MARKET FRAGMENTATION AND MANIPULATION

ABSTRACT

This study investigates the effects of stock trading manipulation on dynamic trading fragmentation and market liquidity with the population of U.S. stocks from 2014 to 2018. We find novel evidence that different types of trading manipulation do not equally impact the trading volume in each exchange. Our findings suggest that manipulation increases the illiquidity curve while the retail trading flow dampens illiquidity, aligning with the Glosten and Milgrom model's predictions.

JEL Codes: G12, G14, D4

Keywords*:* Market Manipulation, Market Liquidity, Trading Volume, Retail Trading

INTRODUCTION

Equity trading in the U.S. is currently dispersed across 16 national exchanges, more than thirty alternative trading systems, and numerous broker-dealers and wholesale market makers (SEC 2021). Based on pre-trade opacity, the trading venues can be separated into lit- and off-exchanges. The bid and ask quote information is posted publicly at lit-exchange, while an off-exchange does not provide price quotation information. Currently, all 16 U.S. national securities exchanges are defined as lit-exchanges and are regulated by U.S. Securities and Exchange Commission (SEC). At the same time, off-exchanges are regulated by the Financial Industry Regulatory Authority (FINRA). FINRA separates off-exchanges broadly into two groups. The first group is the Alternative Trading System (ATS), which matches the buyer and seller without any intermediary. Institutional investors are more likely to utilize ATSs to trade. The second group encompasses over-the-counter (OTC) non-ATS dealers, or wholesale market makers, which provide liquidity by buying and selling stocks as a counterparty. Most marketable orders placed by retail investors in the U.S. have been found to be executed through wholesalers (O'Hara 2015; Boehmer, Jones, Zhang, and Zhang 2021).

Overall, lit- and off-exchanges have different trading system structures, which affect the venue's pricing rule and provide different degrees of transparency and execution quality. Given this highly fragmented trading environment, examining the determinants of the investors' routing order decisions and associated impact on the market has become an important research topic in the literature. Several dynamic trading fragmentation studies show that the final venue routing decision may depend on multiple trade-offs between the transaction cost, execution probability, and information asymmetry risk. Routing volume to a venue could decrease when that venue has a high execution risk, high asymmetry information risk, and low liquidity.

Meanwhile, variation in investors' sentiment is another critical factor that affects routing changes. Any release of macroeconomic and firm news updates investors' beliefs towards the future and affects their sentiment. The change in sentiment not only affects the stock price, volume, and volatility around the event, but also the market liquidity and information asymmetry, thus altering the order routing decision (Chae, 2005; Kurov and Stan, 2018; Menkveld, Yueshen, and Zhu,2017).

The issue of stock manipulation has received considerable critical attention by policymakers and investors since it could cause a significant loss to market participants. For instance, an alleged stock manipulation case in 2016 generated more than 17 million in gross trading proceeds.[i] Yet, most academic studies in the relation between market fragmentation and information shock have only focused on either broad macroeconomic announcements or firm operational announcements. There has been little quantitative analysis of the relation between stock manipulation and market fragmentation due to insufficient data for stock manipulations. Intuitively, manipulation is different from other information shocks or firm announcements in several ways. First, stock market manipulation is typically an intentional action performed by an informed trader seeking profit; hence it is difficult to detect. That is, many traders are unaware of manipulation when it happens. Second, manipulation distorts resource allocation, reducing market efficiency in the short term. Moreover, stock manipulation could harm investor confidence and discourage participation in the long term (Jarrow 1992; Pirrong 1995; Comerton-Forde and Putniņš 2014). In this research, we explore the changes in the trading volume fragmentation around the three types of price manipulations: continuous trading manipulation, end-of-day (EOD) price manipulation and open price manipulation by using a novel source of manipulation data from Nasdaq, and we further investigate the role of retail trading on the market liquidity around continuous trading manipulation. Our baseline analysis includes a U.S. stock population of 1,722 unique firms identified to have at least one manipulation event from 2014.01 to 2018.12.

Our research expands on the innovative financial market misconduct literature that explores the impact of stock manipulations on dynamic trading fragmentation. We observe a significant increase in off-exchange volumeshare at the day after the continuous trading manipulation and open price manipulation, while the insignificant changes for EOD price manipulation, suggesting different manipulation types affect the trading volume share differently. To our knowledge, this is the first study that compares the changes in routing venues on different types of stock trading manipulation.

In addition, our research contributes to the innovative financial market misconduct literature by examining the impact of manipulation on market liquidity and testing the role of retail trading participation. Previous studies on stock manipulation suggest that it could significantly increase stock illiquidity and volatility (Hillion and Suominen, 2004; Comerton-Forde and Putniņš, 2011a; Aggarwal and Wu, 2006). Our research further shows that higher retail trading participation during manipulation events mitigates its detrimental effects on market liquidity. Our results confirm the liquidity provision role for retail trading and show that retail trading induced from manipulation is uninformed.

The remainder of the paper is organized as follows. Section 2 reviews relative literature and develops our hypotheses. Section 3 presents our data and methodology. Section 4 reports our main empirical results of the effects of manipulation on off-exchange trading, and the additional analysis on the consequence of price manipulation changes in off-exchange trading volume. The conclusion and policy implication are presented in section 5.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Market trading fragmentation

Equity trading in the U.S. is remarkably distributed across 16 national exchanges, more than thirty alternative trading systems (ATSs), numerous broker-dealers, and wholesale market makers (SEC 2021). This dispersion can be categorized into lit- and off-exchanges based on pre-trade opacity. Lit-exchanges refer to those where bid and ask quote information are publicly accessible, whereas off-exchanges do not provide such information. As can be seen, given this fragmented trading market, traders have many options in choosing venues to execute their orders. Given the competition among trading venues, the determinant of the order routing decision remains a open question.

Many market microstructure studies have investigated the trade-offs for the routing order decision. In summary, the routing order decision-making process is affected not only by the market structure design of venue, but also by trade-offs between transaction costs, execution quality, and adverse selection concerns.

For instance, Friederich and Payne (2007) examine the trade-offs involved in routing decisions, concluding that the investor's routing decision is driven by the risks associated with execution and asymmetry information. A venue’s routing volume decreases when it has a high execution risk, high asymmetry information risk, and low liquidity. Hatheway, Kwan, and Zheng (2017) note that under the current regulatory environment, most off-exchanges are exempt from the fair-access requirement and do not display quote information. Consequently, these off-exchanges can implement order segmentation through price discrimination and attract more informed order flow from the lit-exchanges. Menkveld, Yueshen, and Zhu (2017) propose that the trade-off lies between execution cost and execution immediacy. Brolley (2020) identifies the key trade-off as that between immediacy and price improvement.

