Does High Frequency Market Manipulation Harm Market Quality?*

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Abstract: Manipulation of financial markets has long been a concern. With the automation of financial markets, the potential for high frequency market manipulation has arisen. Yet, such behavior is hidden within vast sums of order book data, making it difficult to define and to detect. We develop a tangible definition of one type of manipulation, spoofing. Using proprietary user-level identified order book data, we show the determinants of spoofing. Exploiting a Dodd-Frank rule change that exogenously reduced spoofing, we show causal evidence that spoofing increases return volatility, increases trading costs, and decreases price efficiency. The findings indicate that spoofing harms liquidity and price discovery.

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1. Introduction

Modern financial markets are largely automated. With the increased automation, market participants can potentially distort markets to profitably induce short term price movements. One such high-frequency manipulation method is spoofing, which is defined as "bidding or offering with the intent to cancel the bid or offer before execution."[1] In September 2020, JPMorgan was fined $920 million for spoofing metals and U.S. Treasury futures, where it was suggested that spoofing is a common practice.[2,3] The frequency of spoofing activity in financial markets is an empirical question. In addition, the fact that spoofing should be unrelated to real information and therefore does not contribute to price discovery raises the question of how spoofing affects market quality. This paper quantifies the frequency of spoofing and tests whether it harms market quality.

Theory on the impact market manipulation should have on market quality is mixed. Williams and Skrzypacz (2021) address the determinants and market quality impacts of spoofing. They theoretically show that increased spoofing activity leads to slower price discovery, higher return volatility, and wider bid-ask spreads. A successful spoofing strategy impedes price discovery by driving prices away from fundamental values. Because deviations from fundamentals can be corrected, spoofing price movements induce reversals which then increase return volatility. At the same time, if spoofing drives prices away from fundamentals, adverse selection increases and market-makers are forced to raise spreads to remain profitable.

Some theoretical work argues against manipulation being feasible or that it can even improve market quality. Jarrow (1992) shows that when prices do not exhibit momentum,

[1] 2010 Dodd-Frank Act
[2] https://www.reuters.com/article/jp-morgan-spoofing-penalty-idINKBN26K325
[3] https://fortune.com/2022/07/20/former-jpmorgan-trader-reveals-how-his-mentor-taught-him-to-place-and-cancel-bogus-spoof-trades-manipulate-markets/

manipulation is not possible. Cherian and Jarrow (1995) show that a symmetric price response to manipulation renders it unprofitable. Other studies show that manipulation may be associated with improved market quality. Hanson and Oprea (2009) model a manipulator as a noise trader and show that the manipulation strategy encourages information acquisition as the profits to informed traders increase, thereby improving price accuracy. We empirically test these conflicting theories on the existence and effect of market manipulation.

We study Canadian equity markets using the proprietary IIROC dataset, which has trade and quote data with trader identification. We identify spoofing orders by applying six tractable filters to the data. We then examine the prevalence and determinants of spoofing in Canadian equity markets. We find that the average stock-day observation has 586 attempted spoofing orders, with 19 successful. We exploit the passage of the Dodd-Frank Act on July 21, 2010 to estimate the causal effect of spoofing on market quality. Our results are consistent with the theoretical predictions of Williams and Skrzypacz (2021). Spoofing leads to higher return volatility, wider effective and realized spreads, and slower price discovery.

To discourage spoofing activity regulators strategically make the definition ambiguous. We thus draw from recent spoofing court cases to develop our six-step filtering approach. First, all spoofing orders are eventually deleted. Second, spoofing buy (sell) order prices must be greater (less) than the prevailing NBB (NBO). We match potential spoofing orders to genuine orders, which are orders in the opposite direction from the same trader. Third, spoofing orders must be placed within one second of the genuine order. Fourth, the spoofing order volume must be higher than the genuine order volume. Fifth, the spoofing orders must be cancelled within one second of the genuine order being executed or cancelled. Lastly, we require that during the minute a spoofing order is placed, the trader does not actually trade in the same direction as the spoofing order. As it is very challenging to empirically distinguish market making from spoofing manipulation, we purposely use strict criteria that can distinguish between the two. A limitation of such a strict definition is that we will undercount the true spoofing activity.

We begin the empirical analysis by documenting the prevalence and determinants of spoofing activity. In regressions of successful spoofing orders on cross-sectional and lagged market quality characteristics, we find that spoofing is more prevalent when effective spreads, trading volume, order volume, and Hasbrouck σ are high. We find no relation between spoofing and fundamental variables such as earnings per share, book value per share, and the natural log of market cap.

We next focus on the relationship between spoofing and market quality. We estimate OLS panel regressions of market quality measures on successful spoofing events, while controlling for daily returns, Amihud (2002) illiquidity, the log of dollar trading volume, and stock and date fixed effects. Spoofing is statistically and economically positively associated with 1- and 5-minute return volatility, effective spreads, realized spreads, variance ratios, and the Hasbrouck (1993) pricing error. We also find that quoted spreads are negatively associated with spoofing activity.

There is likely a strong endogeneity problem. Spoofing traders likely endogenously select certain stocks and dates to spoof more/less. For instance, Williams and Skrzypacz (2021) predict that spoofers endogenously choose to spoof when markets are not so illiquid that their spoofing orders can be identified by market makers but not so liquid that their spoofing orders are unable to move markets. We document a similar pattern. If spoofing activity is correlated with a stock's ex-ante liquidity, then our OLS estimates suffer from omitted variable bias, as ex-ante liquidity likely predicts market quality.

To overcome this endogeneity concern, we exploit the 2010 Dodd-Frank Act as a shock to spoofing activity. Namely, we observe an increase in spoofing in Canada-only stocks relative to stocks that are also cross-listed in the US because of the more stringent anti-fraud provisions in Dodd-Frank that only apply to US cross-listed stocks. We argue that the shock predicts spoofing activity but does not directly affect market quality differently between cross-listed and Canada-only stocks. Similar to Hendershott, Jones, and Menkveld (2011), we use predicted values from a difference in difference regression to instrument for spoofing in an instrumental variables approach. We estimate the instrumental variable regression of market quality outcomes on our spoofing measure, as well as controls for daily return, Amihud (2002) illiquidity, the log of dollar trading volume, and stock and date fixed effects. The IV analysis shows that spoofing causes increased return volatility, raises effective and realized bid-ask spreads, increases variance ratios, and increases the Hasbrouck (1993) pricing error.

To alleviate concerns that our spoofing detection process captures legitimate orders and cancellations placed by market makers, we conduct a falsification test. For each stock-day, we measure market making activity as the proportion of orders from traders who have at least one outstanding order on each side of the limit order book at the end of each minute and place buy orders between 40% to 60% of the time. In OLS regressions of our market quality measures on market making activity, we find that market making activity is associated with improved market quality. This suggests that our spoofing measure does not capture legitimate market making.

Finally, we conduct a variety of robustness tests. We re-estimate our baseline IV results using varying time windows around the passage of the Dodd Frank Act. We also consider alternative definitions of spoofing, such as the number of attempted spoofing orders, the proportion of spoofing orders, and the proportion of genuine order trading volume. In addition, we examine whether the results are driven by a specific type of spoofing and estimate separate regressions for buy and sell spoofs. Across the varying robustness checks the results remain economically consistent.

This paper contributes to the extant literature on market manipulation (See Putnins, 2012 for a survey) and more specifically to the newer literature on high frequency market manipulation. There is a nascent theoretical literature on spoofing. In general, it is challenging to model limit order book dynamics (Parlour, 1998; Rosu, 2009). Theory has incorporated spoofing behavior into the equilibrium order book behavior. Williams and Skrzypacz (2021) provide an equilibrium model showing that spoofing behavior can harm liquidity, slow price discovery, and elevate volatility. Wang, Hoang, Vorobeychik, and Wellman (2021) also show that the presence of spoofers in an order book that is otherwise informative results in a decrease in investor welfare. Cartea, Jaimungal, and Wang (2020) model how spoofing can be used to increase an investor's revenue, and how potential legal fines can deter spoofing behavior. Using simulated limit order books, Withanawasam, Whigham, and Crack (2018) examine where manipulators may be more prevalent. Our study provides empirical tests of the theoretical implications of spoofing on market quality and confirms that spoofing harms market quality.

Legal scholars have argued more generally about the impact of spoofing. Fischel and Ross (1991) provide a framework for how the legal community analyzes manipulation in markets. McNamara (2016) tackles the ethical and legal implications of high frequency trading, which covers spoofing and other limit order based manipulation strategies. Miller and Shorter (2016) survey the literature on high frequency trading and market manipulation and discuss the regulatory and legislative reaction to crack down on behaviors such as spoofing. Canellos et al. (2016) provide an overview of spoofing cases that have occurred before and after Dodd-Frank. Fox, Glosten, and

Guan (2021) provide a framework to consolidate the varying interpretations of what is and is not considered spoofing. Montgomery (2016) argues that spoofing may in fact improve the liquidity of financial markets. Dalko, Michael, and Wang (2020) argue that spoofing as a manipulative practice only arises because of behavioral biases of investors and microstructural systems.

