***the launch of the new stock exchange, MEMX, induces a higher market fragmentation level and lower market depth of the existing lit exchanges. This increase in the level of market fragmentation leads to a higher price impact for equity trading across all the existing lit exchanges.***

3 Data, Sample Selection and Research Design

This section discusses the datasets that we use throughout this paper, the sample selection process that we take, and the research design we employ. Specifically, we illustrate the filters that we have employed on our datasets and the number of stocks eliminated at each merging process in Section 3.1. We then briefly explain the identification of staggered event time at the stock level in Section 3.2. Section 3.3 and Section 3.4 show the empirical measures that we use for both market fragmentation and price impact. Section 3.5 illustrates the exogenous change in market fragmentation around the introduction of MEMX. Section 3.6 discusses the instrumental variable (IV) approach used in this paper.

3.1 Sample construction

We collect the share code, exchange code, ticker, trading status, delisting code, price, share volume, share outstanding and return without dividends for each security from the CRSP universe from June 1, 2020 to May 28, 2021. We select all U.S. common stocks (share codes 10 and 11). We exclude stocks that changed the listing venues during our sample period based on the change of exchange code. We drop delisted stocks with delisting codes equal to 100 or with no delisting code information on the last trading day. Finally, we remove stocks where the number of observations for returns (return without dividends) or trading volume (share volume) is less than 200. We merge the CRSP data with SEC market structure file and our summarized DTAQ data which comprises our *exchange-based* measures of price impact, depth, market fragmentation, and trade size detailed in Section 3.4. In addition, we use NASDAQ TotalView-ITCH data to conduct order-level analysis in Section 5. Our final sample has 1,176

NYSE-listed stocks, 132 AMEX-listed stocks, and 2,100 NASDAQ-listed stocks. Table 1 shows the procedures of our stock selections and sample characteristics.

[**Table 1**]

3.2 Identify the calendar days when stocks were first traded on MEMX

We use the DTAQ master file to identify the time when a stock was first traded on MEMX. From July 24, 2020, the DTAQ master file started to report an indicator variable "TradedOnMEMX" documenting whether a stock is traded on MEMX. In this paper, we define this variable as $OnMEMX_{i,t}$ for each stock-day observation. In Figure 1, we define the event day (E_i^d) for a stock as the first day when it was traded on MEMX.[19] Although all NMS tickers can be traded on MEMX since October 29, 2020, the exact first day of trading varies across stocks with an initial batch of seven symbols on September 21, 2020. Figure 3 illustrates the time distribution of the first days of trading on MEMX for the stocks in our sample. The figure shows that more than 800 stocks were first traded on MEMX on October 29, 2020. While more than 80% of the stocks in our sample have been traded on MEMX by mid-November, 2020, it is not until late April 2021 that all stocks in our sample have been traded once in a specific trading day on MEMX.

Stocks in our sample also exhibit varied trading patterns after they were first traded on MEMX. In fact, 46.3% of the stocks in our sample were not traded on MEMX on the second calendar day after the first days that they reported trading on MEMX. We illustrate the percentage of stocks traded on MEMX across the days relative to event date in Appendix Table A.2. As we will discuss in Section 3.6, this variation facilitates the estimation of the causal effects using an instrumental variable approach.

[**Figure 3**]

3.3 The measure of market fragmentation

Following Haslag and Ringgenberg (2021), we construct the measure of lit market fragmentation as one minus the Herfindahl Hirschman Index (HHI). Suppose in a trading day t, a stock i trades at the lit exchange ψ with trading volume $Volume_{i,t}^{\psi}$. Then, we define the market share at the exchange ψ for this stock i at trading day t as:

$$s_{i,t}^{\psi} := \frac{Volume_{i,t}^{\psi}}{\sum_{\psi} Volume_{i,t}^{\psi}} \tag{1}$$

[19] The following article (https://www.businesswire.com/news/home/20201029006270/en) also points out "the exchange launched with seven symbols on September 21, 2020 and has methodically added new symbols in four phases since then".

Our measure of market fragmentation based on trading volume can be written as follows:

$$Frag_{i,t}^{volume} := 1 - \sum_{\psi} (s_{i,t}^{\psi})^2 \tag{2}$$

where $\sum_{\psi}(s_{i,t}^{\psi})^2$ is the Herfindhal-Hirschman Index (HHI) which captures the market concentration of trading for the stock i at trading day t. Similarly, we also construct the measure of market fragmentation based on the number of trades across the lit exchanges, $Frag_{i,t}^{trade}$.[20]

3.4 The measure of price impact, depth, and other market quality measures

This section introduces our measures of price impact that are used throughout this paper. We construct both price impact measures based on NBBO and each exchange-based price impact for 13 lit markets. We use DTAQ data to construct our price impact measures.

3.4.1 The measure of price impact based on NBBO

Following Holden and Jacobsen (2014), we construct the dollar-weighted percentage price impact for each stock i at trading day j:

$$PI_{i,t}^{\psi} = \sum_{\kappa} \frac{2D_{\kappa}^{\psi} P_{\kappa}^{\psi} V_{\kappa}(X_{\kappa+5}^{\psi,mid} - X_{\kappa}^{\psi,mid})}{X_{\kappa}^{\psi,mid} \sum_{\kappa} P_{\kappa}^{\psi} V_{\kappa}^{\psi}} \tag{3}$$

Where D_{κ}^{ψ} is $+1$ for a buyer-initiated trade κ and -1 for a seller-initiated trade κ based on Lee and Ready (1991) algorithm at exchange ψ. P_{κ}^{ψ} is the price for trade κ at exchange ψ, and V_{κ}^{ψ} is the trading volume for that trade at exchange ψ. $X_{\kappa}^{\psi,mid}$ is the average of BBO bid price and ask price after the trade κ at exchange ψ. $X_{\kappa+5}^{\psi,mid}$ is the average of BBO bid price and ask price 5 minutes after the trade κ for exchange ψ.

3.4.2 The measure of price impact based on each exchange

We construct our ***exchange-based*** price impact measure similar to Holden and Jacobsen (2014). However, we differ from the previous study in the following: First, we obtain BBO quotes for each lit exchange ψ from DTAQ quotes files and merge them with the trades which are executed at the same exchange.[21] If the trade κ is executed at NYSE (N), for instance,

[20]To illustrate, suppose a stock traded on three lit exchanges with trading volume as 100 shares, 300 shares, and 400 respectively. The value of HHI for this stock on this trading day is 0.40625. Thus, the market fragmentation, $Frag_{i,t}^{volume}$ is equal to 0.59375. An alternative measure used by Gresse (2017) and (Lausen et al., 2021) is the reciprocal of the Herfindhal-Hirschman Index (HHI). We define the alternative variables as: $Frag_{i,t}^{volumeInv} := \frac{1}{\sum_{\psi}(s_{i,t}^{\psi})^2}$ and $Frag_{i,t}^{tradeInv}$.

[21]Specifically, we consider the following lit exchanges: NASDAQ (Q+T), ARCA (P), NYSE (N), BZX (Z), EDGX (K), IEX (V), EDGA (J), BYX (Y), BX (B), National (C), PSX (X), Chicago (M), and AMEX (A). We also calculate the trading statistics for the new exchange–the members exchange–MEMX(U). The details of these exchanges are discussed in Appendix Table A.1]

Holden and Jacobsen (2014)'s measure will merge this trade with the previous NBBO quote, to calculate the midpoint price, X_{κ}^{mid}, the average of the national best bid price and offer price.[22] In other words, the quote matched with this trade can originate from any lit exchange. In contrast, our exchange-based price impact is calculated based on exchange-to-exchange matches between trades and quotes. For a trade executed at NYSE, our approach is to merge this trade with the previous BBO quotes at the NYSE order book regardless of the NBBO quotes. We believe our exchange-based price impact measures capture the variations of the price impact on different exchanges. The details for the computation of the variables are discussed in Appendix C. As shown in Panel A, Table 2, the mean price impact measures for the lit exchanges during our sample period range from 0.144% (Chicago (M)) to 3.010% (National (C)). This is not surprising as the average trade sizes and the average depth at the best bid price are also varied across exchanges.[23]

[**Table 2**]

Figure 4 compares the cross-sectional average of price impact one day before the event days and on event days for primary exchanges. For NBBO price impact and primary exchange-based price impacts, we can observe a small amount of increase before (in grey) and after (in black) the event days for most of the price impact measures.

[**Figure 4**]

Panel B, Table 2 shows the summary statistics for variables from CRSP or from our DTAQ summarization dataset based on NBBO. The average of our market fragmentation variables, $Frag_{i,t}^{trade}$ and $Frag_{i,t}^{volume}$ for 854,973 stock-day observations are 0.752 and 0.714, respectively. The mean price impact based on NBBO is 0.284% lower than most of the exchange-based price impact. We include four control variables–trading volume, volatility[24], market capitalization, and stock price directly from CRSP daily securities files.

3.5 The exogenous change in market fragmentation

This section discusses the exogenous change of the market fragmentation measures $Frag_{i,t}^{trade}$ and $Frag_{i,t}^{volume}$ used in this paper. Figure 1 shows the changes in market fragmentation around the launch of MEMX. Following the notations in econometric literature (De Chaisemartin and d'Haultfoeuille, 2020; Borusyak et al., 2021; Sun and Abraham, 2021; Athey and Imbens, 2022), we denote E_i^d as the first trading day when stock i is traded on MEMX. Stocks with the same event date E_i^d are referred to as cohorts. We define the relative days to event day for stock i

[22] We are aware that a recent study by Hagströmer (2021) suggests that there exists bias when using the midpoint price to estimate the effective spreads. We verify our main results using his weighted midpoint price estimator in Table A.7 the results are similar to our main results in Table 3.

[23] We also calculate the *exchange-based* trade size and *exchange-based* market depth at the best bid price. we define $TradeSize_{i,t}^{\psi}$ as the average trade sizes and $Depth_{i,t}^{\psi}$ as the time-weighted average of the number of shares on the best bid price for each stock i at trading day t.

[24] Defined as the standard deviation of squared daily returns over the past 20-trading days.

as $l_{i,t}^d := t - E_i^d$. To capture the dynamic treatment effects, we construct binary variables for different relative days. For example, we construct indicators $D_{i,t}^0 = \mathbb{1}\{l_{i,t}^d = 0\}$ for the event day of stock i, $D_{i,t}^{-1} = \mathbb{1}\{l_{i,t}^d = -1\}$ for one day before the event day and $D_{i,t}^1 = \mathbb{1}\{l_{i,t}^d = 1\}$ for one day after the event day. For distant relative days, we may construct the binning indicators such as $D_{i,t}^{10+} = \mathbb{1}\{l_{i,t}^d > 10\}$ and $D_{i,t}^{-10-} = \mathbb{1}\{l_{i,t}^d < -10\}$. Our baseline where α_i is the stock fixed effects, λ_t is the day fixed effects and $\mathbf{X}_{i,t}^{'}$ are time-varying controls. K and J are the cutoff relative days that determine how to construct the binning indicators. Intuitive cutoffs are $(K = 5, J = -5)$ and $(K = 10, J = -10)$.

Specifically, we run the following staggered two-way fixed effects regressions:

$$Frag_{i,t}^* = \alpha_i + \lambda_t + \sum_{j=J}^{-1} \gamma_j D_{i,t}^j + \sum_{k=0}^{K} \beta_k D_{i,t}^k + \gamma_{J-} D_{i,t}^{J-} + \beta_{K+} D_{i,t}^{K+} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t} \tag{4}$$

Where the coefficients of interest are γ_j and β_k–the estimated coefficients for the relative days to the event day that stocks are first traded on MEMX.

Figure 1 suggests that on the first day when stocks are traded on MEMX, the market fragmentation for those stocks, on average, increases by about 1.32% (0.0099 / 0.752). We also verify the similar magnitude of increase in market fragmentation as shown in Table A.4 where we present the estimated coefficient of regressing the market fragmentation on the event day indicators $D_{i,t}^0$. We also consider alternative specifications proposed by Borusyak et al. (2021) where they address treatment heterogeneity effects with a three-step imputation method. The estimated coefficients do not change much from our baseline two-way fixed effect model.

While we observe an exogenous shock in market fragmentation on the event day, the fact that insignificant but positive coefficients following the sharp spike on the event day suggest the effects of the change in market fragmentation is partially accrued to the variable construction. This is because all stocks in our sample will be traded on MEMX at some time within our sample period time from June 1, 2020, to May 28, 2021, and by construction, all stocks will have the event days, $D_{i,t}^0$, set to 1 on the calendar days t when they are first traded on MEMX. However, those stocks are not guaranteed to be traded on MEMX for the second day, the third day, or those early days after the launch of MEMX. Appendix Table A.2 shows that only 46.2% of the stocks have been traded on the second days after the first days they are traded on MEMX. The proportion of stocks that are traded on MEMX is monotonically increasing as the relative days increase. On the twentieth day after first traded on MEMX, 84.6% of stocks in our sample are traded on MEMX.

3.6 Instrumental variable approach

Motivated by the variation in whether a stock is traded on MEMX in the early phase after the launch of MEMX, we estimate the causal effects of market fragmentation on price impact in an Instrumental Variable (IV) approach. We estimate the causal effects in a first-difference specification. For each stock i in our sample, we take the first-difference of the indicator variable of "TradedOnMEMX" denoted as $\Delta OnMEMX_{i,t}$. Our $\Delta OnMEMX_{i,t}$ takes on the values of {-1, 0, 1}. In the early phase after the launch of MEMX, we observe more observations of $\{-1, 1\}$ than $\{0\}$ as stocks are changing the status of the indicator variable $OnMEMX_{i,t}$ frequently, from either "traded on MEMX" ($OnMEMX_{i,t} = 1$) to "not traded on MEMX" ($OnMEMX_{i,t} = 0$) and vice versa.

Specifically, we run the following two-stage least square regression:

$$\Delta Frag^*_{i,t} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}'_{i,t}\Phi + \Delta\epsilon_{i,t} \tag{5}$$

$$\Delta PI^{\psi}_{i,t} = \Delta\lambda_t + \mu\Delta \widehat{Frag}^*_{i,t} + \Delta\mathbf{X}'_{i,t}\Gamma + \Delta\epsilon_{i,t} \tag{6}$$

Where equation (5) represents the first-stage regression and equation (6) represents the second-stage regression. Where Δ is the first difference operator, $OnMEMX_{i,t}$ is the indicators if the stock i is traded on MEMX at day t, $\Delta \widehat{Frag}^*_{i,t}$ is the predicted value from the first-stage regression, and $\mathbf{X}'_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchange.

We have two main reasons to justify the use of the IV approach rather than using the static difference-in-differences or the staggered difference-in-differences to estimate the treatment effects of market fragmentation on price impact. First, the fact that all stocks can be potentially traded on MEMX after the introduction of the new exchange poses a challenge for assigning the stocks in our sample to either the treatment group or the control group. Despite all stocks having been traded at least for one trading day on MEMX by the end of April 2021 after the introduction of MEMX, the exact calendar days of the first trading days vary across stocks. This staggered feature at the stock-level rules out the possibility to obtain appropriate treatment effects from the static difference-in-differences estimators. Furthermore, as we show in Table A.2, after stocks were first traded on MEMX, about 46.3% of them were not traded on the second calendar day. Even if we estimate the treatment effects using Callaway and Sant'Anna (2021)'s staggered difference-in-differences estimator, we may fail to capture the effects of market fragmentation on price impact at the stock level if we consider the first trading day on MEMX as the event day. This is because, from the individual stock perspective, the fragmentation level may decrease when a stock is not traded on MEMX due to other factors which may or may not be related to the market conditions for that particular stock.

Second, we have several advantages using the IV approach in our setting. By estimating the model in a first-difference specification, we can capture the variation in market fragmentation at the stock level due to the plausibly exogenous variation in whether a stock is traded on MEMX ($\Delta OnMEMX_{i,t}$) in the early days when stocks were traded on MEMX. The coefficient in the equation (5) also has an economic interpretation—the effects of adding additional exchange on stock-level market fragmentation.

One concern of our instrumental variable approach is that whether a stock is traded on MEMX may be related to the market conditions of the other existing lit exchanges–probably the price impact–raising the reverse causality concerns. To address this concern, we calculate the Pearson Correlation Coefficients between our exchange-based price impact $PI^{\psi}_{i,t}$ and whether a stock is traded on MEMX ($OnMEMX_{i,t}$) after the introduction of MEMX on October 29, 2020, stock-wise. Table A.5 reports the total number of stocks in each direction (positive or negative) of the correlations. In each correlation direction, we report the number of stocks that the p-values of the null hypotheses—the two variables are independent—are larger than 0.01% or smaller than 0.01%, respectively. For example, there are 1,321 (1,422) stocks that have positive (negative) correlations between the price impact in the EDGA (J) exchange and whether the stock is traded on MEMX after the introduction of MEMX. Of these 1299 (1,266) stocks, the correlations of 22 (156) stocks are positively (negatively) significant at the 1% level. The results provide evidence that the reverse causality is unlikely to bias our estimates using our instrumental variable approach. Besides, we also conduct additional robustness tests in Section 4.2 to address the endogeneity issue.

4 Empirical Findings

This section illustrates our main empirical findings. Section 4.1 shows the effects of market fragmentation on price impact. Section 4.2 shows our robustness tests which aim to address a variety of concerns with regard to the validity of our main results in Section 4.1. We conduct a placebo test in Section 4.3. Section 4.4 documents the correlations between market depth at each exchange and the total order volume submitted to MEMX.

4.1 The effects of market fragmentation on price impact

Table 3 reports the effects of market fragmentation on price impact around the launch of MEMX exchange. We run 2SLS regressions of change in price impact on change in market fragmentation as shown in Equation (5) and Equation (6). In the first stage, we use the first-difference of whether a stock is traded on MEMX, $OnMEMX_{i,t}$, as the instrument for our market fragmentation measures, $Frag^{trade}_{i,t}$ and $Frag^{volume}_{i,t}$, respectively. In the second stage, we then regress the NBBO-based price impact and our proposed ***exchange-based*** price impact on the predicted values of (first-difference) market fragmentation. We report the estimated coefficients μ in the second-stage regressions for the independent variables of $\Delta Frag^{trade}_{i,t}$ and $\Delta Frag^{volume}_{i,t}$, separately. We also present the first-stage coefficients δ and weak IV test statistics of Kleibergen and Paap (2006) (K-P) rk F statistics.