Additionally, market and trading conditions also influence order routing in a fragmented market environment. The theoretical model predicts that when the bid-ask spread is wider and market volatility is higher, informed trading increases in off-exchanges while overall off-exchange volume share decreases Zhu (2014). These predictions imply that during periods of high market volatility, order flow should move to exchanges with higher transparency. Garvey, Huang, and Wu (2016) find that high volatility may dampen liquidity in lit exchanges, and they document a positive correlation between volatility and dark trading volume.

Despite the market condition, the investor type may also affect the market volume of lit- and off-exchanges. In many theoretical discussions, retail investors are often categorized as uninformed noise traders, and the assumption that their trade direction would be equally distributed (Shleifer and Summers 1990; Easley, Hvidkjaer, and O'Hara 2002; Foucault, Sraer, and Thesmar 2011). It is possible that investors may hold heterogeneous beliefs towards stock price movement, over one-third of investors may be associated with short-term investments and speculation purpose (Leuz et al. 2021). Such motivations are especially true for the retail investors, who are likely attracted by stocks with lottery features and present a gambling preference (Gao and Lin 2015; Han and Kumar 2013; Dimpfl and Jank 2016) and obtains a strong herding pattern (Barber, Odean, and Zhu 2008). As suggested in the above literature, retail investors are typically uninformed with a marked tendency to engage in speculative trading exhibiting a strong herding preference. In contrast, institutional investors, with access to advanced resources to track and monitor firm activities (Ben-Rephael, Da, and Israelsen 2017; Chen et al. 2020), may be better equipped to detect the unusual market activity, such as stock manipulation events from abnormal price dislocations.

Therefore, we posit that compared to sophisticated institutional investors who equipped with internal surveillance systems to detect potential stock manipulations, retail investors are more likely to react when such manipulations occur. Moreover, if uninformed noise traders base their trading decisions on sentiment, it will lead to more noise trading, exacerbating mispricing and volatility (De Long, Shleifer, Summers, and Waldmann 1990). In fact, majority of marketable orders placed by retail investors in the U.S. equity market are either internalized or executed by wholesale market makers, which categorized as off exchanges (O’Hara 2015; Boehmer, Jones, Zhang, and Zhang 2021).

Stock manipulation

According to Allen and Gale (1992), market manipulation can be subject to three categories: *Information-based manipulation*, in which misleading information is disseminated by informed traders without disclosing any real information; *Action-based manipulation*, where the manipulator acts to intentionally change a firm's value to profit; and *Trade-based manipulation*, where a trader attempts to continually buys or sells the same stock to create a price momentum.

Generally, stock market manipulation is an intentional action performed by an informed trader, and prior literature suggests that stock price manipulation can be conducted internally (Yuan, Xiao, Milonas, and Zou 2009; Aitken, Cumming, and Zhan 2015; Cumming, Ji, Johan, and Tarsalewska 2020). For example, Chakraborty and Yılmaz (2004) suggest that insiders may be more likely to employ manipulative trading strategies when there is uncertainty about the existence of the insider. Likewise, manipulation could also be a result of an internal agency problem. Short-term contracts can encourage firm executives to focus excessively on short term performance, increasing the likelihood of fraudulent behavior (Peng and Roell 2008; 2014) . An equilibrium model from Goldman and Slezak (2006) also shows that the managers compensated with firm stock have an incentive to upwardly biases disclo (Hillion and Suominen 2004)sed information.

In addition, stock price manipulation can also be performed via external market participants. Numerous theoretical and empirical studies provide evidence that financial intermediaries may be incentivized to initiate stock manipulation. For example, Hillion and Suominen's (2004) model shows that a broker may manipulate the closing price to alter a customer's perception of the broker's execution quality. This theoretical prediction is supported empirically in studies by Atanasov, Davies, and Merrick (2015) and McNally, Shkilko, and Smith (2017), who demonstrate that financial intermediaries have magnified the effect of alleged manipulative trades. Bernile, Sulaeman, and Wang (2015) also argue that certain intermediaries, such as institutions, often act as informed investors during a manipulation event, potentially improving price efficiency.

Much of the existing literature on manipulation focuses on its determinants. For instance, Allen and Gale (1992) suggest that profit is the primary motivator for stock manipulation, while Peng and Röell (2014) propose that the presence of noise traders in the market makes stock price manipulation possible. Notably, a study by Comerton-Forde and Putniņš (2014) reveal that stocks with high information asymmetry and low liquidity are more likely to be manipulated. Indeed, manipulation has a significantly detrimental effect on the market by causing price dislocation, resulting in a rise in volatility, volume, and illiquidity (Hillion and Suominen 2004; Aggarwal and Wu 2006; Comerton-Forde and Putniņš 2011a).

Despite extensive theoretical studies on stock manipulation, it remains a significant concern for policymakers and investors due to its potential to dramatically reduce companies' stock prices and inflict substantial losses on investors. A case in point involves a broker-dealer's manipulation scheme, which led to gross trading proceeds of approximately $17.2 million, highlighting the severe financial ramifications of these fraudulent activities (U.S. Attorney's Office District of New Jersey, 2016).

While stock manipulation is an important topic that requires extensive study. However, compared to other financial market research areas, empirical studies on the topic are relatively limited. This scarcity can largely be attributed to the complexity of identifying and quantifying stock manipulation and its inherent unobservability (Alexander and Cumming 2022). Acknowledging this gap in research, our study leverages a novel dataset to examine three specific types of trade-based manipulation: continuous trading manipulation, end-of-day (EOD) price manipulation and open price manipulation.

Based on the classification from Putniņš (2012), both open and close price manipulation are contract-based manipulations that create artificial price movements, which involve buying or selling securities at or shortly after (before) the open (or close) to alter the opening (closing) price.

The EOD prices serve as an important benchmark for trade execution for firms and institutions and are used to determine the net asset value for mutual funds or the settlement value of many derivative financial products. Therefore, manipulating EOD prices can influence corporate investment decisions, such as the likelihood of M&A deal withdrawal, or encourage corporate managers to focus more on short-term outcomes, potentially worsening some corporate financial outcomes (Cumming, Ji, Johan, and Tarsalewska 2020; Cumming, Ji, Peter, and Tarsalewska 2020)

The opening price of a stock generally reflects overnight information. Thus, the artificial price movement caused by open price manipulation can mislead investors, making them believe that the stock price change is driven by new, relevant information. The act of manipulating the opening price can lead to significant price adjustments, as well as an enlargement of the bid-ask spread and increased volatility (Pagano, Peng, and Schwartz 2013). Furthermore, investors who buy these manipulated stocks may suffer losses on their investments (Liu, Wu, Yuan, and Liu 2022).

Continuous trading manipulation differs from opening or closing price manipulation in that it targets potential price manipulation during all market trading hours, not just a single time window. Akter, Cumming, and Ji (2023) show that continuous trading manipulation subsequentially increases after the natural disaster.