The empirical work on spoofing is limited. The reason for the paucity of work on the topic is that it typically requires order book data with trader identifying information. That said, Tao, Day, Ling, and Drapeau (2022) have crafted a strategy to detect spoofing from public order books. Two other papers have identifying account information and study spoofing. Lee, Eom, and Park (2013) use data from Korea and show a positive correlation among spoofing and volatility and a negative correlation with market capitalization. Wang (2019) uses data from Taiwan futures and shows that spoofing is profitable and is correlated with higher volume, bid-ask spreads, and volatility. This paper makes two contributions to the empirical literature. First, we provide another tractable spoofing detection method that aims to be orthogonal to genuine market-making activity. Second, we are the first to provide causal evidence that spoofing negatively impacts market quality.

2. Data and Variable Construction

Our primary data source is the proprietary Investment Industry Regulatory Organization of Canada (IIROC) dataset. The data consists of trade and quote data for 137 Canadian stocks from May 3, 2010 to July 19, 2011. Importantly, trades and orders have masked trader IDs that allow us to track individual trader positions and strategies across time. We observe trades and quotes on the Toronto Stock Exchange (TSX) and Toronto Venture Exchange (TSXV). We also observe Alternative

Trading System (ATS) activity through the Alpha (ALF), Chi-X (CHX), Omega (OMG), Pure (PTX), and MATCH Now (TCM) platforms.

The trade and quote data are timestamped at the 10-millisecond level and contain order submissions, amendments, cancellations, and executions. For each event, we observe trader ID, order ID, price, volume, NBB, NBO, exchange, and other information. Each order is assigned an order ID that can be used to track the status of an order over time. This is crucial for spoofing identification, as it allows us to track an individual trader's cancellations and amendments with precision. We require that each stock-day has at least $1 million in trading volume to remove very illiquid stocks. We drop observations with quoted spreads above 5% to remove potential data errors.[4]

We also obtain accounting data from Compustat to construct EPS excluding extraordinary items (bkvlps), Book value per share (bkvlps), and the natural log of market cap using closing prices from the end of calendar year 2010. For each stock, we compute these cross-sectional firm characteristics in Canadian dollars and use fiscal year 2010 data.

2.1 **Liquidity Measures**

We construct liquidity and market quality measures from the IIROC data. We measure liquidity with time-weighed quoted spreads, volume-weighted effective spreads, volume-weighed realized spreads, and Amihud (2002) illiquidity. We measure market quality with 1- and 5-minute return volatility, variance ratios, and Hasbrouck (1993) pricing error variance.

[4] More details about the IIROC dataset can be found in the internet appendix for *The Competitive Landscape of High-Frequency Trading Firms* by Boehmer, Li, and Saar (2018).

We compute time-weighted quoted spreads by weighting $\frac{NBO-NBB}{NBBO\ midpoint}$ by the time each spread prevails for a given stock-day. We compute volume-weighted effective spreads by weighing $2 \times \frac{|\ Price-NBBO\ midpoint|}{NBBO\ midpoint}$ by the volume at each effective spread. To approximate liquidity provision revenue, we compute volume-weighted realized spreads by weighing $2 \times \frac{|\ Price_t-NBBO\ midpoint_{t+5}|}{NBBO\ midpoint_t}$ by the volume at each realized spread, where $NBBO\ midpoint_{t+5}$ is the NBBO midpoint five minutes after time t. Amihud (2002) illiquidity is computed as the absolute value of daily returns divided by dollar volume for each stock day, multiplied by 10^6.

Return volatilities are computed at the 1- and 5-minute levels and are the standard deviation of returns using trading prices. We compute Lo and McKinley (1988) variance ratios with 1- and 30-minute return variances with $|1 - 30 \times \frac{Var_{1\ minute}(ret)}{Var_{30\ minute}(ret)}|$, a timing choice also used in Rösch, Subrahmanyam, and van Dijk (2016). We compute 1- and 30-minute returns with trade prices. Lastly, we compute Hasbrouck (1993) pricing error σ. Similar to Boehmer and Kelley (2009), we estimate the VAR system with five lags and include four variables: log returns, trade sign indicator equal to 1 if the trading price is greater than the bid-ask average (and 0 if the trade price equals the bid-ask average), signed volume computed as the trade sign times the number of shares traded, and root signed volume computed as the trade sign times the square root of the number of shares traded. We set lagged variables to zero at the beginning of each day. Table 1 Panel A reports liquidity and market quality summary statistics.

INSERT TABLE 1 ABOUT HERE

2.2 Spoofing Measures

As the official definition of spoofing is likely strategically ambiguous, it is difficult to empirically measure the prevalence of spoofing activity. We draw our criteria from the following example of a trader who successfully executes a sell spoofing strategy: suppose a trader wants to buy shares of a stock. The NBB and NBO are currently $99 and $100, respectively. The trader wants to buy at a price less than $99 and will manipulate prices down. First, the trader places a buy order for the shares he wants to buy at $98.75, which is less than the prevailing NBO. He then rapidly places a high volume limit sell order at a price lower than $100 (but higher than $99 to avoid immediate execution) to mimic selling pressure. The market responds to the false selling pressure by adjusting the NBB and NBO down. However, the trader immediately cancels the limit sell orders so they are not executed. Because the market responds to the selling pressure, the NBB decreases and falls below $98.75, which results in the trader's buy order executing. Figure 1 describes this strategy graphically.

INSERT FIGURE 1 ABOUT HERE

Our example yields a more general definition. A trader who is spoofing the market will initially place a "genuine" buy limit order that is intended to be executed. After placing the genuine order, the trader will enter "spoofing" sell orders that will create the impression that the market is facing selling pressure. This will drive prices down and lead to the genuine order being executed.

Finally, the spoofer will cancel the spoofing sell orders. The same story holds with genuine sell orders and spoofing buy orders. We develop six filters to classify orders as spoofing orders.

We separately identify buy and sell spoofing orders. We also require that spoofing activity occurs during the trading hours of 9:30 AM to 4 PM. We describe the procedure for identifying spoofing buy orders in detail[5]. The spoofing identification procedure relies on visible trader IDs to track spoofing strategies.

We first search for spoofing orders without considering the other side's genuine orders. The first filter requires that spoofing orders are eventually deleted. As spoofing strategies consist of rapid entrance and cancellation of orders in the same direction, we expect that a spoofer will cancel a vast majority of their spoofing orders. Our spoofing detection strategy implicitly assumes that spoofing orders are not executed. Although it is likely that some spoofing orders are unintentionally executed, it is difficult to disentangle an executed spoofing order from a non-spoofing order. Second, if a spoofing order is to induce a market response, it must be somewhat aggressive. We require that buy spoofing orders are greater than the previous NBB.

We match each potential buy spoofing order to potential sell (genuine) orders from the same trader ID. Our third criteria requires that spoofing orders occur within one second after the genuine order is placed. This is consistent with a spoofing trader first entering a reasonable genuine order and then subsequently spoofing the market to induce a price response. For there to be a price effect, spoofing orders again must be sufficiently aggressive. Our fourth filter captures this by requiring that each spoofing buy order's volume must be greater than the genuine order's volume.

[5] The procedure to identify spoofing sell orders is nearly identical to the procedure used to identify buy orders. Switching "buy" with "sell" and changing the second filter to require that the spoofing sell order must be less than the NBO yields the spoofing sell order identification procedure.

Spoofing occurs at high frequencies. Our fifth and most aggressive filter requires that spoofing orders are cancelled within one second of the genuine order being either cancelled or executed. Lastly, our sixth filter requires that for a given spoofing buy order, the trader ID must not have executed a buy order in the same minute. This is consistent with the one-sided nature of spoofing. If a trader is trying to manipulate prices in one direction, it is unlikely that they will trade on their spoofing orders (and if they did, then the spoofing strategy would be much less profitable).

We define several spoofing measures. First, we consider spoofing orders that are successful or unsuccessful. Successful spoofing orders are spoofing orders with executed genuine orders, while attempted spoofing orders have genuine orders that are either executed or cancelled. We also consider spoofing order volume. Percent spoofing volume is the volume of successful spoofing orders divided by total order volume. Percent attempted spoofing volume is the volume of attempted spoofing volume divided by total order volume. Lastly, we use the daily trading volume of genuine trades, scaled by the total trading volume. We measure the percent variables in basis points.

Table 1 Panel B presents the stock-day level summary statistics for spoofing activity. In our sample, the average stock-day has around 19 successful spoofing orders and 602 attempted spoofing orders. However, spoofing activity is right skewed, which suggests that spoofing activity may be heavily concentrated within certain time periods or stocks. We disaggregate successful and attempted spoofs into the buy and sell types and find that on average, selling spoofing activity is slightly more common than buying spoofing activity. This suggests that traders who wish to manipulate the market by spoofing tend to do so with downward price pressure.

