Market fragmentation and price impact

Lewen Guo and Pankaj K. Jain*

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Abstract

We investigate the effects of market fragmentation on price impact. Using a newly launched exchange as a quasi-natural experiment, we find an increase in market fragmentation leads to a higher price impact of trading in U.S. equity exchanges. Our IV estimates suggest a 1.6% increase in market fragmentation level induces approximately 4.4 bps to 20.8 bps increases in *exchange-based* price impact. These effects are more pronounced for small stocks than large stocks. Our results suggest the introduction of a lit exchange changes the trading landscape in a multi-market setting, thereby leading to an increase in the price impact of trading.

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

JEL Classification Numbers: D47, G12, G14

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*Lewen Guo and Pankaj K. Jain are at the University of Memphis. Corresponding Author: Lewen Guo. Email: lguo5@memphis.edu and guolewen1994@gmail.com. First version: April 1, 2022. We thank Kelley Anderson, Yasuhiro Arikawa, Jeff Black, Allen Carrion, Kalok Chan, Jingchi Chen, William M. Cheung, Carole Comerton-Forde, Mingze Gao, Peter H. Haslag, Jia He, Shinichi Hirota, Idan Hodor (discussant), Rasheek Irtisam, Chandra Krishnamurti (discussant), Albert S. Kyle, Seokwoo Lee, Sida Li, Zongyuan Li (discussant), Mark Loewenstein, Thomas Marta (discussant), Richie R. Ma, Xiyuan Ma, Joshua Mollner, Xinzhe Niu, Yusuke Osaki, Jason Shachat, Yoshiki Shimizu, Konstantin Sokolov, Jonathan Sokobin, Yasuhiko Tanigawa, Xinyuan Tao (discussant), Vincent van Kervel (discussant), Robert Van Ness, Weike Xu (discussant), Eduard Yelagin, Tianchen Zhao (discussant), Jiang Zhang, and seminar participants at FMA Annual Meeting (2022), AFA PhD Poster (2023), FMCG (2023), FMA Applied Finance Conference (2023), CES Wuhan (2023), AsianFA Annual Conference (2023), AMES Beijing (2023), WEAI Annual Conference (2023), CFRI&CIRF Joint Conference (2023), AMES Singapore (2023), EuropeanFA Annual Conference (2023), MMMA Conference (2023), Tsinghua University, University of Maryland, University of Memphis, and Waseda University for their insightful suggestions. We thank our friends Lidong Cui and Xinzhe Niu for their assistance in providing additional HPC accounts at the University of Memphis to help compute the data used in this paper. Lewen Guo thanks for warm hospitality throughout his visit to The University of Maryland, College Park in 2023.

1 Introduction

Over the past decade, there are ongoing debates among market design literature regarding whether financial assets should be traded in a centralized market where a single market clears all transactions, or in a fragmented market where the same assets can be traded through separate but informationally-connected and coexisting exchanges. Proponents of fragmented market design argue that it enhances price informativeness, and allocation efficiency. The increased intensity of competition among trading venues will also ultimately lower transaction costs. Yet, opponents concern that the benefits of a fragmented market may be outweighed by increased costs associated with the excessive number of trading venues. These concerns involve increased adverse selection costs and increased risk of price crashes due to multi-market arbitrage, reduced market depth from order-splitting, and execution inefficiencies arising from different exchange fee structures. This paper contributes to this continuing debate by examining the effects of market fragmentation on price impact, an important dimension of market liquidity, in the U.S. equity market, with a specific focus on the recent launch of a new lit exchange—the Members Exchange (MEMX).

Exploring this quasi-natural experiment adds several important insights to the existing literature. First, while recent theories such as Malamud and Rostek (2017) and Chen and Duffie (2021) make varying predictions regarding the possible consequences of market fragmentation resulting from the increased total number of trading venues, the empirical evidence of market fragmentation on liquidity is mixed.[1] By analyzing the launch of MEMX which induces an increase in the level of market fragmentation, our paper aims to reconcile these contradictory findings and provide new insights into whether market fragmentation is beneficial or detrimental for market liquidity.

Second, our study distinguishes itself from prior literature by evaluating the effects of market fragmentation arising from the introduction of a lit exchange. While launching a dark pool also fragments the market, this specific type of fragmentation also results

[1] Although Malamud and Rostek (2017) and Chen and Duffie (2021) use different assumptions to derive their equilibrium, one common prediction is that the level of market fragmentation has a positive association with price impact. These studies posit that the price impact of trading in a multi-market setting is influenced by factors such as fluctuations in supply and demand, changes in the slopes of demand curves, changes in market depth due to order splitting, changes in order aggressiveness, and other order book events resulting from the increasing number of the lit exchanges. In contrast with the theories, empirical studies such as O'Hara and Ye (2011) and Gresse (2017) find that the competition among trading venues can lower trading costs, a more recent study by Haslag and Ringgenberg (2021) shows mixed effects of market fragmentation on market quality for stocks with different sizes.

in order flow segmentation.[2] In contrast to the introduction of a dark pool which aims to address the specific trading needs of different market participants, the intention of launching a new lit exchange is not as evident, particularly since most transactions on the lit exchanges are from institutions. Our study contributes by providing empirical evidence on the consequences of launching a new lit exchange, addressing a relatively underexplored aspect in the existing literature.[3]

Third, the unique characteristics of MEMX provide an opportunity to investigate the effects of market fragmentation, rather than being potentially confounded by exchange-specific factors that could also affect the price impact of trading. For example, MEMX does not employ technological innovations such as speed bumps or frequent batch auctions, which could potentially hinder the high-frequency traders from quickly reacting to "stale" quotes.[4] The absence of such features allows us to investigate how market fragmentation affects price impact but not other exchange-specific factors that may also result in increased adverse selection costs.

Furthermore, considering that MEMX is independently owned and backed by major financial institutions such as BlackRock, Fidelity, and Citadel, rather than being supported by three large exchange groups, its stated objectives might not align with the regulators' goal of enhancing competition among trading venues.[5] Our paper is relevant in assessing the costs and benefits of introducing additional new lit exchanges to the already fragmented US equity market and is crucial for both researchers and regulators to evaluate the current market design.

We find the introduction of MEMX deteriorates a specific dimension of market liquidity—

[2]The central arguments in this strand of literature (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) believe that the introduction of dark pools leads to the segmentation of order flow informativeness, potentially harming price discovery. Moreover, a high level of dark trading could increase the adverse selection risk on the lit exchange by concentrating informed traders on the lit exchange.

[3]To our best knowledge, the only paper so far that explores the introduction of MEMX is Watson and Woods (2022). They find when new exchanges (MEMX and MIAX) are introduced, NASDAQ loses a significant amount of market shares while IEX gains market shares.

[4]See Chakrabarty et al. (2020) for a detailed discussion of speed bumps employed by the Investors Exchanges (IEX) and Budish et al. (2014) for a detailed discussion of frequent batch auctions employed by the Chicago Stock Exchange (Chicago). See Foucault et al. (2017) and Shkilko and Sokolov (2020) for latency arbitrage.

[5]Intercontinental Exchange operates NYSE, AMEX, ARCA, National, and Chicago; NASDAQ Inc operates NASDAQ, BX, and PSX; CBOE operates BZX, BYX, EDGA, EDGX. See Table A.1 for details. In the MEMX's official news website, it is stated that *MEMX's mission is to increase competition, improve operational transparency, further reduce fixed costs, and simplify the execution of equity trading in the U.S. The founding members of MEMX represent leading retail brokers, global banks and financial service firms, and market makers – a diverse array of market participants organizing for the common goal of improving markets for retail and institutional investors.*

an increase in market fragmentation level leads to a rise in the price impact of trading. Specifically, we observe a temporary increase in the price impact of trading after the launch of MEMX in major U.S. equity exchanges. Through an instrumental variable approach, we find a 1.6% increase in market fragmentation for a stock results in approximately 2.9 basis points (bps) increase in NBBO-based price impact, and more substantial increases in exchange-based price impact for trading that stock. The effects of market fragmentation on price impact are more pronounced for small stocks compared to large stocks. Further analysis reveals that this increase in price impact primarily results from: i) increased order aggressiveness, ii) reduced market depth at each lit exchange, and iii) a more inelastic order book due to order flow migration when MEMX is introduced. Our results indicate that market fragmentation arising from the introduction of a lit exchange worsens market liquidity in this particular dimension.[6]

Our empirical analysis begins by examining the stylized facts around the introduction of MEMX. We observe a temporary 12.3% (3.7 bps) increase in price impact at the Best Bid and Best Offer (NBBO) level within the first 10 days following the introduction of MEMX. Furthermore, using our proposed exchange-based price impact measure, which captures dynamic variations in price impact at each lit exchange level, we observe the increases in price impact range from 1.0 bps to 20.4 bps at the primary U.S. exchanges.[7]

To estimate the *causal effects* of market fragmentation on price impact, we employ an instrumental variables (IV) approach, which is motivated by the variations of whether a stock is traded on MEMX around the early phase following the launch of the lit exchange. Specifically, we instrument the first-difference of market fragmentation (measured by the Herfindahl-Hirschman Index, 1-HHI) with the first-difference of whether a stock is traded on MEMX on a trading day around the launch of MEMX. In the second stage, the instrumented variables are regressed against the first-difference of price impact.[8] The main identification assumption is that whether a stock is traded on MEMX only affects

[6] Harris et al. (1990) defines four dimensions of market liquidity: width, depth, immediacy, and resiliency. Price impact is closely related to depth.

[7] To measure the price impact of trades, we adopt the methodology proposed by Holden and Jacobsen (2014), with some modifications. Our exchange-based price impact measure captures the dynamic variations in liquidity at each local exchange. For each stock i on each day t, we obtain 13 exchange-specific price impact observations. Additionally, we calculate the price impact based on NBBO quotes, following the method of Holden and Jacobsen (2014). Further details are discussed in Section 3.2.2.

[8] The change in market fragmentation at the individual stock level is contingent upon whether the stock is traded on the MEMX. The DTAQ data's master file contains an indicator variable labeled as "TradedOnMEMX" which denotes whether a stock is traded on MEMX on a specific trading day after July 24, 2020.

our dependent variable, price impact, through market fragmentation level.[9]

Using the IV approach, we find that higher market fragmentation levels lead to an increase in the price impact of trading in the U.S. equity markets. Our results show that if a stock i experienced a 1.6% increase in market fragmentation due to the launch of MEMX, the price impact for trading that stock would increase by approximately 2.9 bps if measured based on NBBO. We also document similar effects of market fragmentation on price impact using our exchange-based price impact measures. Of the 13 existing lit exchanges, 11 exchanges that account for 96.43% of market shares exhibit positive and significant effects of market fragmentation on price impact, with magnitudes ranging from 4.4 bps to 20.8 bps. To assess the economic significance of our results, we note that for a stock with a price of 49.59 USD and 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 even larger if we measure price impact exchange-wise using our proposed exchange-based price impact measures.[10]

Our additional tests indicate that our main results are not prone to various endogeneity concerns and are also unlikely to be solely driven by chance. We test the robustness of our results by examining alternative measures of market fragmentation and price impact, investigating whether the effects of market fragmentation on price impact vary across different stock sizes and listing exchanges, and assessing whether reverse causality and endogenous venue choice issues affect our estimates. The results from these tests confirm the quantitative similarity of our estimated causal effects with our main findings. In addition to the robustness tests, we conduct placebo tests to further strengthen the validity of our results. When deliberately falsifying the true event dates, we fail to find estimates of similar magnitude as demonstrated in our main tests.[11]

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[9] We will discuss the validity of our IV approach in Section 3.6.

[10] The fact that our estimated causal effects of market fragmentation on price impact are close to the realized changes in price impact around the introduction of MEMX verifies that exogenous market fragmentation does contribute to the increases in price impact. For instance, our estimated causal effect of a 1.6% increase in market fragmentation on price impact—a 4.4 bps increase in price impact—is close to the 5.2 bps increase in the realized price impact for the stocks traded on NASDAQ. Likewise, our estimated causal effects of market fragmentation on the price impact of trading on ARCA, NYSE, BZX, and EDGX are 6.1 bps, 8.4 bps, 8.5 bps, and 6.5 bps, respectively, which are also in line with the realized increases in price impact when MEMX was introduced.

[11] First, we investigate whether there are any significant changes in price impact using two pseudo-event dates, which were the 30th trading day before and the 30th trading day after the true event date when MEMX was introduced. As expected, we don't find any significant changes in price impact at the exchange level around these two pseudo-event dates. Second, we conduct a placebo test for our IV estimation of causal effects. This involves generating Bernoulli random variables to replace the true

We also perform two external validity tests using two events: the National Stock Exchange (NSX) halt on May 30, 2014, and the Investors Exchange (IEX) launch on September 2, 2016.[12] As expected, the NSX halt has the opposite effect on price impact compared to the launch of MEMX—the cease of a lit exchange reduces the price impact of trading for other existing exchanges. However, we do not observe any significant changes in price impact around the introduction of IEX. While beyond the scope of this paper, these results suggest that the price impact of trading for existing exchanges could be determined by exchange-specific factors such as speed bumps and the conversion of the dark pool to the lit exchange when such an exchange is introduced.

Why does the price impact of trading increase when launching a new lit exchange? The answers to this question lie in the intuition behind a recent work of Chen and Duffie (2021). We illustrate a simplified version of their theory in Figure 2. Consider the following two scenarios: i) the asset is traded on a centralized exchange as shown in case 1, and ii) the same asset can be traded on two exchanges as shown in case 2. Suppose a strategic trader submits limit orders from 19.0 to 20.0 with 200 shares at each price level, creating a downward step-wise demand schedule (black solid line).[13] A liquidity trader arrives and is willing to sell 300 shares ($\sigma_Q = 300$) with a market order. If the demand schedule is perceived as continuous rather than step-wise, this 300-shares market order will move the price from 20.0 to 19.7. In case 2, we assume that the strategic trader divides the previous limit orders into two halves at each price level and submits them to the two exchanges separately. As a result, 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 two best bid prices, pushing the price down from 20.0 to 19.5, thus increasing the price impact of trading in general.

Building on this intuition, we propose two channels through which the introduction of a new lit exchange affects the price impact of trading: the mechanical channel and the informational channel. The mechanical channel pertains to changes in the order book status caused by order-splitting or order flow migration, as illustrated in Figure 1. These

indicators of whether a stock was traded on MEMX for trading days between October 29, 2020, and 20 days after the calendar days when stocks were first traded on MEMX. We then use these generated variables to run our two-stage least square regressions, as we do in our main regressions. Again, we do not find any significant results for these generated pseudo-series, suggesting that our estimated causal effects are not driven by chance.

[12]NYSE acquired National Stock Exchange on December 14, 2016. NSX was renamed "NYSE National" as a result of the acquisition. IEX was operated as a dark pool prior to September 2, 2016.