Despite the inherent differences in the nature of these three types of price manipulation, we posit that they draw different levels of attention from different types of investors. Institutional investors may pay more attention to opening or closing price manipulations, given their importance as price benchmarks. In contrast, retail investors may pay more attention to stock prices during trading hours. Furthermore, institutional investors, equipped with advanced technology like internal surveillance systems to monitor stock price movements, have an advantage over retail investors with limited resources. Hence, institutional investors may have a superior ability to detect potential manipulation activities and respond quickly. For instance, when the internal surveillance system detects potential price manipulation, institutional investors may decide to abstain from trading, while retail investors may be induced to trade more. As observed by Liu, Wu, Yuan, and Liu (2022), manipulation increases market trading activity and price volatility due to the influx of retail investors. More importantly, the complexity of calculating and identifying continuous trading manipulation may potentially increase market trading activity.

The above stock manipulation and market trading fragmentation details, we suggest the following hypothesis for changes in trading volume share around stock manipulation:

Hypothesis 1: Different trading manipulation types affect the trading volume share differently.

Next, we consider the potential impact of stock manipulation with retail trading volume on the market liquidity. Changes in market venue trading volume due to stock manipulation may be associated with two different impacts on the market liquidity. Initially, stock manipulation can be detrimental, impairing pricing accuracy and driving up trading costs, thereby discouraging market participation and damaging market liquidity (Goldstein and Guembel 2008; Comerton-Forde and Putniņš 2011b). However, there's another perspective to consider. Stock manipulation could potentially drive an upsurge in uninformed trading activity, which, in turn, might contribute to market liquidity. This theory is rooted in the assumption that orders placed by retail investors are generally uninformed, and therefore, these investors are regarded as noise traders (Black 1986; Foucault, Sraer, and Thesmar 2011). This hypothesis is further supported by empirical studies such as the one conducted by Greene and Smart (1999), who explored noise trading activity around the publication of the "Investment Dartboard" in the Wall Street Journal. Their research found a positive correlation between increased noise trading and market liquidity. Similarly, Barrot, Kaniel, and Sraer (2016) demonstrate that retail trading can play a crucial role in providing liquidity, particularly in instances where institutional liquidity dries up.

Based on the market structure model from Glosten and Milgrom (1985), an increase in noise trading results in a decrease in adverse selection risk, assuming that informed trading is exogenously given and does not depend on the level of the noise trading. Therefore, with the reduction in adverse selection cost, market makers are likely to decrease the spreads when encountering a larger proportion of noise traders.

Therefore, we posit that if the stock manipulation succeeds in triggering more uninformed retail trading participation, then the increased proportion of noise trading after manipulation should provide liquidity and decrease quoted spreads. Given such considerations, our second hypothesis is as follows:

Hypothesis 2a: While manipulation typically hampers market liquidity, an increase in retail trading could potentially offset this negative impact.

However, in contrast to the Glosten and Milgrom (1985) model, Kyle's (1985) model assumes that the volume of informed trading can be endogenously determined. This implies that informed traders could modify their trading strategy based on the volume of uninformed trading. Consequently, during a stock manipulation period, informed traders might resort to more aggressive trading tactics. This increase in informed trading could counterbalance the effects of the increased noise trading, resulting the changes in retail trading volume having a negligible effect on market liquidity. Given this perspective, we propose an alternative hypothesis on market liquidity around stock manipulation:

Hypothesis 2b: Although manipulation generally diminishes market liquidity, the volume of retail trading does not necessarily alleviate this negative effect.

DATA AND METHODLOGY

Data and sample

We follow the approach of Aitken, Cumming, and Zhan (2015) by using suspected manipulation cases since they have real financial consequences. our manipulation data was sourced from Nasdaq. Nasdaq Trade Surveillance collects data on suspected manipulation cases for over 50 stock exchanges worldwide. This data not only serves as a critical tool for surveillance authorities in respective countries, but also have been used by numbers of recent academic research focusing on market misconduct (Aitken, Cumming, and Zhan 2015, 2017; Cumming, Ji, Johan, and Tarsalewska 2020; Cumming, Ji, Peter, and Tarsalewska 2020; Akter, Cumming, and Ji 2023).

In our study, we specifically examined three types of trading manipulation: End-of-day (EOD) price manipulation, Open price manipulation and continuous trading manipulation. The EOD (open) price manipulation measurements detect the abnormal EOD (open) price dislocation. The price movement is considered dislocated if the price has been four standard deviations away from its mean price change during the past 100-trading day benchmarking period, and then reverts to the mean price the subsequent trading period. Continuous trading manipulation measurement uses multiple metrics that are picked by surveillance authorities to capture potential market trading manipulation activities. Specifically, said measurement detects an abnormal 30-minute change of liquidity, returns, and transaction costs based on certain rules.

We only include stocks traded in U.S., as we aim to examine volume share changes in the U.S. equity market markets. To minimize the influence of potential confounding firm events that might affect the order flow, we exclude firms from our sample that have earnings, repurchasing, or M&A announcements on the identified dates with potential price manipulation. Our trading volume and market liquidity measures are constructed using data from the NYSE TAQ database. Control variables in our analysis include daily volume, price, spread and intraday volatility, which are derived from CRSP; firm size, calculated from Compustat; and the proxy for market volatility, VIX index, sourced from CBOE. Furthermore, we employ the retail identification methodology from Boehmer, Jones, Zhang, and Zhang (2021) to pinpoint market orders placed by retail investors and proxy the identified volume as the retail volume. The appendix presents detailed methodology behind the identification of three types of trading manipulation and the definition of all variables used in the analysis.

TABLE 1: Summary statistics

This table presents summary statistics for the variables used in the main analysis. The sample includes 1,722 firms (534,495 firm-day observations in 21 trading days window) that traded in U.S. equity market and were identified have at least one closing price manipulation event from 2014.01 through 2018.12. The observations are on a firm-day level. Independent variable definitions are provided in Appendix.