We find the change of market fragmentation positively affects the change of price impact around the launch of MEMX across most of the lit exchanges. A one-standard-deviation (0.102) increase in market fragmentation ($Frag^{trade}_{i,t}$) will induce approximately 26.5 bps (0.102×0.026×10,000) increase in NBBO price impact. The effects are not only statistically significant at the 1% level but also economically significant. For a stock with a price of 49.59 USD and with a trading volume of 1.731 million shares per day, the estimated increase in transaction costs due to the increased price impact is about 24,550 USD if the stock experiences a 1.1% exogenous increase in market fragmentation.

Perhaps the most striking finding in Table 3 is the fact that price impact at each ***existing*** lit exchange is also affected by market fragmentation. A stock exhibiting more fragmentation in trading due to the launch of MEMX will suffer an increase in price impact for 11 out of 13 lit existing exchanges. The magnitude of the effects ranges from 40.8 bps to (in NASDAQ (Q+T)) 3,090 bps (in BX (B)). The results are similar with regards to both market fragmentation measure based on trade ($Frag_{i,t}^{trade}$) and measure based on volume ($Frag_{i,t}^{volume}$).

Our results are consistent with the theoretical predictions proposed by Malamud and Rostek (2017) and Chen and Duffie (2021) of how market fragmentation, to be more precise, the increase in a number of exchanges will affect the price impact of trading. In the equilibrium of their models, the price impact in all existing exchanges will increase if the total number of exchanges increases. Our results support their predictions as we show that 11 out of 13 lit exchanges exhibit positively significant coefficients in our second-stage regressions.

[**Table 3**]

4.2 Robustness tests

We conduct several robustness tests to address the concerns with regard to the validity of our main results in Table 3. First, we use different measures of market fragmentation and price impact to conduct our main regressions to address the concern that different measures may lead to contradicted results. Our results in Table A.6 using the inverse of HHI index proposed by Gresse (2017) and Lausen et al. (2021), in Table A.7 using the weighted midpoint proposed by Hagströmer (2021) to calculate the price impact, and in Table A.8 using the 15-second-based price impact jointly confirm that our main findings in Table 3 are unlikely to be driven by the measures that we choose.

Second, we address the concerns that there may exist heterogeneous effects of fragmentation on price impact across stocks. Evidence from Haslag and Ringgenberg (2021) suggests that market fragmentation may impair liquidity for small stocks. Since these small stocks are more likely to be listed at the NASDAQ stock exchange, we also separate our sample into subsamples where stocks are grouped by their listing exchanges. Table A.9 shows the effects of market fragmentation on price impact are stronger for stocks listed on NASDAQ and on AMEX than stocks listed on NYSE, though the coefficients of our main regressions are still positively significant at major stock exchanges regardless of the listing exchanges. In addition, following Haslag and Ringgenberg (2021), we also add market capitalization quintile interacted with market fragmentation to our main regression equations to capture if the effects of the exogenous change of market fragmentation on price impact differ across different sizes of stocks. Table A.10 illustrates that after controlling for the sizes of the stock, we can still find the positive relations between market fragmentation and price impact.

The third concern about the validity of our main findings results from the endogeneity problem in our specification. While the introduction of MEMX on October 29, 2020, is a plausibly exogenous event, trading stock for the first time on MEMX sometimes multiple days after the launch is probably not exogenous. There exists the possibility that our instruments—$\Delta OnMEMX_{i,t}$—may be linked to market conditions on other exchanges. thus biasing our estimates. For example, the reverse causality will be a problem if the high price impact on other existing lit exchanges encourages the broker-dealers to route orders to MEMX for execution. Though, as shown in Table A.5, we observe weak correlations between whether a stock is traded on MEMX after the introduction of MEMX and the exchange-based price impact, we still provide robustness tests in the regressions setting. We deal with the issue by restricting our sample period from 10 trading days (October 15, 2020) before the introduction of MEMX, to October 29, 2020. We include 945 stocks that were traded on the first day (October 29, 2020) when the MEMX are introduced. By restricting the sample for the first day when MEMX is introduced, we can resolve the reverse causality concern that price impact can affect the decision to trade on MEMX. Table A.11 shows that among 13 exchanges, 8 exchanges exhibit positively significant coefficients of market fragmentation on price impact. Among those 5 insignificant coefficients, 4 of them are positive.

We summarize our robustness tests in Table 4. Readers can find the details of our results for these robustness tests in our Appendix A.

[**Table 4**]

4.3 Placebo tests

To validate our main results, we conduct placebo tests that falsify our true indicator variable, $OnMEMX_{i,t}$. Specifically, we generate a Bernoulli random variable, $OnPLA\hat{C}EBO_{i,t}$, with the probability of 1/3 (2/3) that the variable will be 0 (1) after October 29, 2020 when MEMX starts to trade all NMS symbols.[25] We also assume that all stocks will be always traded on MEMX after 20 days when they are first traded on MEMX. This means for $t > E_i^d + 20$ we manually set the values of $OnPLA\hat{C}EBO_{i,t}$ to be 1. In total, we generate ten series of $OnPLA\hat{C}EBO_{i,t}$.

Table 5 reports the results of our placebo tests. We run 2SLS regressions of price impact on market fragmentation similar to the regression in Table 3. In the first-stage, instead of instrumenting first-difference of market fragmentation on the true indicator variable, $\Delta OnMEMX_{i,t}$, we instrument $\Delta Frag^*_{i,t}$ on the randomly generated variable, $\Delta OnPLA\hat{C}EBO_{i,t}$. We use ten different generated series of $OnPLA\hat{C}EBO_{i,t}$ and report the number of second-stage estimated coefficients μ in four categories–positively not significant at 10% level (+), positively significant at 10% level ($+^*$), negatively not significant at 10% level ($-$) and negatively significant at 10% level ($-^*$).

The results in Table 5 suggest that our estimated causal effects of market fragmentation on price impact in Table 3 are unlikely driven by chance. All of our estimated coefficients in

[25]The values of $OnPLA\hat{C}EBO_{i,t}$ before October 29, 2020 are all set to 0.

regressions based on ten different generated random variables across all lit exchanges are not significant at the 10% level. The coefficients are also roughly equally distributed in + and − categories suggesting if we falsify the dates when stocks are traded on MEMX, we cannot observe any significant effects of market fragmentation on price impact.

[**Table 5**]

4.4 Market depth and total order volume submitted to MEMX

In this section, we investigate the impact of order flow shifting to MEMX on market depth for each lit exchange around the launch of MEMX. Chen and Duffie (2021) predicts that introducing a new exchange facilitates traders to split orders across different exchanges, therefore, reducing the market depth of existing lit markets. We use the total order volume (in millions) submitted to MEMX as a proxy for the order flow shifting to MEMX. For each stock i at trading day t, we obtain the total order volume on MEMX, denoted as $ORDERVOL_{i,t}^{MEMX}$, from SEC market structure files where they summarize the total order volume for each lit exchange, separately. We then run the following regressions to gauge the impact of order flow shifting to MEMX on market depth:

$$\ln BIDDepth_{i,t}^{\psi} = \alpha_i + \lambda_t + \pi ORDERVOL_{i,t}^{MEMX} + \mathbf{X}_{it}^{\prime}\Gamma + \epsilon_{i,t} \tag{7}$$

$$\ln ASKDepth_{i,t}^{\psi} = \alpha_i + \lambda_t + \pi ORDERVOL_{i,t}^{MEMX} + \mathbf{X}_{it}^{\prime}\Gamma + \epsilon_{i,t} \tag{8}$$

Where $\ln BIDDepth_{i,t}^{\psi}$ ($\ln ASKDepth_{i,t}^{\psi}$) is the natural logarithm of time-weighted market depth for the best bid (ask) prices for stock i at trading day t. $ORDERVOL_{i,t}^{MEMX}$ is the total volume (in million) for all orders submitted to MEMX for tock i at trading day t. $\mathbf{X}_{it}^{\prime}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. α_i is the stock fixed effect and λ_t is the day fixed effect.

As we show in our simplified example (from one exchange to two exchange) in Figure 2, the practice of shredding the parent order into two equal child orders lead to a 50% of reduction in the market depth in Exchange A. However, in reality, we have a much more complicated situation where the number of exchanges increases from 13 to 14. Our results in Table 6 document a negative association between the market depth at other existing lit exchanges and the order flow shifting to MEMX in the early days after the launch of the exchange. We estimate the coefficients π with different estimation windows, for example, thirty days pre and post (-10, 9), fifty days pre and post (-20, 19), and twenty days pre and post (-60, 59). We find most of the estimated coefficients of $ORDERVOL_{i,t}^{MEMX}$, π, are negative and significant. The negative correlations are stronger for primary exchanges such as NASDAQ, ARCA, NYSE, BZX, EDGX, and IEX than peripheral exchanges such as EDGA, BYX, BX, National, PSX, Chicago, and AMEX. The results hold for both market depth at the best bid side and the best ask side. Besides, our results also suggest economic significance. For example, a one million additional order volume submitted to MEMX is associated with an approximately 1.20%

(1.34%) decrease in market depth at the best bid (ask) side for NASDAQ. For each estimation window, we also report the average R-squared across 13 regressions. Although the average R-squared decreases as the estimation windows increases, the variations of our key dependent variable, $ORDERVOL_{i,t}^{MEMX}$, along with other control variables such as $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$ explain approximately 70% of the variation in market depth. Our results validate the prediction proposed by the model of Chen and Duffie (2021) that market depth is reduced as a consequence of order-splitting activities and order flow shifting when MEMX is introduced.

[**Table 6**]

5 Discussion of mechanisms

The previous sections have provided empirical evidence that exogenous changes in market fragmentation arising from launching a new exchange induce a larger price impact in equity trading. This section discusses the probable mechanisms through which the introduction of a new lit exchange may affect price impact. We consider three potential explanations: the change in order aggressiveness, the change in order book slope and the asymmetric changes in liquidity supply and demand around the launch of MEMX. All three explanations support that the change of order book structure around the introduction of MEMX may result in an increase in price impact. We use NASDAQ TotalView-ITCH data to conduct order-level analysis in this section.

5.1 Change in order aggressiveness

One possible channel through which market fragmentation leads to a higher price impact of trading may be attributed to the changes in order aggressiveness around the introduction of MEMX. Chen and Duffie (2021) predicts that fragmentation increases overall order aggressiveness due to traders' order-splitting activities and their objective is to maximize the payoff of their demand schedules. Also, empirical evidence from Griffiths et al. (2000) suggests that order aggressiveness is positively associated with the price impact. If the introduction of MEMX increases the overall order aggressiveness of the orders that submit to the limit order book, then it is very likely that the increased price impact that we observe can be, at least partially, attributed to this channel. Our results which we will discuss in the following paragraphs support this channel.

We test this potential channel using NASDAQ TotalView-ITCH data. The dataset comprises all orders that are entered into the NASDAQ trading system. After reconstructing the limit order book whose procedure is discussed in detail in Appendix C, we follow the approach of Biais et al. (1995) and classify orders which result in inside BBO trades, large trades (marketable orders walk the LOB in NASDAQ), small trades (orders executed at BBO but with trade size smaller than the depth at BBO), and improvement in BBO (either order improving the BBO price or improving the BBO depth) into aggressive orders. We also classify orders that result in addition in LOB, revision in LOB, cancellation in LOB, and deletion in LOB into unaggressive orders. For each stock-day observation, the variables are in percentage and their summary statistics are reported in Appendix B, Table B.1. We then run the following regression for each order aggressiveness type:

$$\%Order^{*}_{i,t} = \alpha_i + \lambda_t + \omega \mathbb{1}(t >= E^d_i) + \mathbf{X}'_{it}\Gamma + \epsilon_{i,t} \tag{9}$$

Where $\%Order^{*}_{i,t}$ represents the percentage of orders in that category, for instance, the percentage of orders that result in large trades. E^d_i is the calendar day that when stock i is first traded on MEMX. $\mathbb{1}$ represents the indicator function. $\mathbf{X}'_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. We select the sample with trading days t between $E^d_i - 20$ and $E^d_i + 19$. The estimate ω, which captures the changes in the percentage of orders in each category is of our interest.

Table 7 presents the results of the changes in order aggressiveness around the launch of MEMX. Panel A reports the results on the buy (bid) side and Panel B reports the results on the sell (ask) side. We find the introduction of MEMX is associated with the increases in the proportion of the orders in the aggressive order types. For example, on the buy side, the introduction of MEMX is associated with 0.15%, 0.13%, and 0.67% increases for aggressive orders that result in large trades, small trades, and improvement in BBO, respectively. The regression coefficients are all significant at 1% level. On the contrary, we find the introduction of MEMX is negatively associated with the proportion of the orders in the unaggressive types though the magnitude of the association is weaker than that for the aggressive orders types. For robustness tests, we select the sample with a longer estimation window and report the results in Appendix B, Table B.2. The results in Table B.2 are similar to the results in Table 7. R-Squared in Table B.2 is all slightly smaller than those in Table 7 suggesting that there are more noises in the unobserved error terms of the models if we expand the estimation window. Similarly, we conduct a falsified test where we select the sample with trading days t between $E^d_i - 60$ and $E^d_i - 21$. The results are reported in Table B.3. Not surprisingly, we find almost no significant associations between the falsified introduction of MEMX and the proportion of the orders in aggressive order types. These results confirm that the increased order aggressiveness after the introduction of MEMX could possibly explain the increased price impact that we observe when trading is more fragmented.

[Table 7]

5.2 Change in orderbook slope

Our second possible channel that may explain the higher price impact after the introduction of MEMX for more fragmented stocks is the changes in the slopes of the limit order book around the launch of the new exchange. As we show in Figure 2, the slope of the (inverse) demand schedule becomes less steep in the two exchanges case compared to the centralized exchange case. If the introduction of MEMX decreases the steepness of the slopes (more inelastic) in the limit order book for each local exchange, the price impacts will be larger for executing the same quantities that walk the book in the more exchanges case than the centralized exchange case.

To test this channel, we follow Kalay et al. (2004) and Næs and Skjeltorp (2006), and construct two stock-day level measures of order book slopes for both the bid side and the ask side of the limit order book in NASDAQ stock exchange. We only show the formulas for the ask side since the computation procedure for the bid side is the same as the ask side.

Specifically, we denote the order book status, including prices p and quantities v at a particular time during the regular trading hours as s. We denote τ as the tick level with $\tau = 0$ representing the bid-ask midpoint and $\tau = 1$ representing the best quote. Furthermore, let p_0^A denote the bid-ask midpoint price and let p_τ^A denote the price at tick level τ. We also denote ν_0^A as the accumulated total quantities (shares) at tick level τ. Then, we then calculate the average slope for the ask side at order book status s for stock i on the trading day t as:

$$SE_{i,t,s}^{NS} = \frac{1}{10}(\frac{\nu_1^A}{p_1^A/p_0^A - 1} + \sum_{\tau=1}^{10} \frac{\nu_{\tau+1}^A/\nu_\tau^A - 1}{p_{\tau+1}^A/p_\tau^A - 1}) \tag{10}$$

Suppose we observe the total number of status s for stock i on the trading day t, and denote it as $N_{i,t,s}^{SE}$. Then, our measure for the stock-day level measure of the order book slope can be written as:

$$SLOPEASK_{i,t}^{NS} = \frac{SE_{i,t,s}^{NS}}{N_{i,t,s}^{SE}} \tag{11}$$

The superscript NS represents this measure is based on Næs and Skjeltorp (2006).

Alternatively, we also construct the slope measure based on Kalay et al. (2004). We first calculate the average slope at order book status s for stock i on trading day t as:

$$SE_{i,t,s}^{Kalay} = \frac{1}{10}(\sum_{\tau=0}^{10} \frac{(\nu_{\tau+1}^A - \nu_\tau^A)/TQ_{i,t,s}}{p_{\tau+1}^A/p_\tau^A - 1}) \tag{12}$$

Where $TQ_{i,t,s}^A$ denotes the total shares supplied within $\tau = 10$ ticks on the ask side of the orderbook status s for stock i on trading day t. Then, our measure based on Kalay et al. (2004) could be written as:

$$SLOPEASK_{i,t}^{Kalay} = \frac{SE_{i,t,s}^{Kalay}}{N_{i,t,s}^{SE}} \tag{13}$$

One major difference between the method proposed by Næs and Skjeltorp (2006) and us is that we don't take the average of the slope in the bid side, $SLOPEBID_{i,t}^*$, and the slope in the ask side, $SLOPEASK_{i,t}^*$ to get the average "stock-day" slope. Therefore, our calculated $SLOPEBID_{i,t}^*$ are negative while $SLOPEBID_{i,t}^*$ are positive for most of the stock-day observations throughout our sample period. When the slopes are less steep, the values of the slopes for the bid side will become larger (less negative) and the values of the slopes for the ask side will become smaller (less positive). We run the following four regressions for two different estimation windows:

$$SLOPEBID_{i,t}^{NS} = \alpha_i + \lambda_t + \rho\mathbb{1}(t >= \tilde{E}_i^d) + \mathbf{X}_{it}'\Gamma + \epsilon_{i,t} \tag{14}$$

$$SLOPEBID_{i,t}^{Kalay} = \alpha_i + \lambda_t + \rho\mathbb{1}(t >= \tilde{E}_i^d) + \mathbf{X}_{it}'\Gamma + \epsilon_{i,t} \tag{15}$$

$$SLOPEASK_{i,t}^{NS} = \alpha_i + \lambda_t + \rho\mathbb{1}(t >= \tilde{E}_i^d) + \mathbf{X}_{it}'\Gamma + \epsilon_{i,t} \tag{16}$$

$$SLOPEASK_{i,t}^{Kalay} = \alpha_i + \lambda_t + \rho\mathbb{1}(t >= \tilde{E}_i^d) + \mathbf{X}_{it}'\Gamma + \epsilon_{i,t} \tag{17}$$

Where $\tilde{E}_i^d$ represents the first day that the stock i is quoted on MEMX. $\mathbb{1}$ represents the indicator function. $\mathbf{X}_{it}'$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. The regression coefficients ρ which captures the changes in average orderbook slopes is of our interest. We expect the ρ is negative for the bid side and positive for the ask side if the introduction of MEMX makes the orderbook slopes less steep and more inelastic.