[13]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).

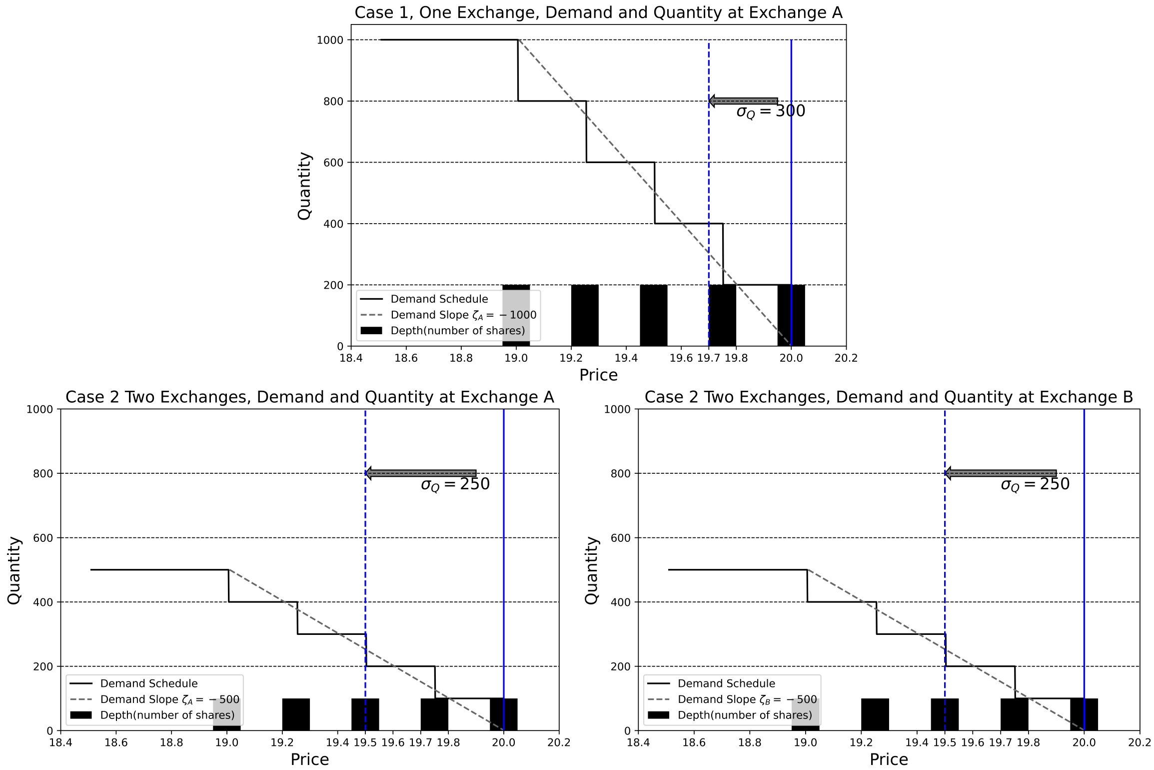

Figure 1: This figure presents the changes in the limit order book slopes and order aggressiveness from one exchange to two exchanges.

changes may make the order book slope more inelastic, but they alone may not necessarily result in a higher price impact of trading without incoming market orders. To observe a realized increase in price impact, liquidity traders must submit more aggressive orders. We conjecture that this increase in order aggressiveness occurs through the informational channel, as traders can obtain more information from additional asset prices offered by the new lit exchange. Our empirical analysis shows that both the mechanical channel and the informational channel contribute to the increased price impact observed when MEMX is introduced.

We examine the mechanical channel by conducting two order-level tests. First, we test how order flow is migrated to MEMX around the introduction of MEMX. We calculate 13 exchange-wise measures of market depth which are defined as the time-weighted average number of shares at best bid (ask) prices at stock-day level. Also, we obtain the total number of shares of all orders submitted to MEMX from SEC market structure files.[14] We find that higher order volume submitted to MEMX is associated with decreased market

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

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 conjecture that market depth is reduced with increased market fragmentation partly due to the migration of order flows from existing exchanges to MEMX.

Second, we investigate the changes in order book slopes surrounding the introduction of MEMX using NASDAQ TotalView-ITCH data. If order flow migration has a significant impact on the limit order book, we expect to observe structural changes in the order book slopes, as illustrated in Figure 1. By constructing two stock-day level measures of order book slopes based on Kalay et al. (2004) and Næs and Skjeltorp (2006), as anticipated, we observe that the order book slopes become less steep and more inelastic after the introduction of MEMX. Regarding the order book slopes on the bid (ask) side, the introduction of MEMX is associated with an approximate reduction of 16.8% (12.6%) in the absolute slopes.

The changes in order book slopes may also be linked to an under-explored phenomenon observed by Haslag and Ringgenberg (2021), which shows that market fragmentation could harm the liquidity of small stocks. Small stocks, typically characterized by larger quoted spreads and more inelastic slopes, are more vulnerable to the impact of slope changes resulting from order flow migration, in contrast to large stocks. Especially, as slopes become more inelastic, small stocks with shallower slopes may experience greater price impact compared to large stocks with steeper slopes. Our empirical results validate this explanation. When categorizing stocks into five size quintiles, we observe more pronounced effects of market fragmentation on price impact for small stocks compared to large ones. Interestingly, small stocks, characterized by smaller absolute slopes, actually experience the most substantial percentage decrease (27.0%) in the average absolute slopes, in contrast to large stocks, which encounter only a 12.1% reduction in the average absolute slopes after the introduction of MEMX.

Turning to the test of informational channel. We examine the changes in order aggressiveness around the introduction of MEMX. We reconstruct the limit order book of NASDAQ stock exchange using the order-level NASDAQ TotalView-ITCH data. And following the approach in Biais et al. (1995), we calculate the percentage of aggressive orders and unaggressive orders, respectively. We compare the changes in the proportion of aggressive orders and unaggressive orders around the launch of MEMX. Our findings suggest 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. Our findings are consistent with the empirical evidence in Griffiths et al. (2000) which suggests that order aggressiveness is positively associated with the price impact. Since the introduction of MEMX is associated with increases in overall order aggressiveness, which is also predicted by Chen and Duffie (2021), the increases in price impact can also be attributed to this informational channel.

We also verify both the informational channel and the mechanical channel contribute to the increases in the price impact of trading using a series of Monte Carlo simulations. By simulating a 14-exchange trading system with order routing, we find our simulated price impact is positively correlated with order aggressiveness (the informational channel) and order flow migration to the 14th exchange (the mechanical channel). In our Monte Carlo simulations, we have two structural parameters—the order aggressiveness parameter and the order flow migration parameter. When the order aggressiveness parameter increases about 40%, the exchange-based price impact increases about 0.41 bps to 22.1 bps. Likewise, when the order flow migration parameter, which represents the market shares on the 14th exchange, increases from 4% to 20%, the exchange-based price impact will increase about 1.19 bps to 4.93 bps. The results from these simulations align with our empirical evidence that the increased price impact can be attributed to both the informational channel and the mechanical channel.

Besides, we investigate the order flow segmentation channel by analyzing changes in off-exchange trading volume around the introduction of MEMX. Following Hatheway et al. (2017), we construct the stock-day level off-exchange ratios defined as the number of trades executed at the off-exchange venues divided by the total number of trades. We find no significant changes in the off-exchange ratios following the introduction of MEMX, indicating that the observed increases in price impact are unlikely to be driven by the order flow segmentation channel.

Related literature. We contribute to the literature by providing empirical evidence to recent theoretical papers deliberated on market design (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).[15] While economists debate theoretically on whether markets should be

[15]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

designed to be centralized or fragmented, empirical evidence on this aspect is elusive given the intricate causes and consequences of market fragmentation.[16] 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.[17]

Specifically, our paper tests the theoretical predictions 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 models. 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.[18] 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. While our paper is not testing all the consequences 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, informationally and

(Mendelson, 1987; Chowdhry and Nanda, 1991; Stoll, 2001; Baruch et al., 2007).

[16] 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.

[17] 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).

[18] 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.

mechanically.[19]

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. The conventional view of the informational price impact, building upon the seminal works of Glosten and Milgrom (1985) and Kyle (1985), suggests that if some traders have private information on the efficient price of the asset at some time in the future, market makers who scrutinize the order book information are likely to adjust their quotes accordingly—widening the spreads or adversely setting the quotes. Therefore, price impact arises from the adverse selection costs. While early empirical studies (Dufour and Engle, 2000; Chiyachantana et al., 2004; Cont et al., 2014; Chiyachantana et al., 2017) intensively focused on the determinants of price impact through this informational channel, recent theoretical studies such as Malamud and Rostek (2017) and Chen and Duffie (2021) suggest that the variations in price impact could also be explained by the mechanical channel in a multi-market setting. Thus, our paper complements previous empirical studies and provides additional evidence on the determinants of price impact.

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 the 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 setting—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

[19] For example, welfare effects. See Bernales et al. (2020) for details.

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 the large stocks. Our paper has two major differences compared with Haslag and Ringgenberg (2021). First, we focus on a relatively 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 datasets. These new 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.[20] 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 Data

This section discusses the institutional details of the new lit exchange MEMX in Section 2.1. We illustrate some stylized facts about the new exchange and the growing importance of this new exchange. Section 2.2 discusses the datasets used throughout this paper.

[20] 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.

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.[21] 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.[22] 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 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.

[21]See Figure E.1.

[22]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/.

2.2 Data

We use public datasets including the Center for Research in Security Prices (CRSP), Daily Trade and Quotes (DTAQ), NASDAQ TotalView-ITCH (ITCH), and SEC market structure files throughout this paper.

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.

Our measures of market fragmentation, price impact, and market depth are based on DTAQ data. Our measures of order book slopes and order aggressiveness are based on ITCH data. We also obtain total number shares of all orders submitted to MEMX from SEC market structure file. After merging these data at the ticker-day level, we obtain our final sample which comprises 1,176 NYSE-listed stocks, 132 AMEX-listed stocks, and 2,100 NASDAQ-listed stocks. Our full sample has an average of 3,393 stocks on each trading day and a total number of 854,973 observations. We also use 10 days, 20 days, or 60 days estimation window before and after the introduction of MEMX throughout this paper. Table A.2 shows the sample selection process and sample statistics.

3 Measurements, Stylized Facts, and Research Design

This section discusses the measures that we use throughout this paper (Section 3.1 and Section 3.2), the stylized facts about the changes in price impact around the introduction of MEMX (Section 3.3)), the calendar days when stocks were first traded on MEMX (Section 3.4)).

Using the variations in the first days when stocks were first traded on MEMX, Section 3.5 illustrates the exogenous change in market fragmentation due to the introduction of MEMX. Furthermore, we take advantage of such variation and proposes an instrumental variable (IV) approach in Section 3.6 to estimate the causal effects of market fragmentation on price impact.

3.1 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). Our paper differs from Haslag and Ringgenberg (2021) in that 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.[23] Suppose in a trading day t, a stock i trades at the lit exchange ψ with trading volume $Volume^{\psi}_{i,t}$. Then, we define the market share at the exchange ψ for this stock i at trading day t as:

$$s^{\psi}_{i,t} := \frac{Volume^{\psi}_{i,t}}{\sum_{\psi} Volume^{\psi}_{i,t}} \tag{1}$$

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

$$Frag^{volume}_{i,t} := 1 - \sum_{\psi} (s^{\psi}_{i,t})^2 \tag{2}$$

where $\sum_{\psi} (s^{\psi}_{i,t})^2$ 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, $Frag^{trade}_{i,t}$.[24]

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

This subsection introduces our measures of price impact that are used throughout this paper. We construct both price impact measures based on NBBO and each exchange-

[23]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.

[24]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, $Frag^{volume}_{i,t}$ 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: $Frag^{volumeInv}_{i,t} := \frac{1}{\sum_{\psi} (s^{\psi}_{i,t})^2}$ and $Frag^{tradeInv}_{i,t}$.

based price impact for 13 lit markets. We use DTAQ data to construct our price impact measures.

3.2.1 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 t:

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

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.

3.2.2 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.[25] If the trade κ is executed at NYSE (N), for instance, 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.[26] 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,

[25] 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 are discussed in Appendix Table A.1

[26] 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 B.2 the results are similar to our main results in Table 3.

Table 1, 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.[27]

Panel B, Table 1 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[28], market capitalization, and stock price directly from CRSP daily securities files.

[**Table 1**]

3.3 Changes in price impact around the introduction of MEMX

We examine the changes in price impact around the introduction of MEMX. Panel A, Table 2 reports the results from the following simple OLS regression:

$$PI_{i,t}^{\psi} = \alpha_i + \eta POST_{i,t} + \mathbf{X}_{i,t}^{'}\Phi + \epsilon_{i,t} \tag{4}$$

Where PI_{ψ} is our measure of price impact defined as in Equation 3. $POST_{i,t}$ is an indicator variable that equals one after October 29, 2020. ψ denotes the exchange. $\mathbf{X}_{i,t}^{'}$ are the controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. α_i is the stock fixed effect.

Our results in Panel A, Table 2 suggest a temporary increase in price impact at both the NBBO level and at each exchange level. Controlling for stock-day level variables and the stock-fixed effect, we find the price impact of trading increases by 3.7 basis points at the NBBO level within 10 days when MEMX is introduced. Similarly, we document increases of 1.0 bps to 20.4 bps in price impact at the primary U.S. exchanges using our proposed exchange-based price impact measures. Most of the coefficients on the variable—$POST_{i,t}$—are significant at the 5% level. A simple comparison in Panel B,

[27] 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.

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

Table 2 between the average price impact 10 days prior to the introduction of MEMX and the average price impact 10 days after yields quantitatively similar results.

[**Table 2**]

We conduct additional tests to in Appendix A from Table A.7 to Table A.11. Table A.7 reports the changes in price impact around a 20-day estimation window around the introduction of MEMX. We find similar results as in Panel A, Table 2. Table A.8 reports the changes in the 15-seconds-based price impact around the introduction MEMX. The results are also quantitatively similar to the results shown in Panel A, Table 2. Table A.9 reports the changes in price impact around two pseudo-events—30 trading days before, and 30 trading days after the true date when MEMX is introduced. We fail to find significant changes around these two pseudo-events for most of the exchange-based price impact.

Table A.10 reports the changes in price impact a 20-day estimation window around the halt of the National Stock Exchange (NSX) on May 30, 2014.[29] Interestingly, we find the exact opposite results for this event compared with the event of the introduction of MEMX. Specifically, we the halt of NSX reduces the price impact of trading for NBBO-based price impact. At the exchange level, we also find the price impact of trading stocks in ARCA, NYSE, BZX, EDGX, EDGA, BYX, BX, PSX, and AMEX decrease, though the significance of coefficients varies by exchanges. In contrast, we fail to find significant changes in price impact around the introduction of Investors Exchange (IEX) on September 2, 2016. Table A.11 illustrates our results in the changes of price impact using the introduction of IEX as the event. While it is beyond the scope of this paper to study the exchange-specific factors such as speed bump, and the conversion of a dark pool to a lit exchange which may also affect the price impact of trading.