	N	Mean	STDEV	25th Pctl	Median	75th Pctl
Off-Exchange Volume Share (%)	534,495	32.905	12.867	24.043	30.431	39.055
Retail Volume Share (%)	534,495	8.346	11.429	3.020	4.963	9.069
Closing Price ($)	534,495	52.096	92.066	17.620	35.220	63.680
Market Volatility (VIX)	534,495	14.585	4.207	11.840	13.430	15.970
Firm Intraday Volatility (%)	534,494	2.454	2.160	1.251	1.899	2.952
Log(MktCap)	534,495	14.900	1.720	13.745	14.879	16.044
Quoted Spread ($)	534,494	0.066	0.182	0.014	0.028	0.063

Quoted Spread (%)	534,495	0.173	0.375	0.051	0.097	0.184
Effective Spread (%)	534,495	0.125	0.248	0.038	0.068	0.131
Realized Spread (%)	534,495	0.041	0.242	-0.005	0.014	0.048
Price Impact (%)	534,495	0.084	0.241	0.024	0.049	0.096

Our final sample included 1,722 unique firms traded in the U.S. market and were identified to have at least one stock manipulation event during our sample period from 2014.01 through 2018.12. Our sample does not extend beyond 2018 is driven by commercial sensitivities associated with more recent data. Table 1 shows summary statistics for all variables. The average daily off-exchange volume share is 32.91%, and the off-exchange trading volume share for the most firms is between 24.04% and 39.06%. The average daily trading volume initiated by retail investors takes around 8.35% of the total trading volume. The percentiles of the Retail Volume Share (%) measures show that there is a wide variation in retail trading; the 25th percentile of the proportion of retail trading volume is 3.02%, and the 75th percentile number is 9.07%. The market volatility, proxied by the CBOE VIX index, is 14.59 on average during the sample period. The average closing price is $52.10, and the average firm size is 14.879 (expressed as a natural logarithm), corresponding to $2.8 million market capitalization. The average value for the quoted spread is 0.066 in dollar value and 0.173 as a percentage. The average value for effective spreads, realized spread, and price impact is 0.125, 0.041, and 0.084, in percentages, respectively.

Research design

To test the first hypothesis and address any potential endogeneity concerns, we employ the following regression model.

$$Dvolshare_{i,t+1} = \alpha + \beta_1 Manipulation_{i,t} + \beta_2 InvP_{i,t+1} + \beta_3 Spread_{i,t+1} + \beta_4 \log(MktCap)_{i,t+1} + \beta_5 IntraVolatility_{i,t+1} + \beta_6 MarketVolatility_{t+1} + \epsilon_{i,t+1} \quad (1)$$

The dependent variable, $Dvolshare_{i,t+1}$, is the proportion of the volume traded in the off-exchange for stock i on the day following the detection of potential stock trading manipulation (t+1). $Manipulation_{i,t}$ is an indicator variable, which is equal to 1 for stock i on the price manipulation day and equal to 0 otherwise. For control purposes, we include variables at the stock level: the natural log of market capitalization (*log(MktCap)*), the stock's return variance ($IntraVolatility$), the inverted closing price(*InvP*), and the bid-ask spread (*Spread*) (Stoll 2000; Hendershott and Moulton 2011; Malinova and Park 2015) Additionally, we control for market volatility ($MarketVolatility$) by using the VIX index sourced from CBOE (Comerton-Forde, Malinova, and Park 2018), and we also include industry-fixed effects.

For the second hypothesis, we're focused on understanding the influence of stock price manipulation and retail trading on market liquidity. Accordingly, we've adopted four metrics that serve as proxies for various facets of market liquidity to provide a multi-dimensional view. These metrics include the quoted spread, effective spread, realized spread, and price impact. Each of these measurements is weighted by the trading price and presented as a percentage to control the influence of the stock price on the spreads.

The most commonly used liquidity measurement is quoted spread, which is the" advertised" cost of a trade, and it reflects a market center's posted willingness to trade. Specifically, the percent quoted spread we use is computed as the difference between the ask and bid prices, then scaled by the quoted midpoint.

Next, the effective spread measures the" actual" cost of trading. The effective spread is the most relevant measure to assess trading costs for marketable orders since the half-effective spread measures the cost for removing liquidity with a marketable order. The percent effective spread we use is calculated as follows:

$$EffectiveSpread(\%) = 2D_t \frac{P_t - M_t}{M_t} \times 100 \quad (2)$$

Where D_t is the trade direction that is signed based on Lee and Ready's (1991) algorithm. D_t is equals +1 for buyer-initiated trades and equals -1 for seller-initiated trades.

The effective spread can be further decomposed into two measures: the realized spread, which measures the inventory risk for market makers, and the price impact, which measures the adverse selection risk. The percent realized spread is calculated as follows:

$$RealizedSpread(\%) = 2D_t \frac{P_t - M_{t+5}}{M_t} \times 100 \quad (3)$$

Where M_{t+5} is the bid-ask midpoint five minutes after trade at t.

Finally, price impact reflects the portion of the transaction cost due to the presence of informed marketable orders. Intuitively, price impact is the informed trader's profit and thus is a proxy for adverse selection. An increase in the price impact indicates a higher adverse selection risk and an increase in the adverse selection costs for liquidity providers. The percent price impact is calculated as follows:

$$PriceImpact(\%) = 2D_t \frac{M_{t+5} - M_t}{M_t} \times 100 \quad (4)$$

The above four liquidity measures are calculated from the TAQ database and aggregated at the daily frequency by share-weighting average for all trades occurring during continuous trading hours. In general, a lower value corresponds to better liquidity.

We apply the following difference-in-difference model to validate our second hypothesis about the influence of stock price manipulation and retail trading on market liquidity:

$$Liquidity_{i,t} = \alpha + \beta_1 Post_{i,t} + \beta_2 Retail_i + \beta_3 Post_{i,t} \times Retail_i + \gamma Controls_{i,t} + FE + \epsilon_{i,t} \quad (5)$$

Where $Post_{i,t}$ is a dummy variable equals one if the date is after manipulation and equals zero before it takes place. The dependent variable, $Liquidity_{i,t}$ is our measures for market liquidity and adverse selection risk that discussed above. If the manipulation has toxic effects on the market liquidity, then the Post coefficient β_1 should be statistically significantly related to the dependent variable in each regression, in the direction that implies less liquidity and high adverse selection.

Given that $Retail_i$ identifies whether the stock i has raised attention by retail investors at the manipulation day, the sign and the statistical significance of the estimated coefficient β_3 is the focus of our research.

One on hand, if retail trading acts as noise trading, based on the Glosten-Milgrom model, the increased proportion of noise trading should narrow quoted spreads after stock manipulation. Therefore, we should expect the coefficient β_3 to be negative and significant. On the other hand, based on Kyle's model prediction, if the effects of increased noise trading are offset by increased informed trading, the coefficient β_3 could be insignificant.

We include a vector of stock-level controls that have been identified from previous literature (i.e., stock price, firm size, trading volume and firm-level volatility). Additionally, *F.E.* represents a vector of fixed effects, which include industry and month fixed effects to absorb any variation which is common across industries and unobserved heterogeneity.

RESULTS

Changes in trading volumeshare around stock trading manipulation

Table 2 compares mean and median tests for off-exchange trading volume share on the manipulation event day (t=0) and the day after (t=1) with the non-event day, focusing on three different types of trading manipulation variables. On the day potentially affected by continuous trading manipulation, the average off-exchange trading volume share is 37.34%, whereas it is 36.64% without such manipulation. There is a significant difference in both the mean and median off-exchange trading volume share between the continuous trading manipulation and non-manipulation days. Regarding End-of-Day (EOD) price manipulation, the average off-exchange trading volume share is 38.15% on the manipulation day and 39.18% on the non-manipulation day, with a negative and significant difference. A similar pattern is observed for open price manipulation, where the mean off-exchange trading volume share differs significantly between the manipulation day and the non-event day. This initial result in Table 2 implies that different types of trading manipulation can have varying effects on off-exchange trading volume.