Table 8 reports the results of the changes in orderbook slope around the launch of MEMX. As we expect, the introduction of MEMX decreases the steepness of limit orderbook slopes for stocks trading on the NASDAQ exchange. For two different estimation windows, we find the values of slopes for the bid side are becoming larger (less negative) and the values of the slopes for the ask side are become smaller (less positive) suggesting that orderbook slopes are becoming less steep and the demand schedules are becoming more inelastic. These results support the channel that the changes in the slopes of the limit orderbook around the launch of new exchange also contributes to the observed increasing price impact in a more fragmented market.

[**Table 8**]

5.3 Asymmetric changes in liquidity supply and demand

The third possible channel that we propose is the asymmetric changes in liquidity supply and demand around the introduction of MEMX. When a new lit exchange is introduced, Chen and Duffie (2021) predicts that strategic traders will split orders from existing lit exchanges forming different demand schedules (limit orders) as we show in Figure 2. We conjecture that the liquidity supply–the depth of limit orders resting on the limit order book at each tick (price level)–will decrease as the increasing number of lit exchanges. In contrast, on the liquidity demand side, “liquidity traders” submit aggregated market orders at each lit exchange in Chen and Duffie (2021)'s model. The quantities (trade sizes) are exogenous random variables, independently and identically distributed across exchanges and periods. Therefore, we should also find relatively small or insignificant changes in trade sizes compared with the changes in market depth following the introduction of MEMX. With a relatively larger trade size of liquidity trades (market orders) compared with the size of market depth (unmarketable limit orders) when trading becomes more fragmented, it is more likely that trades will exhaust the depth of the order book and move the price dramatically. Thus, the price impact will increase mechanically at each existing exchange. Empirically, we use the market depth at best bid prices as the proxy for liquidity supply and use the (ISO) trade sizes as the proxy for liquidity demand. ISO is an order that automatically executes in a designated market center even if there exists better prices at other venues (Chakravarty et al., 2012). We believe the ISO trades, which can be identified in our data, are good proxies for the liquidity trades to a specific exchange as discussed in the model of Chen and Duffie (2021). In Chen and Duffie (2021)'s model, they argue that the liquidity trades are i.i.d across liquidity traders. Liquidity traders collectively submit exogenous quantities to a specific exchange.

Table 9 reports the liquidity supply and liquidity demand dynamics around the launch of MEMX. We calculate the average of market depth at the best bid price ($BIDDepth^{\Psi}_{i,t}$), trade size ($TradeSize^{\Psi}_{i,t}$), and ISO trade size ($ISOTradeSize^{\Psi}_{i,t}$), respectively before the introduction of MEMX (PRE) for major exchanges. Similarly, we calculate the average of these variables after the introduction of MEMX ($POST$). We also calculate the percentage differences ($DIFF\%$) and absolute differences between the PRE and $POST$. $*$, $**$, $***$ indicates statistical significance at the 1%, 5%, and 10% level for two sample *t*-test, respectively between PRE and $POST$. We also validate our results using different estimation windows. We find that in the liquidity supply side there are sharp decreases in market sharp decreases in market depth for major exchanges immediately after the introduction of MEMX. For instance, the market depth decreases about 9.33%, 5.15%, 8.67%, 2.33% and 4.35% within 20 days after the launch of MEMX for NASDAQ, ARCA, NYSE, BZX, and EDGX—the five primary exchanges which comprise 81.88% dollar volume for all of the lit exchanges–respectively. First, we find trade sizes remain relatively unchanged around the launch of MEMX for these major exchanges discussed above. Second, we find that despite some exchanges experiencing significant decreases in the trade sizes of ISO trades, their magnitudes are small compared with the decreases in the supply side–market depth at the bid. Our results suggest the increased price impact of trading can be attributed to such asymmetric impacts on the liquidity demand and liquidity supply arising from the launch of MEMX.

[**Table 9**]

6 Conclusions

In this paper, we document ***positive*** causal effects of market fragmentation on price impact using a newly launched exchange as a quasi-natural experiment. We find the launch of the MEMX exchange causes the exogenous increase in market fragmentation which induces the increase of price impact in other existing lit markets. While previous studies have extensively examined the effects of dark pools on market quality. We have little evidence that what would be the consequence of adding another new exchange on top of the existing 13 exchanges. Our paper fills this gap and provides evidence supporting the theoretical model proposed by Chen and Duffie (2021), at least, in part.

But we should be cautious about the policy implications of the results presented in this paper. Price impact is just one aspect of market quality. It is also a particular dimension of market liquidity. As shown in the model of Chen and Duffie (2021), although price impact will increase in more fragmented markets which seems to be detrimental for traders, the aggregated price informativeness is, on the contrary, an increase in the multi-market setting. In addition, Malamud and Rostek (2017) shows that fragmented markets surprisingly yield higher welfare than centralized markets. We encourage future research deliberates on these topics as equity markets deserve to be well-designed and serve the purpose of enhancing the economy.

References

Aquilina, M., Budish, E., and O'neill, P. (2022). Quantifying the high-frequency trading "arms race". *The Quarterly Journal of Economics*, 137(1):493–564.

Athey, S. and Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics*, 226(1):62–79.

Babus, A. and Parlatore, C. (2021). Strategic fragmented markets. *Journal of Financial Economics*.

Baldauf, M. and Mollner, J. (2021). Trading in fragmented markets. *Journal of Financial and Quantitative Analysis*, 56(1):93–121.

Baruch, S., Andrew Karolyi, G., and Lemmon, M. L. (2007). Multimarket trading and liquidity: theory and evidence. *The Journal of Finance*, 62(5):2169–2200.

Battalio, R. H. (1997). Third market broker-dealers: Cost competitors or cream skimmers? *The Journal of Finance*, 52(1):341–352.

Bernales, A., Garrido, N., Sagade, S., Valenzuela, M., and Westheide, C. (2018). A tale of one exchange and two order books: Effects of fragmentation in the absence of competition.

Bernales, A., Garrido, N., Sagade, S., Valenzuela, M., and Westheide, C. (2020). Trader competition in fragmented markets: Liquidity supply versus picking-off risk.

Biais, B., Hillion, P., and Spatt, C. (1995). An empirical analysis of the limit order book and the order flow in the paris bourse. *the Journal of Finance*, 50(5):1655–1689.

Boneva, L., Linton, O., and Vogt, M. (2016). The effect of fragmentation in trading on market quality in the uk equity market. *Journal of Applied Econometrics*, 31(1):192–213.

Borusyak, K., Jaravel, X., and Spiess, J. (2021). Revisiting event study designs: Robust and efficient estimation. *Working Paper*.

Buti, S., Rindi, B., and Werner, I. M. (2017). Dark pool trading strategies, market quality and welfare. *Journal of Financial Economics*, 124(2):244–265.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Cespa, G. and Vives, X. (2022). Exchange competition, entry, and welfare. *The Review of Financial Studies*, 35(5):2570–2624.

Chakravarty, S., Jain, P., Upson, J., and Wood, R. (2012). Clean sweep: Informed trading through intermarket sweep orders. *Journal of Financial and Quantitative Analysis*, 47(2):415–435.

Chen, D. and Duffie, D. (2021). Market fragmentation. *American Economic Review*, 111(7):2247–74.

Chiyachantana, C., Jain, P. K., Jiang, C., and Sharma, V. (2017). Permanent price impact asymmetry of trades with institutional constraints. *Journal of Financial Markets*, 36:1–16.

Chiyachantana, C. N., Jain, P. K., Jiang, C., and Wood, R. A. (2004). International evidence on institutional trading behavior and price impact. *The Journal of Finance*, 59(2):869–898.

Chowdhry, B. and Nanda, V. (1991). Multimarket trading and market liquidity. *The Review of Financial Studies*, 4(3):483–511.

Colliard, J.-E. and Foucault, T. (2012). Trading fees and efficiency in limit order markets. *The Review of Financial Studies*, 25(11):3389–3421.

Comerton-Forde, C. and Putniņš, T. J. (2015). Dark trading and price discovery. *Journal of Financial Economics*, 118(1):70–92.

Cont, R., Kukanov, A., and Stoikov, S. (2014). The price impact of order book events. *Journal of nancial econometrics*, 12(1):47–88.

Daures-Lescourret, L. and Moinas, S. (2020). Fragmentation and strategic market-making. *Available at SSRN 2498277*.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–96.

De Fontnouvelle, P., Fishe, R. P., and Harris, J. H. (2003). The behavior of bid-ask spreads and volume in options markets during the competition for listings in 1999. *The Journal of Finance*, 58(6):2437–2463.

Degryse, H., De Jong, F., and Kervel, V. v. (2015). The impact of dark trading and visible fragmentation on market quality. *Review of Finance*, 19(4):1587–1622.

Dufour, A. and Engle, R. F. (2000). Time and the price impact of a trade. *The Journal of Finance*, 55(6):2467–2498.

Foley, S. and Putniņš, T. J. (2016). Should we be afraid of the dark? dark trading and market quality. *Journal of Financial Economics*, 122(3):456–481.

Foucault, T. and Menkveld, A. J. (2008). Competition for order flow and smart order routing systems. *The Journal of Finance*, 63(1):119–158.

Goldstein, I., Spatt, C. S., and Ye, M. (2021). Big data in finance. *The Review of Financial Studies*, 34(7):3213–3225.

Gresse, C. (2017). Effects of lit and dark market fragmentation on liquidity. *Journal of Financial Markets*, 35:1–20.

Griffiths, M. D., Smith, B. F., Turnbull, D. A. S., and White, R. W. (2000). The costs and determinants of order aggressiveness. *Journal of Financial Economics*, 56(1):65–88.

Hagströmer, B. (2021). Bias in the effective bid-ask spread. *Journal of Financial Economics*, 142(1):314–337.

Hamilton, J. L. (1979). Marketplace fragmentation, competition, and the efficiency of the stock exchange. *The Journal of Finance*, 34(1):171–187.

Haslag, P. H. and Ringgenberg, M. C. (2021). The demise of the nyse and nasdaq: Market quality in the age of market fragmentation. *Working Paper*.

Hatheway, F., Kwan, A., and Zheng, H. (2017). An empirical analysis of market segmentation on us equity markets. *Journal of Financial and Quantitative Analysis*, 52(6):2399–2427.

Holden, C. W. and Jacobsen, S. (2014). Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions. *The Journal of Finance*, 69(4):1747–1785.

Irtisam, R. and Sokolov, K. (2021). Do stock exchanges specialize? evidence from the new jersey transaction tax proposal. *Evidence from the New Jersey Transaction Tax Proposal (October 4, 2021)*.

Kalay, A., Sade, O., and Wohl, A. (2004). Measuring stock illiquidity: An investigation of the demand and supply schedules at the tase. *Journal of Financial Economics*, 74(3):461–486.

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of econometrics*, 133(1):97–126.

Kwan, A., Masulis, R., and McInish, T. H. (2015). Trading rules, competition for order flow and market fragmentation. *Journal of Financial Economics*, 115(2):330–348.

Lausen, J., Clapham, B., Gomber, P., and Bender, M. (2021). Drivers and effects of stock market fragmentation-insights on sme stocks. *Working Paper*.

Lee, T. (2019). Latency in fragmented markets. *Review of Economic Dynamics*, 33:128–153.

Malamud, S. and Rostek, M. (2017). Decentralized exchange. *American Economic Review*, 107(11):3320–62.

Malinova, K. and Park, A. (2020). 'sniping'in fragmented markets. *Available at SSRN 3534367*.

Mendelson, H. (1987). Consolidation, fragmentation, and market performance. *Journal of Financial and Quantitative Analysis*, 22(2):189–207.

Menkveld, A. J., Yueshen, B. Z., and Zhu, H. (2017). Shades of darkness: A pecking order of trading venues. *Journal of Financial Economics*, 124(3):503–534.

Næs, R. and Skjeltorp, J. A. (2006). Order book characteristics and the volume–volatility relation: Empirical evidence from a limit order market. *Journal of Financial Markets*, 9(4):408–432.

Obizhaeva, A. A. and Wang, J. (2013). Optimal trading strategy and supply/demand dynamics. *Journal of Financial Markets*, 16(1):1–32.

O'Hara, M. and Ye, M. (2011). Is market fragmentation harming market quality? *Journal of Financial Economics*, 100(3):459–474.

Pagnotta, E. S. and Philippon, T. (2018). Competing on speed. *Econometrica*, 86(3):1067–1115.

Parlour, C. A. and Seppi, D. J. (2003). Liquidity-based competition for order flow. *The Review of Financial Studies*, 16(2):301–343.

Rostek, M. and Yoon, J. H. (2021). Exchange design and efficiency. *Econometrica*, 89(6):2887–2928.

Rust, J. and Hall, G. (2003). Middlemen versus market makers: A theory of competitive exchange. *Journal of Political Economy*, 111(2):353–403.

Saint-Jean, V. (2021). Promise at dawn: Market fragmentation and liquidity when dark pools are suspended. *Available at SSRN 4034594*.

Shkilko, A., Sokolov, K., and Yelagin, E. (2021). Who benefits from securities exchange innovation? *Available at SSRN 3836084*.

Stoll, H. R. (2001). Market fragmentation. *Financial Analysts Journal*, 57(4):16–20.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Upson, J. and Van Ness, R. A. (2017). Multiple markets, algorithmic trading, and market liquidity. *Journal of Financial Markets*, 32:49–68.

Üslü, S. (2019). Pricing and liquidity in decentralized asset markets. *Econometrica*, 87(6):2079–2140.

Wittwer, M. (2021). Connecting disconnected financial markets? *American Economic Journal: Microeconomics*, 13(1):252–82.

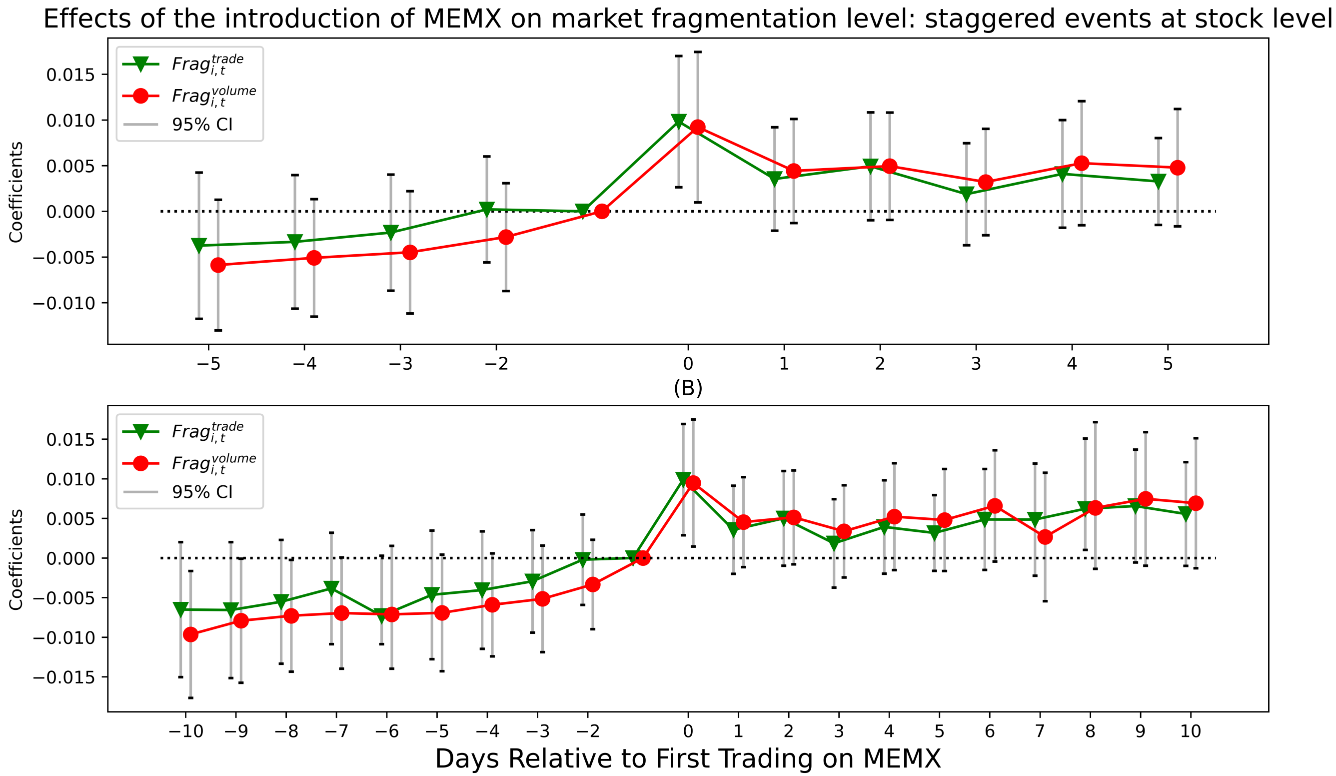

Figure 1: This figure reports the coefficients, γ_j and β_k estimated from the following staggered event-study regressions: $Frag^*_{it} = \alpha_i + \lambda_t + \sum_{j=J}^{-1} \gamma_j D^j_{it} + \sum_{k=0}^{K} \beta_k D^k_{it} + \gamma_{J-} D^{J-}_{it} + \beta_{K+} D^{K+}_{it} + \mathbf{X}'_{it}\Gamma + \epsilon_{it}$. Where $Frag^*_{i,t}$ is the market fragmentation for stock i at trading day t either based on the number of trades or trading volume. $D^j_{i,t}$, and $D^k_{i,t}$ are the indicators for j or k days relative to the event day–the first days that stocks trade on MEMX. D^{J-}_{it} and D^{K+}_{it} are binning indicators for the relative days larger than J and K. $\mathbf{X}'_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. Details are discussed in Section 3.5. Figure (A) reports the case when $K = 5$ and $J = -5$ while figure (B) reports the case when $K = 10$ and $J = -10$.