2.3 Market-making Measure

A valid concern with our spoofing identification filters is that we are measuring orders and cancellations associated with typical market making or liquidity provision activity. We generate measures of liquidity provision to show that our results are likely not driven by market making. A trader-minute is considered market making if the proportion of buy orders is between 40% to 60% and the trader has at least one order outstanding at the end of the minute for each side of the market. Our market making measure is defined as the standardized percent of orders associated with market-making activity for each stock day.

3. Spoofing Activity

We begin by examining the determinants of spoofing activity. We regress spoofing activity on 1-day lagged market quality and liquidity measures, as well as cross sectional firm characteristics. Specifically, we estimate regressions of the following form:

$$
\begin{aligned}
spoofing_{i,t} = \beta_0 + \ & \beta_1 Amihud_{i,t-1} + \beta_2 Volatility_{i,t-1} + \beta_3 QuotedSpread_{i,t-1} \\
& + \beta_4 EffectiveSpread_{i,t-1} + \beta_5 RealizedSpread_{i,t-1} + \beta_6 LnVolume_{i,t-1} \\
& + \beta_7 LnOrderVolume_{i,t-1} + \beta_8 DailyRet_{i,t-1} + \beta_9 HasbrouckSigma_{i,t-1} \\
& + \beta_{10} EPS_i + \beta_{11} BVPS_i + \beta_{12} LnMKTCAP_i + \epsilon_{i,t}
\end{aligned}
$$

We measure spoofing with the number of successful spoofing orders. From our dataset of spoofing orders, we also compute the unique number of trader IDs for each stock-day that are associated with spoofing orders.

INSERT TABLE 2 ABOUT HERE

Table 2 Panel A describes the determinants of stock-day level spoofing activity. Columns (1) and (2) present results for the number of successful spoofing orders, while Columns (3) and (4) present results for the number of spoofing traders.

In all four specifications, spoofing activity has no consistent relation with lagged Amihud (2002) liquidity and lagged daily return. The negative coefficient on lagged 1-minute return volatility suggests that spoofing tends to occur in less volatile stocks. Lagged effective spread and realized spreads positively predict spoofing and the number of spoofing traders, while quoted spreads negatively predict spoofing activity. In particular, the positive coefficient on lagged realized spreads suggest that spoofing activity is higher when potential liquidity provision revenue is higher. In all four columns, log dollar trading volume and log order volume have a positive effect on spoofing activity, which suggests that spoofing activity is increasing in trading and quoting activity. The number of successful spoofs also tends to increase as lagged price inefficiency (measured by Hasbrouck (1993) pricing error σ) increases. This is consistent with the idea that spoofing traders may target stocks with relatively easy to manipulate prices. Lastly, we find that cross-sectional firm characteristics such as EPS, book value per share do not consistently predict the number of successful spoofing trades and spoofing traders, while the natural log of market cap positively predicts spoofing activity. Because the natural log of market cap and book value per share likely also capture some time-invariant liquidity aspects, our results ultimately suggest that spoofing activity is not determined by fundamentals but rather is influenced by market quality characteristics.

Skrzypacz and Williams (2021) predict that spoofing activity should be most active in markets with moderate liquidity. As the regression specification in Table 2 does not account for a nonlinear relation between spoofing and liquidity, we compute the average proportion of spoofing orders or spoofing volume relative to 40 liquidity quantiles. We measure liquidity with either number of orders or trading volume. The results are shown in Figure 2. We find that the theoretical prediction holds at the stock-day level when proxying for liquidity with trading volume: attempted spoofing orders are single peaked in liquidity.

INSERT FIGURE 2 ABOUT HERE

We next turn to the intraday distribution of spoofing activity. As the choice to spoof is likely endogenous, there may be different times of day that spoofing traders tend to employ the strategy. Figure 3 Panel A plots the average number of marketwide successful spoofing orders for each hour. We observe that spoofing activity is typically most active in the beginning and the end of each trading day, and that the most actively spoofed hour is from 10:00 AM to 11:00 AM. Figure 3 Panel B plots the average number of successful spoofing traders for each hour and shows similar results. As the market open and close periods are typically the most actively traded (Lee, Mucklow, and Ready 1993), it is likely that spoofing traders will manipulate stock prices by taking advantage of the increased attention. If more traders and/or algorithms are watching orders arrive to trade on predictable price movements, it may be easier to spoof the market. These results are consistent with those in Lee, Eom, and Park (2013) who also find that their measure of spoofing is highest around the market open and close.

INSERT FIGURE 3 ABOUT HERE

4. Relation between Spoofing and Market Quality

Guided by the theoretical predictions in Williams and Skrzypacz (2021), we examine the relation between spoofing activity and market quality. Namely, increased spoofing activity should be associated with higher return volatility, higher bid-ask spreads, and slower price discovery. Table 3 presents the results for panel regressions of liquidity or price efficiency measures on spoofing and controls. For each market quality measure, we estimate regressions of the following form:

$$\ln(market\_quality_{it}) = \beta_1 Spoofing_{it} + \beta_2 Return_{it} + \beta_3 Volume_{it} + \beta_4 Amihud_{it} + \gamma_t + \zeta_i + \epsilon_{it}$$

Where $Spoofing_{it}$ is the standardized number of successful spoofing orders, $Return_{it}$ is the daily stock return, $Volume_{it}$ is the log dollar volume, and $Amihud_{it}$ is the Amihud (2002) illiquidity measure. We denote date and stock fixed effects with γ_t and ζ_i, respectively. We include several liquidity controls because the decision to spoof likely depends on a stock's liquidity (as shown in Table 2). Our controls for log dollar volume and Amihud (2002) illiquidity help control for contemporaneous liquidity, while the daily return control alleviates concerns that spoofing traders might tend to target stocks with high or low returns. Stock fixed effects sweep out time-invariant stock-specific variation, such as industry. Day fixed effects sweep out marketwide time variation, such as marketwide liquidity shocks.

INSERT TABLE 3 ABOUT HERE

The results in Table 3 show a clear positive relation between spoofing activity and most of our inverse market quality measures. As the specification is log-linear with a standardized independent variable, the interpretation of β_1 is that a one standard deviation increase in successful spoofing orders is associated with a $100 \times \beta_1$ percent increase in the dependent variable.

Spoofing increases return volatility. We find that a one standard-deviation increase in successful spoofing orders is associated with a 3.79% and 2.24% increase in 1- and 5-minute return volatility, respectively. This is consistent with the idea that spoofing can move markets. If a spoofing trader can induce a temporary mispricing, then the process of inducing and correcting the manipulation will mechanically cause return volatility to increase.

Spoofing increases effective and realized bid-ask spreads but is associated with decreased quoted spreads. A one standard-deviation increase in successful spoofing orders is associated with a 30.09% increase in the volume-weighted effective spread and 13.68% increase in the volume-weighted realized spread. However, we find that spoofing is strongly negatively associated with quoted spreads: a one-standard deviation increase in successful spoofing orders is associated with a 3.21% decrease in the quoted spread.

Lastly, spoofing slows price discovery. A one standard-deviation increase in successful spoofing orders increases the variance ratio measure by 6.82% and Hasbrouck (1993) pricing error σ by 9.11%. As the variance ratio measure increases, the ratio of 30 1-minute volatilities and 30-minute volatility deviates more from 1. This is evidence that increased spoofing activity drives price movements away from a random walk process, which suggests impeded price efficiency. The Hasbrouck (1993) procedure decomposes stock returns into random walk (efficient) and stationary (pricing error) components. Hasbrouck σ measures the variance of the pricing errors. Larger dispersion in pricing errors suggests a less efficient price process that tends to deviate more from true prices. Thus, the Hasbrouck σ result suggests that spoofing is also associated with lower price efficiency.

A potential shortcoming in our spoofing identification approach is that we cannot determine a trader's true intent and thus may be instead measuring genuine market-making activity. We believe it unlikely that genuine market-making activity will manifest in our measures because of our sixth filter: a trader must not place a spoofing order in the same second that they trade in that direction. Our sixth filter likely removes much market-making activity as market-making liquidity providers are more likely (or are required) to have balanced strategies. For example, the TSX appoints market makers who are required to maintain a two-sided market. Furthermore, if our spoofing variable measures market-making activity, then the results would contradict the existing literature on market-making. Market making should decrease spreads and improve market quality, which is the opposite of what we find. This suggests that our measure does not capture market-making activity. We provide further evidence that our results are not driven by market making with our analysis in Section 6.1.

Although we control for likely confounders and include stock and day fixed effects, it is possible that there are time-varying stock-specific unobservable or omitted variables that may bias our estimates. Thus, the results in this section can be viewed as associations between spoofing and market quality and are largely consistent with existing theoretical and empirical studies. Our finding that effective and realized spreads widen is consistent with Wang (2019), and the finding that return volatility is higher is consistent with Lee, Eom, and Park (2013). However, to our knowledge, we are the first to relate spoofing activity directly to price discovery measures such as variance ratios and Hasbrouck (1993) pricing errors.