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

While it is straightforward to identify when MEMX is eligible to start trading all stocks on MEMX (October 29, 2020), it is complicated to identify when a particular stock is first traded on MEMX. We use the DTAQ master file to identify the time when

[29]The National Stock Exchange halts trading because it changed its pricing structure to charge both sides of a trade a fee for securities priced $1 or more, a departure from other public trading venues that usually charge one side and pay a rebate to another.

a stock is first traded on MEMX. From July 24, 2020, the DTAQ master file starts 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. We define the event day ($E_i^d = 0$) for a particular stock i as the first day when it is traded on MEMX.[30] 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 had been traded on MEMX.

Stocks in our sample also exhibit varied trading patterns after they are first traded on MEMX. In fact, 46.3% of the stocks in our sample are 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.3. As we will discuss in Section 3.6, this variation facilitates the estimation of the causal effects using an instrumental variable approach.

[**Figure 3**]

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**]

3.5 The exogenous change in market fragmentation

This section discusses the changes in the market fragmentation measures– $Frag_{i,t}^{trade}$ and $Frag_{i,t}^{volume}$–used in this paper around the introduction of MEMX. Figure 2 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;

[30] 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".

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 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:

$$Frag_{i,t}^* = \alpha_i + \lambda_t + \sum_{j=J}^{-1} \gamma_j D_{i,t}^j + \sum_{k=0}^{K} \beta_k D_{i,t}^k + \gamma_{J-} D_{i,t}^{J-} + \beta_{K+} D_{i,t}^{K+} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t} \tag{5}$$

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

Figure 2 suggests that on the first days when stocks were 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.5 where we present the estimated coefficient from the regression of the market fragmentation on the relative 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 were 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.3 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.

[**Figure 2**]

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 the 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:

$$\Delta Frag^{*}_{i,t} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}^{'}_{i,t}\Phi + \Delta\epsilon_{i,t} \tag{6}$$

$$\Delta PI^{\psi}_{i,t} = \Delta\lambda_t + \mu\widehat{\Delta Frag^{*}_{i,t}} + \Delta\mathbf{X}^{'}_{i,t}\Gamma + \Delta\epsilon_{i,t} \tag{7}$$

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, $\widehat{\Delta Frag^{*}_{i,t}}$ is the predicted value from the first-stage regression, and $\mathbf{X}^{'}_{i,t}$ 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.3, 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 $PI_{i,t}^{\psi}$ and whether a stock is traded on MEMX ($OnMEMX_{i,t}$) after the introduction of MEMX on October 29, 2020, stock-wise. Table A.6 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 1,299 (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 additional tests which aim to address a variety of concerns with regard to the validity of our main results in Section 4.1.

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, $Frag_{i,t}^{trade}$ and $Frag_{i,t}^{volume}$, 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 $\Delta Frag_{i,t}^{trade}$ and $\Delta Frag_{i,t}^{volume}$, 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 1.6% increase in market fragmentation level ($Frag_{i,t}^{trade}$) will induce approximately 2.9 bps ($0.011 \times 0.026 \times 10{,}000$) increases 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 1.6% exogenous increase in market fragmentation.

Table 3 also shows that price impact measured at each *existing* lit exchange level 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 4.4 bps to (in NASDAQ (Q+T)) 20,8 bps (in BX (B)). The magnitude of the effects are similar for the regressions using either market fragmentation measures based on trade ($Frag_{i,t}^{trade}$) or measures based on trading 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 Additional tests

4.2.1 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 B.1 using the inverse of HHI index proposed by Gresse (2017) and Lausen et al. (2021), in Table B.2 using the weighted midpoint proposed by Hagströmer (2021) to calculate the price impact, and in Table B.3 using the 15-second-based price impact jointly confirm that our main findings in Table 3 are unlikely to be driven by different 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 sub-samples where stocks are grouped by their listing exchanges. Table B.4 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 B.5 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.6, 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 MEMX is 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 B.6 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.

In addition, we also validate the results in Table 2 using 1) different estimation windows; 2) two pseudo-events; 3) two external validity tests using two different events. We summarize all these robustness tests in Table 4. Also, we briefly explain the rationales for why we need to conduct these tests and how we conduct them in Table 4. Readers can find the details of our results for these robustness tests in our Appendix A and Appendix B.

[Table 4]

4.2.2 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, $\widetilde{OnPLACEBO}_{i,t}$, 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.[31] We also assume that all stocks will be always traded on MEMX after 20 days when they are first traded

[31]The values of $\widetilde{OnPLACEBO}_{i,t}$ before October 29, 2020 are all set to 0.

on MEMX. This means for $t > E_i^d + 20$ we manually set the values of $On\widetilde{PLACEBO}_{i,t}$ to be 1. In total, we generate ten series of $On\widetilde{PLACEBO}_{i,t}$.

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 the 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, $\Delta On\widetilde{PLACEBO}_{i,t}$. We use ten different generated series of $On\widetilde{PLACEBO}_{i,t}$ 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 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 were traded on MEMX, we cannot observe any significant effects of market fragmentation on price impact.

[**Table 5**]

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 mechanisms through which the introduction of a new lit exchange may affect price impact. We consider three channels: the mechanical channel (Section 5.1), the informational channel (Section 5.2), and the order flow segmentation channel (Section 5.3). Our results in this section suggest that the increased price impact due to the introduction of MEMX can be explained by both the mechanical channel and the informational channel rather than the order flow segmentation channel.

5.1 The mechanical channel

One possible channel through which market fragmentation leads to a higher price impact of trading may be attributed to the mechanical channel. As we show in Figure 1, the introduction of a new lit exchange will change the order book status of the existing lit exchange. Therefore, we conduct two order-level tests to investigate how the order book status is altered when MEMX is launched.

First, we investigate how the order flow is migrated to MEMX and how it affects the market depth of the existing lit exchanges around the introduction of MEMX. Using the total order volume (in millions) submitted to MEMX as a proxy for the order flow migration, we then run the following regressions to gauge the impact of order flow migration to MEMX on market depth:

$$\ln BIDDepth^{\psi}_{i,t} = \alpha_i + \lambda_t + \pi ORDERVOL^{MEMX}_{i,t} + \mathbf{X}'_{i,t}\Gamma + \epsilon_{i,t} \tag{8}$$

$$\ln ASKDepth^{\psi}_{i,t} = \alpha_i + \lambda_t + \pi ORDERVOL^{MEMX}_{i,t} + \mathbf{X}'_{i,t}\Gamma + \epsilon_{i,t} \tag{9}$$

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, obtained from the SEC market structure files where they summarize the total order volume at the stock-day level for each lit exchange. $\mathbf{X}'_{i,t}$ 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 1, 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 migration to MEMX in the early days after the launch of the exchange. We estimate the coefficients π with different estimation windows, for example, ten days pre and post (-10, 9), twenty days pre and post (-20, 19), and sixty days pre and post (-60, 59). We find most of the estimated coefficients of $ORDERVOL^{MEMX}_{i,t}$, 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 migration when MEMX is introduced.

[**Table 6**]

Second, we investigate if there are changes in the slopes of the limit order book around the launch of the new exchange. As we show in Figure 1, 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 at each existing exchange, we can suspect that the price impact of trading will be larger in the fragmented case than in the centralized exchange case for executing the same quantities if the execution of the orders will lead to the "walking the book".

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 using ITCH data for stocks traded on the NASDAQ stock exchange. 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:

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

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:

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

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 absolute values of 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:

$$SLOPEBID_{i,t}^{NS} = \alpha_i + \rho POST_{i,t} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t} \tag{14}$$

$$SLOPEBID_{i,t}^{Kalay} = \alpha_i + \rho POST_{i,t} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t} \tag{15}$$

$$SLOPEASK_{i,t}^{NS} = \alpha_i + \rho POST_{i,t} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t} \tag{16}$$

$$SLOPEASK_{i,t}^{Kalay} = \alpha_i + \rho POST_{i,t} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t} \tag{17}$$

Where $POST_{i,t}$ is an indicator variable that equals one after October 29, 2020. $\mathbf{X}_{i,t}^{'}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. The regression coefficients ρ which capture the changes in average order book slopes are of our interest. We expect the ρ to be negative for the bid side and positive for the ask side if the introduction of MEMX makes the order book slopes less steep and more inelastic.

Table 7 reports the results of the changes in order book slopes around the launch of MEMX. As we expect, the introduction of MEMX decreases (increases) the steepness (inelasticity) of the limit order book 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 becoming smaller (less positive) suggesting that order book slopes are becoming less steep and the demand schedules are becoming more inelastic.

Overall, our results support the mechanical channel that the changes in the order book status around the launch of the new exchange may potentially contribute to the observed increases in price impact after the introduction of MEMX.

[**Table 7**]

5.1.1 Order slopes and heterogeneous effects of market fragmentation on price impact

In this section, we relate the changes of order book slopes to the heterogeneous effects of market fragmentation on liquidity across stocks of different sizes as first documented by Haslag and Ringgenberg (2021). In their study, they conjecture market fragmentation deteriorates the liquidity of small stocks due to the possible increased "front-running" risks. As liquidity is dispersed across venues, quotes can be more likely to be "picked-off" by informed traders. Thus market makers need to widen the spreads to compensate the risks associated with these small stocks. We provide an additional explanation on why market fragmentation deteriorates the liquidity of small stocks.

First, we investigate the heterogeneous effects of market fragmentation on price impact based on the approach of Haslag and Ringgenberg (2021). For each stock during our sample period from June 1, 2020 to May 28, 2021, we calculate the average of market capitalization ($Marketcap_{i,t}$). Then we sort stocks into quintiles based on their logarithm of market capitalization. Quntile 1 represents the smallest stocks while quntile 5 represents the largest stocks. For each quintile and each exchange ψ, we run the 2SLS regressions as in Table 3.

Figure 5 shows the heterogeneous effects of market fragmentation on price impact for stocks in different size quintiles. The y-axis shows the estimated coefficients μ obtained from the 2SLS regressions, while the x-axis represents the quintiles of stocks. The figure suggests that the effects of market fragmentation on price impact are more pronounced for smaller stocks, specifically those in quintile 1 and quintile 2, compared to larger stocks, such as those in quintile 4 and quintile 5.

[**Figure 5**]

We further examine the changes in order book slopes within different size quintiles. Figure 6 illustrates the order book slopes before and after the introduction of MEMX across five size quintiles. As expected, large stocks in quintiles 4 and 5 exhibit steeper order book slopes compared to small stocks. While stocks in different quintiles all experience decreases in absolute order book slopes, the percentage of decrease is more significant for small stocks than for large stocks. For instance, the average order book slopes for stocks in quintile 1 at the bid side experience a reduction of 27.0% (from −42,258.28 to −30,833.37) in absolute values, in contrast to stocks in quintile 5 with a decrease of 12.1% (from −210,181.5 to −184,692.3). The magnitudes of the changes are similar at the ask side. Thus, the different percentage changes in order book slopes may possibly explain that the effects of market fragmentation on price impact, caused by the introduction of MEMX, will be more pronounced for small stocks in comparison to large stocks.

[**Figure 6**]

5.2 The informational channel

As shown in Figure 1, the condition to observe a realized increase in price impact depends on the order aggressiveness of the liquidity traders. We refer this channel as the informational channel.

We test changes in order aggressiveness around the introduction of MEMX using ITCH data. Since the ITCH data comprises all orders that are entered into the NASDAQ trading system, we can reconstruct the limit order book using all relevant messages from the ITCH.[32] After reconstructing the limit order book, 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 C, Table C.1. We

[32] The procedure is discussed in Appendix D.

then run the following regression for each order aggressiveness type:

$$\%Order^{*}_{i,t} = \alpha_i + \lambda_t + \omega \mathbb{1}(t >= E^d_i) + \mathbf{X}'_{i,t}\Gamma + \epsilon_{i,t} \tag{18}$$

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. $\mathbf{X}'_{i,t}$ 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 8 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 the 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 C, Table C.2. The results in Table C.2 are similar to the results in Table 8. R-Squared in Table C.2 is all slightly smaller than those in Table 8 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 C.3. Not surprisingly, we find almost no significant associations between the falsified introduction of MEMX and the changes in 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 8**]

5.3 Monte Carlo simulations

To further investigate both the mechanical channel and the informational channel, we simulate a U.S. equity market with 14 exchanges and calculate our exchange-based price impact with varying degrees of order aggresiveness and order flow migration (market shares). In our simulated trading system, we have two types of trades—strategic traders submitting limit orders and liquidity traders submitting market orders–on all the lit exchanges randomly. Strategic traders submit limit orders with log-normally distributed quantity ($Q_{limit} \sim LogNormal(7.5, 1)$) across all 14 exchanges equally with the limit prices following uniform distributions ranging from \$19.51 (\$20.50) to \$20.00 (\$20.01) in the bid (ask) side. For each submitted limit order, we also generate uniformly distributed price elasticity from 0.01 to 1. We then form a demand schedule for each submitted limit order. For example, if a limit order with 1,000 shares at \$20.00 with price elasticity of 0.1 will split the 1,000 shares into ten 100-shares child orders across 10 price ticks from \$20.00 to \$19.90 with a incremental of \$0.01. If this order has a price elasticity of 0.5, then we only divide the parent order into two 500-shares child orders on two consecutive price ticks (\$20.00 and \$19.99). Liquidity traders submit market orders where the sizes ($Q_{market} \sim LogNormal(\sigma_Q, 0.25)$) of their submitted orders also follow a lognormal distribution with the mean, σ_Q, as the *order aggressiveness* parameter in the trading system.

We assume the first 13 exchanges having fixed basic market share and the last exchange having varying share ($s^{\psi=14}$) ranging from 4% to 20%. The basic market share for the first 13 exchanges is set as $s^{\psi=i} \in S$. Where $S =$[0.2, 0.1, 0.1, 0.1, 0.1, 0.05, 0.05, 0.02, 0.01, 0.01, 0.01, 0.01, 0.005]. These market shares represent the percentage of limit orders are submitted to the corresponding exchange. Using the previous example, each 500-shares child order will be further splitted across 14 exchanges. The first exchange which has 20% of the market shares will receive two limit orders of 100 shares at \$19.99 and \$20.00, respectively. The remaining exchanges will also receive two limit orders with the sizes corresponding to their market shares. Further, if the 14th exchange only has 4% of the market shares which means the addition of all market shares is less than 1, the remaining market shares will be equally added to prior 13 exchanges. The market share of the 14th exchange, $s^{\psi=14}$, represents the *order flow migration* parameter in the trading system.