TABLE 2. Comparison of mean and median tests

This table presents a comparison of means and median tests for three manipulation types and off-exchange trading volume share at the manipulation event day (t=0) and the day after (t=1) with no-event day. Off-exchange trading volume share is measured by total trading volume in off-exchanges divided by total trading volume during the market hour. *Continuous* is an indicator variable that equals one at the day t when the firm i was identified to have a potential continuous trading manipulation and zero otherwise. *EOD* is an indicator variable that equals one at the day t when the firm i was identified to have a potential end-of-day price manipulation, and *OPEN* is an indicator variable that equals one at the day t when the firm i was identified to have a potential open price manipulation. The sample includes all firms that were identified to have at least one price manipulation alert from 01/2014-12/2018. ***, *, * indicate the significance of 1%, 5%, and 10% levels, respectively.

Types of the Trading Manipulation		Off-exchange Trading Volume Share (%)			
		Mean		Median	
		t=0	t=1	t=0	t=1
Continuous	1	37.34	37.20	37.01	36.69
	0	36.64	36.64	35.90	35.90
	Difference	0.70***	0.56***	1.11***	0.79***
EOD	1	38.15	39.12	38.13	39.04
	0	39.18	39.18	38.45	38.45
	Difference	-1.03***	-0.06	-0.32	0.58
OPEN	1	36.27	37.35	36.26	37.31
	0	37.17	37.17	36.64	36.64
	Difference	-0.90***	0.18	-0.38	0.67***

Table 3 further breakdown the changes in off-exchanges volumeshare for each type of trading manipulation by firm liquidity. Firms were categorized into quintiles based on their average quoted spread on non-event days. Subsequently, average changes in off-exchange volume were calculated. Panel A of Table 3 depicts the off-exchange volume shares on the manipulation event day (t=0), and Panel B provides insights for the following day (t=1). In line with the findings in Table 2, various types of trading manipulations yield different impacts on off-exchange trading volumeshare.

For continuous trading manipulation, there was a rise in off-exchange trading volume share across all quintiles both on the day of the event and the following day. On the event day, firms in the higher quintiles experienced a more pronounced increase in off-exchange trading compared to firms in the lower quintiles. For instance, firms in the Q5 quintile experienced an average growth of 2.548% in their off-exchange volume share during continuous trading manipulation events, whereas those in the Q1 quintile noted an average uptick of 1.848%.

Conversely, since EOD manipulation primarily targets end-of-day prices and these prices typically revert to normal the day after, this kind of trading manipulation might not induce substantial shifts in off-exchange volume shares. As a result, the data for the following day (t=1) is varied. Similarly, with OPEN price manipulation, the changes in off-exchange volume shares are inconsistent: there's a decline in off-exchange volume shares for firms in both the lowest and highest quintiles on the event day, but an increase is evident the day after for all firms except those in Q1.

TABLE 3. Change in off-exchange trading volume share by liquidity quintile.

This table presents a breakdown of the changes in off-exchange volume share by firm liquidity for three trading manipulation events. Firms are sorted into quintiles based on the firm's quote spread on the non-event day. Firms in quintile 1 (quintile 5) are the firms with the lowest (highest) liquidity. The change in off-exchange volume share is calculated as the difference between the average trading volume given on the event day and the average off-exchange volumeshare on non-event day. *Continuous* is an indicator variable that equals one at the day t when the firm i was identified to have a potential continuous trading manipulation and zero otherwise. *EOD* is an indicator variable that equals one at the day t when the firm i was identified to have a potential end-of-day price manipulation, and *OPEN* is an indicator variable that equals one at the day t when the firm i was identified to have a potential open price manipulation. The sample includes all firms that were identified to have at least one price manipulation alert from 01/2014-12/2018.

Panel A. Change in Off-exchange volumeshare (%) at the day with trading manipulation

	Continuous		**EOD**		**Open**	
	Average	Stdev.	Average	Stdev.	Average	Stdev.
Q1	1.848	11.403	-1.341	21.356	-1.762	14.375
Q2	1.876	11.288	-1.200	20.331	-0.217	12.522
Q3	2.186	11.153	-0.759	17.449	0.537	12.187
Q4	2.676	10.158	-0.585	16.336	0.167	11.697
Q5	2.548	9.484	-2.115	12.487	-0.392	10.043

Panel B. Change in Off-exchange volumeshare (%) at the day after with trading manipulation

	Continuous		**EOD**		**Open**	
	Average	Stdev.	Average	Stdev.	Average	Stdev.
Q1	1.114	11.026	-1.961	22.620	-0.705	14.144
Q2	1.024	10.617	0.512	19.360	0.511	11.968
Q3	0.980	10.182	0.448	17.806	0.837	11.418
Q4	1.350	9.604	-0.497	14.945	1.483	11.407
Q5	1.418	8.869	0.336	12.656	0.376	9.955

Table 4 presents the findings of the association between various types of stock trading manipulation and off-exchange trading volume share. In column (1), the results indicate that continuous trading manipulation is associated with a 0.72 percent increase in the off-exchange trading volume share on the day after the manipulation. To assess the economic significance of this change, we note that this implies an average increase of 12,225 shares with approximately $187,816 in notional value traded off-exchange. On the other hand, in column (2), the coefficient for *EOD* is negative but insignificant (coeff. = -0.0829, t = -0.24), suggesting that this type of price manipulation does not significantly affect the trading routing pattern, and the off-exchange volume share does not significantly change. Lastly, the coefficient for open price manipulation is positive and significant, implying a 0.77 percent rise in off-exchange trading volume share on the day after manipulation. This corresponds to an increase of around 8,271 shares or about $54,441 in notional value traded off-exchange.

TABLE 4. The association between stock manipulation and off-exchange trading.

This table presents the panel regression results of the determinants of off-exchange trading volume share with industry-fixed effects. The dependent variable is the off-exchange trading volume share, which is measured by total trading volume in off-exchanges divided by total trading volume during the market hour. The main independent variables are three manipulation indicators, *Continuous* is an indicator variable that equals one at the day t when the firm i was identified to have a potential continuous trading manipulation and zero otherwise. *EOD* is an indicator variable that equals one at the day t when the firm i was identified to have a potential end-of-day price manipulation, and *OPEN* is an indicator variable that equals one at the day t when the firm i was identified to have a potential open price manipulation. The sample includes all firms that were identified to have at least one price manipulation alert from 01/2014-12/2018. Control variable definitions are provided in the Appendix. The model controls for industry-fixed effects. The robust t-statistics are indicated in parenthesis, and ***, *, * indicate p-values of 1%, 5%, and 10%, respectively. The standard errors are clustered by stocks.