5. Causal Effect of Spoofing on Market Quality

Our results in Table 3 may suffer from omitted variable bias or simultaneity bias, as it is likely that spoofing traders endogenously respond to current liquidity or market quality conditions that may make spoofing strategies more profitable or effective. We exploit variation in spoofing induced by the 2011 Dodd-Frank Act.

The 2011 Dodd-Frank Act was enacted on July 21, 2010 in the aftermath of the Global Financial Crisis. The legislation provided broad reforms to the US financial industry and was primarily related to regulating banks and mortgage markets. However, Dodd-Frank also increased investor protection in financial markets. The act's amendment to the Commodity Exchange Act was the first legislation to explicitly ban spoofing activities, although it was directed at commodity futures markets. Dodd-Frank also strengthened the antifraud provisions of the Securities Exchange Act of 1934. The amendment to §15(c)(1)(A) extended the ban on broker or dealer manipulation from off-exchange markets to brokers or dealers operating on national securities exchanges.

As the act only applies to the U.S., we exploit the difference in spoofing between U.S. cross-listed and Canadian-only stocks to study the causal effect of spoofing on market quality. We follow the approach used in Hendershott, Jones, and Menkveld (2011) and exploit this shock in an instrumental variables (IV) approach.

Because we study the trading activity of cross-listed firms on Canadian exchanges, our first stage is only economically valid if there is a regulation that bridges Dodd-Frank to trading on Canadian markets. This is achieved through the Exchange Act of 1934's section on foreign securities exchanges[6]. Specifically, the provision on Foreign Securities Exchanges bans brokers and dealers from violating SEC regulations when trading on international exchanges if the stocks are "organized under the laws of" the United States. Because cross-listed stocks must comply with U.S. regulations, their stocks are likely protected from manipulation from U.S. traders, even on Canadian exchanges.

There are two possible channels by which Dodd-Frank affects Canada-only stocks compared to cross-listed stocks. First, there was a direct effect through the amendment to §15(c)(1)(A) that more clearly banned on-exchange manipulation by brokers and dealers. Second, there is an attention effect from the spoofing provision in Dodd-Frank, which was the first regulation to formally discuss (and ban) spoofing. While the regulation explicitly banned spoofing in commodity futures markets and allowed enforcement by the CFTC, it is plausible that U.S. traders decreased their spoofing activity in cross-listed stocks relative to Canada-only stocks due to expected heightened regulatory attention from U.S. regulators. While we highlight two potential channels in which Dodd-Frank affects spoofing activity, these are all contained in the same shock and thus do not violate the instrumental variables assumptions.

To avoid confounders due to a long time-horizon, we restrict the sample to the first 100 days, with July 21, 2010 being the 48th day in the sample. Our results are robust to both shorter and longer windows and are presented in Section 6.3.

[6] 15 U.S. Code § 78dd

Our first stage estimate is the difference-in-differences regression of the standardized number of spoofing orders on the interaction between $TREAT_i$, which is an indicator equal to 1 if the stock is not cross-listed on a US market, and $POST_t$, which is an indicator equal to 1 if the date is on or after July 21, 2010. We include controls for daily return, log of dollar trading volume, and Amihud (2002) illiquidity. We also include stock and date fixed effects and cluster standard errors by stock and date. The first-stage results are presented in Table 4. An instrument is valid if it satisfies both the relevance and exclusion restrictions.

INSERT TABLE 4 ABOUT HERE

The relevance condition requires that the instrument's predictive power on the endogenous variable is sufficiently strong. The coefficient on the $TREAT_i \times POST_t$ interaction term is positive and highly significant and shows that the Dodd-Frank Act increased average daily spoofing activity in Canadian-exchange stocks by 0.67 standard deviations relative to cross-listed stocks. The T-statistic on $TREAT_i \times POST_t$ is 4.44 and the Kleinbergen-Paap (2006) F-statistic (shown in Table 5) is greater than 19, which suggests that our first stage is powerful. The highly statistically and economically significant first stage is evidence that the relevance condition is satisfied.

The exclusion restriction requires that the instrument only affects our second stage dependent variables through the endogenous variable. In this case, the exclusion restriction would be violated if Dodd-Frank affected market quality through a channel other than the change in spoofing in Canada vs. cross-listed stocks that is also orthogonal to the second stage model's control variables. Because we include both stock and date fixed effects that sweep out time-invariant stock-level market quality characteristics and market-level trends in market quality, any confounders would have to be both time-varying and stock-specific. We believe that such a confounder is unlikely.

INSERT TABLE 5 ABOUT HERE

Our second stage estimates are shown in Table 5. We regress the market quality measures from Table 3 on the predicted standardized spoofing values from Table 4. We again control for daily return, log dollar volume, and Amihud (2002) illiquidity. We include stock and date fixed effects and cluster standard errors by stock and date. The results provide causal evidence that spoofing activity hurts both liquidity and market quality. Our estimates are both statistically and economically significant.

Spoofing causes increased return volatility. A one standard-deviation increase in instrumented spoofing activity is associated with a 13.45% increase in 1-minute return volatility and a 9.21% increase in 5-minute return volatility.

The causal effect of spoofing on effective and realized spreads is large: a one standard-deviation increase in instrumented spoofing increases the volume-weighted effective spread by 71.75% and volume-weighted realized spread by 28.02%. The large magnitude likely reflects the first-order effect that spoofing activity has on transaction costs, as market makers likely adjust their spreads in response to spoofing strategies. We document a positive effect of spoofing on quoted spreads, but the relation is statistically insignificant. This is in stark contrast with the results in Table 3, which shows a statistically significant and economically large negative relation between spoofing and quoted spreads. This highlights the importance of identification in this setting, as the much larger and positive coefficients in the IV specifications suggest that there is endogeneity in the OLS specification.

Price discovery is also significantly impeded. A one standard-deviation increase in instrumented spoofing is associated with a 39.36% increase in the variance ratio and a 30.69% increase in Hasbrouck (1993) pricing error σ. These results indicate that spoofing causes economically and statistically significant deviations from efficient prices. The larger causal magnitude may be a result of the fact that spoofing activity is more prevalent in stocks with worse ex-ante price efficiency (as shown in Table 2)

These results are all larger in magnitude than the estimates in Table 3. This may be due to two distinct reasons. While we believe that we have uncovered a causal estimate of spoofing's effect on market quality, we are measuring the causal effect of spoofing on market quality where the variation in spoofing is solely driven by the shock that Dodd-Frank affected Canadian-only and US cross-listed stocks differently. We acknowledge that the extent that spoofing affected market quality differently during this period influences our magnitudes and can limit generalizability. Second, the larger IV point estimates suggest that there are omitted variables that confound the association estimates in Table 4. For example, the main concern with association regressions is that there are omitted time-varying and stock specific variables that also are correlated with both spoofing and market quality. The larger point estimates suggest that the OLS results in Table 4 suffer from omitted variable bias where the unobserved confounders are negatively (positively) correlated with spoofing but positively (negatively) correlated with the inverse measures of market quality.

6. Robustness

We apply a battery of robustness tests to ensure that our results are not driven by market-making activity, our choice of spoofing measure, our timing choice in the IV analysis, or the type of spoofing activity.

6.1 **Market Making**

One potential concern is that our spoofing detection filters are picking up market making activity. We conduct a falsification test to show that unlike spoofing, market-making activity improves market quality. We repeat the OLS estimations from Table 3 with market-making activity instead of spoofing. Our market-making variable is defined as the standardized percentage of orders associated with market-making activity (as defined in Section 2.3).

INSERT TABLE 6 ABOUT HERE

Table 6 shows that market-making activity decreases return volatility, lowers spreads, and lowers variance ratios and Hasbrouck σ. These results are consistent with the existing literature that increased algorithmic trading improves liquidity (Hendershott, Jones, and Menkveld, 2011; Brogaard, Hendershott, and Riordan, 2014). These results are also the opposite of what we find for spoofing activity, which suggests that our spoofing measures are likely not capturing genuine market-making activity.

6.2 Alternative Spoofing Definitions

Our main results measure spoofing as the standardized number of successful spoofing orders. We test alternative definitions of spoofing in this section. Namely, we use the standardized number of attempted spoofing orders, the proportion of total order volume that are attempted spoofing orders, and the proportion of total trading volume that are successful genuine trades associated with spoofing orders.

We define the number of attempted spoofing orders as all spoofing orders that pass all six filters from Section 2.2, but do not require that the associated genuine orders are executed. Thus, attempted spoofing orders contain both the successful and unsuccessful spoofing orders. We have shown in previous sections that successful spoofing strategies tend to harm market quality. However, it is also likely that attempted spoofing strategies do too.