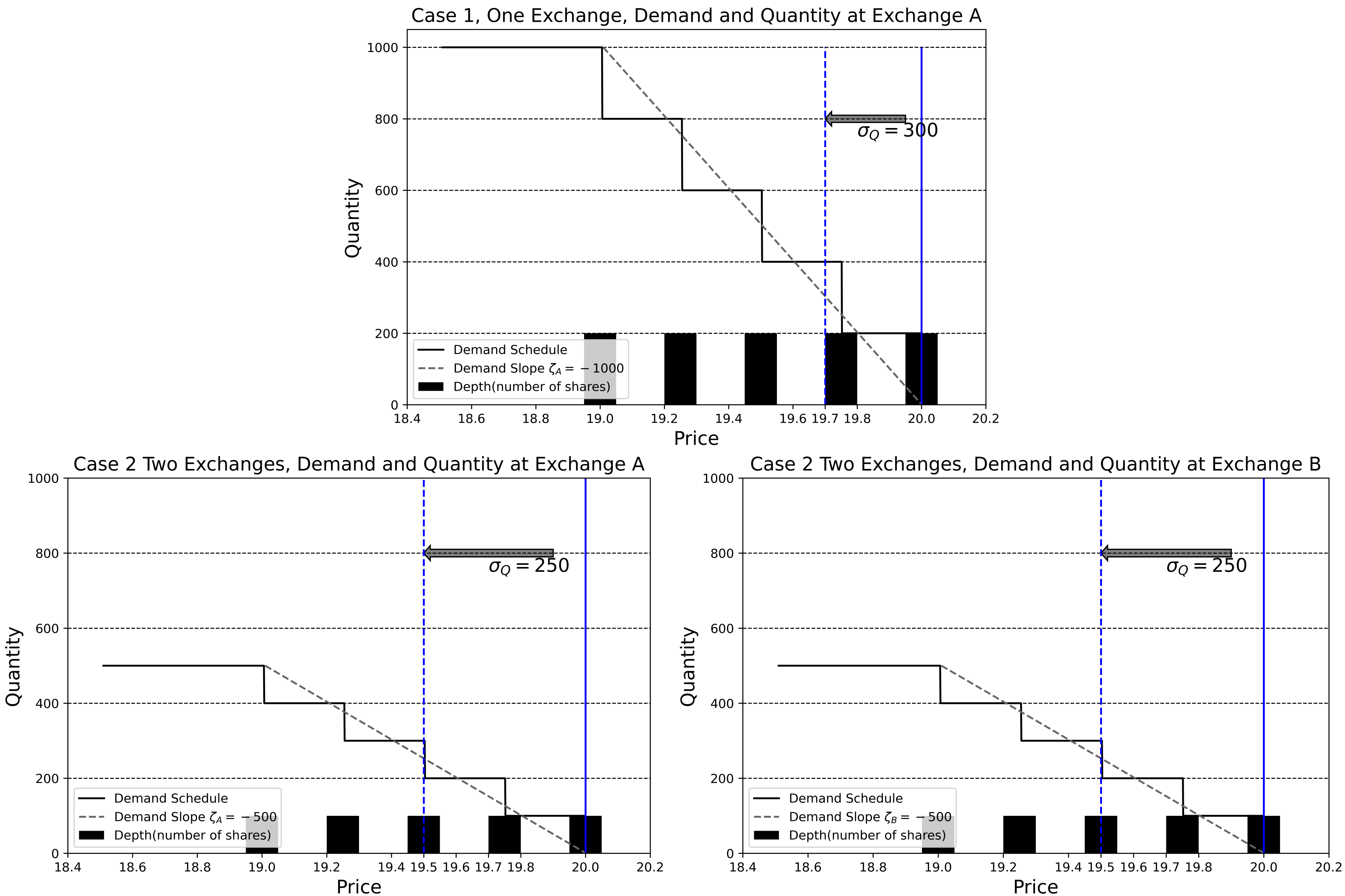

Figure 2: This figure presents the change of demand schedules from one exchange to two exchanges.

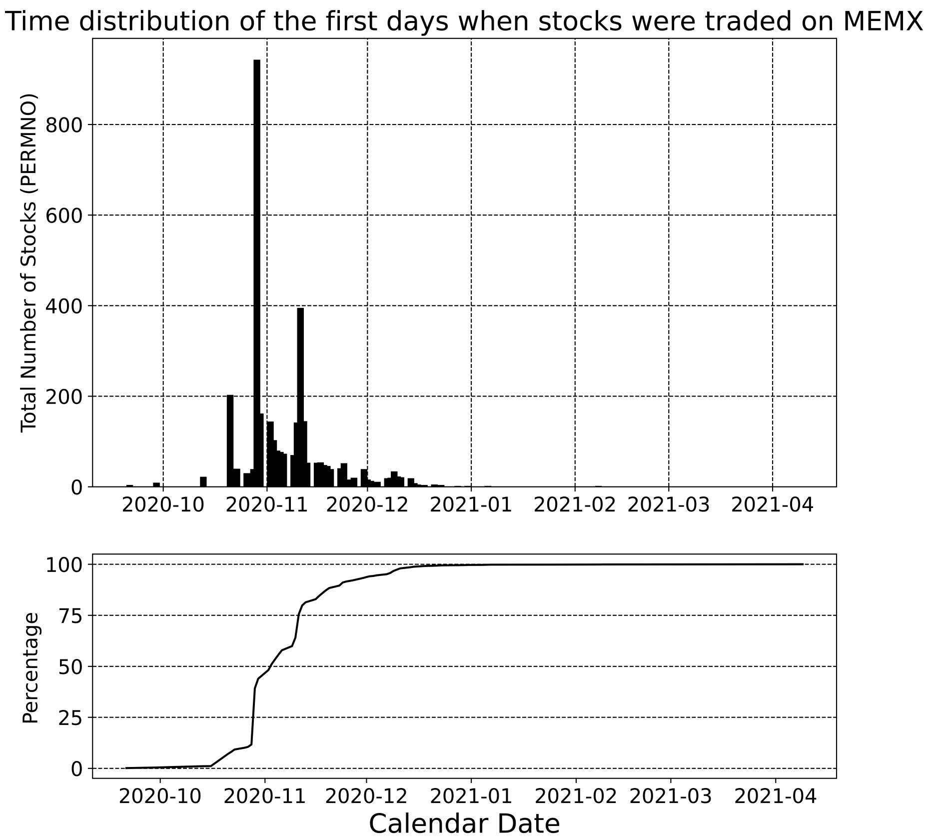

Figure 3: This figure presents the time distribution of the events–the first days that the stocks are traded on MEMX.

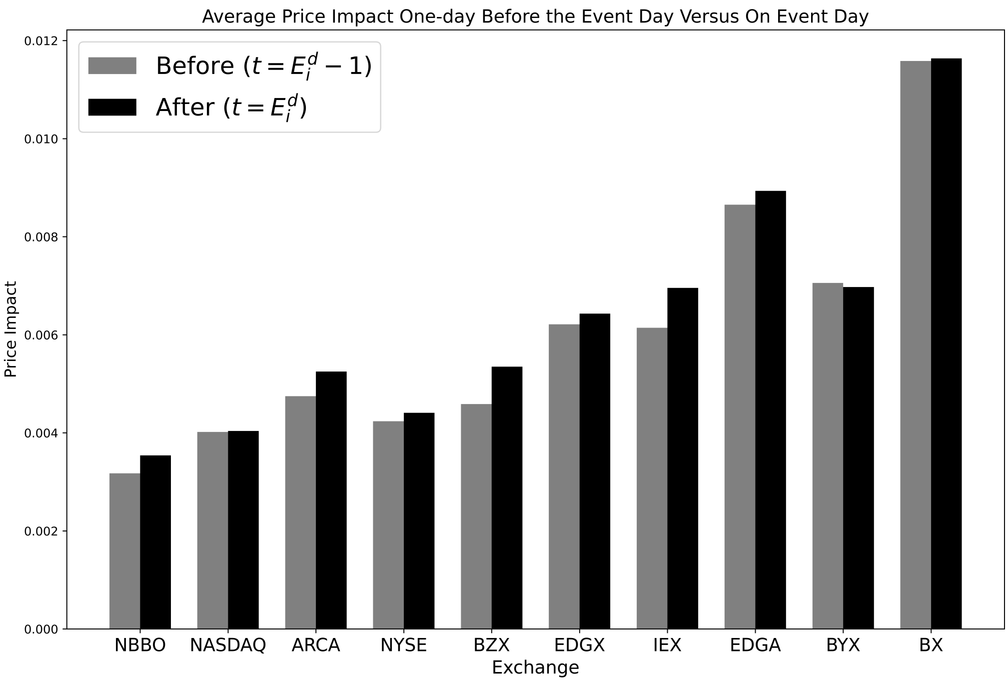

Figure 4: This figure presents the mean price impact one-day before the event days and on the event days–the first calendar days when stocks trade on MEMX.

Table 1. Stock filters and sample selections
This table presents our stock filters and samples. Panel A shows the stock filters that we employ to construct our sample starting from June 1, 2020 to May 28, 2021. We select all U.S. common stocks (share codes 10 and 11 in CRSP) from all securities listed on the NYSE, the American Stock Exchange(AMEX), and the NASDAQ. During our sample period, we exclude delisted stocks, stocks that changed the listing exchange, and stocks where the number of the observations in returns or trading volume are less than 200. We merge the filtered CRSP data with our summarized TAQ data. Panel B shows the daily average stocks and total stock-day observations of our samples. Full sample comprises all observations during our sample period. Details are discussed in Section 3.1

Panel A: Stock filters

CRSP filters	NYSE	AMEX	NASDAQ
Common stocks listed on NYSE, NASDAQ and AMEX at the last trading day in our sample period	1,382	153	2,696
Stocks that changed the listing exchange	−4	−5	−38
Stocks that were delisted	−13	−2	−31
Stocks with less than 200 observations of returns or trading volume	−181	−13	−487
	1,184	133	2,140
TAQ filters			
After merging with TAQ	−8	−1	−40
	1,176	**132**	**2,100**

Panel B: Samples

	Full sample
Daily average stocks	3392.8
Total stock-day observations	854,973

Table 2. Descriptive statistics

This table reports the descriptive statistics. Panel A reports by exchange trading statistics. For each lit exchange ψ, we report the average dollar volume ($DollarVolume_t^{\psi}$) and the average number of trades ($Trade_t^{\psi}$) over our sample period from June, 1, 2020 to May, 28, 2021. We report mean (Mean), median (p50), and the number of observations (N) for our calculated variables: price impact ($PI_{i,t}^{\psi}$), depth at best bid ($BIDDepth_{i,t}^{\psi}$) and trade size ($TradeSize_{i,t}^{\psi}$). Panel B reports CRSP and NBBO-based statistics. We report mean (Mean), standard deviation (STD), 1 percentile (p1), median (p50), 99 percentiles (p99) and the number of observations for the following variables: $Frag_{i,t}^{trade}$, market fragmentation based on the number of trades across lit exchanges; $Frag_{i,t}^{volume}$ market fragmentation based on the trading volume; $OnMEMX_{i,t}$, the indicators if the stock i is traded on MEMX at trading day t; $PI_{i,t}$, price impact based on NBBO; $BIDDepth_{i,t}$, depth at national best bid; $Volume_{i,t}$, trading volume in shares (in thousand) from CRSP; $Volatility_{i,t}$, the standard deviation of squared returns over the past 20-trading days; $Marketcap_{i,t}$, the product of the number of shares outstanding and share price (in million); $Price_{i,t}$ the closing price from CRSP.

Panel A: By Exchange Trading Statistics

Exchange(ψ)	$DollarVolume_t^{\psi}$	$PI_{i,t}^{\psi}$ (Price Impact)			$BIDDepth_{i,t}^{\psi}$ (Bid)			$TradeSize_{i,t}^{\psi}$		
Name (DTAQ Code)	Market%	Mean	p50	N	Mean	p50	N	Mean	p50	N
NASDAQ (Q+T)	32.13%	0.345%	0.174%	831,573	692.7	209.5	834,529	100.2	65.21	852,604
ARCA (P)	15.56%	0.444%	0.287%	818,696	488.2	170.9	833,499	93.03	58.44	839,708
NYSE (N)	12.70%	0.462%	0.164%	743,705	471.9	169.9	807,655	115.4	78.09	770,168
EDGX (K)	10.88%	0.684%	0.386%	820,922	639.0	268.9	831,391	108.8	68.73	842,914
BZX (Z)	10.61%	0.414%	0.225%	812,563	329.7	143.3	834,011	76.06	52.99	834,157
IEX (V)	5.48%	0.518%	0.142%	689,641	228.8	146.7	678,831	87.15	75.25	813,854
EGDA (J)	2.97%	0.814%	0.526%	775,284	131.0	104.8	827,060	64.85	55.72	795,623
BYX (Y)	2.67%	0.642%	0.404%	794,356	149.7	104.2	829,492	67.37	52.89	815,679
BX (B)	1.51%	1.040%	0.372%	706,585	147.3	108.4	728,813	67.97	51.24	774,183
National (C)	1.50%	3.010%	0.968%	702,374	138.3	101.3	727,236	62.52	51.00	758,275
PSX (X)	1.39%	1.970%	0.498%	656,811	218.7	122.1	735,222	88.80	74.17	688,593
Chicago (M)	1.03%	0.144%	0.000%	395,321	309.6	100.4	689,647	680.1	79.80	419,131
AMEX (A)	0.53%	0.409%	0.146%	624,317	167.1	100.5	725,177	62.57	44.3	660,934

continue

Panel B: CRSP and NBBO-based Statistics

Variables	Mean	STD	p1	p50	p99	N
$Frag_{i,t}^{trade}$	0.752	0.102	0.368	0.771	0.883	854,973
$Frag_{i,t}^{volume}$	0.714	0.117	0.188	0.740	0.852	854,973
$Frag_{i,t}^{tradeInv}$	4.547	1.468	1.581	4.371	8.515	854,976
$Frag_{i,t}^{volumeInv}$	3.915	1.179	1.231	3.840	6.746	854,976
$OnMEMX_{i,t}$	0.490	0.500	0	0	1	854,973
$PI_{i,t}^{NBBO}$	0.284%	0.534%	−0.278%	0.157%	2.190%	839,332
$Depth_{i,t}$	1,045	4,802	111.3	276.2	13,483	854,869
$Volume_{i,t}$	1,822	8,632	0.906	363.5	25,066	854,973
$Volatility_{i,t}$	0.038	0.037	0.008	0.030	0.153	854,858
$Marketcap_{i,t}$	10,356	62,343	11.46	880.0	174,396	854,973
$Price_{i,t}$	55.13	150.0	0.630	21.60	468.0	854,973
$ORDERVOL_{i,t}^{MEMX}$	496.3	2,332	0	26.31	8,397	458,856

Table 3. The effect of market fragmentation on price impact

This table reports the effects of market fragmentation on price impact. For each exchange ψ, we run a two-stage least square regression as the following:

First-stage: $\Delta Frag^{*}_{i,t} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}^{'}_{it}\Phi + \Delta\epsilon_{it}$

Second-stage: $\Delta PI^{\psi}_{i,t} = \Delta\lambda_t + \mu\Delta\widehat{Frag}^{*}_{i,t} + \Delta\mathbf{X}^{'}_{it}\Gamma + \Delta\epsilon_{it}$

Where Δ is the first difference operator, $OnMEMX_{i,t}$ is the indicators if the stock i is traded at MEMX on day t, $\Delta\widehat{Frag}^{*}_{i,t}$ is the predicted value from the first-stage regression, and $\mathbf{X}^{'}_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchanges. N denotes the number of observations. Standard errors clustered at both stock and day levels are reported in parentheses. We report the second-stage estimates (μ), first-stage estimates (δ), and weak IV test statistics. Kleibergen and Paap (2006) (K-P) rk F statistics are reported. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

	Second-stage					First-stage	
Dependent:	Independent:					Estimates	Tests
$\Delta PI^{\psi}_{i,t}$	$\Delta\widehat{Frag}^{trade}_{i,t}$	$\Delta\widehat{Frag}^{volume}_{i,t}$	Controls	Day FE	N	δ	K-P
NBBO	0.0260*** (0.003)		Y	Y	834,156	0.0140***	199.6
		0.0241*** (0.003)	Y	Y		0.0150***	169.2
NASDAQ (Q+T)	0.0400*** (0.007)		Y	Y	824,218	0.0134***	195.3
		0.0376*** (0.007)	Y	Y		0.0143***	164.2
ARCA (P)	0.0554*** (0.007)		Y	Y	805,977	0.0106***	225.2
		0.0491*** (0.006)	Y	Y		0.0120***	170.3
NYSE (N)	0.0768*** (0.015)		Y	Y	714,984	0.0066***	152.6
		0.0660*** (0.013)	Y	Y		0.0077***	111.9
BZX (Z)	0.0771*** (0.009)		Y	Y	798,129	0.0093***	207.2
		0.0691*** (0.008)	Y	Y		0.0104***	158.4
EDGX (K)	0.0590*** (0.007)		Y	Y	808,862	0.0119***	213.1
		0.0534*** (0.007)	Y	Y		0.0131***	169.0
IEX (V)	0.0562** (0.026)		Y	Y	644,892	0.0063***	140.7
		0.0524** (0.024)	Y	Y		0.0068***	75.4
EDGA (J)	0.0785*** (0.017)		Y	Y	756,034	0.0082***	204.1
		0.0713*** (0.016)	Y	Y		0.0090***	125.3
BYX (Y)	0.0763*** (0.014)		Y	Y	774,033	0.0085***	192.6
		0.0669*** (0.013)	Y	Y		0.0097***	139.5
BX (B)	0.1894*** (0.052)		Y	Y	684,579	0.0056***	117.8
		0.1671*** (0.047)	Y	Y		0.0064***	74.6
National (C)	−0.0925 (0.100)		Y	Y	680,021	0.0050***	100.0
		−0.0816 (0.089)	Y	Y		0.0057***	62.5
PSX (X)	0.3033** (0.121)		Y	Y	613,467	0.0045***	69.7
		0.2744** (0.108)	Y	Y		0.0050***	50.1
Chicago (M)	−0.0004 (0.029)		Y	Y	299,690	0.0038***	32.6
		−0.0005 (0.030)	Y	Y		0.0037***	24.3
AMEX (A)	0.0869*** (0.025)		Y	Y	571,535	0.0058***	83.1
		0.0804*** (0.025)	Y	Y		0.0062***	51.9

Table 4. Robustness Tests
This table summarizes the robustness tests that we conduct. We address several concerns with regard to the validity of our main results by conducting various robustness tests. We illustrate the details of how we address them and the results are reported in the tables in Appendix A.