	$Dvolshare_{t+1}$	**$Dvolshare_{t+1}$**	**$Dvolshare_{t+1}$**	**$Dvolshare_{t}$**
	(1)	**(2)**	**(3)**	**(4)**
Continuous	0.7157***			
	(13.17)			
EOD		-0.0829		
		(-0.24)		
OPEN			0.7567***	-0.6018**
			(3.76)	*(-2.49)*
Inverse Price	2.3816***	3.5291***	1.7780**	1.7653**
	(3.70)	*(4.07)*	*(2.09)*	*(2.09)*
Spread	-0.5146**	-3.2001***	-7.3447***	-7.6133***
	(-2.57)	*(-5.70)*	*(-2.62)*	*(-2.75)*
Market Cap	-0.9504***	1.1143***	-1.8967***	-1.8602***
	(-9.16)	*(4.21)*	*(-11.11)*	*(-10.95)*
Firm Intraday Volatility	0.5193***	0.0189	0.2085***	0.1998***
	(12.13)	*(0.30)*	*(3.97)*	*(4.00)*
Market Volatility	-0.2161***	-0.1381***	-0.2488***	-0.2432***
	(-17.32)	*(-3.19)*	*(-8.89)*	*(-9.06)*
Constant	44.2728***	24.8834***	56.7899***	56.5226***
	(23.63)	*(5.65)*	*(20.01)*	*(18.93)*
Industry-fixed effects	Yes	Yes	Yes	Yes
Observations	626,097	42,735	49,921	52,557
R-squared	0.168	0.155	0.166	0.164

In addition, in Table 4, column (4), we test the contemporaneous effect of open price manipulation on the off-exchange trading volume share. Interestingly, the coefficient of *OPEN* is negative and significant, indicating that there is less volume routed to off-exchange venues at day with potential open price manipulation. A plausible explanation may be that brokers, using their internal surveillance systems, can detect potential open manipulation. As a result, they may choose to route orders to lit exchanges, which often offer greater transparency and reduced execution risk compared to off-exchange venues.

Overall, the results in Table 4 reveal that the coefficients for the three manipulation indicators move in different directions, reflecting the diverse effects of various manipulation types on trading venue fragmentation. These insights align with our hypothesis and illuminate the complex dynamics of trading.

Changes in market liquidity around stock trading manipulation

All the analyses conducted in the paper so far focus on changes in the trading venue fragmentation around the stock trading manipulation event. We now proceed to the next hypothesis to investigate the impact of stock manipulation on market liquidity, and to evaluate the participation of retail trading in this context. To do so, we compare average liquidity measures before and after stock manipulation by conducting a 10-day event window, t [-5,5]. We focus on continuous trading manipulation for this hypothesis, as it is the type of manipulation most closely associated with significant changes in routing volume in trading venues , as previously discussed in hypothesis 1.

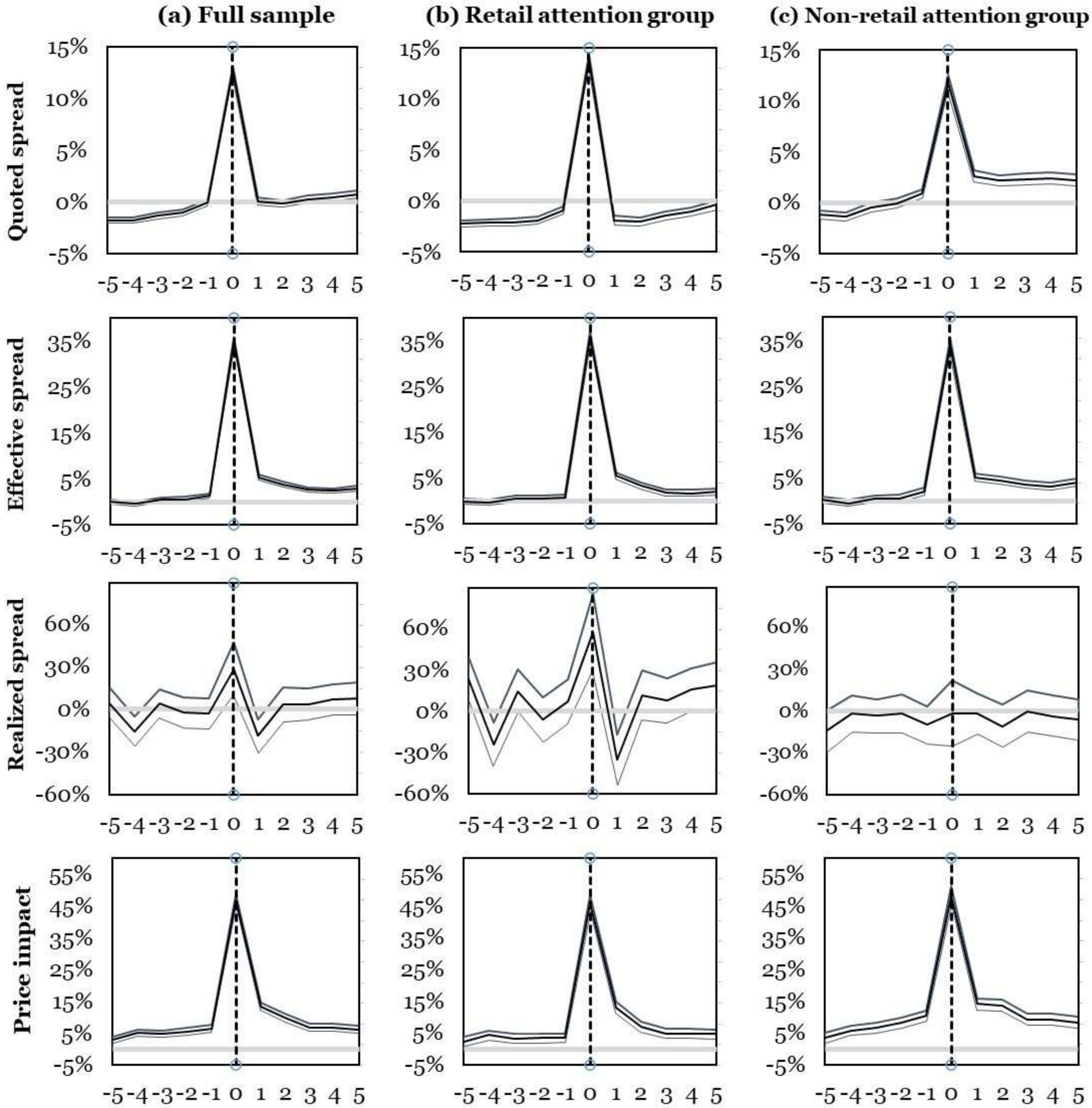
Figure 1 shows the time-series of these liquidity measures in the 10 days around a manipulation event, relative to the benchmark average liquidity measures. Our benchmark is calculated using an estimation window from t= -30 to t=-6. Panel (a) illustrates the findings for all stocks in our sample. Panel (b) and (c) offer a more refined view, presenting subsample categorized by whether or not the manipulation event caught the attention of retail investors.