We measure the proportion of attempted spoofing order volume to total order volume by summing attempted spoofing order volume and dividing by total order volume for each stock-day. Measuring spoofing in levels affords relatively clean measurement, but a valid concern is that spoofing levels are too small to plausibly affect market quality. By measuring spoofing in proportions, we can examine how market quality responds to spoofing even after adjusting for the total level of orders.

Lastly, we measure the proportion of total trading volume of genuine trades. For all the successful genuine trades associated with spoofing orders, we sum the volume at the stock-day level and divide by one-way stock-day trading volume. Spoofing orders likely cause the bulk of the negative effects on market quality, but it is also plausible that genuine orders have an effect. For example, a market maker may observe rapid selling activity but may not realize that the selling activity was spoofing until she realizes that there was a genuine trade executed in the opposite direction, and then a subsequent price correction.

For each alternative spoofing measure, we re-estimate the IV approach from Tables 4 and 5. First stage IV results are presented in Table 7 and second stage regressions are presented in Table 8.

INSERT TABLE 7 ABOUT HERE

INSERT TABLE 8 ABOUT HERE

The results remain robust across the different measures. We standardize each spoofing measure for interpretation and comparability. Table 7 shows that our IV first stage is again powerful, with an economically meaningful increase in spoofing in Canada-only stocks relative to cross-listed ones. Table 8 shows that the different spoofing definitions yield results similar to those in Table 5. Namely, spoofing tends to increase the effective spread the most, but also has both a statistically and economically significant relation with the other market quality variables (with the exception of quoted spreads).

6.3 **IV Timing**

Our results in Tables 4 and 5 use the 100-day window from the beginning of our sample, where day 48 is the Dodd-Frank Act's passage. In this section, we show that our results are robust to different window choices. We reestimate our empirical approach from Tables 4 and 5 with two new time windows. First, we select a shorter window that starts 40 days before and ends 40 days after Dodd-Frank's passage. Next, we select a longer window that starts at the beginning of our sample and ends on the 150th day of our sample.

INSERT TABLE 9 ABOUT HERE

Table 9 shows the alternative first stage regressions. Regardless of the chosen window, Canada-only stocks continue to experience a statistically and economically significant increase in spoofing activity relative to U.S. cross-listed stocks after Dodd Frank is passed.

INSERT TABLE 10 ABOUT HERE

Table 10 shows that our second stage estimates are robust to the chosen window. Both windows yield positive and significant coefficients on standardized predicted spoofing orders except for quoted spreads and have similar magnitudes to the results in Table 5. Because the Flash Crash occurs early in our sample and is not included in our shorter window, these tests also alleviate concerns that our results are driven by the Flash Crash.

6.4 **Spoofing Type**

In our previous analyses, we aggregate spoofing across types. That is, our aggregate spoofing measure contains both buy and sell spoofing activity. In this section, we test whether different spoofing types affect market quality differently. We repeat our main IV estimate for successful buy and sell spoofs separately. Our first stage estimates are again strong. The coefficient on

$TREAT_i \times POST_t$ is 0.449 for buy spoofs (T = 3.99, F = 10.02) and 0.570 for sell spoofs (T = 4.27, F = 7.55), which suggests that each first-stage estimate is powerful. Table 11 presents our second-stage IV results with buy and sell spoofing. Panel A presents results for buy spoofs, while Panel B presents results for sell spoofs.

INSERT TABLE 11 ABOUT HERE

Both spoofing buys and sells yield results similar to those in Table 5. Regardless of the spoofing type, spoofing activity worsens market quality. We find that spoofing buys tend to have a larger effect on market quality, as each coefficient on predicted spoofing is larger (in magnitude) in Panel A than in Panel B.

7. **Conclusion**

We document evidence of widespread spoofing in Canadian equity markets and provide causal evidence that spoofing harms market quality. Consistent with theory, spoofing increases return volatility, increases effective and realized spreads, and slows price discovery.

We develop a tractable six-step filtering process to identify spoofing orders and study the prevalence of spoofing. We show that spoofing activity can be predicted by some ex-ante market-quality variables and not by firm fundamentals. OLS regressions show that on average, spoofing activity is associated with worse market quality. Using the 2010 Dodd-Frank Act, we exploit the variation in spoofing in US-Canada cross-listed and Canada-only stocks as an instrument for spoofing activity and provide causal evidence that spoofing harms market quality.

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Appendix

Table A1. Variable definitions

Variable	Definition
Spoofing measures	
Successful spoofs	Number of successful spoofing orders as defined by the procedure in Section 2.2. A successful spoof must have an associated genuine order that is also executed.
Attempted spoofs	Number of attempted spoofing orders as defined by the procedure in Section 2.2. Includes both successful and unsuccessful spoofs, meaning that the associated genuine order does not have to be executed.
Percent spoofing volume	The order volume from successful spoofing orders divided by the total daily order volume.
Percent attempted spoofing volume	The order volume associated with attempted spoofing orders divided by the total daily order volume.
Percent of genuine spoofing trades	The trading volume associated with genuine orders divided by total daily trading volume. Genuine orders are defined in Section 2.2 and are the legitimate orders placed on the opposite side of spoofing orders.
Market characteristics	
1-minute return volatility	Standard deviation of 1-minute returns.
5-minute return volatility	Standard deviation of 5-minute returns.
Quoted spread	Time-weighted quoted spread, where each quoted spread is $\frac{NBO-NBB}{NBBO\ midpoint}$.
Effective spread	Volume-weighted effective spread, where each effective spread is $2\times\frac{\lvert Price-NBBO\ midpoint\rvert}{NBBO\ midpoint}$.
Realized spread	Volume-weighted realized spread, where each realized spread is $2\times\frac{\lvert Price_t-NBBO\ midpoint_{t+5}\rvert}{NBBO\ midpoint_t}$.
Variance ratio	Lo and McKinley (1988) variance ratios using 1 and 30-minute return variances: $\lvert 1-30\times\frac{Var_{1\ minute}(ret)}{Var_{30\ minute}(ret)}\rvert$.
Hasbrouck σ	Standard deviation of pricing errors from VAR system with five lags and four variables: log returns, trade sign indicator equal to 1 if the trading price is greater than the bid-ask average (and 0 if the trade price equals the bid-ask average), signed volume computed as the trade sign times the number of shares traded, and root signed volume computed as the trade sign times the square root of the number of shares traded.
Dollar trading volume	Total one-way trading volume.
Order volume	Total order volume.

Daily return	Percent return for the trading day.
Market-making	Percent of orders associated with market-making activity. As defined in Section 2.3, market-making trader-minutes must have proportion of buy orders between 40% to 60% and must have an outstanding order at the end of the minute for each side.
Fundamental characteristics	
EPS	Diluted EPS excluding extraordinary items (epsfx) using earliest fiscal year data after January 1, 2010 and before December 31, 2012.
Book value per share	Book value per share (bkvlps) using earliest fiscal year data after January 1, 2010 and before December 31, 2012.
Ln(Market cap)	$\ln\,(price \times shares\ outstanding)$ using earliest fiscal year data after January 1, 2010 and before December 31, 2012.

Figure 1: Spoofing Example

Figure 1 provides a graphical representation of the sell spoofing example described in Section 2.2.