Concerns	Details	Tables
Alternative Fragmentation Measures	Inverse of HHI index used by Gresse (2017) and Lausen et al. (2021)	Table A.6
Alternative Price Impact Measures	Price impact based on Hagströmer (2021) estimator	Table A.7
	Price impact based on the 15-seconds interval after a trade	Table A.8
Heterogeneous Effects across Stocks	Sub-sample analysis based on the listing exchange	Table A.9
	Small stocks versus large stocks	Table A.10
Reverse Causality & Endogenous Venue Choice	Observations from October 15th to October 29th, 2020 for 935 stocks traded on MEMX on the first day when MEMX is introduced	Table A.11
Order Routing & NMS Order Protection Rule	Price impact based on ISO trades only	Table A.12
External Validity	The introduction of MIAX Pearl Equities Exchange (MIAX)	Table A.13

Table 5. Placebo tests.

This table reports the placebo tests of the results in our main table, Table 4. We construct ten random indicators which we use as artificial indicators if the stock i is traded on MEMX at day t. We denote them as $On\widehat{PLACEBO}_{i,t}$. The construction of the placebo indicators is discussed in detail in Section 4.2. Specifically, we run the following two-stage least (2SLS) regression using the random generated variable $\Delta On\widehat{PLACEBO}_{i,t}$ in replace of the $\Delta OnMEMX_{i,t}$ in the first-stage:

First-stage: $\Delta Frag^{*}_{i,t} = \Delta\lambda_t + \delta\Delta On\widehat{PLACEBO}_{i,t} + \Delta\mathbf{X}'_{it}\Phi + \Delta\epsilon_{it}$

Second-stage: $\Delta PI^{\psi}_{i,t} = \Delta\lambda_t + \mu\Delta\widehat{Frag}^{*}_{i,t} + \Delta\mathbf{X}'_{it}\Gamma + \Delta\epsilon_{it}$

We run ten 2SLS regressions of market fragmentation on price impact using ten different generated random variables of $OnPLACEBO_{i,t}$. We classify the estimated coefficients μ in the second-stage regression into four categories–positively not significant at 10% level (+), positively significant at 10% level ($+^*$), negatively not significant at 10% level ($-$) and negatively significant at 10% level ($-^*$)

Dependent:	Independent:							
$\Delta PI^{\psi}_{i,t}$	$\Delta\widehat{Frag}^{trade}_{i,t}$				$\Delta\widehat{Frag}^{volume}_{i,t}$			
	Number of coefficients μ are:							
	$+$	$+^*$	$-$	$-^*$	$+$	$+^*$	$-$	$-^*$
NBBO	8	0	2	0	8	0	2	0
NASDAQ (Q+T)	8	0	2	0	10	0	0	0
ARCA (P)	4	0	6	0	4	0	6	0
NYSE (N)	5	0	5	0	3	0	7	0
BZX (Z)	7	0	3	0	6	0	4	0
EDGX (K)	5	0	5	0	6	0	4	0
IEX (V)	5	0	5	0	7	0	3	0
EDGA (J)	4	0	6	0	4	0	6	0
BYX (Y)	6	0	4	0	5	0	5	0
BX (B)	6	0	4	0	5	0	5	0
National (C)	6	0	4	0	5	0	5	0
PSX (X)	2	0	8	0	2	0	8	0
Chicago (M)	3	0	7	0	5	0	5	0
AMEX (A)	2	0	8	0	2	0	8	0

Table 6. The effects of order flow shifting to MEMX on market depth.
This table reports the effects on market depth across existing lit exchanges due to order flow shifting to MEMX around the launch of MEMX. For each lit exchange ψ with a specific estimation window, we estimate the following regressions:
$\ln BIDDepth^{\psi}_{i,t} = \alpha_i + \lambda_t + \pi ORDERVOL^{MEMX}_{i,t} + \mathbf{X}^{'}_{it}\Gamma + \epsilon_{i,t}$
$\ln ASKDepth^{\psi}_{i,t} = \alpha_i + \lambda_t + \Pi ORDERVOL^{MEMX}_{i,t} + \mathbf{X}^{'}_{it}\Gamma + \epsilon_{i,t}$
Where $\ln BIDDepth^{\psi}_{i,t}$ ($\ln ASKDepth^{\psi}_{i,t}$) is the natural logarithm of time-weighted market depth for the best bid (ask) prices for stock i at trading day t. $ORDERVOL^{MEMX}_{i,t}$ is the total volume (in million) for all orders submitted to MEMX for tock i at trading day t. $\mathbf{X}^{'}_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. α_i is the stock fixed effect and λ_t is the day fixed effect. We select the 10 days, 20 days and 60 days estimation windows around October 29, 2020, which is the official day that all stocks are allowed to be traded on MEMX. We denote them as (−10, +9), (−20, +19) and (−60, +59). Each cell reports the coefficient of the regression of the log of market depth at each lit exchange ψ on order volume for MEMX. Standard errors clustered at both stock and day levels are reported in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively. We report the average of the number of observations (Average N) and the average of R-squared for the regressions in the same estimation windows.

	Estimation Windows					
Exchange: ψ	(−10, +9)		(−20, +19)		(−60, +59)	
	π (Bid)	Π (Ask)	π (Bid)	Π (Ask)	π (Bid)	Π (Ask)
NASDAQ (Q+T)	−0.0120***	−0.0134***	−0.0190***	−0.0201***	−0.0317***	−0.0313***
	(0.0029)	(0.0022)	(0.0039)	(0.0035)	(0.0084)	(0.0114)
ARCA (P)	−0.0122***	−0.0080***	−0.0175***	−0.0128***	−0.0202***	−0.0145**
	(0.0019)	(0.0012)	(0.0031)	(0.0026)	(0.0040)	(0.0072)
NYSE (N)	−0.0102***	−0.0071***	−0.0116***	−0.0101***	−0.0343***	−0.0292***
	(0.0021)	(0.0017)	(0.0029)	(0.0029)	(0.0081)	(0.0111)
BZX (Z)	−0.0101***	−0.0076***	−0.0116***	−0.0087***	−0.0135***	−0.0073**
	(0.0023)	(0.0019)	(0.0023)	(0.0020)	(0.0025)	(0.0029)
EDGX (K)	−0.0108***	−0.0046**	−0.0138***	−0.0074***	−0.0187***	−0.0082
	(0.0026)	(0.0016)	(0.0022)	(0.0023)	(0.0027)	(0.0062)
IEX (V)	−0.0128***	−0.0046	−0.0155***	−0.0091**	0.0255*	0.0304***
	(0.0020)	(0.0049)	(0.0025)	(0.0043)	(0.0131)	(0.0109)
EDGA (J)	−0.0052**	−0.0042*	−0.0117***	−0.0100***	−0.0159***	−0.0128***
	(0.0021)	(0.0023)	(0.0034)	(0.0030)	(0.0022)	(0.0036)
BYX (Y)	−0.0043	−0.0071*	−0.0052*	−0.0061**	−0.0074***	−0.0045**
	(0.0032)	(0.0038)	(0.0028)	(0.0029)	(0.0026)	(0.0021)
BX (B)	−0.0043*	−0.0037**	−0.0070***	−0.0047**	−0.0102***	−0.0069***
	(0.0021)	(0.0014)	(0.0021)	(0.0021)	(0.0023)	(0.0026)
National (C)	−0.0101***	−0.0013	−0.0103***	−0.0043	−0.0132***	−0.0081*
	(0.0022)	(0.0012)	(0.0022)	(0.0029)	(0.0022)	(0.0048)
PSX (X)	−0.0109***	−0.0017	−0.0080***	−0.0036	−0.0073**	−0.0013
	(0.0024)	(0.0029)	(0.0028)	(0.0034)	(0.0029)	(0.0049)
Chicago (M)	−0.0153	−0.0044	−0.0118	−0.0086	−0.0352***	−0.0288***
	(0.0111)	(0.0092)	(0.0073)	(0.0066)	(0.0091)	(0.0079)
AMEX (A)	−0.0011	−0.0066**	−0.0057*	−0.0079**	−0.0065***	−0.0055
	(0.0018)	(0.0024)	(0.0033)	(0.0032)	(0.0021)	(0.0035)
Average N	60,114	60,114	120,758	120,758	364,296	364,296
Average R-Squared	75.2%	76.2%	74.0%	74.4%	66.0%	60.9%

Table 7. Changes in order aggressiveness around the introduction of MEMX.

This table presents the changes in order aggressiveness for stocks trading on NASDAQ stock exchange around the launch of MEMX. For each stock i at trading day t, we use NASDAQ TotalView-ITCH data to classify all the orders entered in the NASDAQ trading system into eight categories based on their aggressiveness. We follow the approach used by Biais et al. (1995) and classify orders that result in inside BBO trades, large trades (marketable orders walk the LOB in NASDAQ), small trades (orders executed at BBO but with trade size smaller than the depth at BBO), and improvement in BBO (either order improving the BBO price or improving the BBO depth) into aggressive orders. We also classify orders that result in addition in LOB, revision in LOB, cancellation in LOB, and deletion in LOB into unaggressive orders. For each stock-day observation, the variables are in percentage and their summary statistics are reported in Appendix B, Table B.1. We select the sample with trading days t between $E_i^d - 20$ and $E_i^d + 19$ in this table and report a different estimation window in Appendix B, Table B.2 and a falsified estimation window in Appendix B, Table B.3. We report the results for the buy side and sell side separately in Panel A and Panel B. We run the following regression for each order aggressiveness type:

$\%Order^*_{i,t} = \alpha_i + \lambda_t + \omega \mathbb{1}(t >= E_i^d) + \mathbf{X}'_{it}\Gamma + \epsilon_{i,t}$

Where $\%Order^*_{i,t}$ represents the percentage of orders in that category, for instance, the percentage of orders that result in large trades. E_i^d is the calendar day that when stock i is first traded on MEMX. $\mathbb{1}$ represents the indicator function. $\mathbf{X}'_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively. Standard errors clustered at both stock and day levels are reported in parentheses. N denotes the number of observations.

Panel A: Buy Side

	Aggressive orders (%) result in:				Unaggressive orders (%) result in:			
	Inside BBO Trades	Large Trades	Small Trades	Improvement in BBO	Addition in LOB	Revision in LOB	Cancellation in LOB	Deletion in LOB
ω	0.0039***	0.1478***	0.1355***	0.6694***	−0.6230***	−0.1633	0.0088	−0.2111**
	(0.0015)	(0.0259)	(0.0243)	(0.1559)	(0.1520)	(0.1670)	(0.0177)	(0.0891)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y	Y	Y	Y	Y
N	64,558	89,484	130,564	135,738	136,192	136,017	64,458	136,190
R-Squared	35.7%	46.2%	25.1%	65.0%	58.6%	67.4%	43.6%	57.3%

Panel B: Sell Side

	Aggressive orders (%) result in:				Unaggressive orders (%) result in:			
	Inside BBO Trades	Large Trades	Small Trades	Improvement in BBO	Addition in LOB	Revision in LOB	Cancellation in LOB	Deletion in LOB
ω	0.0055***	0.1294***	0.1021***	0.6580***	−0.5857***	−0.1395	−0.0099	−0.2020**
	(0.0018)	(0.0238)	(0.0193)	(0.1379)	(0.1346)	(0.1752)	(0.0233)	(0.0880)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y	Y	Y	Y	Y
N	64,794	93,242	131,417	135,737	136,192	136,056	67,476	136,190
R-Squared	37.2%	48.5%	22.0%	65.5%	59.8%	73.8%	36.6%	64.4%

Table 8. Changes in orderbook slope around the introduction of MEMX.
This table presents the changes in order book slopes for stocks trading on the NASDAQ stock exchange around the launch of MEMX. For each stock i at trading day t, we use NASDAQ TotalView-ITCH data to reconstruct the limit order book and calculate the order book slopes for the ask side as well as the bid side following Equation (10) and Equation (12) based on Næs and Skjeltorp (2006) and Kalay et al. (2004), respectively. We run the following four regressions for two different estimation windows:

$SLOPEBID_{i,t}^{NS} = \alpha_i + \lambda_t + \rho \mathbb{1}(t >= \tilde{E}_i^d) + \mathbf{X}_{it}^{'}\Gamma + \epsilon_{i,t}$
$SLOPEBID_{i,t}^{Kalay} = \alpha_i + \lambda_t + \rho \mathbb{1}(t >= \tilde{E}_i^d) + \mathbf{X}_{it}^{'}\Gamma + \epsilon_{i,t}$
$SLOPEASK_{i,t}^{NS} = \alpha_i + \lambda_t + \rho \mathbb{1}(t >= \tilde{E}_i^d) + \mathbf{X}_{it}^{'}\Gamma + \epsilon_{i,t}$
$SLOPEASK_{i,t}^{Kalay} = \alpha_i + \lambda_t + \rho \mathbb{1}(t >= \tilde{E}_i^d) + \mathbf{X}_{it}^{'}\Gamma + \epsilon_{i,t}$

Where $\tilde{E}_i^d$ represents the first day that the stock i is quoted on MEMX. $\mathbb{1}$ represents the indicator function. $\mathbf{X}_{it}^{'}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively. Standard errors clustered at both stock and day levels are reported in parentheses. N denotes the number of observations. All the dependent variables are winsorized at 1% and 99% to eliminate the outliers.

		Bid Side ($SLOPEBID_{i,t}^{*}$)		Ask Side ($SLOPEASK_{i,t}^{*}$)	
		NS	Kalay	NS	Kalay
$\tilde{E}_i^d - 40 < t < \tilde{E}_i^d + 39$	ρ	6011.0***	1.331***	−5584.5***	−1.532***
		(1866.0)	(0.2692)	(1490.8)	(0.2545)
	Controls	Y	Y	Y	Y
	Day FE	Y	Y	Y	Y
	Stock FE	Y	Y	Y	Y
	N	233,320	233,320	233,320	233,320
	R-Squared	83.5%	88.9%	85.7%	89.3%
$\tilde{E}_i^d - 20 < t < \tilde{E}_i^d + 19$	ρ	3349.8**	0.5732**	−3619.7**	−0.7241***
		(1679.3)	(0.2553)	(1384.9)	(0.2270)
	Controls	Y	Y	Y	Y
	Day FE	Y	Y	Y	Y
	Stock FE	Y	Y	Y	Y
	N	133,961	133,961	133,961	133,961
	R-Squared	83.4%	88.7%	86.0%	89.1%

Table 9. Liquidity supply and demand dynamics around the launch of MEMX.
This table presents the changes in liquidity supply and the changes in liquidity demand across primary lit exchanges around the launch of MEMX. We use market depth at best bid prices, $BIDDepth^{\psi}_{i,t}$, as the proxy for liquidity supply. We use trade sizes,$TradeSize^{\psi}_{i,t}$, and Intermarket Sweep Orders (ISO) trade sizes, $ISOTradeSize^{\psi}_{i,t}$ as the proxy for liquidity demand. We discuss the proxies in detail in Section 4.3. We select the 20 days and the 60 days estimation windows around October 29, 2020, which is the official day that all stocks are allowed to be traded on MEMX. We denote them as (−20, +19) and (−60, +59). We report the averages of market depth at best bid prices, $BIDDepth^{\psi}_{i,t}$, trade sizes, $TradeSize^{\psi}_{i,t}$, and ISO trade sizes, $ISOTradeSize^{\psi}_{i,t}$ for PRE (days before October 29, 2020), POST (after October 29, 2020), DIFF% (the differences in percentage between POST and PRE), and DIFF (differences between POST and PRE), respectively. Standard errors clustered at both stock and day levels are reported in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, 1% level for two sample t-test, respectively.

		Liquidity-supplying Side: Market Depth at Bid		Liquidity-demanding Side: Trade Size		ISO Trade Size	
Exchange: ψ		(−20, +19)	(−60, +59)	(−20, +19)	(−60, +59)	(−20, +19)	(−60, +59)
NASDAQ (Q+T)	*PRE*	726.56	760.69	102.23	103.22	104.85	106.54
	POST	658.75	630.14	102.13	101.65	99.98	97.43
	DIFF%	−9.33%	−17.2%	−0.10%	−1.52%	−4.65%	−8.55%
	DIFF	−67.80***	−130.55***	−0.107	−1.569***	−4.872***	−9.113***
ARCA (P)	*PRE*	501.79	526.53	97.36	97.45	103.01	104.43
	POST	475.95	469.92	99.42	95.90	103.18	98.61
	DIFF%	−5.15%	−10.8%	2.11%	−1.60%	0.17%	−5.62%
	DIFF	−25.84**	−56.61***	2.055**	−1.556***	0.172	−5.827***
NYSE (N)	*PRE*	560.24	519.08	115.62	119.23	122.05	120.57
	POST	511.68	478.45	121.73	120.48	116.07	116.64
	DIFF%	−8.67%	−7.83%	5.28%	1.05%	−4.90%	−3.26%
	DIFF	−48.56***	−40.62***	6.109	1.255	−5.979***	−3.93***
BZX (Z)	*PRE*	338.25	337.95	77.04	77.92	82.53	83.50
	POST	330.36	326.70	77.06	77.61	80.69	80.19
	DIFF%	−2.33%	−3.33%	0.02%	−0.40%	−2.23%	−3.96%
	DIFF	−7.894	−11.25***	0.015	−0.313	−1.843***	−3.305***
EDGX (K)	*PRE*	629.79	649.50	110.22	109.57	114.04	114.81
	POST	602.42	634.45	112.09	112.05	113.74	112.80
	DIFF%	−4.35%	−2.32%	1.70%	2.27%	−0.26%	−1.75%
	DIFF	−27.37***	−15.06***	1.871**	2.484***	−0.299	−2.007***

Appendix A

Table A.1. The description of exchange and its code in DTAQ data.
This table illustrates our abbreviations of lit exchanges (exchange), the participant id in DTAQ (DTAQ Code), and the full names of the exchange (Description). Sources are from the NYSE DTAQ client manual.

Exchange	DTAQ Code	Description
NASDAQ	Q	NASDAQ Stock Exchange, LLC (in Tape C securities)
NASDAQ	T	NASDAQ Stock Market, LLC (in Tape A, B securities)
ARCA	P	NYSE Arca, Inc
NYSE	N	New York Stock Exchange, LLC
BZX	Z	Cboe BZX Exchange, Inc
EDGX	K	Cboe EDGX Exchange
IEX	V	The Investors' Exchange, LLC
EDGA	J	Cboe EDGA Exchange
BYX	Y	Cboe BYX Exchange
BX	B	NASDAQ OMX BX, Inc
National	C	NYSE National, Inc
PSX	X	NASDAQ OMX PSX, Inc
Chicago	M	Chicago Stock Exchange, Inc.
AMEX	A	NYSE American, LLC
MEMX	U	Members Exchange

Table A.2. The number of stocks traded on MEMX after they are first traded on MEMX.