In terms of the order arrival rates, we assume the order arrival rates of both market orders and limit orders follow Poisson distributions. Therefore, we simulate the timestamps of the orders based on exponential distributions with $T_{Q_{market}} \sim Exp(35, 600)$

and $T_{Q_{market}} \sim Exp(4, 5850)$. These fixed parameters facilitate us to obtain dynamic variations in the limit order book.

We apply a price-time rule and an order routing system to execute the orders. First, we allow market orders to arrive randomly at any exchange. A buy (sell) market order will only execute against the limit orders on the ask (bid) side of the limit order book and the trade direction will be assigned based on the market order. When executing the market order, the resting orders at the arrived exchange will be executed first against with the incoming market order. If the size of the market order exceeds the depth at the arrived exchange, the non-executable part will be routed to the exchange with the best price. If multiple exchanges have the same best prices, we assume the orders will be routed to the first exchange (exchange with smallest label) among all the exchanges which have the best prices.

We update and document the limit order book for each exchange when new orders arrive. We keep the best prices at both the bid side and the ask side and calculate the midpoint of the best bid and the best ask for each exchange. We also document the execution price, the quantity, the trade direction, the timestamp, the executed exchange for every trade executed. Finally, as in Section 3.1 and Section 3.2, we calculate market fragmentation and price impact using Equation 2 and Equation 3, respectively.

Turning to our main focus, Table 9 reports the results for a series of Monte Carlo simulations. We report 15-seconds exchange-based price impact for different level of the order aggressiveness parameter (σ_Q) and different order flow migration ($s^{\psi=14}$). Panel A reports the level of price impact in basis points with a fixed order flow migration parameter ($s^{\psi=14}$) and a varying degree of order aggressiveness parameter ranging from $\sigma_Q = 5$ to $\sigma_Q = 7$. While panel B reports the simulated price impact based on a fixed order aggressiveness parameter ($\sigma_Q = 6$) and a varying degree of order flow migration ranging from $s^{\psi=14} = 0.04$ to $s^{\psi=14} = 0.20$. Each level of $s^{\psi=14}$ and σ_Q is based on 100 random draws. We also report the standard errors in parentheses.

We find both order aggressiveness parameter and order flow migration parameter are, in general, positively correlated with the price impact of trading at each exchange. For example, comparing with $\sigma_Q = 5$, 13 out of 14 exchange-based price increase when we set the order aggressiveness parameter as $\sigma_Q = 7$. The magnitude of the increases range from 0.41 bps to 22.1 bps. Similarly, when we increase the order flow migration parameter from 0.04 to 0.20, the price impact of trading increases about from 1.19 bps to 4.93 bps depending on the specific exchange. These results are consistent with our prior empirical evidence that both the mechanical channel (the order flow migration) and the informational channel (the increased order aggressiveness) could possibly contribute to the observed increase in price impact when the new exchange is launched.

[**Table 9**]

5.4 The order flow segmentation channel

Prior studies such as Comerton-Forde and Putniņš (2015) and Hatheway et al. (2017) document that the price impact of trading may be also determined by the information contents of the order flow. For example, Hatheway et al. (2017) finds that trades executed at the dark venue are less informed, and therefore the introduction of a dark pool may segregate the order flows based on their information. One of the possible channels for observing the increased price impact of existing exchanges after the introduction of MEMX is possibly due to the order flow segmentation—trades with large information contents used to be executed in the off-exchange venues are now migrated to the new lit exchange or other existing exchanges.

To rule out this possible channel, we follow Hatheway et al. (2017) and construct the stock-day level off-exchange ratios defined as the number of trades executed at the off-exchange venues divided by the total number of trades. Similarly, we also define the dollar volume executed at the off-exchange venues divided by the total dollar volume as our additional measure of the off-exchange ratios. We then regress these ratios on i) the indicator for a stock i after the first day when it is traded on MEMX, and on ii) the indicator that equals to one after October 29, 2020. Results in Table C.5 suggest that there are no significant changes in the off-exchange ratios around the introduction of MEMX exchange. Therefore, we conclude that the increases in price impact are unlikely to be driven by the order flow segmentation channel.

6 Conclusion

In this paper, we document the causal effects of market fragmentation on price impact using a newly launched exchange as a quasi-natural experiment. We find the launch of MEMX 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.

Our paper contributes to both the strand of literature understanding the determinants of price impact and the increasing number of studies on market fragmentation. Particularly, our findings suggest the introduction of a new lit exchange affects the price impact of trading through both the mechanical channel and the informational channel. Therefore, regulators should carefully evaluate the costs and benefits when introducing market fragmentation as the gains from increasing the number of exchanges may not outweigh the costs associated with it.

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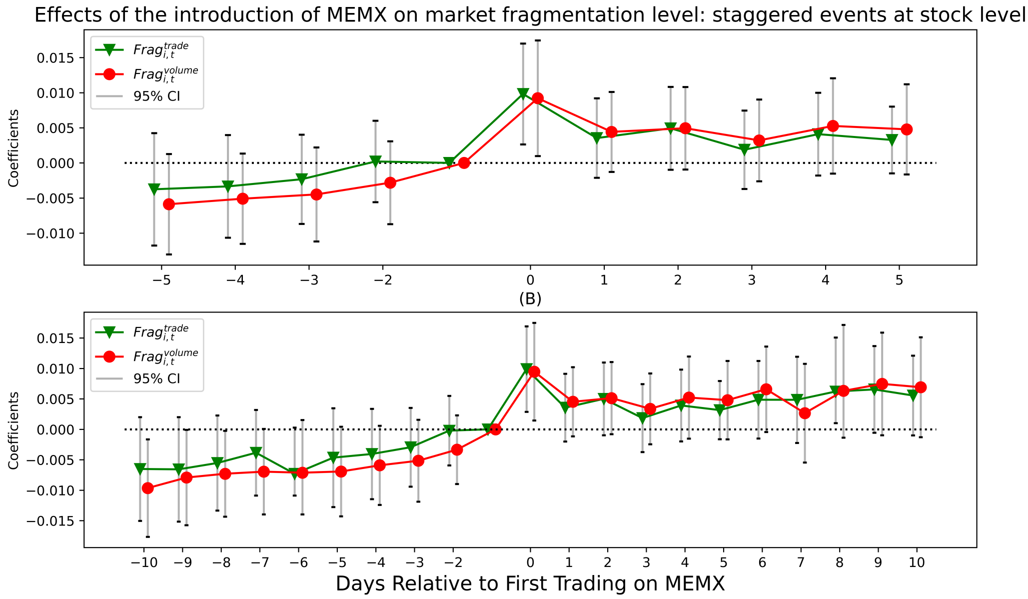

Figure 2: This figure reports the coefficients, γ_j and β_k estimated from the following regressions: $Frag^*_{i,t} = \alpha_i + \lambda_t + \sum_{j=J}^{-1} \gamma_j D^j_{i,t} + \sum_{k=0}^{K} \beta_k D^k_{i,t} + \gamma_{J-} D^{J-}_{i,t} + \beta_{K+} D^{K+}_{i,t} + \mathbf{X}'_{i,t}\Gamma + \epsilon_{i,t}$. 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. $D^{J-}_{i,t}$ and $D^{K+}_{i,t}$ are binning indicators for the relative days larger than J and K. $\mathbf{X}'_{i,t}$ 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 $J = -10$.

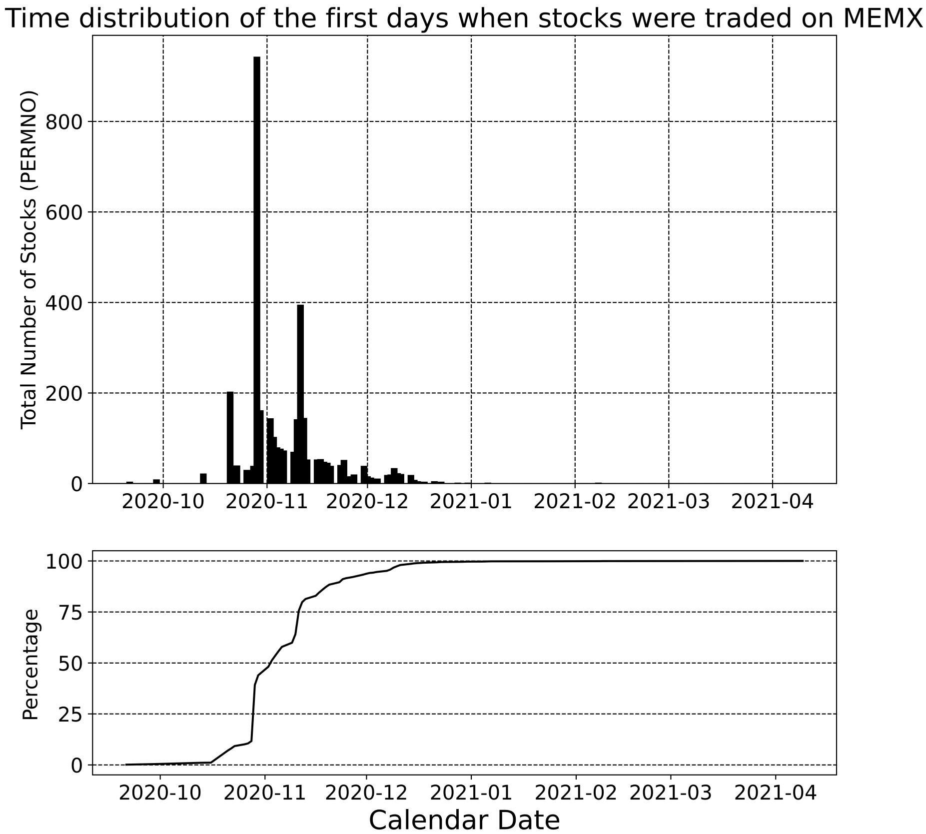

Figure 3: This figure presents the time distribution of the first days when stocks are traded on MEMX.

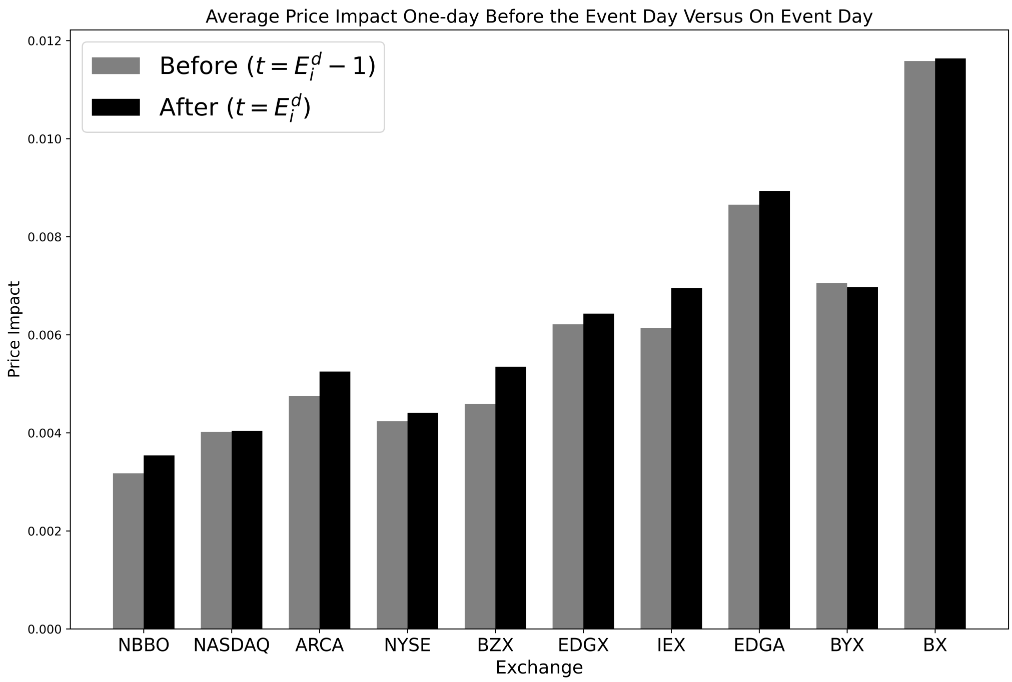

Figure 4: This figure presents the mean price impact one-day before the first calendar days when stocks are traded on MEMX and the first days when stocks are traded on MEMX.

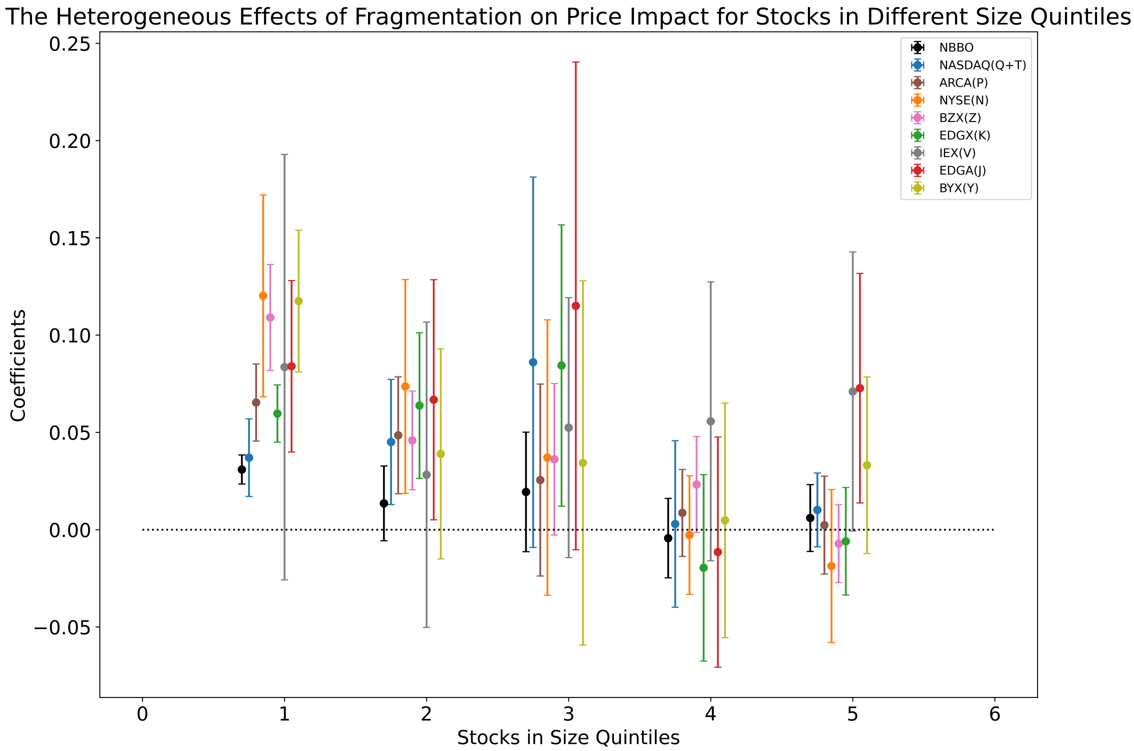

Figure 5: This figure presents the hetergenous effects of fragmentation on price impact for stocks in different size quintiles. We sort stocks into quintiles based on their average $Marketcap_{i,t}$ during our sample period from June 1, 2020 to May, 28, 2021. The x-axis indicates the quintiles of the stocks. For each quintile and each exchange ψ, we run the 2SLS regressions as in Table 3. The y-axis shows the coefficients μ in the second stage of 2SLS.