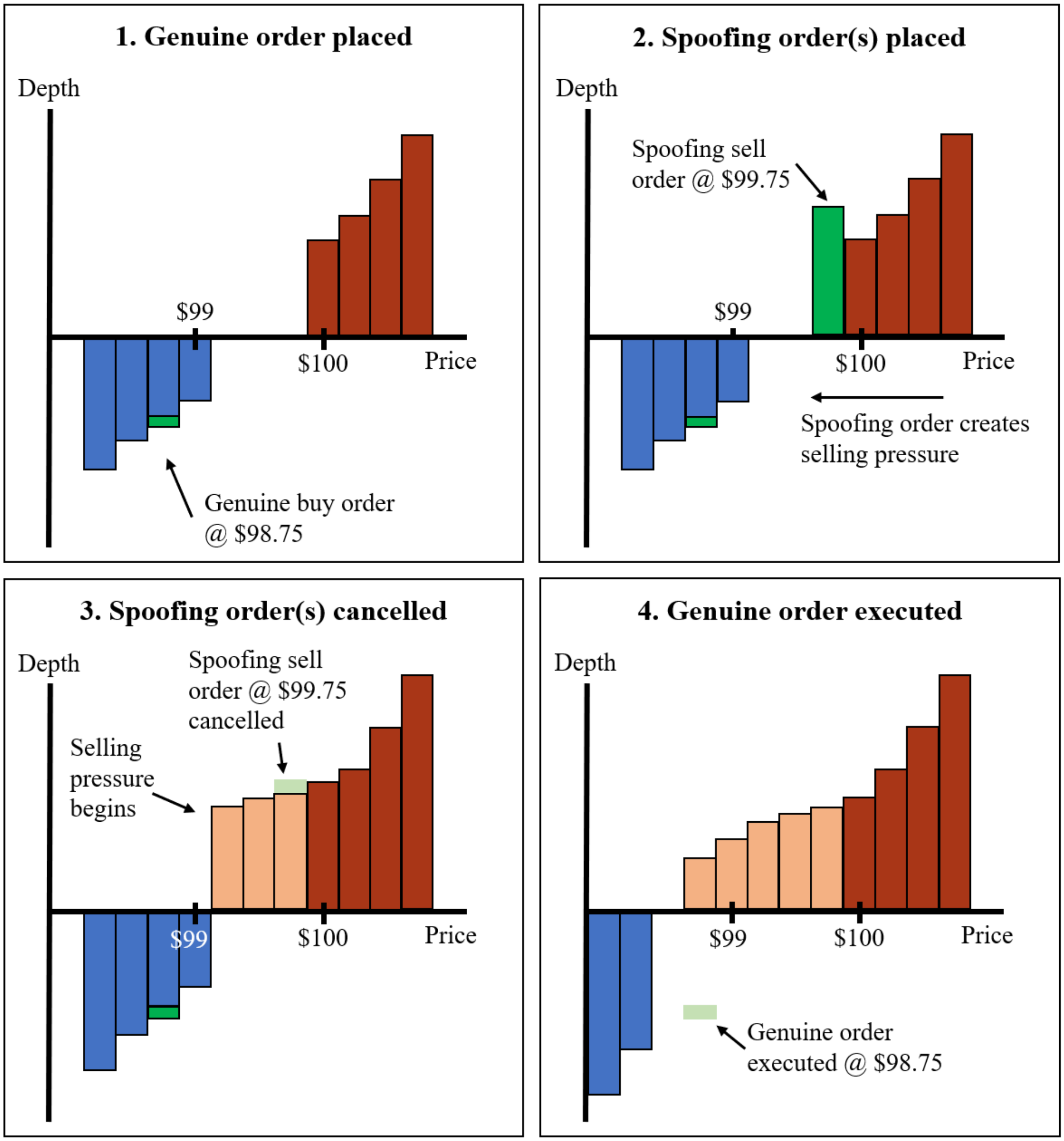
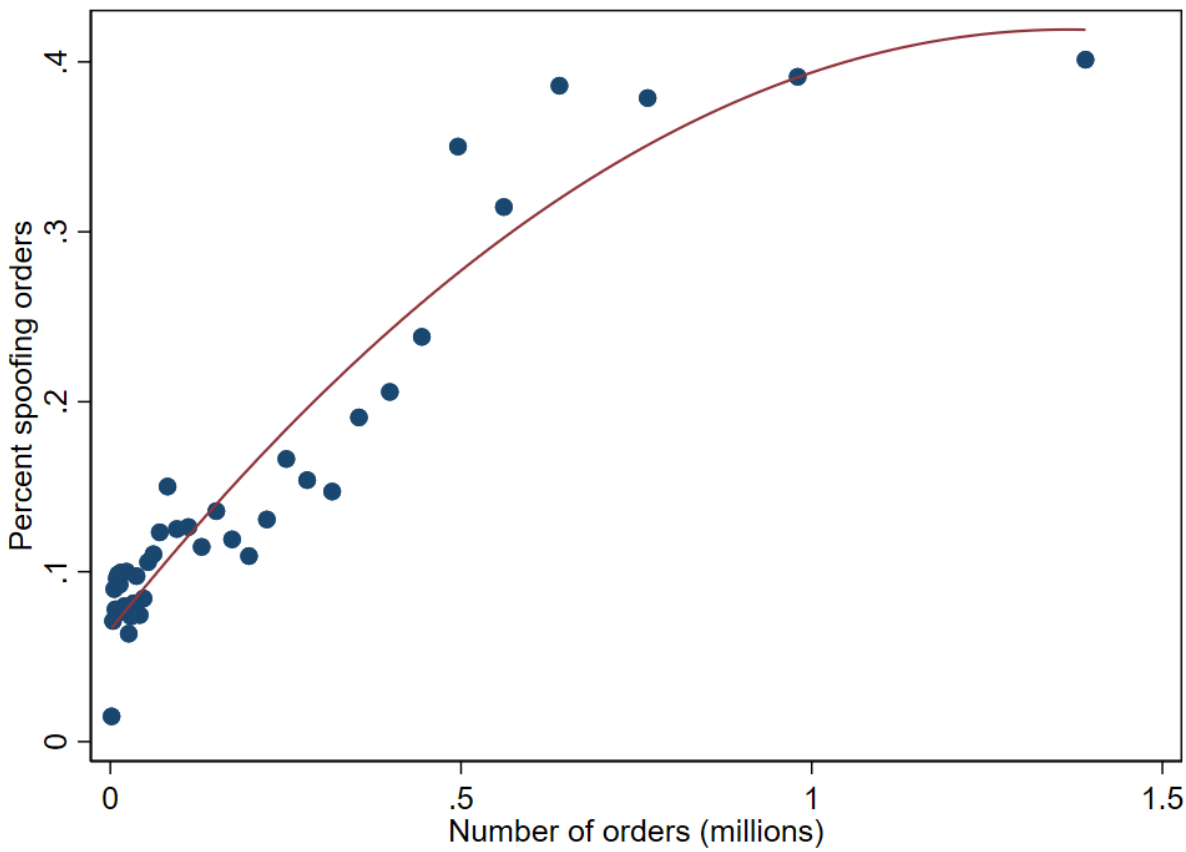


Figure 2: Spoofing and Liquidity

Figure 2 plots the average percentage of daily attempted spoofing orders for 40 liquidity-sorted quantiles. Panel A defines liquidity as the number of orders (in millions), while Panel B defines liquidity as trading volume (millions).