As expected, all the liquidity measures experience a sharp increase on the day of manipulation (t=0), confirming that stock manipulation harms liquidity. In addition, the price impact increases by over 45% compared to the benchmark, highlighting an escalation in information asymmetry risk. The spreads quickly drop back to near the benchmark level the following trading day (t=1). Still, the post-manipulation spreads are relatively greater than with the pre-manipulation spreads.

It is significant to note that the patterns for the quoted spread differ distinctly between the retail attention group (Panel b) and the non-retail attention group (Panel c). For the former, the quoted spread falls below the benchmark level in the days following manipulation, whereas for the latter, it continues to hover above the benchmark. This variation underscores that the influence of stock manipulation on market liquidity may vary, contingent on whether or not the manipulation garners the attention of retail investors.

FIGURE 1: Daily market liquidity around manipulation event

These figures present the time-series of liquidity measures from t=-5 to t=5, relative to the control period of the manipulation at t=[-30,-6].The grey line represents the upper and lower bands of 95% percent confidence interval. The vertical lines at t=0 represent the manipulating event day. The sample includes all stocks that experienced continuous trading manipulation during 2014.01-2018.12. Panel (a) shows the results for all stocks in sample, and panel (b) and (c) are sub-s that categorized by whether this event has been raised attention by retail investor.



We first conduct a 10-day event window, t[-5,5], to examine the immediate influence of stock manipulation and retail attention on market liquidity. Table 5 reports the results of estimating equation (3). As the data reveals, the manipulation coefficient is positive and highly statistically significant across all liquidity measures, thereby implying that stock manipulation inflicts a detrimental impact on liquidity. For instance, the *Post* (coeff. =0.9785, t-stat=4.49) in column (1) suggests that the average percent quoted spread widens up by 0.98 bps after stock manipulation.

Notably, the key coefficient of interest, β_3 , describing the post manipulation period for stocks that attracted retail attention during the manipulation day, is negative (close to -1.02 for quoted spread, and -0.16 for effective spread) and statistically significant at conventional levels.

Additionally, the coefficient of interaction term is statistically insignificant in column (3) for the realized spread (inventory risk), while it is negative and statistically significant in column (4) for price impact (asymmetric information). As such, our findings show a negative association between price impact and uninformed trading.

When considering the outcomes in columns (3) and (4) together, the results reinforce the notion that retail investors behave like noise traders. Furthermore, the overall findings in Table 4 are in line with the predictions of Glosten and Milgrom's model, positing that increased retail trading prompted by stock manipulation decreases asymmetric information risk. Therefore, the presence of retail trading helps to attenuate the rise in illiquidity due to stock manipulation.

To investigate whether the findings from Table 5 could last for a longer period, we expanded our analysis to a 20 day window, t[-10,10]. The results are presented in Table 6. Again, the interaction terms between manipulation and retail attention for quoted spread and effective spread remain negative and statistically significant, with values of -0.4957 and -0.2305 respectively. These values signify that high retail trading participation during the manipulation day could mitigates the negative impact on the liquidity from manipulation.

Furthermore, while the interaction term's coefficient for realized spread is insignificant, it is negative and statistically significant for price impact. This again points to the idea that stocks experiencing high retail trading on the manipulation day display comparatively less informed order flow following the manipulation. Overall, the findings in Table 6 echo those in Table 4, underscoring support for the Glosten and Milgrom model. Specifically, we observe that an augmented proportion of noise trading post-manipulation enhances liquidity and narrows quoted spreads. The involvement of retail trading thus emerges as a crucial factor, acting to alleviate the detrimental consequences of stock manipulation on market liquidity.

CONCLUSION

This study has undertaken a rigorous examination of the effects of stock trading manipulation on off-exchange trading volume and market liquidity, with a particular focus on the role of retail trading. Through various analyses, the paper delineates a multifaceted relationship between different types of stock price manipulation and off-exchange trading volume, revealing disparate impacts based on the nature of the manipulation.

Our results confirm a noticeable toxic effect of manipulation on market liquidity, with all liquidity measures experiencing a sharp increase on the manipulation day. However, the involvement of retail trading presents a nuanced picture. We found that the increased proportion of noise trading, as a consequence of manipulation, serves to decrease asymmetric information risk. serves to decrease asymmetric information risk. The evidence supports the Glosten and Milgrom model's predictions, portraying retail trading as a mitigating force against the rise in illiquidity due to manipulation.

From a practical standpoint, our findings are likely to be of interest to regulators and policymakers, shedding light on how retail trading participation affects the outcomes of stock manipulation. In sum, our paper is the first to document the impact of price manipulation on retail volume and trading fragmentation. Our findings significantly contribute to the broader field of finance, offering novel insights into the role of retail trading in the context of stock manipulation.

TABLE 5. The results of stock manipulation on market quality in 10 days window

This table reports coefficient estimates for OLS regressions of 10-days event window (five trading days before and after) from regressing market quality measures (in bps) on manipulation event day dummy *Post*, retail attention dummy Retail D, and their interaction term with controls. The dependent variables are: Average time-weighted percent quoted spread, average percent effective spread, average percent price impact computed based on 5-minute interval, average percent realized spread computed based on 5-minute intervals. All control variables are described in Appendix. The sample includes all stocks that have at least one continuous trading manipulation alert during 01.2014-12.2018. All regressions include the industry and month fixed effects, and the standard errors are double clustered at the firm and date level. T-Stats are reported in parentheses. Standard errors are double clustered at the stock and date level, and ***, **, * indicate p-values of 1%, 5%, and 10%, respectively.