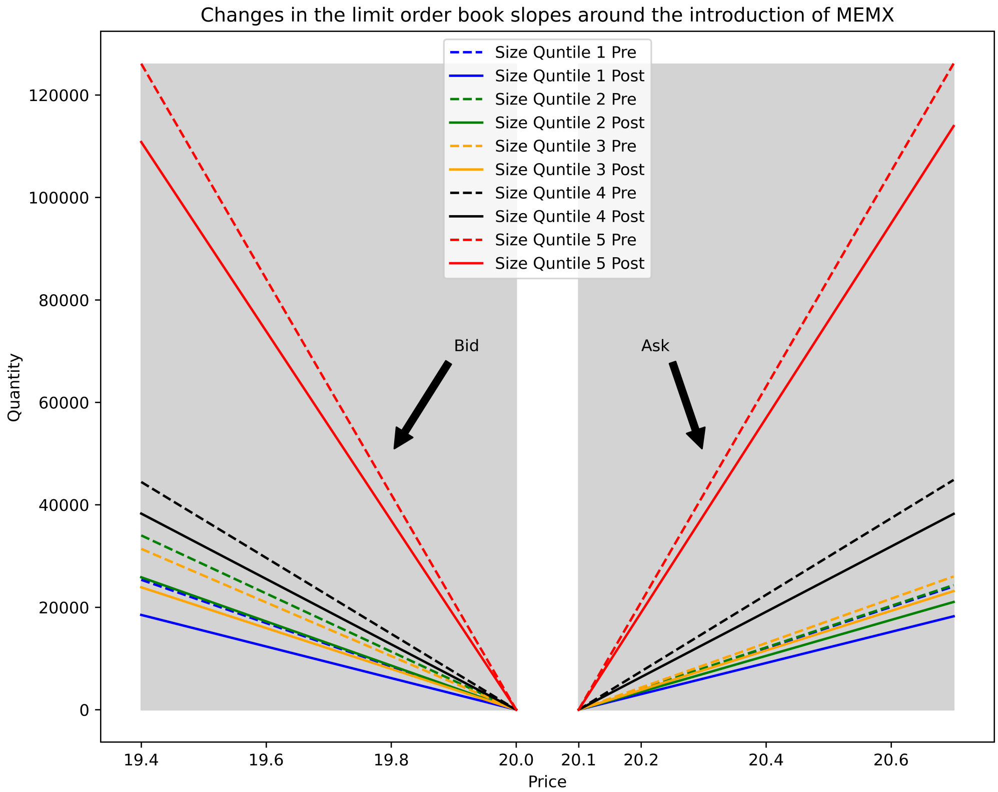

Figure 6: This figure shows the changes in the limit order book slopes across different size quintiles around the introduction of MEMX. For each size quintile, we calculate the average of order book slopes prior to and after the introduction of MEMX using a 10-day estimation window. The x-axis indicates the hypothetical stock prices. The y-axis indicates the hypothetical cumulative shares quantity.

Table 1. 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: Exchange-based 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
$OnMEMX_{i,t}$	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 2. The changes in price impact around the introduction of MEMX

This table reports the changes in price impact around the introduction of MEMX. In Panel A, we run an OLS regression for each exchange ψ as the following:

$PI^{\psi}_{i,t} = \alpha_i + \eta POST_{i,t} + \mathbf{X}^{'}_{i,t}\Phi + \epsilon_{i,t}$

Where PI_{ψ} is our measures of price impact defined as in Equation 3. $POST_{i,t}$ is an indicator variable that equals one after October 29, 2020. ψ denotes the exchange. $\mathbf{X}^{'}_{i,t}$ are the controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. α_i is the stock fixed effect. We select a 10-day estimation window around October 29, 2020, which is the first day that all stocks can be traded on MEMX. We denote it as $(-10, +9)$. Standard errors clustered at both stock and day levels are reported in parentheses. We also report the number of observations (N) and the adjusted R-squared (Adj. R-sq.). *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively. Panel B reports the percentage changes in price impact (Percentage%) and the changes in basis points (Bps) between the average of price impact prior to the introduction of MEMX ($POST_{i,t} = 0$) and after the introduction of MEMX ($POST_{i,t} = 1$) at each exchange level ψ.

Panel A: Regression-based estimates of changes in price impact around the introduction of MEMX

Dependent: $PI^{\psi}_{i,t}$	Independent: $POST_{i,t}$	Controls	Stock FE	N	Adj. R-sq.
NBBO	0.00037** (0.0001)	Y	Y	67,905	21.9%
NASDAQ (Q+T)	0.00053** (0.0002)	Y	Y	65,016	19.4%
ARCA (P)	0.00068*** (0.0002)	Y	Y	63,622	16.9%
NYSE (N)	0.00047*** (0.0002)	Y	Y	57,658	21.4%
BZX (Z)	0.00047*** (0.0002)	Y	Y	63,258	24.5%
EDGX (K)	0.00085** (0.0003)	Y	Y	63,973	19.7%
IEX (V)	0.00081** (0.0003)	Y	Y	55,447	17.9%
EDGA (J)	0.00062** (0.0002)	Y	Y	59,146	26.8%
BYX (Y)	0.00071*** (0.0002)	Y	Y	61,213	20.4%
BX (B)	0.00101** (0.0004)	Y	Y	52,790	17.1%
National (C)	0.00294*** (0.0007)	Y	Y	51,912	51.4%
PSX (X)	0.00064 (0.0008)	Y	Y	48,468	22.8%
Chicago (M)	0.00055** (0.0002)	Y	Y	29,591	7.9%
AMEX (A)	0.00003 (0.0002)	Y	Y	47,578	9.9%

Panel B: Percentage changes in price impact around the introduction of MEMX

Exchange ψ	$POST_{i,t} = 0$		$POST_{i,t} = 1$	Percentage%	Bps
NBBO	0.294%	$\Rightarrow$	0.331%	12.3%$\Uparrow$	3.7 bps$\Uparrow$
NASDAQ (Q+T)	0.361%	$\Rightarrow$	0.413%	14.4%$\Uparrow$	5.2 bps$\Uparrow$
ARCA (P)	0.438%	$\Rightarrow$	0.509%	16.1%$\Uparrow$	7.1 bps$\Uparrow$
NYSE (N)	0.382%	$\Rightarrow$	0.438%	14.6%$\Uparrow$	5.6 bps$\Uparrow$
BZX (Z)	0.420%	$\Rightarrow$	0.465%	10.7%$\Uparrow$	4.5 bps$\Uparrow$
EDGX (K)	0.560%	$\Rightarrow$	0.644%	15.0%$\Uparrow$	8.4 bps$\Uparrow$
IEX (V)	0.552%	$\Rightarrow$	0.641%	16.3%$\Uparrow$	8.1 bps$\Uparrow$
EDGA (J)	0.816%	$\Rightarrow$	0.880%	7.9%$\Uparrow$	6.4 bps$\Uparrow$
BYX (Y)	0.647%	$\Rightarrow$	0.720%	11.2%$\Uparrow$	7.3 bps$\Uparrow$
BX (B)	1.043%	$\Rightarrow$	1.152%	10.4%$\Uparrow$	10.9 bps$\Uparrow$
National (C)	3.028%	$\Rightarrow$	3.322%	9.7%$\Uparrow$	29.4 bps$\Uparrow$
PSX (X)	1.967%	$\Rightarrow$	2.035%	3.5%$\Uparrow$	6.8 bps$\Uparrow$
Chicago (M)	0.124%	$\Rightarrow$	0.180%	44.2%$\Uparrow$	5.6 bps$\Uparrow$
AMEX (A)	0.467%	$\Rightarrow$	0.477%	2.2%$\Uparrow$	1.0 bps$\Uparrow$

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

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

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, PI_{ψ} is our measures of price impact defined as in Equation 3, and $\mathbf{X}^{'}_{i,t}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. ψ denotes the exchange. 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: $\Delta PI^{\psi}_{i,t}$	Independent: $\Delta\widehat{Frag}^{trade}_{i,t}$	$\Delta\widehat{Frag}^{volume}_{i,t}$	Controls	Day FE	N	Estimates δ	Tests K-P
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 to validate our main results in Table 2 and Table3. Panel A reports the tests we conduct related to Table 2. Panel B reports the tests we conduct related to Table 3. We briefly summarize the concerns that our results and how we conduct the tests to address these concerns. We illustrate the details of how we address them and the results are reported in the tables in both Appendix A and Appendix B.

Panel A: Additional tests related to Table 2

Concerns	Tests	Tables
Larger Estimation Window	A 20-day estimation window around the introduction of MEMX	Table A.7
Alternative Price Impact Measures	Price impact based on the 15-seconds interval after a trade	Table A.8
Pseudo-events	Event day as the 30th trading day before the true date when MEMX is introduced Event day as the 30th trading day after the true date when MEMX is introduced	Table A.9
External Validity	The halt of the National Stock Exchange (NSX)	Table A.10
	The introduction of the Investors Exchange (IEX)	Table A.11

Panel B: Additional tests related to Table 3

Concerns	Tests	Tables
Alternative Fragmentation Measures	Inverse of HHI index used by Gresse (2017) and Lausen et al. (2021)	Table B.1
Alternative Price Impact Measures	Price impact based on Hagströmer (2021) estimator	Table B.2
	Price impact based on the 15-seconds interval after a trade	Table B.3
Heterogeneous Effects across Stocks	Sub-sample analysis based on the listing exchange	Table B.4
	Small stocks versus large stocks	Table B.5
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 B.6

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 $\widetilde{OnPLACEBO}_{i,t}$. The construction of the placebo indicators is discussed in detail in Section 4.2.2. Specifically, we run the following two-stage least (2SLS) regression using the random generated variable $\Delta\widetilde{OnPLACEBO}_{i,t}$ in replace of the $\Delta OnMEMX_{i,t}$ in the first-stage:

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

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

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 migration to MEMX on existing exchange's market depth
This table reports the effects on market depth across existing lit exchanges due to order flow migration to MEMX around the launch of MEMX. For each lit exchange ψ with a specific estimation window, we estimate the following regressions:
$\ln BIDDepth^{\psi}_{i,t} = \alpha_i + \lambda_t + \pi ORDERVOL^{MEMX}_{i,t} + \mathbf{X}^{'}_{i,t}\Gamma + \epsilon_{i,t}$
$\ln ASKDepth^{\psi}_{i,t} = \alpha_i + \lambda_t + \Pi ORDERVOL^{MEMX}_{i,t} + \mathbf{X}^{'}_{i,t}\Gamma + \epsilon_{i,t}$
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. $\mathbf{X}^{'}_{i,t}$ 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 (Average R-sq) 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-sq	75.2%	76.2%	74.0%	74.4%	66.0%	60.9%

Table 7. Changes in order book slopes 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:
$SLOPEBID_{i,t}^{NS} = \alpha_i + \rho POST_{i,t} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t}$
$SLOPEBID_{i,t}^{Kalay} = \alpha_i + \rho POST_{i,t} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t}$
$SLOPEASK_{i,t}^{NS} = \alpha_i + \rho POST_{i,t} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t}$
$SLOPEASK_{i,t}^{Kalay} = \alpha_i + \rho POST_{i,t} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t}$
Where $POST_{i,t}$ is an indicator variable that equals one after October 29, 2020. $\mathbf{X}_{i,t}^{'}$ 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. We also report the number of observations (N) and the adjusted R-squared (Adj. R-sq.) 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
(−10, +9)	ρ	8141.7***	0.8680**	−5819.8***	−0.7966**
		(1424.8)	(0.3115)	(1530.3)	(0.2946)
	Controls	Y	Y	Y	Y
	Stock FE	Y	Y	Y	Y
	N	67,965	67,965	67,965	67,965
	Adj R-sq	83.9%	88.8%	87.6%	89.7%

Table 8. 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 C, Table C.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 C, Table C.2 and a falsified estimation window in Appendix C, Table C.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:

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

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. $\mathbf{X}_{i,t}^{'}$ 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 9. Variations in price impact with changes in order aggressiveness and order flow migration

This table reports the results for a series of Monte Carlo Simulations. We simulate a 14-exchange equity market with a varying degree of order aggressiveness σ_Q (Panel A) and a varying degree of order flow migration $s^{\psi=14}$ (Panel B). We report 15-seconds exchange-based price impact as in Equation 3 based on different levels of σ_Q and $s^{\psi=14}$. The higher σ_Q represents the larger sizes of market orders. The higher $s^{\psi=14}$ represents the larger market shares of the 14th exchanges. Each level of σ_Q or $s^{\psi=14}$ is based on 100 random draws. Standard errors are reported in parentheses. We discuss the details of the simulations in Section 5.3.