Panel A: Spoofing Order Percentage



Panel B: Spoofing Volume Percentage

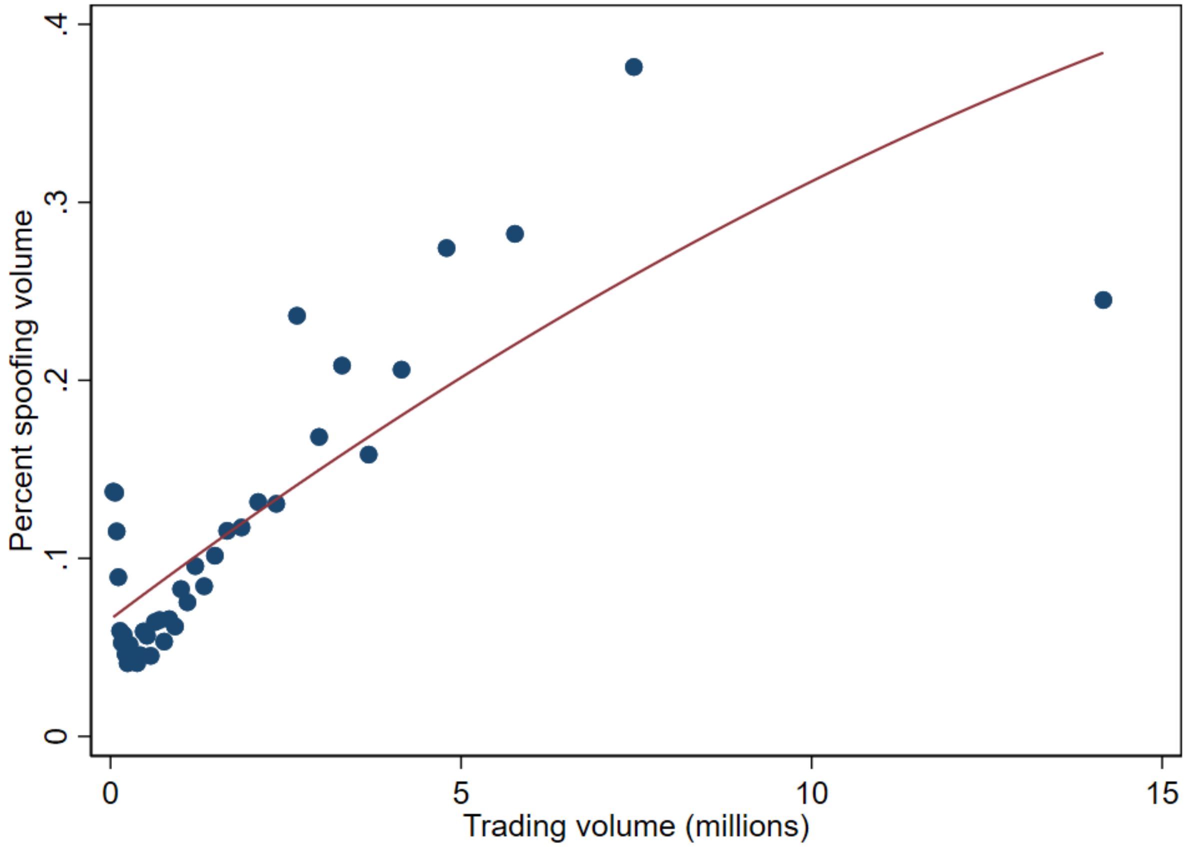
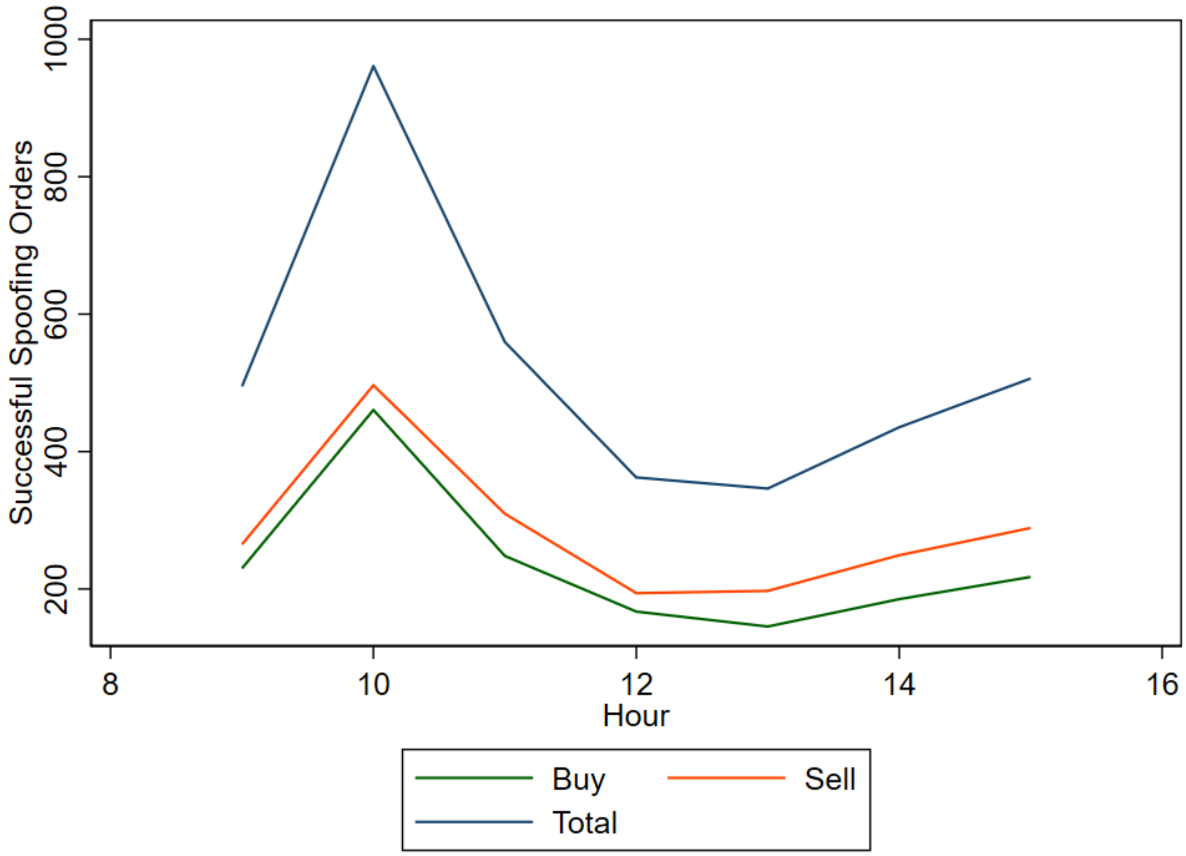


Figure 3: Intraday Spoofing Activity

Figure 3 plots the average marketwide spoofing activity by hour. Panel A shows the average number of successful spoofing orders, while Panel B shows the number of spoofing traders.

Panel A: Intraday Spoofing Orders



Panel B: Intraday Spoofing Traders

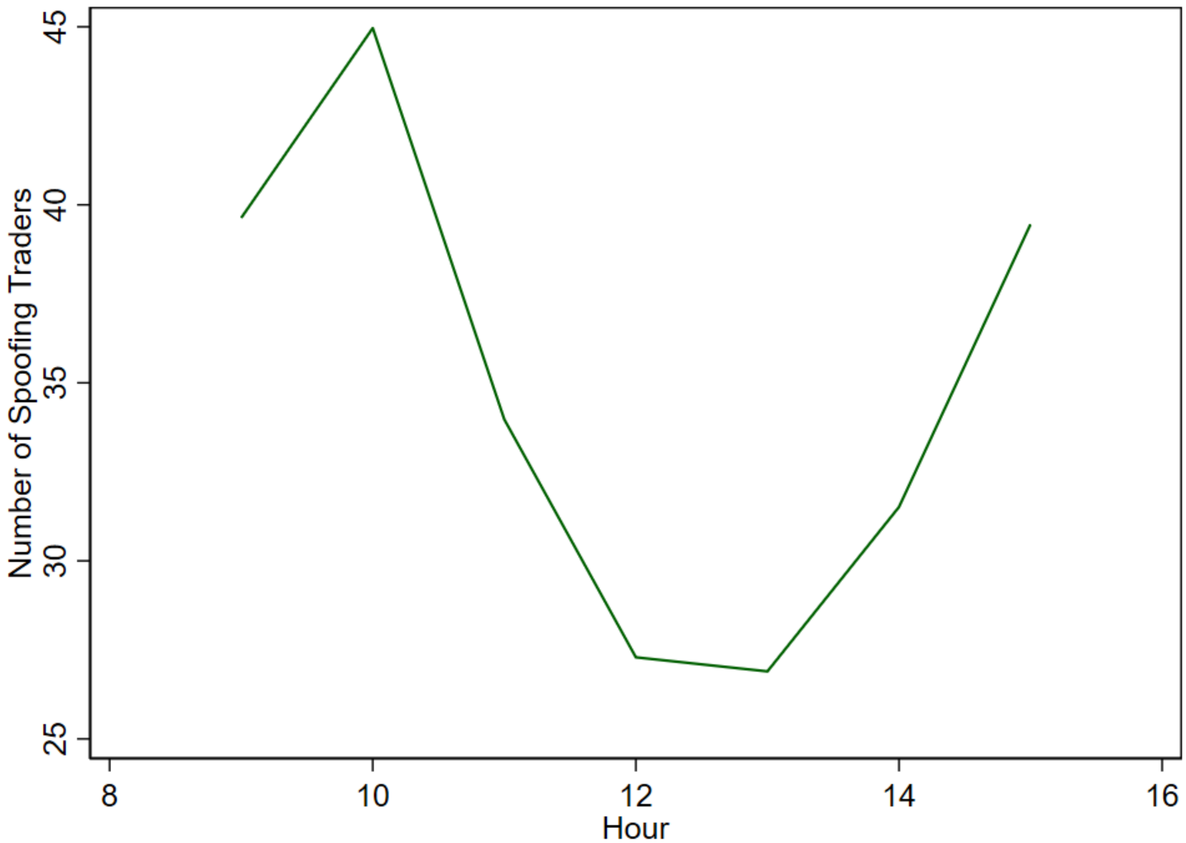


Table 1: Summary Statistics

Panel A presents stock-day level summary statistics for market quality measures. All Panel A variables except for the variance ratio, daily return, and dollar volume are reported in basis points. Panel B presents stock-day level summary statistics for spoofing activity. All variables are winsorized at the 1% and 99% levels.

Panel A: Market Characteristics

	Mean	SD	p10	Median	p90	N
1-minute return volatility	10.01	6.54	4.47	7.94	18.2	20603
5-minute return volatility	19.11	11.14	8.98	16	33.39	20603
Quoted spread	91.91	80.14	22.90	64.93	200.24	20603
Effective spread	20.41	32.47	3.59	9.48	43.04	20603
Realized spread	40.39	35.65	14.67	29.59	74.74	20603
Variance ratio	1.4	1.99	0.10	.65	3.49	20582
Hasbrouck price error σ	1.85	2.27	0.30	1.01	4.23	20504
p90 Hasbrouck error	2.72	3.15	0.47	1.51	6.31	20504
p100 Hasbrouck error	16.85	22.47	3.26	9.58	35.72	20504
Daily return	0	.02	-0.02	0	.02	20603
Dollar trading volume	52332438	71917648	1796324.75	20071224	1.548e+08	20603

Panel B: Spoofing Activity

	Mean	SD	p10	Median	p90	N
Successful spoofs	19.23	55.06	0.00	2	47	20603
Successful buy spoofs	8.05	20.93	0.00	1	22	20603
Successful sell spoofs	8.87	24.9	0.00	1	23	20603
Attempted spoofs	602.45	2637.96	0.00	28	874	20603
Attempted buy spoofs	215.81	823.02	0.00	13	403	20603
Attempted sell spoofs	248.53	1033.31	0.00	13	423	20603
Percent spoofing volume (bp)	.38	.81	0.00	.08	1.01	20603
Percent attempted spoofing volume (bp)	11.31	39.11	0.00	2.37	16.93	20603
Percent of genuine spoofing trades (bp)	20.27	49.27	0.00	3.84	47.67	20603

Table 2: Spoofing Characteristics

Table 2 describes spoofing activity in our sample in regressions of the form: $spoofing_{i,t} = \beta X_{i,t-1} + \epsilon_{i,t}$, where $X_{i,t-1}$ is a vector of 1-day lagged independent variables and $spoofing_{i,t}$ is either the number of successful spoofing orders or the number of traders that spoof for stock i on day t. Standard errors are clustered by stock and day.