	(1) **Quoted Spread**	**(2)** **Effective Spread**	**(3)** **Realized Spread**	**(4)** **Price Impact**
Post	0.9785***	0.2381***	0.0985	0.0577
	(4.49)	*(3.40)*	*(0.52)*	*(1.05)*
Retail	-0.0564	-0.3362***	-0.0509	-0.2946***
	(-0.24)	*(-3.44)*	*(-0.44)*	*(-4.48)*
Post x Retail	-1.0233***	-0.1561*	0.0846	-0.1212*
	(-3.82)	*(-1.80)*	*(0.42)*	*(-1.73)*
Inverse Price	41.2696***	25.2840***	27.3583***	9.3765***
	(9.47)	*(10.19)*	*(9.65)*	*(7.95)*
Market Cap	-1.9828***	-2.1772***	-0.5311***	-1.4891***
	(-9.67)	*(-18.92)*	*(-4.53)*	*(-21.42)*
Log(Volume)	-6.5788***	-2.4409***	-1.6304***	-1.1911***
	(-30.48)	*(-24.25)*	*(-12.89)*	*(-19.38)*
Firm Intraday Volatility	2.8243***	1.5767***	0.0055	1.5460***
	(17.29)	*(20.10)*	*(0.06)*	*(22.44)*
Intercept	116.7842***	67.1209***	29.8496***	39.6612***
	(41.09)	*(52.88)*	*(18.40)*	*(55.64)*
Industry Fixed Effect	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes
Observations	247,654	247,572	247,571	247,571
R-squared	0.217	0.507	0.061	0.365

TABLE 6. The results of stock manipulation on market quality in 20 days window

This table reports coefficient estimates for OLS regressions of 20-days event window (Ten trading days before and after) from regressing market quality measures (in bps) on manipulation event day dummy *Post* , retail attention dummy Retail D and their interaction term with controls. The dependent variables are Average timeweighted percent quoted spread, average percent effective spread, average percent price impact computed based on 5-minute interval, average percent realized spread computed based on 5-minute intervals. All control variables are described in Appendix I. The sample includes all stocks that have at least one continuous trading manipulation alert during 01.2014-12.2018. All regressions include the industry and month fixed effects, and the standard errors are double clustered at the firm and date level. T-Stats are reported in parentheses. Standard errors are double clustered at the stock and date level, and ***, **, * indicate p-values of 1%, 5%, and 10%, respectively.

	(1) **Quoted Spread**	**(2)** **Effective Spread**	**(3)** **Realized Spread**	**(4)** **Price Impact**
Post	0.6585***	0.2130**	0.1366	0.0748
	(3.74)	*(2.02)*	*(0.99)*	*(0.57)*
Retail	-0.2326	-0.2562*	-0.1432	-0.1129
	(-1.19)	*(-1.92)*	*(-1.53)*	*(-1.27)*
Post x Retail	-0.4957**	-0.2305*	0.0892	-0.3195**
	(-2.20)	*(-1.68)*	*(0.60)*	*(-2.25)*
Inverse Price	40.6742***	43.9938***	28.6484***	15.3508***
	(10.84)	*(12.54)*	*(13.07)*	*(8.67)*
Market Cap	-1.9905***	-1.7260***	-0.5565***	-1.1760***
	(-11.73)	*(-12.33)*	*(-5.33)*	*(-11.81)*
Log(Volume)	-6.4478***	-3.4748***	-1.6290***	-1.8381***
	(-35.07)	*(-25.87)*	*(-14.86)*	*(-18.31)*
Firm Intraday Volatility	2.9441***	2.2426***	-0.0602	2.2962***
	(22.42)	*(21.19)*	*(-0.55)*	*(19.16)*
Intercept	114.9060***	71.9524***	30.2231***	41.7453***
	(45.72)	*(39.04)*	*(22.07)*	*(35.04)*
Industry Fixed Effect	Yes	Yes	Yes	Yes
Month Fixed Effect	Yes	Yes	Yes	Yes
Observations	484,774	484,623	484,622	484,621
R-squared	0.211	0.356	0.064	0.112

APPENDIX. Description of Variables

<table>
<tr><th>Variable</th><th>Description</th><th>Source</th></tr>
<tr><td>Manipulation (Continuous)</td><td>An indicator variable that equals 1 if the number of Continuous Trading Manipulation alert is greater than one, and 0 otherwise. The continuous trading manipulation metric detects abnormal 30-minute change of liquidity, returns and transaction cost based on the following rules:
1. For every 30-minute window (j) after opening of the current trading day (t), calculate the following metrics for every security in the market.
(a) Total trading value over the past 30 mins (Val)
(b) Total trading volume over the past 30 mins (Vol)
(c) Return over the past 30 mins (Ret)
(d) Average effective spread over the past 30 mins (EffSpr)
(e) Average quoted spread over the past 30 mins (QuotedSpr)
2. For every security in the market, calculate the average value of the above metrics for each 30-minute window (j) over the past 30 trading days (t-1 to t-31).
3. For the j^{th} 30-minute window of the current trading day (t)
(a) For security i, calculate the difference (Security $\text{Delta}_{i,j,t,m}$) between metric m for the current window (j) and the average metric value for the same window (j) over the past 30 trading days. (Note that for the trading volume and trading value metric, the difference is calculated as the percentage change.)
(b) Calculate the average value of $\text{Delta}_{i,j,t,m}$ across all securities (Mkt $\text{Delta}_{j,t,m}$). Note that for the 30-minute return metric, index returns is used to calculate the average delta.
(c) Calculate the difference between (Security $\text{Delta}_{i,j,t,m}$) and (Mkt $\text{Delta}_{j,t,m}$) for the current trading day (Current _ Security $\text{Delta}_{i,j,t,m}$) and the average daily difference over the past 30 trading days (Hist Security $\text{Delta}_{i,j,t,m}$)
(d) If there are 3 or more metrics with (CurrentSecurity $\text{Delta}_{i,j,t,m}$) that is more than 3 standard deviations away from HistSecurity $\text{Delta}_{i,j,t,m}$, increase the number of Continuous Trading Manipulation alert by one.</td><td>Nasdaq Trade Surveillance</td></tr>
</table>

(Appendix Continued)

Variable	Description	Source
EOD	An indicator variable that equals 1 if the stock EOD price at day t in the 15 minutes before the continuous trading period is dislocated four standard deviations away from its from its mean price change during the past 100-trading-day benchmarking period, and then reverts back to the benchmark price range the following morning, and 0 otherwise.	Nasdaq Trade Surveillance
Open	An indicator variable that equals 1 if the stock open price at day t in the 15 minutes before the continuous trading period is dislocated four standard deviations away from its from its mean price change during the past 100-trading-day benchmarking period, and then reverts back to the benchmark price range, and 0 otherwise.	Nasdaq Trade Surveillance
Post	Dummy variable equals one if the time is after manipulation day, and zero before	
Retail	Dummy variable equals one if the proportion of retail trading volume at the manipulation day (t=0) is higher than the benchmark calculated by averaging t=-30 to t=-6. The retail trading volume is identified by using Boehmer et al. (2021) methodology. The proportion of retail trading volume is calculated as the total retail trading volume at day t divided by the total trading volume at day t	TAQ
Market Volatility	Daily close CBOE Volatility Index (VIX)	CBOE
Bid-ask spread	Also refer as Quoted Spread ($), measured as daily high price minus daily low price	CRSP
Firm Intraday Volatility	100*percentage difference between daily high and low price	CRSP
Inverse Price	One over daily closing price	CRSP
Market Cap	The natural log of the firm market value defined as the number of outstanding shares (in 1,000) multiplied by the market price per share	Compustat
Log(Volume)	The natural log of the daily share volume	CRSP

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