This table reports the number of stocks traded on MEMX after the event days, E_i^d–the first calendar days that stocks are traded on MEMX. We report the number of stocks traded on MEMX ($OnMEMX = 1$) and the number of stocks not traded on MEMX ($OnMEMX = 0$) for the first 20 calendar days after stocks is first traded on MEMX.

$t =$	$OnMEMX = 0$	$OnMEMX = 1$	Total Stocks
E_i^d	0	3,408	3,408
$E_i^d + 1$	1,576	1,830	3,406
$E_i^d + 2$	1,684	1,720	3,404
$E_i^d + 3$	1,654	1,753	3,407
$E_i^d + 4$	1,577	1,828	3,405
$E_i^d + 5$	1,389	2,018	3,407
$E_i^d + 6$	1,305	2,101	3,406
$E_i^d + 7$	1,279	2,128	3,407
$E_i^d + 8$	1,110	2,298	3,408
$E_i^d + 9$	973	2,435	3,408
$E_i^d + 10$	964	2,439	3,403
$E_i^d + 11$	925	2,481	3,406
$E_i^d + 12$	834	2,573	3,407
$E_i^d + 13$	779	2,625	3,404
$E_i^d + 14$	686	2,722	3,408
$E_i^d + 15$	667	2,738	3,405
$E_i^d + 16$	632	2,773	3,405
$E_i^d + 17$	540	2,864	3,404
$E_i^d + 18$	563	2,841	3,404
$E_i^d + 19$	542	2,861	3,403
$E_i^d + 20$	526	2,880	3,406

Table A.3. Paired t-test for the change of cross-sectional market fragmentation around the introduction of MEMX.

This table reports the cross-sectional mean of the market fragmentation, $Frag_{\bar{i},t}$, and the mean of the first-difference of the market fragmentation, $\Delta Frag_{\bar{i},t}$, around the introduction of MEMX. E_i^d is the calendar day that when stock i is first traded on MEMX. The number of stocks (N) in the sample is reported. The number in the bracket indicates the total number of stocks with positive changes in market fragmentation. *, **, *** indicates statistical significance at the 5%, 1%, 0.1% level, respectively.

$t=$	$Frag_{\bar{i},t}^{trade}$	$Frag_{\bar{i},t-1}^{trade}$	$\Delta Frag_{\bar{i},t}^{trade}$	N
E_i^d	0.773	0.761	0.011***	3,406
	(0.002)	(0.002)	(0.002)	[1,950]
E^d+3	0.763	0.765	−0.002	3,403
	(0.002)	(0.002)	(0.001)	[1,667]
E^d-3	0.761	0.760	0.001	3,402
	(0.002)	(0.002)	(0.002)	[1,741]
E^d+7	0.764	0.762	0.002	3,405
	(0.001)	(0.002)	(0.001)	[1,691]
E^d-7	0.758	0.762	−0.004*	3,403
	(0.002)	(0.002)	(0.001)	[1,671]
E^d+20	0.769	0.767	0.002	3,400
	(0.001)	(0.002)	(0.001)	[1,709]
E^d-20	0.753	0.755	−0.002	3,399
	(0.002)	(0.002)	(0.001)	[1,635]

Table A.4. Exogenous change in market fragmentation.
This table shows the magnitude of an exogenous change in market fragmentation when stocks are first traded on MEMX. Our results are based on both ***TWFE*** estimates and Borusyak et al. (2021) ***(BSJ)*** estimates. Column (1) and Column (2) report the estimated coefficients based on the following regressions: $Frag^{*}_{i,t} = \alpha_i + \lambda_t + \beta_0 D^0_{i,t} + \mathbf{X}'_{it}\Gamma + \epsilon_{it}$. Where $D^0_{i,t}$ is a indicator variable if the stock i is first traded on MEMX, and $\mathbf{X}'_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. Column (3) and Column (4) report three-step imputation estimates of Borusyak et al. (2021). Standard errors are reported in parentheses. For TWFE estimates the standard errors are clustered at both stock and day levels. For BJS estimates the asymptotic standard errors are clustered at the stock level. N denotes the number of observations in regressions. *** indicates statistical significance at the 1% level.

	TWFE		*BJS*	
	(1) $Frag^{trade}_{i,t}$	(2) $Frag^{volume}_{i,t}$	(3) $Frag^{trade}_{i,t}$	(4) $Frag^{volume}_{i,t}$
Exogenous Change (β_0)	0.0125***	0.0159***	0.0103***	0.0135***
	(0.0023)	(0.0028)	(0.0015)	(0.0018)
Controls	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y
Day FE	Y	Y	Y	Y
N	854,858	854,858	381,897	381,897

Table A.5. Validity of the instrumental variables: reverse causality and endogenous venue choice.
This table reports the correlations between exchange-based price impact and whether stocks are traded on MEMX ($OnMEMX_{i,t}$) after the introduction of MEMX on October 29, 2020. We select the stocks which are not always traded on MEMX after the introduction of MEMX. For each stock i, we calculate the Pearson Correlation Coefficients between each exchange-based price impact (PI^{ψ}) and whether the stock is traded on MEMX ($OnMEMX$) over our sample period from October 29, 2020, to May 28, 2021. We report the total number of stocks (Total N stocks) which are either positively (+) or negatively (−) correlated. We also report the total number of stocks that the p-values of the null hypotheses–the two variables are independent–are larger than 0.01 or smaller than 0.01, respectively. The number in brackets represents the number of stocks.

			Null Hypotheses: Two variables are independent	
$\psi =$:	$Corr(PI^{\psi}, OnMEMX)$	Total N stocks	p-values > 0.01 (N stocks)	p-values < 0.01 (N stocks)
NASDAQ (Q+T)	+	[1,055]	[1,027]	[28]
	−	[1,728]	[1,515]	[213]
ARCA (P)	+	[1,090]	[1,059]	[31]
	−	[1,681]	[1,467]	[214]
NYSE (N)	+	[996]	[969]	[27]
	−	[1,754]	[1,513]	[241]
BZX (Z)	+	[1100]	[1066]	[34]
	−	[1,679]	[1,511]	[168]
EDGX (K)	+	[990]	[958]	[32]
	−	[1,792]	[1,557]	[235]
IEX (V)	+	[1,599]	[1,572]	[27]
	−	[1,066]	[938]	[128]
EDGA (J)	+	[1,321]	[1,299]	[22]
	−	[1,422]	[1,266]	[156]
BYX (Y)	+	[1,079]	[1,061]	[18]
	−	[1,687]	[1,480]	[207]
BX (B)	+	[1,215]	[1,196]	[19]
	−	[1,383]	[1,211]	[172]
National (C)	+	[1,387]	[1,284]	[103]
	−	[1,275]	[999]	[258]
PSX (X)	+	[1,249]	[1,236]	[13]
	−	[1,350]	[1,201]	[149]
Chicago (M)	+	[1,386]	[1,378]	[8]
	−	[956]	[845]	[111]
AMEX (A)	+	[1,289]	[1,281]	[8]
	−	[1,286]	[1,199]	[87]

Table A.6. The effect of market fragmentation on price impact based on alternative fragmentation measures.
This table reports the effects of market fragmentation on price impact using the alternative measures of market fragmentation proposed by Gresse (2017) and Lausen et al. (2021)—the reciprocal of the HHI, $Frag_{i,t}^{tradeInv}$ and $Frag_{i,t}^{volumeInv}$. For each exchange ψ, we run a two-stage least square regression as the following:
First-stage: $\Delta Frag_{i,t}^{*} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}_{it}^{'}\Phi + \Delta\epsilon_{it}$
Second-stage: $\Delta PI_{i,t}^{\psi} = \Delta\lambda_t + \mu\Delta \widehat{Frag}_{i,t}^{*} + \Delta\mathbf{X}_{it}^{'}\Gamma + \Delta\epsilon_{it}$
Where Δ is the first difference operator, $OnMEMX_{i,t}$ is the indicators if the stock i is traded at MEMX on day t, $\Delta\widehat{Frag}_{i,t}^{*}$ is the predicted value from the first-stage regression, and $\mathbf{X}_{it}^{'}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchanges. N denotes the number of observations. Standard errors clustered at both stock and day levels are reported in parentheses. We report the second-stage estimates (μ), first-stage estimates (δ), and weak IV test statistics. Kleibergen and Paap (2006) (K-P) rk F statistics are reported. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

Second-stage						First-stage	
Dependent:	Independent:					Estimates	Tests
$\Delta PI_{i,t}^{\psi}$	$\Delta\widehat{Frag}_{i,t}^{tradeInv}$	$\Delta\widehat{Frag}_{i,t}^{volumeInv}$	Controls	Day FE	N	δ	K-P
NBBO	0.0023*** (0.0003)		Y	Y	834,156	0.1570***	328.5
		0.0031*** (0.0004)	Y	Y		0.1185***	236.9
NASDAQ (Q+T)	0.0035*** (0.0007)		Y	Y	824,218	0.1525***	308.0
		0.0047*** (0.0009)	Y	Y		0.1141***	220.4
ARCA (P)	0.0042*** (0.0006)		Y	Y	805,977	0.1408***	298.3
		0.0055*** (0.0007)	Y	Y		0.1066***	207.2
NYSE (N)	0.0047*** (0.0009)		Y	Y	714,984	0.1092***	171.1
		0.0062*** (0.0013)	Y	Y		0.0819***	130.6
BZX (Z)	0.0055*** (0.0007)		Y	Y	798,129	0.1305***	275.5
		0.0074*** (0.0009)	Y	Y		0.0977***	191.3
EDGX (K)	0.0047*** (0.0006)		Y	Y	808,862	0.1487***	305.6
		0.0063*** (0.0008)	Y	Y		0.1118***	212.5
IEX (V)	0.0035** (0.0016)		Y	Y	644,892	0.1013***	160.7
		0.0050** (0.0023)	Y	Y		0.0719***	95.5
EDGA (J)	0.0052*** (0.0011)		Y	Y	756,034	0.1243***	236.9
		0.0071*** (0.0015)	Y	Y		0.0909***	150.7
BYX (Y)	0.0053*** (0.0010)		Y	Y	774,033	0.1224***	246.7
		0.0070*** (0.0013)	Y	Y		0.0931***	164.3
BX (B)	0.0109*** (0.0030)		Y	Y	684,579	0.0973***	126.8
		0.0150*** (0.0042)	Y	Y		0.0709***	87.2
National (C)	−0.0053 (0.0057)		Y	Y	680,021	0.0877***	113.6
		−0.0073 (0.0080)	Y	Y		0.0637***	67.7
PSX (X)	0.0165** (0.0066)		Y	Y	613,467	0.0833***	75.3
		0.0231** (0.0092)	Y	Y		0.0595***	56.0
Chicago (M)	−0.0000 (0.0017)		Y	Y	299,690	0.0657***	35.9
		−0.0000 (0.0023)	Y	Y		0.0484***	25.0
AMEX (A)	0.0044*** (0.0013)		Y	Y	571,535	0.1152***	101.3
		0.0063*** (0.0019)	Y	Y		0.0806***	58.5

Table A.7. The effect of market fragmentation on price impact based on alternative price impact measures.
This table reports the effects of market fragmentation on price impact using the alternative measures of price impact based on the weighted midpoint prices proposed by (Hagströmer, 2021). For each exchange ψ, we run a two-stage least square regression as the following:
First-stage: $\Delta Frag^*_{i,t} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}'_{it}\Phi + \Delta\epsilon_{it}$
Second-stage: $\Delta \widetilde{PI}^{\psi}_{i,t} = \Delta\lambda_t + \mu\Delta\widehat{Frag}^*_{i,t} + \Delta\mathbf{X}'_{it}\Gamma + \Delta\epsilon_{it}$
Where Δ is the first difference operator, $OnMEMX_{i,t}$ is the indicators if the stock i is traded at MEMX on day t, $\Delta\widehat{Frag}^*_{i,t}$ is the predicted value from the first-stage regression, and $\mathbf{X}'_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchanges. N denotes the number of observations. Standard errors clustered at both stock and day levels are reported in parentheses. We report the second-stage estimates (μ), first-stage estimates (δ), and weak IV test statistics. Kleibergen and Paap (2006) (K-P) rk F statistics are reported. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

Second-stage						First-stage	
Dependent:	Independent:					Estimates	Tests
$\Delta \widetilde{PI}^{\psi}_{i,t}$	$\Delta\widehat{Frag}^{trade}_{i,t}$	$\Delta\widehat{Frag}^{volume}_{i,t}$	Controls	Day FE	N	δ	K-P
NASDAQ (Q+T)	0.0455*** (0.0089)		Y	Y	824,218	0.0135***	195.3
		0.0428*** (0.0085)	Y	Y		0.0143***	164.2
ARCA (P)	0.0527*** (0.0090)		Y	Y	805,977	0.0106***	225.2
		0.0467*** (0.0078)	Y	Y		0.0120***	170.4
NYSE (N)	0.0801*** (0.0169)		Y	Y	714,984	0.0066***	152.6
		0.0689*** (0.0144)	Y	Y		0.0077***	111.9
BZX (Z)	0.0898*** (0.0101)		Y	Y	798,129	0.0094***	207.2
		0.0805*** (0.0090)	Y	Y		0.0104***	158.4
EDGX (K)	0.0792*** (0.0103)		Y	Y	808,862	0.0119***	213.1
		0.0718*** (0.0094)	Y	Y		0.0132***	169.0
IEX (V)	0.0401 (0.0363)		Y	Y	644,892	0.0063***	140.8
		0.0374 (0.0034)	Y	Y		0.0068***	75.4
EDGA (J)	0.0861*** (0.0173)		Y	Y	756,034	0.0082***	204.1
		0.0782*** (0.0163)	Y	Y		0.0090***	125.3
BYX (Y)	0.0802*** (0.0159)		Y	Y	774,033	0.0085***	192.6
		0.0703*** (0.0142)	Y	Y		0.0097***	139.5
BX (B)	0.1509*** (0.0422)		Y	Y	684,579	0.0056***	117.8
		0.1331*** (0.0386)	Y	Y		0.0064***	74.6
National (C)	−0.0168 (0.0783)		Y	Y	680,021	0.0050***	100.0
		−0.0148 (0.0692)	Y	Y		0.0057***	62.5
PSX (X)	0.2547** (0.1151)		Y	Y	613,467	0.0045***	69.7
		0.2305** (0.1027)	Y	Y		0.0050***	50.1
Chicago (M)	0.0051 (0.0293)		Y	Y	299,690	0.0038***	32.6
		0.0052 (0.0301)	Y	Y		0.0037***	24.3
AMEX (A)	0.0974*** (0.0278)		Y	Y	571,535	0.0058***	83.1
		0.0901*** (0.0265)	Y	Y		0.0063***	51.9

Table A.8. The effect of market fragmentation on price impact based on the 15-seconds-based price impact.
This table reports the effects of market fragmentation on price impact using the alternative measures of price impact–the 15-seconds-based price impact $PI15$. For each exchange ψ, we run a two-stage least square regression as the following:
First-stage: $\Delta Frag^{*}_{i,t} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}'_{it}\Phi + \Delta\epsilon_{it}$
Second-stage: $\Delta PI15^{\psi}_{i,t} = \Delta\lambda_t + \mu\Delta\widehat{Frag}^{*}_{i,t} + \Delta\mathbf{X}'_{it}\Gamma + \Delta\epsilon_{it}$
Where Δ is the first difference operator, $OnMEMX_{i,t}$ is the indicators if the stock i is traded at MEMX on day t, $\Delta\widehat{Frag}^{*}_{i,t}$ is the predicted value from the first-stage regression, and $\mathbf{X}'_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchanges. N denotes the number of observations. Standard errors clustered at both stock and day levels are reported in parentheses. We report the second-stage estimates (μ), first-stage estimates (δ) and weak IV test statistics. Kleibergen and Paap (2006) (K-P) rk F statistics is reported. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

Second-stage						First-stage	
Dependent: $\Delta PI15^{\psi}_{i,t}$	Independent: $\Delta\widehat{Frag}^{trade}_{i,t}$	$\Delta\widehat{Frag}^{volume}_{i,t}$	Controls	Day FE	N	Estimates δ	Tests K-P
NASDAQ (Q+T)	0.0238*** (0.0055)		Y	Y	824,218	0.0135***	195.3
		0.0224*** (0.0053)	Y	Y		0.0143***	164.2
ARCA (P)	0.0341*** (0.0054)		Y	Y	805,977	0.0106***	225.2
		0.0302*** (0.0047)	Y	Y		0.0120***	170.4
NYSE (N)	0.0335*** (0.0103)		Y	Y	714,986	0.0066***	152.6
		0.0288*** (0.0089)	Y	Y		0.0077***	111.9
BZX (Z)	0.0463*** (0.0053)		Y	Y	798,129	0.0094***	207.2
		0.0415*** (0.0049)	Y	Y		0.0104***	158.4
EDGX (K)	0.0313*** (0.0047)		Y	Y	808,862	0.0119***	213.1
		0.0283*** (0.0042)	Y	Y		0.0132***	169.0
IEX (V)	0.0191 (0.0210)		Y	Y	644,892	0.0063***	140.8
		0.0178 (0.00198)	Y	Y		0.0068***	75.4
EDGA (J)	0.0534*** (0.0126)		Y	Y	756,034	0.0485***	204.1
		0.0485*** (0.0120)	Y	Y		0.0090***	125.3
BYX (Y)	0.0484*** (0.0097)		Y	Y	774,033	0.0085***	192.6
		0.0424*** (0.0087)	Y	Y		0.0097***	139.5
BX (B)	0.0825** (0.0342)		Y	Y	684,579	0.0056***	117.8
		0.0728** (0.0304)	Y	Y		0.0064***	74.6
National (C)	−0.0160 (0.0787)		Y	Y	680,021	0.0050***	100.0
		−0.0141 (0.0696)	Y	Y		0.0057***	62.5
PSX (X)	0.2582*** (0.0887)		Y	Y	613,467	0.0045***	69.7
		0.2336*** (0.0772)	Y	Y		0.0050***	50.1
Chicago (M)	−0.0064 (0.0141)		Y	Y	299,690	0.0038***	32.6
		−0.0066 (0.0148)	Y	Y		0.0037***	24.3
AMEX (A)	0.0476** (0.0211)		Y	Y	571,538	0.0058***	82.9
		0.0441** (0.0200)	Y	Y		0.0063***	51.9