	Panel A: Fixed $s^{\psi=14} = 0.12$, Varying σ_Q				
	$\sigma_Q = 5$	$\sigma_Q = 5.5$	$\sigma_Q = 6$	$\sigma_Q = 6.5$	$\sigma_Q = 7$
$PI^{\psi=1}$	26.55 (1.34)	26.38 (1.15)	20.66 (1.02)	18.86 (0.89)	21.21 (1.20)
$PI^{\psi=2}$	25.05 (1.28)	27.78 (1.14)	24.87 (0.96)	22.90 (1.06)	25.46 (1.29)
$PI^{\psi=3}$	26.90 (1.37)	29.97 (1.22)	26.73 (1.08)	24.62 (1.12)	28.02 (1.34)
$PI^{\psi=4}$	24.94 (1.33)	29.80 (1.20)	28.13 (1.13)	26.34 (1.09)	29.53 (1.27)
$PI^{\psi=5}$	26.57 (1.36)	30.80 (1.22)	28.72 (1.13)	25.13 (1.26)	28.50 (1.24)
$PI^{\psi=6}$	22.14 (1.26)	27.68 (1.11)	27.44 (1.05)	26.25 (1.11)	29.11 (1.34)
$PI^{\psi=7}$	22.78 (1.25)	28.20 (1.10)	27.07 (1.04)	27.53 (1.08)	28.58 (1.41)
$PI^{\psi=8}$	16.70 (1.03)	24.43 (0.97)	26.03 (0.96)	25.76 (1.04)	28.91 (1.32)
$PI^{\psi=9}$	12.06 (0.85)	21.46 (0.90)	24.23 (0.92)	24.91 (1.00)	30.29 (1.24)
$PI^{\psi=10}$	12.98 (0.85)	21.34 (0.91)	24.92 (0.95)	26.09 (1.01)	30.76 (1.25)
$PI^{\psi=11}$	12.25 (0.84)	21.82 (0.87)	24.95 (0.94)	25.52 (0.97)	29.24 (1.29)
$PI^{\psi=12}$	11.58 (0.85)	21.74 (0.91)	24.38 (0.97)	25.14 (0.99)	29.82 (1.33)
$PI^{\psi=13}$	9.31 (0.78)	21.15 (0.92)	24.88 (1.02)	26.38 (1.07)	31.42 (1.31)
$PI^{\psi=14}$	27.78 (1.45)	32.28 (1.26)	30.43 (1.12)	27.89 (1.18)	29.82 (1.37)
	Panel B: Fixed $\sigma_Q = 6$, Varying s^{ψ}				
	$s^{\psi} = 0.04$	$s^{\psi} = 0.08$	$s^{\psi} = 0.12$	$s^{\psi} = 0.16$	$s^{\psi} = 0.20$
$PI^{\psi=1}$	21.09 (1.19)	20.46 (1.14)	21.63 (1.21)	20.65 (1.13)	19.79 (1.01)
$PI^{\psi=2}$	24.68 (1.32)	25.74 (1.25)	25.25 (1.35)	25.30 (1.22)	26.24 (1.20)
$PI^{\psi=3}$	26.66 (1.26)	28.43 (1.27)	27.99 (1.34)	27.46 (1.33)	27.85 (1.27)
$PI^{\psi=4}$	27.06 (1.39)	28.78 (1.20)	29.53 (1.28)	28.95 (1.26)	28.39 (1.36)
$PI^{\psi=5}$	27.26 (1.27)	27.48 (1.46)	28.56 (1.23)	28.71 (1.40)	28.76 (1.24)
$PI^{\psi=6}$	27.65 (1.24)	29.26 (1.29)	29.14 (1.34)	29.45 (1.35)	30.00 (1.28)
$PI^{\psi=7}$	27.93 (1.28)	28.05 (1.43)	28.46 (1.41)	27.89 (1.39)	29.91 (1.28)
$PI^{\psi=8}$	27.39 (1.19)	28.86 (1.25)	29.07 (1.30)	31.01 (1.25)	30.96 (1.23)
$PI^{\psi=9}$	29.13 (1.16)	28.51 (1.26)	30.30 (1.24)	30.33 (1.33)	31.67 (1.31)
$PI^{\psi=10}$	27.68 (1.35)	29.01 (1.35)	30.86 (1.25)	31.31 (1.28)	32.28 (1.24)
$PI^{\psi=11}$	26.03 (1.32)	28.26 (1.25)	29.32 (1.29)	29.83 (1.35)	30.72 (1.26)
$PI^{\psi=12}$	27.75 (1.23)	28.44 (1.24)	29.79 (1.33)	31.89 (1.33)	32.35 (1.26)
$PI^{\psi=13}$	27.84 (1.23)	29.60 (1.27)	31.47 (1.36)	31.50 (1.27)	32.77 (1.28)
$PI^{\psi=14}$	28.37 (1.25)	29.75 (1.37)	30.31 (1.36)	29.93 (1.42)	30.81 (1.29)

Online Appendix for Market Fragmentation and Price Impact

Appendix A

This section includes 10 tables that we have discussed in our main manuscript. Table A.1 reports the information for the current U.S. exchanges. Panel A reports the abbreviations for the exchanges, the corresponding participant id in DTAQ (DTAQ Code), and the full names of the exchanges. Panel B documents the data center address for each exchange. Panel C documents the fees structure of all the exchanges by the end of 2022.

Table A.2 shows the sample selection process and sample statistics. Panel A shows the detailed sample section process. 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. Panel B reports that our full sample has an average of 3,393 stocks on each trading day and a total number of 854,973 observations. We also use 10 days, 20 days, or 60 days estimation windows before and after the introduction of MEMX. These estimation windows have on average 3,398 stocks with a total number of 67,965 observations, 3,400 stocks with a total number of 135,997 observations, and 3,402 stocks with a total number of 408,234 observations, respectively.

Table A.3 reports the number of stocks traded on MEMX after stocks were first traded on MEMX. We report whether these stocks were traded on MEMX ($OnMEMX$) for the first 20 days after they were first traded on MEMX. We find that about 46.3% of the stocks were not traded on the second calendar day after they were first traded on MEMX. After 20 days when stocks were first traded on MEMX, 84.6% of the stocks were traded on those days.

Table A.4 reports the paired t-test for the changes in the market fragmentation level between two trading days around the introduction of MEMX. Between the first days when stocks were first traded on MEMX and the days that one day before they were first traded on MEMX, the market fragmentation level increases by approximately 1.6%. 1,950 stocks experience increases in the level of market fragmentation on the first days when they were traded on MEMX. However, we fail to observe significant changes in the market fragmentation level between the other two days before or after the introduction of MEMX.

Table A.5 shows the magnitude of changes in market fragmentation when stocks were first traded on MEMX. Table A.5 reports the results based on the TWFE estimates and Borusyak et al. (2021) (BSJ) estimates, respectively. Column (1) and Column (2) report the estimated coefficients based on the following regressions: $Frag^{*}_{i,t} = \alpha_i + \lambda_t + \beta_0 D^0_{i,t} + \mathbf{X}'_{i,t}\Gamma + \epsilon_{i,t}$. Where $D^0_{i,t}$ is a indicator variable if the stock i is first traded on MEMX, and $\mathbf{X}'_{i,t}$ 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). Both specifications suggest a significant increase in the market fragmentation level on the first days when stocks were first traded on MEMX.

Table A.6 shows the validity of our instrumental variables. 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 of trading—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.6 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 1,299 (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.

Table A.7 reports our robustness tests related to Table 2 in our main manuscript. Table A.7 shows the changes in price impact around a larger (a 20-day) estimation window around the introduction of MEMX. Our findings in Table A.7 are, in general, consistent with the findings in Table 2 except for the exchange of PSX (X) where the coefficient on $POST_{i,t}$ is negatively significant. We conjecture a concurrent confounding event—the temporary relocation of the Nasdaq PSX data center—on October 24, 2020 may induce noises for estimating the effects on price impact due to the introduction of MEMX. Table A.8 reports the changes in 15-seconds-based price impact around a 10-day estimation window around the introduction of MEMX. The results are quantitatively similar to the results in Table 2.

Table A.9 reports the changes in price impact around two pseudo-events—30 trading days before, and 30 trading days after the true date when MEMX is introduced. We fail to find significant changes around these two pseudo-events for most of the exchange-based price impact.

Table A.10 reports the changes in price impact a 20-day estimation window around the halt of the National Stock Exchange (NSX) on May 30, 2014. The National Stock Exchange halts trading because it changed its pricing structure to charge both sides of a trade a fee for securities priced $1 or more, a departure from other public trading venues that usually charge one side and pay a rebate to another. Interestingly, we find the exact opposite results for this event compared with the event of the introduction of MEMX. Specifically, we the halt of NSX reduces the price impact of trading for NBBO-based price impact. At the exchange level, we also find the price impact of trading stocks in ARCA, NYSE, BZX, EDGX, EDGA, BYX, BX, PSX, and AMEX decrease, though the significance of coefficients varies by exchanges. In contrast, we fail to find significant changes in price impact around the introduction of the Investors Exchange (IEX) on September 2, 2016. Table A.11 illustrates our results in the changes of price impact using the introduction of IEX as the event. While it is beyond the scope of this paper to study the exchange-specific factors such as speed bump, and the conversion of a dark pool to a lit exchange which may also affect the price impact of trading.

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.

Panel A: List of U.S Exchange

Exchange	DTAQ Code	Description
NASDAQ	Q+T	NASDAQ Stock Exchange, LLC
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
MIAX	H	MIAX Pearl, LLC
LTSE	L	Long-Term Stock Exchange, Inc.

Panel B: Data Center Location

Exchange	Data Center Address
EDGA EDGX BYX BZX	NY5 Equinix Data Center, 800 Secaucus Rd, Secaucus, NJ 07094
NYSE AMEX ARCA National Chicago	1700 MacArthur Blvd, Mahwah, NJ 07430
NASDAQ BX PSX	NY11 Equinix Data Center, 1400 Federal Blvd, Carteret, NJ 07008
IEX	CenturyLink (NJ2X) data center, 1919 Park Ave, Weehawken, NJ 07086
MEMX MIAX LTSE	NY4 Equinix Data Center, 755 Secaucus Rd, Secaucus, NJ 07094

Panel C: Exchange Fees Structure

Maker-taker	NASDAQ, ARCA, BZX, EDGX, IEX, PSX, Chicago, AMEX, MEMX, MIAX, LTSE
Inverted	BYX, EDGA, BX, National

Table A.2. 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 observations in returns or trading volume is 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. The full sample comprises all observations during our sample period. Details are discussed in Section 2.2

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	(+60, -59)	(+20, -19)	(-10, +9)
Daily average stocks	3,393	3,402	3,400	3,398
Total stock-day observations	854,973	408,234	135,997	67,965

Table A.3. 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 they first traded on MEMX, E_i^d represents the first calendar days that stocks were 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.4. Paired t-test for the changes in market fragmentation level around the introduction of MEMX

This table reports the cross-sectional mean of the market fragmentation level, $Frag_{\bar{i},t}$, 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.5. Exogenous changes in the level of market fragmentation
This table shows the magnitude of an exogenous change in market fragmentation when stocks were 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: $Frag^{*}_{i,t} = \alpha_i + \lambda_t + \beta_0 D^{0}_{i,t} + \mathbf{X}'_{i,t}\Gamma + \epsilon_{i,t}$. Where $D^{0}_{i,t}$ is a indicator variable if the stock i is first traded on MEMX, and $\mathbf{X}'_{i,t}$ 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.6. 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	
ψ =:	$Corr(PI^{\psi}, OnMEMX)$	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.7. Robustness: The changes in price impact around the introduction of MEMX using a 20-day estimation window

This table reports the changes in price impact around the introduction of MEMX around a 20-day estimation window around October 29, 2020. For each exchange ψ, we run a OLS regression as the following:

$PI^{\psi}_{i,t} = \alpha_i + \eta POST_{i,t} + \mathbf{X}'_{i,t}\Phi + \epsilon_{i,t}$

Where PI_{ψ} is our measures of price impact defined as in Equation 3. $POST_{i,t}$ is an indicator variable that equals one after October 29, 2020. ψ denotes the exchange. $\mathbf{X}'_{i,t}$ are the controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. α_i is the stock fixed effect. We select a 20-day estimation window around October 29, 2020, which is the first day that all stocks can be traded on MEMX. Standard errors clustered at both stock and day levels are reported in parentheses. We also report the number of observations (N) and the adjusted R-squared (Adj. R-sq.). *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

Dependent: $PI^{\psi}_{i,t}$	Independent: $POST_{i,t}$	Controls	Stock FE	N	Adj. R-sq.
NBBO	0.00024** (0.0001)	Y	Y	135,885	21.1%
NASDAQ (Q+T)	0.00033** (0.0001)	Y	Y	130,377	15.6%
ARCA (P)	0.00040*** (0.0001)	Y	Y	127,818	15.9%
NYSE (N)	0.00019 (0.0001)	Y	Y	116,274	17.7%
BZX (Z)	0.00020 (0.0001)	Y	Y	126,998	22.4%
EDGX (K)	−0.00056 (0.0003)	Y	Y	128,401	19.1%
IEX (V)	0.00125*** (0.0003)	Y	Y	110,451	16.0%
EDGA (J)	0.00052** (0.0002)	Y	Y	118,890	24.5%
BYX (Y)	0.00056*** (0.0002)	Y	Y	123,080	20.1%
BX (B)	0.00014 (0.0003)	Y	Y	106,874	16.2%
National (C)	0.00146** (0.0006)	Y	Y	104,974	49.5%
PSX (X)	−0.00143** (0.0006)	Y	Y	98,960	22.9%
Chicago (M)	0.00022* (0.0001)	Y	Y	59,278	6.0%
AMEX (A)	−0.00010 (0.0001)	Y	Y	95,552	9.2%

Table A.8. Robustness: The changes in price impact around the introduction of MEMX using 15-seconds-based price impact

This table reports the changes in price impact around the introduction of MEMX around a 10-day estimation window around October 29, 2020 using 15-seconds-based price impact. For each exchange ψ, we run a OLS regression as the following:

$PI15^{\psi}_{i,t} = \alpha_i + \eta POST_{i,t} + \mathbf{X}^{'}_{i,t}\Phi + \epsilon_{i,t}$

Where $PI15_{\psi}$ is our measures of 15-seconds-based price impact. $POST_{i,t}$ is an indicator variable that equals one after October 29, 2020. ψ denotes the exchange. $\mathbf{X}^{'}_{i,t}$ are the controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. α_i is the stock fixed effect. We select a 10-day estimation window around October 29, 2020, which is the first day that all stocks can be traded on MEMX. Standard errors clustered at both stock and day levels are reported in parentheses. We also report the number of observations (N) and the adjusted R-squared (Adj. R-sq.). *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

Dependent: $PI15^{\psi}_{i,t}$	Independent: $POST_{i,t}$	Controls	Stock FE	N	Adj. R-sq.
NASDAQ (Q+T)	0.00033** (0.0001)	Y	Y	65,016	16.0%
ARCA (P)	0.00053*** (0.0001)	Y	Y	63,622	16.0%
NYSE (N)	0.00026** (0.0001)	Y	Y	57,659	17.5%
BZX (Z)	0.00023* (0.0001)	Y	Y	63,258	26.1%
EDGX (K)	0.00062** (0.0002)	Y	Y	63,973	19.1%
IEX (V)	0.00018 (0.0003)	Y	Y	55,447	22.4%
EDGA (J)	0.00048*** (0.0002)	Y	Y	59,146	23.4%
BYX (Y)	0.00064*** (0.0002)	Y	Y	61,213	14.3%
BX (B)	0.00046* (0.0003)	Y	Y	52,790	8.99%
National (C)	0.00166*** (0.0006)	Y	Y	104,974	32.7%
PSX (X)	0.00124** (0.0004)	Y	Y	48,468	12.3%
Chicago (M)	0.00014** (0.0001)	Y	Y	29,591	8.5%
AMEX (A)	−0.00004 (0.0001)	Y	Y	47,579	10.2%

Table A.9. The changes in price impact around two pseudo-events

This table reports the changes in price impact around two pseudo-events–September 17, 2020 and December 11, 2020. For each exchange ψ, we run a OLS regression as the following:

$PI^{\psi}_{i,t} = \alpha_i + \eta POST_{i,t} + \mathbf{X}^{'}_{i,t}\Phi + \epsilon_{i,t}$

Where PI_{ψ} is our measures of price impact defined as in Equation 3. $POST_{i,t}$ is an indicator variable that equals one after the pseudo-event. ψ denotes the exchange. $\mathbf{X}^{'}_{i,t}$ are the controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. α_i is the stock fixed effect. We select a 10-day (-10, $+9$) estimation window around two pseudo-events, September 17, 2020 and December 11, 2020. We report the results for the two pseudo-events in Panel A and Panel B, respectively. We also report the number of observations (N) and the adjusted R-squared (Adj. R-sq.). Standard errors clustered at both stock and day levels are reported in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

Panel A: Pseudo-event one

Dependent: $PI^{\psi}_{i,t}$	Independent: $POST_{i,t}$	Controls	Stock FE	N	Adj. R-sq.
NBBO	0.00032 (0.0002)	Y	Y	68,000	19.4%
NASDAQ (Q+T)	0.00028 (0.0002)	Y	Y	65,145	15.0%
ARCA (P)	0.00007 (0.0001)	Y	Y	64,030	17.3%
NYSE (N)	−0.00030 (0.0003)	Y	Y	56,944	31.1%
BZX (Z)	−0.00005 (0.0002)	Y	Y	63,757	25.2%
EDGX (K)	0.00130*** (0.0003)	Y	Y	63,867	22.6%
IEX (V)	−0.00014 (0.0003)	Y	Y	46,600	12.8%
EDGA (J)	−0.00047 (0.0003)	Y	Y	59,672	27.2%
BYX (Y)	−0.00036 (0.0002)	Y	Y	61,801	23.3%
BX (B)	0.00062 (0.0006)	Y	Y	53,801	18.5%
National (C)	0.00024 (0.0005)	Y	Y	52,988	51.3%
PSX (X)	−0.00005 (0.0008)	Y	Y	49,811	29.6%
Chicago (M)	0.00006 (0.0001)	Y	Y	26,851	10.3%
AMEX (A)	0.00054* (0.0003)	Y	Y	48,608	14.3%

Panel B: Pseudo-event two

Dependent: $PI^{\psi}_{i,t}$	Independent: $POST_{i,t}$	Controls	Stock FE	N	Adj. R-sq.
NBBO	0.00013 (0.0003)	Y	Y	68,087	12.1%
NASDAQ (Q+T)	−0.00014 (0.0006)	Y	Y	40,778	2.0%
ARCA (P)	−0.00001 (0.0002)	Y	Y	65,599	6.2%
NYSE (N)	0.00001 (0.0001)	Y	Y	59,865	20.4%
BZX (Z)	−0.00012 (0.0001)	Y	Y	64,752	10.8%
EDGX (K)	−0.00051*** (0.0002)	Y	Y	65,770	16.3%
IEX (V)	−0.00035 (0.0004)	Y	Y	59,164	18.6%
EDGA (J)	−0.00023 (0.0002)	Y	Y	61,914	28.3%
BYX (Y)	0.00002 (0.0002)	Y	Y	63,366	20.6%
BX (B)	−0.00015 (0.0004)	Y	Y	55,512	17.1%
National (C)	0.00056 (0.0008)	Y	Y	54,329	50.1%
PSX (X)	0.00052 (0.0007)	Y	Y	52,429	24.7%
Chicago (M)	0.00012 (0.0001)	Y	Y	31,164	9.6%
AMEX (A)	−0.00038** (0.0001)	Y	Y	50,082	9.5%

Table A.10. The changes in price impact around the halt of the National Stock Exchange
This table reports the changes in price impact around the halt of the National Stock Exchange on June 2, 2014. For each exchange ψ, we run a OLS regression as the following:

$PI^{\psi}_{i,t} = \alpha_i + \eta POST_{i,t} + \mathbf{X}^{'}_{i,t}\Phi + \epsilon_{i,t}$

Where PI_{ψ} is our measures of price impact defined as in Equation 3. $POST_{i,t}$ is an indicator variable that equals one June 2, 2014. ψ denotes the exchange. $\mathbf{X}^{'}_{i,t}$ are the controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. α_i is the stock fixed effect. We select a 20-day (−20, +19) estimation window. We also report the number of observations (N) and the adjusted R-squared (Adj. R-sq.). Standard errors clustered at both stock and day levels are reported in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

Dependent: $PI^{\psi}_{i,t}$	Independent: $POST_{i,t}$	Controls	Stock FE	N	Adj. R-sq.
NBBO	−0.00011** (0.0000)	Y	Y	145,768	10.4%
NASDAQ (Q+T)	0.00010 (0.0002)	Y	Y	59,465	10.8%
ARCA (P)	−0.00173*** (0.0005)	Y	Y	135,863	15.9%
NYSE (N)	−0.00014 (0.0001)	Y	Y	53,062	9.5%
BZX (Z)	−0.00025 (0.0002)	Y	Y	130,648	12.8%
EDGX (K)	−0.00222*** (0.0004)	Y	Y	135,037	16.0%
EDGA (J)	−0.00093*** (0.0003)	Y	Y	123,675	28.1%
BYX (Y)	−0.00028 (0.0003)	Y	Y	126,662	13.8%
BX (B)	−0.00030 (0.0001)	Y	Y	110,290	8.4%
PSX (X)	−0.00042** (0.0002)	Y	Y	90,215	5.7%
Chicago (M)	0.00049 (0.0005)	Y	Y	10,660	21.0%
AMEX (A)	−0.00076* (0.0004)	Y	Y	13,405	5.8%

Table A.11. The changes in price impact around the introduction of IEX

This table reports the changes in price impact around the introduction of IEX. For each exchange ψ, we run a OLS regression as the following:

$PI^{\psi}_{i,t} = \alpha_i + \eta POST_{i,t} + \mathbf{X}^{'}_{i,t}\Phi + \epsilon_{i,t}$

Where PI_{ψ} is our measures of price impact defined as in Equation 3. $POST_{i,t}$ is an indicator variable that equals one after September 2, 2016. ψ denotes the exchange. $\mathbf{X}^{'}_{i,t}$ are the controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. α_i is the stock fixed effect. We select a 20-day (-20, $+19$) estimation window around September 2, 2016, which is the first day that all stocks can be traded on IEX. We also report the number of observations (N) and the adjusted R-squared (Adj. R-sq.). Standard errors clustered at both stock and day levels are reported in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

Dependent:	Independent:				
$PI^{\psi}_{i,t}$	$POST_{i,t}$	Controls	Stock FE	N	Adj. R-sq.
NBBO	0.00008 (0.0001)	Y	Y	143,326	13.0%
NASDAQ (Q+T)	-0.00032^{**} (0.0001)	Y	Y	56,222	22.8%
ARCA (P)	-0.00014 (0.0003)	Y	Y	130,245	20.2%
NYSE (N)	0.00010 (0.0001)	Y	Y	49,985	14.1%
BZX (Z)	-0.00003 (0.0002)	Y	Y	128,304	14.7%
EDGX (K)	0.00030 (0.0003)	Y	Y	131,814	11.1%
EDGA (J)	-0.00026 (0.0003)	Y	Y	118,546	27.1%
BYX (Y)	-0.00017 (0.0002)	Y	Y	124,014	29.7%
BX (B)	0.00003 (0.0006)	Y	Y	112,525	52.7%
National (C)	0.00070 (0.0006)	Y	Y	8,976	11.3%
PSX (X)	-0.00019 (0.0006)	Y	Y	95,472	33.1%
Chicago (M)	-0.00139 (0.0012)	Y	Y	7,208	16.7%
AMEX (A)	-0.00037 (0.0005)	Y	Y	9,275	2.6%

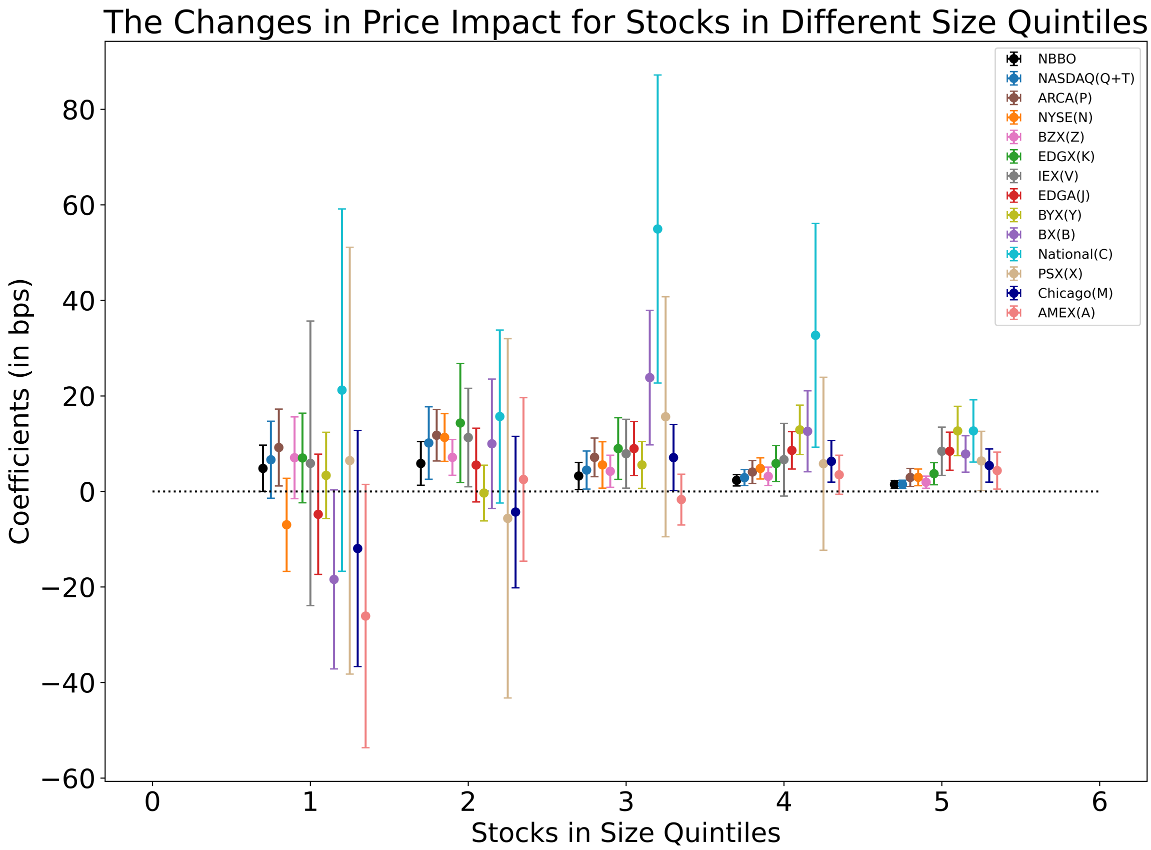

Fig A. 1. This figure presents the changes in price impact for stocks in different size quintiles. We sort stocks into quintiles based on their average $Marketcap_{i,t}$ during our sample period from June 1, 2020 to May, 28, 2021. X-axis indicates the quintiles of the stocks. For each quintile and each exchange ψ, we run the following regression: $PI^{\psi}_{i,t} = \alpha_i + \eta POST_{i,t} + \mathbf{X}'_{i,t}\Phi + \epsilon_{i,t}$. The regression is based on the 10 days $(-10, +9)$ estimation window.

Appendix B

This section reports the results of our robustness tests related to our estimated causal effects of market fragmentation on price impact.

Using alternative fragmentation measures proposed by Gresse (2017) and Lausen et al. (2021), Table B.1 shows the results of the effect of market fragmentation on price impact using the same methodology as in Table 3. Similar to the results shown in Table 3, we find a higher level of market fragmentation induces a higher price impact of trading in most of the existing exchanges.

Table B.1. 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: $\Delta Frag_{i,t}^{*} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}_{i,t}^{'}\Phi + \Delta\epsilon_{i,t}$
Second-stage: $\Delta PI_{i,t}^{\psi} = \Delta\lambda_t + \mu\Delta\widehat{Frag_{i,t}^{*}} + \Delta\mathbf{X}_{i,t}^{'}\Gamma + \Delta\epsilon_{i,t}$
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 $\mathbf{X}_{i,t}^{'}$ 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: $\Delta PI_{i,t}^{\psi}$	Independent: $\Delta\widehat{Frag_{i,t}^{tradeInv}}$	$\Delta\widehat{Frag_{i,t}^{volumeInv}}$	Controls	Day FE	N	Estimates δ	Tests 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

In contrast with Table B.1, Table B.2 and Table B.3 use different measures of price impact to estimate the causal effects of market fragmentation on price impact. Specifically, we report the results using the price impact based on the estimator proposed by Hagströmer (2021) and the 15-seconds-based price impact as the dependent variables in Table B.2 and Table B.3, respectively. Our results in these two tables are quantitatively similar to the results in our main table.

Table B.2. 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: $\Delta Frag^{*}_{i,t} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}^{'}_{i,t}\Phi + \Delta\epsilon_{i,t}$
Second-stage: $\Delta\widetilde{PI}^{\psi}_{i,t} = \Delta\lambda_t + \mu\Delta\widehat{Frag}^{*}_{i,t} + \Delta\mathbf{X}^{'}_{i,t}\Gamma + \Delta\epsilon_{i,t}$
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 $\mathbf{X}^{'}_{i,t}$ 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: $\Delta\widetilde{PI}^{\psi}_{i,t}$	$\Delta\widehat{Frag}^{trade}_{i,t}$	Independent: $\Delta\widehat{Frag}^{volume}_{i,t}$	Controls	Day FE	N	Estimates δ	Tests 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 B.4 and Table B.5 consider the heterogeneous effects across stocks. In Table B.4, we report the effects of market fragmentation on price impact based on the listing exchanges of the stocks in our sample. We report the effects for the NYSE-listed stocks, NASDAQ-listed stocks, and AMEX-listed stocks, respectively. Our main results still

Table B.3. 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: $\Delta Frag^{*}_{i,t} = \Delta\lambda_t + \delta \Delta OnMEMX_{i,t} + \Delta \mathbf{X}^{'}_{i,t}\Phi + \Delta\epsilon_{i,t}$
Second-stage: $\Delta PI15^{\psi}_{i,t} = \Delta\lambda_t + \mu \Delta\widehat{Frag}^{*}_{i,t} + \Delta \mathbf{X}^{'}_{i,t}\Gamma + \Delta\epsilon_{i,t}$
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 $\mathbf{X}^{'}_{i,t}$ 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

hold regardless of the listing exchanges of the stocks. though the magnitude and the significance of causal effects are stronger for the NASDAQ-listed stocks than the NYSE-listed stocks and the AMEX-listed stocks.