Table A.9. The effects of market fragmentation on price impact by the listing exchange.
This table reports the effects of market fragmentation on price impact by the listing exchange. We separate our sample into three subsamples based on the stock's listing exchange. As in Table 3., for each exchange ψ we run a two-stage least square regression as the following:
First-stage: $\Delta Frag_{i,t}^{trade} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}_{it}^{'}\Phi + \Delta\epsilon_{it}$
Second-stage: $\Delta PI_{i,t}^{\psi} = \Delta\lambda_t + \mu\Delta\widehat{Frag}_{i,t}^{trade} + \Delta\mathbf{X}_{it}^{'}\Gamma + \Delta\epsilon_{it}$
Where Δ is the first difference operator, $OnMEMX_{i,t}$ is the indicator if the stock i is traded at MEMX on day t, $\Delta\widehat{Frag}_{i,t}^{*}$ is the predicted value from the first-stage regression, and $\mathbf{X}_{it}^{'}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchanges. We report the second-stage estimates (μ), and their standard errors (in parentheses) clustered at both stock and day levels. N denotes the number of observations. N Stocks [in square bracket] denotes the number of stocks. The coefficients in bold denotes the exchange of the listing exchange. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

	(1)		(2)		(3)	
	NYSE-listed		NASDAQ-listed		AMEX-listed	
Exchange (ψ):	μ (s.e.)	N [N Stocks]	μ (s.e.)	N [N Stocks]	μ (s.e.)	N [N Stocks]
NBBO	0.0166* (0.0092)	289,278 [1,176]	0.0228*** (0.0037)	512,836 [2,100]	0.0749*** (0.0152)	32,042 [132]
NASDAQ (Q+T)	0.0491*** (0.0181)	291,998 [1,176]	**0.0323***** (0.0080)	506,792 [2,100]	0.1296*** (0.0346)	25,428 [131]
ARCA (P)	0.0412* (0.0242)	291,325 [1,176]	0.0512*** (0.0084)	488,949 [2,100]	0.1143*** (0.0271)	25,703 [131]
NYSE (N)	**0.0316***** (0.0096)	292,952 [1,176]	0.0851*** (0.0197)	407,879 [2,079]	0.2488** (0.1236)	14,153 [128]
BZX (Z)	0.0299 (0.0220)	290,670 [1,176]	0.0734*** (0.0101)	484,158 [2,099]	0.1977*** (0.0435)	23,301 [131]
EDGX (K)	0.0059 (0.0177)	291,217 [1,176]	0.0580*** (0.0077)	491,954 [2,100]	0.1281*** (0.0303)	25,691 [131]
IEX (V)	0.0773** (0.0315)	264,169 [1,176]	0.0509 (0.0327)	368,564 [2,060]	0.0957 (0.1291)	12,159 [126]
EDGA (J)	0.0402 (0.0459)	286,380 [1,174]	0.0758*** (0.0166)	450,300 [2,081]	0.1791** (0.0836)	19,354 [129]
BYX (Y)	0.0219 (0.0347)	289,189 [1,176]	0.0724*** (0.0148)	464,658 [2,098]	0.2283*** (0.0657)	20,186 [131]
BX (B)	0.2004* (0.1178)	278,791 [1,170]	0.1870*** (0.0587)	393,169 [1,977]	0.1670 (0.1660)	12,619 [116]
National (C)	−0.3009 (0.2958)	277,936 [1,170]	−0.0494 (0.1063)	389,536 [2,019]	−0.0186 (0.2595)	12,549 [121]
PSX (X)	0.1265 (0.3018)	261,331 [1,165]	0.3578*** (0.1299)	342,234 [1,978]	−0.1460 (0.6703)	9,902 [115]
Chicago (M)	0.0052 (0.0600)	142,392 [1,149]	−0.0095 (0.0295)	155,148 [1,878]	−0.3688 (1.5115)	2,148 [92]
AMEX (A)	0.1119 (0.0680)	248,164 [1,163]	0.0376 (0.0518)	296,801 [1,933]	**0.1382***** (0.0254)	26,570 [131]

Table A.10. The effects of market fragmentation on price impact by the market size quintile.

This table reports the effects of market fragmentation on price impact by the market size quintiles. For each trading day t, we sort the stocks into quintiles and construct quintile dummies for each stock-day observation following Haslag and Ringgenberg (2021). For each exchange ψ, we run a two-stage least square regression as the following:

First-stage: $\Delta Frag_{i,t}^{trade} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \sum_{m\neq3}\xi_m Quintile_m + \sum_{m\neq3}\phi_m \Delta OnMEMX_{i,t} \times Quintile_m + \Delta\mathbf{X}_{it}^{'}\Phi + \Delta\epsilon_{it}$

Second-stage: $\Delta PI_{i,t}^{\psi} = \Delta\lambda_t + \mu\widehat{\Delta Frag}_{i,t}^{trade} + \sum_{m\neq3}\iota_m \widehat{\Delta Frag_{i,t}^{trade}} \times Quintile_m + \sum_{m\neq3}\zeta_m Quintile_m + \Delta\mathbf{X}_{it}^{'}\Gamma + \Delta\epsilon_{it}$

Where Δ is the first difference operator, $OnMEMX_{i,t}$ is the indicator if the stock i is traded at MEMX on day t, $\widehat{\Delta Frag}_{i,t}^{*}$ is the predicted value from the first-stage regression, and $\mathbf{X}_{it}^{'}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchanges. $Quintile$ is an indicator variable which equals 1 when a firm is in that market captialization quintile, and zero otherwise, where quintile 5 is the largest firms. We report the second-stage estimates (μ), and their standard errors (in parentheses) clustered at both stock and day levels. N denotes the number of observations.

	$\Delta PI_{i,t}^{NBBO}$	$\Delta PI_{i,t}^{Q+T}$	$\Delta PI_{i,t}^{P}$	$\Delta PI_{i,t}^{N}$	$\Delta PI_{i,t}^{Z}$	$\Delta PI_{i,t}^{K}$	$\Delta PI_{i,t}^{V}$	$\Delta PI_{i,t}^{J}$	$\Delta PI_{i,t}^{Y}$	$\Delta PI_{i,t}^{B}$	$\Delta PI_{i,t}^{C}$	$\Delta PI_{i,t}^{X}$	$\Delta PI_{i,t}^{M}$	$\Delta PI_{i,t}^{A}$
$\widehat{\Delta Frag}_{i,t}^{trade}$	0.0298*	0.0865**	0.0404*	0.0219	0.0430**	0.0725**	0.0664**	0.1306**	0.0491	0.2407*	−0.2234	0.8780**	0.0237	−0.0097
	(0.016)	(0.043)	(0.024)	(0.034)	(0.020)	(0.034)	(0.032)	(0.060)	(0.043)	(0.142)	(0.271)	(0.416)	(0.079)	(0.039)
$\widehat{\Delta Frag_{i,t}^{trade}} \times Quintile_1$	0.0017	−0.0444	0.0336	0.0917**	0.0665***	−0.0138	0.0107	−0.0413	0.0730	0.0105	0.2479	−0.7141	0.2310	0.1216**
	(0.016)	(0.045)	(0.027)	(0.042)	(0.025)	(0.034)	(0.060)	(0.061)	(0.045)	(0.103)	(0.305)	(0.444)	(0.198)	(0.058)
$\widehat{\Delta Frag_{i,t}^{trade}} \times Quintile_2$	−0.0176	−0.0575	−0.0146	0.0658	−0.0022	−0.0050	−0.0376	−0.0795	−0.0295	−0.1098	0.0201	−0.6146	0.0052	0.3456*
	(0.017)	(0.042)	(0.028)	(0.043)	(0.023)	(0.038)	(0.047)	(0.064)	(0.049)	(0.179)	(0.355)	(0.460)	(0.104)	(0.180)
$\widehat{\Delta Frag_{i,t}^{trade}} \times Quintile_4$	−0.0319*	−0.0776*	−0.0336	−0.0155	−0.0145	−0.0474	−0.0222	−0.0933	−0.0179	−0.1556	0.1709	−0.8130	−0.0804	−0.0200
	(0.018)	(0.045)	(0.026)	(0.034)	(0.020)	(0.037)	(0.041)	(0.060)	(0.049)	(0.154)	(0.280)	(0.406)	(0.081)	(0.056)
$\widehat{\Delta Frag_{i,t}^{trade}} \times Quintile_5$	−0.0283	−0.0767*	−0.0374	−0.0440	−0.0565**	−0.0943**	−0.0388	−0.0570	−0.0120	−0.1730	0.1959	−0.7729	−0.0838	−0.0069
	(0.017)	(0.042)	(0.026)	(0.037)	(0.023)	(0.039)	(0.049)	(0.068)	(0.046)	(0.149)	(0.294)	(0.443)	(0.085)	(0.051)
$\sum_{m\neq3} Quintile_m$	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	834,156	824,218	805,977	714,984	798,129	808,862	644,892	756,034	774,033	684,579	680,021	613,467	299,690	571,535

Table A.11. The effects of market fragmentation on price impact—addressing reverse causality and endogenous venue choice concerns.
This table reports the effects of market fragmentation on price impact based on a sample of 945 stocks which were traded on MEMX starting from the first day (October 29, 2020) when the MEMX was introduced. The sample period is from October 15, 2020 to October 29, 2020. For each exchange ψ, we run a two-stage least square regression as the following:

First-stage: $Frag^{trade}_{i,t} = \alpha_i + \lambda_t + \delta OnMEMX_{i,t} + \mathbf{X}^{'}_{it}\Phi + \epsilon_{it}$

Second-stage: $PI^{\psi}_{i,t} = \alpha_i + \lambda_t + \mu \widehat{Frag}^{trade}_{i,t} + \mathbf{X}^{'}_{it}\Gamma + \epsilon_{it}$

Where $OnMEMX_{i,t}$ is the indicator if the stock i is traded at MEMX on day t, $\widehat{Frag}^{*}_{i,t}$ is the predicted value from the first-stage regression, and $\mathbf{X}^{'}_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchanges. In this table, the dependent variables are winsorized at 99% and 1% percentiles. We report the second-stage estimates (μ), and their standard errors (in parentheses) clustered at stock levels. N denotes the number of observations. We report the second-stage coefficients estimates, and their standard errors (in parentheses) clustered at both stock level. N denotes the number of observations.

	$PI^{NBBO}_{i,t}$	$PI^{Q+T}_{i,t}$	$PI^{P}_{i,t}$	$PI^{N}_{i,t}$	$PI^{Z}_{i,t}$	$PI^{K}_{i,t}$	$PI^{V}_{i,t}$	$PI^{J}_{i,t}$	$PI^{Y}_{i,t}$	$PI^{B}_{i,t}$	$PI^{C}_{i,t}$	$PI^{X}_{i,t}$	$PI^{M}_{i,t}$	$PI^{A}_{i,t}$
$\widehat{Frag}^{trade}_{i,t}$	0.0371***	0.0337***	0.0375**	0.0501***	0.0632***	0.0440**	0.1296**	0.1386***	0.0322	0.0712	0.1000	0.0873	0.1116**	−0.0203
	(0.011)	(0.013)	(0.017)	(0.019)	(0.017)	(0.018)	(0.063)	(0.035)	(0.024)	(0.072)	(0.098)	(0.176)	(0.050)	(0.036)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	10,187	10,132	10,126	9,977	10,118	10,131	9,661	10,035	10,045	9,751	9,776	9,372	4,263	9,192

Table A 13. External Validity: The effect of market fragmentation on price impact based on introduction of MIAX Pearl Equities Exchange (MIAX)

This table reports the effects of market fragmentation on price impact. For each exchange ψ, we run a two-stage least square regression as the following:

First-stage: $\Delta Frag^{*}_{i,t} = \Delta\lambda_t + \delta\Delta OnMIAX_{i,t} + \Delta\mathbf{X}^{'}_{it}\Phi + \Delta\epsilon_{it}$

Second-stage: $\Delta PI^{\psi}_{i,t} = \Delta\lambda_t + \mu\Delta\widehat{Frag}^{*}_{i,t} + \Delta\mathbf{X}^{'}_{it}\Gamma + \Delta\epsilon_{it}$

Where Δ is the first difference operator, $OnMIAX_{i,t}$ is the indicators if the stock i is traded at MIAX on day t, $\Delta\widehat{Frag}^{*}_{i,t}$ is the predicted value from the first-stage regression, and $\mathbf{X}^{'}_{it}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchanges. N denotes the number of observations. Standard errors clustered at both stock and day levels are reported in parentheses. We report the second-stage estimates (μ), first-stage estimates (δ) and weak IV test statistics. Kleibergen and Paap (2006) (K-P) rk F statistics is reported. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

Second-stage						First-stage	
Dependent:		Independent:				Estimates	Tests
$\Delta PI^{\psi}_{i,t}$	$\Delta\widehat{Frag}^{trade}_{i,t}$	$\Delta\widehat{Frag}^{volume}_{i,t}$	Controls	Day FE	N	δ	K-P
NBBO	0.0105 (0.007)		Y	Y	834,156	0.0036***	149.5
		0.0105 (0.007)	Y	Y		0.0036***	58.8
NASDAQ (Q+T)	0.0073 (0.014)		Y	Y	824,218	0.0035***	146.2
		0.0073 (0.014)	Y	Y		0.0035***	63.6
ARCA (P)	−0.0125 (0.010)		Y	Y	805,977	0.0034***	146.6
		−0.0123 (0.010)	Y	Y		0.0034***	67.3
NYSE (N)	0.0261* (0.015)		Y	Y	714,984	0.0032***	134.3
		0.0276* (0.016)	Y	Y		0.0030***	62.7
BZX (Z)	0.0217** (0.009)		Y	Y	798,129	0.0034***	141.6
		0.0224** (0.010)	Y	Y		0.0033***	66.3
EDGX (K)	0.0162* (0.010)		Y	Y	808,862	0.0035***	149.1
		0.0162* (0.010)	Y	Y		0.0035***	67.2
IEX (V)	0.1407*** (0.040)		Y	Y	644,892	0.0033***	134.1
		0.1522*** (0.046)	Y	Y		0.0030***	67.1
EDGA (J)	0.0845*** (0.016)		Y	Y	756,034	0.0034***	142.4
		0.0879*** (0.019)	Y	Y		0.0032***	66.7
BYX (Y)	0.0489*** (0.013)		Y	Y	774,033	0.0034***	142.6
		0.0507*** (0.014)	Y	Y		0.0032***	67.7
BX (B)	0.1723*** (0.050)		Y	Y	684,579	0.0031***	128.6
		0.1691*** (0.051)	Y	Y		0.0032***	72.4
National (C)	0.2807*** (0.093)		Y	Y	680,021	0.0029***	115.0
		0.2767*** (0.095)	Y	Y		0.0030***	63.2
PSX (X)	0.0276 (0.093)		Y	Y	613,467	0.0029***	126.6
		0.0276 (0.092)	Y	Y		0.0029***	65.9
Chicago (M)	0.0614* (0.031)		Y	Y	299,690	0.0026***	63.6
		0.0680* (0.035)	Y	Y		0.0023***	29.5
AMEX (A)	0.0826* (0.045)		Y	Y	571,535	0.0025***	101.7
		0.0773*** (0.042)	Y	Y		0.0027***	59.8

Appendix B

Table B.1. Summary statistics for the percentage of orders in different aggressive categories.
This table presents the summary statistics for the percentage of orders in different aggressive categories. For each stock i at trading day t trading on NASDAQ stock exchange, we use NASDAQ TotalView-ITCH data to classify all the orders entered in NASDAQ trading system into eight categories based on their aggressiveness. We follow the approach used by Biais et al. (1995) and classify orders into which result in inside BBO trades, large trades (marketable orders walk the LOB in NASDAQ), small trades (orders executed at BBO but with trade size smaller than the depth at BBO), and improvement in BBO (either orders improving the BBO price or improving the BBO depth) aggressive orders. For unaggressive orders, we classify them into orders that result in addition in LOB, revision in LOB, cancellation in LOB, and deletion in LOB. We report mean (Mean), standard deviation (STD), 1 percentile (p1), median (p50), 99 percentiles (p99) and the number of observations (N) for these different orders categories. The variables are in percentage. We select the sample with trading days t between $E_i^d - 20$ and $E_i^d + 19$ where the E_i^d represents the first calendar day that stock i is traded on MEMX.

		$\%Order^*_{i,t}$	N	Mean	STD	p1	p50	p99
Aggressive	Buy	Inside BBO Trades	64,764	0.050	0.088	0.002	0.026	0.354
		Large Trades	89,552	1.754	1.136	0.239	1.578	5.496
		Small Trades	130,582	1.304	1.097	0.102	1.081	5.128
		Improvement in BBO	135,762	20.72	7.422	4.732	20.46	38.75
	Sell	Inside BBO Trades	64,966	0.0494	0.091	0.002	0.026	0.348
		Large Trades	93,292	1.711	1.070	0.245	1.534	5.371
		Small Trades	131,437	1.185	1.072	0.111	0.984	4.513
		Improvement in BBO	135,753	20.38	7.457	4.395	20.27	38.36
Unaggressive	Buy	Addition in LOB	136,209	24.31	7.157	8.314	24.11	40.63
		Revision in LOB	64,631	0.296	0.585	0.007	0.111	2.648
		Cancellation in LOB	136,207	42.11	4.163	28.93	42.99	48.03
		Deletion in LOB	136,034	9.979	8.252	1.109	7.365	38.23
	Sell	Addition in LOB	136,209	24.17	7.089	8.554	23.90	40.37
		Revision in LOB	67,641	0.327	0.638	0.007	0.120	2.887
		Cancellation in LOB	136,207	41.95	4.481	27.29	43.03	47.98
		Deletion in LOB	136,073	10.71	9.120	1.203	7.688	42.14

Table B.2. Changes in order aggressiveness around the introduction of MEMX (60 days window).
This table presents the changes in order aggressiveness for stocks trading on NASDAQ stock exchange around the launch of MEMX. For each stock i at trading day t, we use NASDAQ TotalView-ITCH data to classify all the orders entered in NASDAQ trading system into eight categories based on their aggressiveness. We follow the approach used by Biais et al. (1995) and classify orders that result in inside BBO trades, large trades (marketable orders walk the LOB in NASDAQ), small trades (orders executed at BBO but with trade size smaller than the depth at BBO), and improvement in BBO (either orders improving the BBO price or improving the BBO depth) into aggressive orders. We also classify orders that result in addition in LOB, revision in LOB, cancellation in LOB, and deletion in LOB into unaggressive orders. For each stock-day observation, the variables are in percentage and their summary statistics are reported in Appendix B, Table B.1. We select the sample with trading days t between $E_i^d - 60$ and $E_i^d + 59$ in this table. We report the results for buy side and sell side separately in Panel A and Panel B. We run the following regression for each order aggressiveness type:

$$\%Order^*_{i,t} = \alpha_i + \lambda_t + \omega \mathbb{1}(t >= E_i^d) + \mathbf{X}'_{it}\Gamma + \epsilon_{i,t}$$

Where $\%Order^*_{i,t}$ represents the percentage of orders in that category, for instance, the percentage of orders that result in large trades. E_i^d is the calendar day that when stock i is first traded on MEMX. $\mathbb{1}$ represents the indicator function. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively. Standard errors clustered at both stock and day levels are reported in parentheses. N denotes the number of observations.