Following the approach from Haslag and Ringgenberg (2021), we investigate the effects of market fragmentation on price impact based on the size of the stocks. By constructing a dummy variable based on the average market capitalization during our sample period from June 1, 2020 to May 28, 2021, we interact this quintile dummies with the changes in the level of market fragmentation. Results in Table B.5 suggest that the effects of market fragmentation on price impact still prevail even if we control for the market capitalization of the stocks. Table B.5 shows that 8 out of 13 exchanges exhibit positive coefficients on the variables of $Frag^{trade}_{i,t}$.

Though, as shown in Table A.6, 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 MEMX is 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 B.6 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.

Table B.4. 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: $\Delta Frag^{trade}_{i,t} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \Delta\mathbf{X}^{'}_{i,t}\Phi + \Delta\epsilon_{i,t}$
Second-stage: $\Delta PI^{\psi}_{i,t} = \Delta\lambda_t + \mu\Delta\widehat{Frag^{trade}_{i,t}} + \Delta\mathbf{X}^{'}_{i,t}\Gamma + \Delta\epsilon_{i,t}$
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 $\mathbf{X}^{'}_{i,t}$ 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 denote 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 B.5. 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: $\Delta Frag_{i,t}^{trade} = \Delta\lambda_t + \delta\Delta OnMEMX_{i,t} + \sum_{m\neq 3}\xi_m Quintile_m + \sum_{m\neq 3}\phi_m \Delta OnMEMX_{i,t} \times Quintile_m + \Delta\mathbf{X}_{i,t}^{'}\Phi + \Delta\epsilon_{i,t}$

Second-stage: $\Delta PI_{i,t}^{\psi} = \Delta\lambda_t + \mu\Delta\widehat{Frag_{i,t}^{trade}} + \sum_{m\neq 3}\iota_m \Delta\widehat{Frag_{i,t}^{trade} \times} Quintile_m + \sum_{m\neq 3}\zeta_m Quintile_m + \Delta\mathbf{X}_{i,t}^{'}\Gamma + \Delta\epsilon_{i,t}$

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 $\mathbf{X}_{i,t}^{'}$ 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 capitalization quintile and zeroes otherwise, where quintile 5 is the largest quintile of stocks based on their market capitalization. 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. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

	$\Delta PI_{i,t}^{NBBO}$	$\Delta PI_{i,t}^{Q+T}$	$\Delta PI_{i,t}^{P}$	$\Delta PI_{i,t}^{N}$	$\Delta PI_{i,t}^{Z}$	$\Delta PI_{i,t}^{K}$	$\Delta PI_{i,t}^{V}$	$\Delta PI_{i,t}^{J}$	$\Delta PI_{i,t}^{Y}$	$\Delta PI_{i,t}^{B}$	$\Delta PI_{i,t}^{C}$	$\Delta PI_{i,t}^{X}$	$\Delta PI_{i,t}^{M}$	$\Delta PI_{i,t}^{A}$
$\Delta\widehat{Frag_{i,t}^{trade}}$	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)
$\Delta\widehat{Frag_{i,t}^{trade} \times} Quintile_1$	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)
$\Delta\widehat{Frag_{i,t}^{trade} \times} Quintile_2$	−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)
$\Delta\widehat{Frag_{i,t}^{trade} \times} Quintile_4$	−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)
$\Delta\widehat{Frag_{i,t}^{trade} \times} Quintile_5$	−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)
$\sum_{m\neq 3} Quintile_m$	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 B.6. 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 MEMX is 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: $Frag^{trade}_{i,t} = \alpha_i + \lambda_t + \delta OnMEMX_{i,t} + \mathbf{X}^{'}_{i,t}\Phi + \epsilon_{i,t}$

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

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 $\mathbf{X}^{'}_{i,t}$ 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 and day levels. N denotes the number of observations. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively.

	$PI^{NBBO}_{i,t}$	$PI^{Q+T}_{i,t}$	$PI^{P}_{i,t}$	$PI^{N}_{i,t}$	$PI^{Z}_{i,t}$	$PI^{K}_{i,t}$	$PI^{V}_{i,t}$	$PI^{J}_{i,t}$	$PI^{Y}_{i,t}$	$PI^{B}_{i,t}$	$PI^{C}_{i,t}$	$PI^{X}_{i,t}$	$PI^{M}_{i,t}$	$PI^{A}_{i,t}$
$\widehat{Frag^{trade}_{i,t}}$	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

Appendix C

This section includes 5 tables that relate to the channels of why the introduction of MEMX induces a higher price impact of trading.

Table C.1 reports the summary statistics for the percentage of orders in different aggressive categories. 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.

Consistent with the results in Table 8, we select the sample with a longer estimation window, (-60, +59) and report the results in Table C.2. We also conduct falsified tests in Table C.3 where we fail to find significant associations between the falsified introduction of MEMX and the changes in the proportion of the orders in aggressive order types.

Similar to Table 7, Table C.4 reports the changes in order book slopes round the introduction of MEMX based on the first quoting days instead of the day (October 29, 2020) when MEMX is introduced. Not surprisingly, we find the similar results as in Table 7—the introduction of MEMX decreases (increases) the steepness (inelasticity) of the limit order book slopes for stocks trading on the NASDAQ exchange.

Results in Table C.5 suggest that there are no significant changes in the off-exchange ratios around the introduction of MEMX exchange. Therefore, we conclude that the increases in price impact are unlikely to be driven by the order flow segmentation channel.

Table C.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 C.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 C, Table C.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 the buy side and the sell side separately in Panel A and Panel B. We run the following regression for each order aggressiveness type:

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

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 C.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 (orders improving the BBO price or orders 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 C, Table C.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 the buy side and the sell side separately in Panel A and Panel B. We run the following regression for each order aggressiveness type:

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

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%

Table C.4. Changes in order book slopes around the introduction of MEMX based on the first quoting days.

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:

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

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

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

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

Where $\tilde{E}_i^d$ represents the first day that the stock i is quoted on MEMX. $\mathbb{1}$ represents the indicator function. $\mathbf{X}_{i,t}^{'}$ 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. We also report the number of observations (N) and the R-squared (R-sq.). 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-sq	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-sq	83.4%	88.7%	86.0%	89.1%

Table C.5 Changes in the market shares of the off-exchange trades around the introduction of MEMX

This table presents the changes in the market shares of the off-exchange trades around the launch of MEMX. For each stock i at trading day t, the market shares of the off-exchange trades are defined as the number of trades executed at the off-exchange venues divided by the total number of trades denoted as $OffRatio_{i,t}^{trade}$. Similarly, we define the dollar volume executed at the off-exchange venues divided by the total dollar volume as $OffRatio_{i,t}^{volume}$. We run the following two sets of regressions:

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

$\%OffRatio_{i,t}^{*} = \alpha_i + \upsilon POST_{i,t} + \mathbf{X}_{i,t}^{'}\Gamma + \epsilon_{i,t}$

Where E_i^d represents the first day that the stock i is traded on MEMX. $\mathbb{1}$ represents the indicator function. $\mathbf{X}_{i,t}^{'}$ are controls which comprise of $Volatility_{i,t}$, $Volume_{i,t}$, $Marketcap_{i,t}$ and $Price_{i,t}$. $POST_{i,t}$ is an indicator variable that equals one after October 29, 2020. *, **, *** indicates statistical significance at the 10%, 5%, 1% level, respectively. We also report the number of observations (N) and the adjusted R-squared (Adj. R-sq.). Standard errors clustered at both stock and day levels are reported in parentheses.

		$OffRatio_{i,t}^{trade}$	$OffRatio_{i,t}^{volume}$
$\tilde{E}_i^d - 20 < t < \tilde{E}_i^d + 19$	υ	0.0019	0.0007
		(0.0018)	(0.0017)
	Controls	Y	Y
	Day FE	Y	Y
	Stock FE	Y	Y
	N	136,265	136,265
	Adj R-sq	68.8%	53.9%
$(-20, +19)$	υ	-0.0011	-0.0035
		(0.0030)	(0.0027)
	Controls	Y	Y
	Stock FE	Y	Y
	N	136,170	136,170
	Adj R-sq	65.3%	51.1%

Appendix D

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 D.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 D.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 order book based on the workflow in the Figure D.1.

For a stock on a trading day, we start from an empty limit order book. 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 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) that 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 orders having 50 shares totaling the market depth to 150 shares.

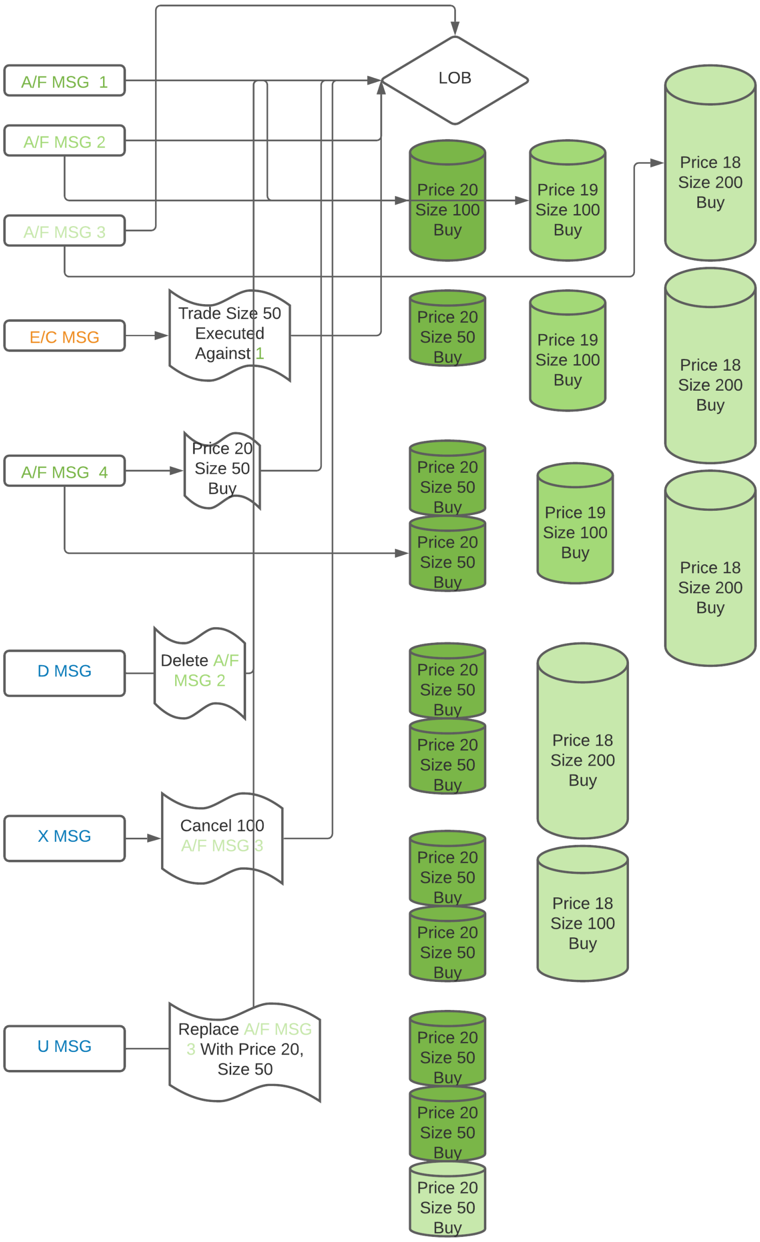

Figure D.1: Workflow of reconstructing the limit order book from messages

Appendix E

Figure E.1 shows the time-series of the market shares for MEMX.

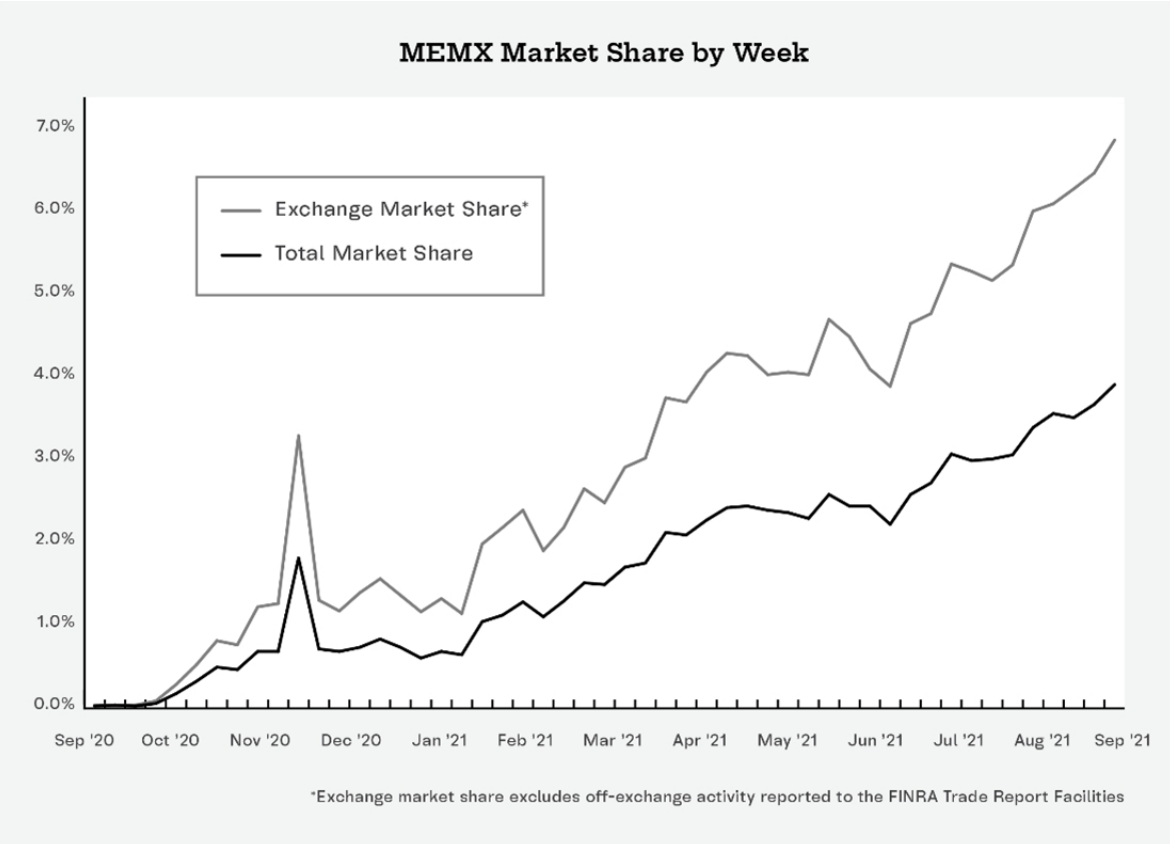

Figure E.1: MEMX share by week. Source: MEMX exchange.