Panel A: Buy Side

	Aggressive orders (%) result in:				Unaggressive orders (%) result in:			
	Inside BBO Trades	Large Trades	Small Trades	Improvement in BBO	Addition in LOB	Revision in LOB	Cancellation in LOB	Deletion in LOB
ω	0.0068**	0.1457***	0.1686***	0.8330***	−0.3799**	−0.8807***	0.0035	0.0334
	(0.0030)	(0.0318)	(0.0252)	(0.1493)	(0.1763)	(0.2022)	(0.0129)	(0.1120)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y	Y	Y	Y	Y
N	204,835	279,830	392,235	406,946	408,382	407,826	194,257	408,365
R-Squared	19.9%	37.9%	19.1%	59.6%	53.2%	58.2%	39.6%	49.4%

Panel B: Sell Side

	Aggressive orders (%) result in:				Unaggressive orders (%) result in:			
	Inside BBO Trades	Large Trades	Small Trades	Improvement in BBO	Addition in LOB	Revision in LOB	Cancellation in LOB	Deletion in LOB
ω	0.0051**	0.1440***	0.1735***	0.8499***	−0.3930**	−0.9119***	−0.0311	0.0744
	(0.0017)	(0.0283)	(0.0212)	(0.1376)	(0.1584)	(0.2031)	(0.0237)	(0.1092)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y	Y	Y	Y	Y
N	205,296	288,424	395,086	406,935	408,382	408,032	200,437	408,370
R-Squared	31.2%	40.1%	16.4%	59.3%	52.6%	63.1%	33.7%	54.6%

Table B.3. Changes in order aggressiveness around a falsified event (20 days window).

This table presents the changes in order aggressiveness for stocks trading on NASDAQ stock exchange around a fasified event. For each stock i at trading day t, we set the event day as $E_i^d - 40$, which is the 40 days prior to the real event date–the first calendar date when stock is traded on MEMX. We use NASDAQ TotalView-ITCH data to classify all the orders entered in NASDAQ trading system into eight categories based on their aggressiveness. We follow the approach used by Biais et al. (1995) and classify orders that result in inside BBO trades, large trades (marketable orders walk the LOB in NASDAQ), small trades (orders executed at BBO but with trade size smaller than the depth at BBO), and improvement in BBO (either orders improving the BBO price or improving the BBO depth) into aggressive orders. We also classify orders that result in addition in LOB, revision in LOB, cancellation in LOB, and deletion in LOB into unaggressive orders. For each stock-day observation, the variables are in percentage and their summary statistics are reported in Appendix B, Table B.1. We select the sample with trading days t between $E_i^d - 60$ and $E_i^d - 21$ in this table. We report the results for buy side and sell side separately in Panel A and Panel B. We run the following regression for each order aggressiveness type:

$$\%Order^*_{i,t} = \alpha_i + \lambda_t + \omega \mathbb{1}(t >= E_i^d) + \mathbf{X}'_{it}\Gamma + \epsilon_{i,t}$$

Where $\%Order^*_{i,t}$ represents the percentage of orders in that category, for instance, the percentage of orders that result in large trades. E_i^d is the calendar day that when stock i is first traded on MEMX. $\mathbb{1}$ represents the indicator function. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively. Standard errors clustered at both stock and day levels are reported in parentheses. N denotes the number of observations.

Panel A: Buy Side

	Aggressive orders (%) result in:				Unaggressive orders (%) result in:			
	Inside BBO Trades	Large Trades	Small Trades	Improvement in BBO	Addition in LOB	Revision in LOB	Cancellation in LOB	Deletion in LOB
ω	0.0005	−0.0518	−0.0135	−0.3612*	0.2809	0.1509	0.0260*	−0.0477
	(0.0016)	(0.0323)	(0.0166)	(0.1845)	(0.1740)	(0.2565)	(0.0146)	(0.1226)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y	Y	Y	Y	Y
N	66,923	95,710	132,272	135,853	136,202	136,171	67,850	136,188
R-Squared	41.4%	42.5%	32.1%	65.8%	61.6%	60.9%	39.8%	54.5%

Panel B: Sell Side

	Aggressive orders (%) result in:				Unaggressive orders (%) result in:			
	Inside BBO Trades	Large Trades	Small Trades	Improvement in BBO	Addition in LOB	Revision in LOB	Cancellation in LOB	Deletion in LOB
ω	−0.0005	−0.0142	−0.0375**	−0.1826	0.3046*	−0.2517	0.0119	0.1676
	(0.0015)	(0.0287)	(0.0165)	(0.1741)	(0.1706)	(0.2510)	(0.0185)	(0.1243)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Day FE	Y	Y	Y	Y	Y	Y	Y	Y
Stock FE	Y	Y	Y	Y	Y	Y	Y	Y
N	66,807	98,791	133,000	135,893	136,202	136,192	68,779	136,193
R-Squared	38.6%	45.4%	29.6%	64.3%	60.3%	64.6%	35.7%	58.4%

Appendix C

Trades and quotes filters

We select the sample period from June 1, 2020 to May 28 2021–252 trading days. For each trading day, we apply four filters to obtain the trades that we use for calculating our exchange-based measures. They are:
① Trades with sales condition which are labeled as "_O__", "_O_X", "_O_I", "@O__", "@O_X", and "@O_I". These are opening trades, cross trades, and odd lot trades. This filter eliminates approximately 0.012% of the total trades.
② Trades that executed in regular hours from 9:30am to 4:00pm. This filter eliminates about 2.756% of the total trades.
③ Trades with trade correction indicator which are not regular trades–only trades with trade correction indicator as "00" are included. This filter eliminates about 0.002% of the total trades.
④ Trades that executed off-exchange. We exclude the trades that have the timestamp for the column of "Trade Reporting Facility(TRF) Timestamp". This will not only exclude all the trades with "Exchange" as "D" but also exclude trades that are disseminated by FINRA Alternative Display Facility (ADF) or FINRA Trade Reporting Facility (TRF). This filter eliminates a large proportion of trades which accounts for approximately 28.594% of the total trades.

After applying for these filters our average number of trades is about 43.8 million during our sample period. Table C.1 shows the number of trades (in perctage) deleted by our filters imposed on raw DTAQ trades files.

Similarly, we apply the following filters to our DTAQ raw quotes files. To save computing time, we didn't compute the number of quotes deleted when we were computing the our exchange-based measure. For the trading day of June 6, 2020, we have 1,518,221,158 quotes. Our quote filters are:
① We drop duplicated quotes for each symbol at the same exchange at the same timestamp and keep the last quote.
② We select quotes during regular trading hours from 9:30am to 4:00pm.
③ We delete quotes with quote condition as "I", "N", "U". These quotes are order imbalance quotes and non-firm quotes.
④ We delete quotes when either bid price or ask price is zero.
⑤ We delete quotes with bid-ask spread larger than $10 and the bid(ask) price $5 smaller(larger) than previous midprice. This is similar to Holden and Jacobsen (2014)'s where they delete quotes with bid-ask spread larger than $5. We set a larger threshold for deletion. Therefore, our filter here is more conservative. After applying the filters with both trades files and quote files, we merge each trade with the quote before that trade and the quote five minutes later after that trade.

Table C.1. DTAQ Trade filters.
This table reports the number of trades deleted by our filters imposed on raw DTAQ trades files to compute our exchange-based measures. Filter #1 drops opening trades, cross trades, and odd lot trades. Filter #2 drops trades outside regular trading hours. Filter #3 drops trades which are not labeled as regular. Filter #4 drops the off-exchange trades.

	Raw	Filter #1	Filter #2	Filter #3	Filter #4	Avg Final
Avg Number of Trades	63,890,638	(7,893)	(1,816,750)	(1,065)	(18,298,492)	43,766,317
Percentage	100%	−0.012%	−2.756%	−0.002%	−28.594%	68.636%

Reconstructing the limit orderbook (LOB) for the NASDAQ stock exchange using NASDAQ TotalView-ITCH data

Decode the raw ITCH files

We extract the messages from ITCH raw files. We are decoding the version 5 of NASDAQ TotalView-ITCH, and the documentation can be found at the following website. There are four types of messages in the ITCH data–system related messages, stock related messages, order related messages, and trade related messages.

System related messages include: "S", system message recording the status of trading system of NASDAQ stock exchange.

Stock related messages include: "R", stock directory messages documenting all the stocks traded on NASDAQ stock exchange on this trading day; "H", stock trading action messages documenting the trading status of all stocks traded on NASDAQ; "Y", Reg SHO short sale price test restricted indicator messages recording the short sales restrictions; "L", market participant position messages documenting the participants of market makers; "W" market wide circuit breaker status messages documenting the status of the market-level circuit breaker; "K", IPO quoting period update messages; "J", limit up limit down (LULD) auction collar messages; "h", operational halt messages.

Order related messages include: "A", add order with no MPID attribution messages; "F", add order with MPID attribution messages; "E" order executed (in part or full) with no MPID attribution messages; "C" order executed with price messages; "X" order cancellation messages; "D" order deletion messages; "U" order replacement messages.

Trade related messages include: "P", trades occur because of non-displayable orders; "Q", trades due to crossing; "B" broken trades.

Reconstructing the limit orderbook

Once we decode all the messages, we can reconstruct the limit orderbook based on the workflow in the Figure C.1.

For a stock at a trading day, we start from an empty limit orderbook. Suppose we receive three add order messages (A/F messages)–MSG 1, MSG 2, and MSG 3. MSG 1 is a limit order to buy 100 shares at the price of \$20, MSG 2 is a limit order to buy 100 shares at the price of \$19, and MSG 3 is a limit order to buy 200 shares at the price of \$18. Now we have depth at three price levels, \$20, \$19 and \$18. Then, suppose a trade executed message (E/C) arrives, it says it will execute against MSG 1 with a trade size of 50 shares. After deducting 50 shares

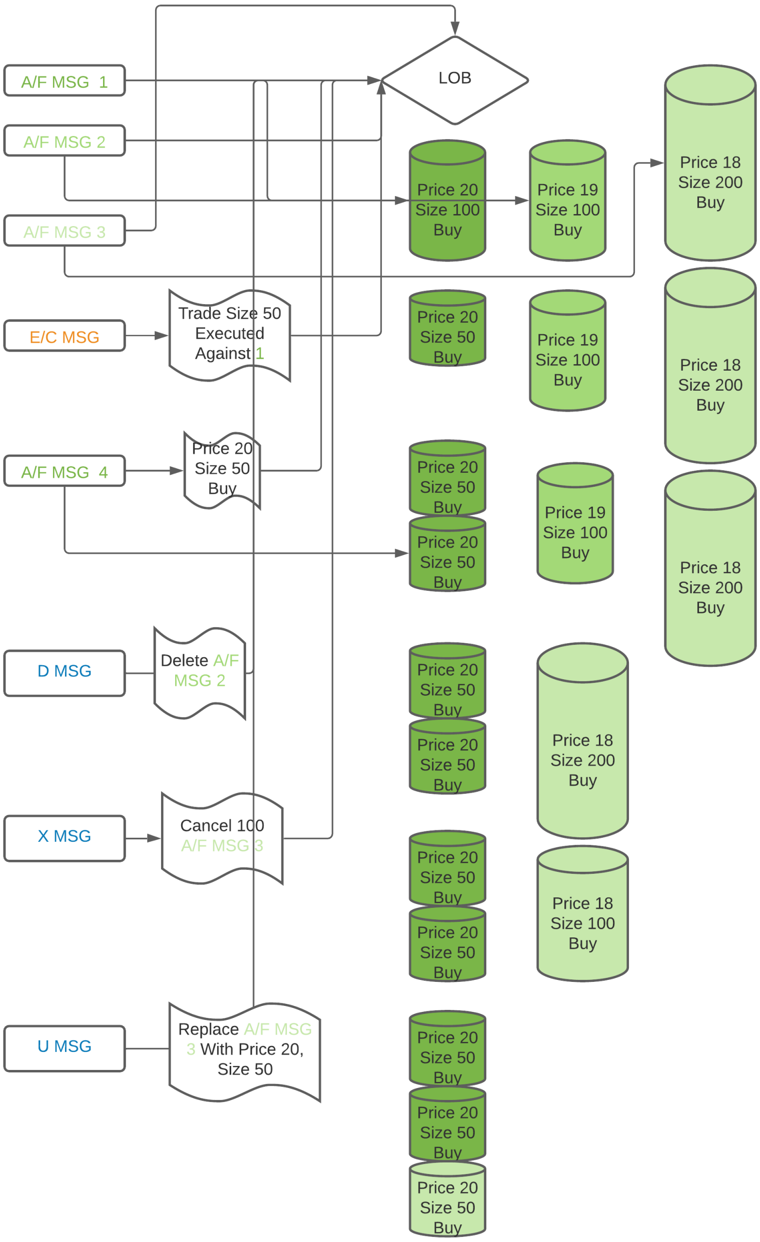

Figure C.1: Workflow of reconstructing the limit orderbook from messages

against the order from MSG 1, now the best bid is \$20 with 50 shares. Following the previous trade comes another add order message, MSG 4 which is a limit order to buy 50 shares at \$20. Now we have two orders resting on the best bid with each order having 50 shares. Suppose a deletion message (D) which deletes the previous order of MSG 2 comes, then we completely remove the order at the second best bid (\$19 with 100 shares). Now we only have two price levels at the bid sides. Our next message in the workflow is a cancellation message (X) which cancels 100 shares of the order of MSG 3. Now the second best bid only has 100 shares. Our last message is a replacement message (U) which revises the order of MSG 3 with a new price of \$20 and 50 shares. Now we have three orders resting on the best bid with each of the order having 50 shares totaling the market depth to 150 shares.

Appendix D

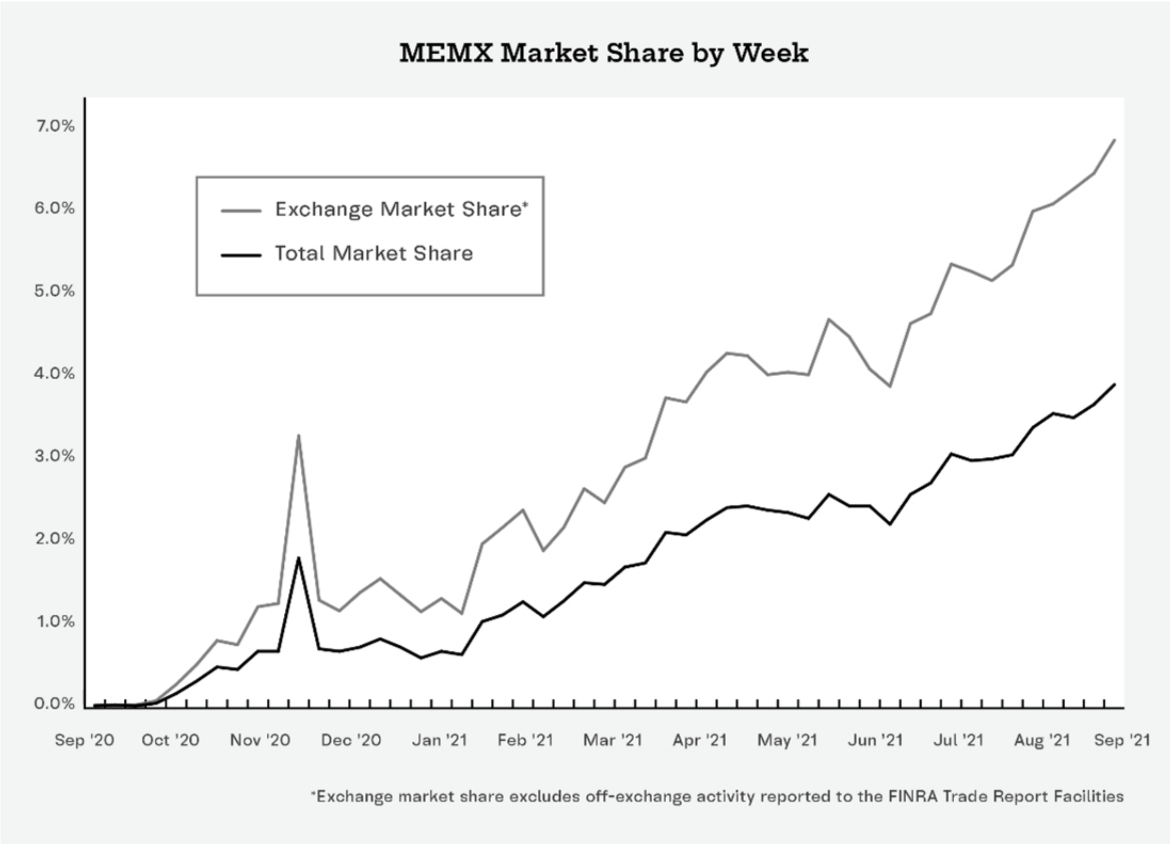

Figure D.1: MEMX share by week. Source: MEMX exchange.