	(1) Spoofs	(2) Spoofs	(3) Traders	(4) Traders
Amihud illiquidity	94.45	-369.62	26.92	-161.84
	(0.49)	(-0.62)	(0.68)	(-1.48)
1-minute return volatility	-23.35***	-23.70**	-2.82***	-1.69
	(-3.52)	(-2.59)	(-2.73)	(-1.13)
Effective spread	23.54***	28.13***	1.60**	2.30***
	(4.53)	(4.23)	(2.59)	(3.28)
Quoted spread	-5.43***	-7.74***	-0.56*	-0.68**
	(-3.29)	(-3.55)	(-1.97)	(-2.43)
Realized spread	8.84**	14.20**	2.53***	2.93***
	(2.20)	(2.28)	(3.88)	(3.39)
Dollar trading volume	9.09***	10.19***	1.13***	0.82
	(4.06)	(2.77)	(3.34)	(1.43)
Order volume	11.95***	14.53***	3.17***	3.36***
	(5.38)	(4.30)	(8.22)	(6.58)
Daily return	13.96	50.65	0.00	8.38
	(0.39)	(0.79)	(0.00)	(0.87)
Variance ratio	1.26**	1.74**	0.19**	0.19**
	(2.55)	(2.68)	(2.41)	(2.11)
Hasbrouck σ	4.31	13.80***	-0.63	0.02
	(1.34)	(3.06)	(-1.00)	(0.03)
EPS		-0.90		-0.17
		(-1.50)		(-1.25)
Book value per share		0.02		0.09**
		(0.16)		(2.17)
Ln(Market cap)		4.56**		0.14
		(2.42)		(0.37)
Observations	18,940	8,647	18,940	8,647
Adjusted R-squared	0.308	0.348	0.459	0.405

Table 3: Spoofing and Market Quality

Table 3 presents results of the following regression equation: $\ln(MarketQuality_{it}) = \beta_1 Spoofing_{it} + \beta_2 Return_{it} + \beta_3 Volume_{it} + \beta_4 Amihud_{it} + \gamma_t + \zeta_i + \epsilon_{it}$, where $MarketQuality_{it}$ is 1-minute return volatility, 5-minute return volatility, time-weighted quoted spread, volume-weighted effective spread, volume-weighted realized spread, variance ratio, or Hasbrouck (1993) pricing error σ. $Spoofing_{it}$ is the standardized number of successful spoofing orders, $Return_{it}$ is the daily stock return, $Volume_{it}$ is log dollar trading volume, and $Amihud_{it}$ is the Amihud (2002) illiquidity measure. We include stock and date fixed effects with γ_t and ζ_i, respectively and cluster standard errors by stock and day.

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
Spoofing orders	0.0379***	0.0224***	-0.0321**	0.3009***	0.1368***	0.0682***	0.0911***
	(6.23)	(4.16)	(-2.13)	(13.36)	(11.66)	(3.81)	(6.16)
Daily return	0.0181	0.4928**	0.0168	-0.1080	0.5964***	-3.7211***	-0.1684
	(0.10)	(2.55)	(0.06)	(-0.30)	(2.62)	(-5.74)	(-0.74)
Dollar trading volume	0.1308***	0.1735***	-0.0213*	-0.0154	0.1365***	-0.2895***	-0.1559***
	(14.90)	(18.04)	(-1.93)	(-0.94)	(11.63)	(-11.72)	(-11.19)
Amihud illiquidity	14.8807***	17.8949***	5.5366***	11.0581***	16.6876***	-28.1892***	7.1210***
	(11.99)	(13.52)	(3.85)	(6.55)	(11.21)	(-8.46)	(4.88)
Observations	20,597	20,597	20,597	20,597	20,597	20,577	20,500
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.0826	0.110	0.00390	0.182	0.108	0.0182	0.0540

Table 4: First Stage IV Estimate

Table 4 presents results for the following regression equation: $Spoofing_{it} = \beta_1 Post_t \times Treat_i + \beta_2 Amihud_{it} + \beta_3 Ret_{it} + \beta_4 Volume_{it} + \gamma_t + \zeta_i + \epsilon_{it}$, where $Spoofing_{it}$ is the standardized number of successful spoofing orders for stock i on day t, $Post_{it}$ is an indicator variable equal to 1 if the date t is on or after June 21, 2010, and $Treat_{it}$ is an indicator variable equal to 1 if stock i is not cross-listed on a U.S. exchange. $Amihud_{it}$ is the Amihud (2002) illiquidity measure, Ret_{it} is daily stock return, and $Volume_{it}$ is the log dollar trading volume. We include stock and date fixed effects with γ_t and ζ_i, respectively and cluster standard errors by stock and day.

	(1) Spoofing Orders
Post × Treat	0.67***
	(4.44)
Amihud illiquidity	3.46*
	(1.82)
Daily return	1.04
	(1.57)
Dollar trading volume	0.15***
	(4.32)
Observations	7,919
Stock FE	Yes
Date FE	Yes
Within R-squared	0.0595
F statistic	7.097

Table 5: Second-stage IV Estimates

Table 5 presents results for the following regression equation: $\ln(MarketQuality_{it}) = \beta_1 \widehat{Spoofing}_{it} + \beta_2 Return_{it} + \beta_3 Volume_{it} + \gamma_t + \zeta_i + \epsilon_{it}$, where $MarketQuality_{it}$ is 1-minute return volatility, 5-minute return volatility, time-weighted quoted spread, volume-weighted effective spread, volume-weighted realized spread, variance ratio, or Hasbrouck (1993) pricing error σ. $\widehat{Spoofing}_{it}$ is the predicted standardized number of successful spoofing orders for stock i on day t from the first-stage IV regression, $Return_{it}$ is the daily stock return, $Volume_{it}$ is log dollar trading volume, and $Amihud_{it}$ is the Amihud (2002) illiquidity measure. We include stock and date fixed effects with γ_t and ζ_i, respectively and cluster standard errors by stock and day.

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
$\widehat{Spoofing}$	0.1345***	0.0921**	0.0061	0.7175***	0.2802***	0.3936***	0.3069***
	(3.21)	(2.17)	(0.10)	(6.63)	(4.54)	(3.15)	(4.30)
Daily return	-0.2977	0.1162	0.0409	-0.4824	0.2729	-3.6526***	0.0220
	(-1.16)	(0.42)	(0.11)	(-0.78)	(0.82)	(-4.04)	(0.06)
Dollar trading volume	0.1059***	0.1476***	-0.0216	-0.0487	0.1075***	-0.3254***	-0.1649***
	(8.75)	(11.34)	(-1.50)	(-1.53)	(5.59)	(-8.51)	(-7.26)
Amihud illiquidity	10.5554***	14.3292***	1.7206	8.3553***	13.2420***	-32.7779***	1.7379
	(7.67)	(11.86)	(1.11)	(2.92)	(9.30)	(-6.25)	(0.83)
Observations	7,919	7,919	7,919	7,919	7,919	7,913	7,899
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	19.70	19.70	19.70	19.70	19.70	19.74	19.61

Table 6: Falsification

Table 6 presents results of the following regression equation: $\ln(MarketQuality_{it}) = \beta_1 MarketMaking_{it} + \beta_2 Return_{it} + \beta_3 Volume_{it} + \beta_4 Amihud_{it} + \gamma_t + \zeta_i + \epsilon_{it}$, where $MarketQuality_{it}$ is 1-minute return volatility, 5-minute return volatility, time-weighted quoted spread, volume-weighted effective spread, volume-weighted realized spread, variance ratio, or Hasbrouck (1993) pricing error σ. $MarketMaking_{it}$ is the standardized percent of orders associated with market-making activity, $Return_{it}$ is the daily stock return, $Volume_{it}$ is log dollar trading volume, and $Amihud_{it}$ is the Amihud (2002) illiquidity measure. We include stock and date fixed effects with γ_t and ζ_i, respectively and cluster standard errors by stock and day.

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
Market-making	-0.0137***	-0.0118***	-0.0139**	-0.0286***	-0.0054	-0.0266**	-0.0412***
	(-3.72)	(-2.78)	(-2.52)	(-3.40)	(-0.96)	(-2.14)	(-4.67)
Daily return	0.0032	0.4753**	-0.0315	-0.0341	0.6481***	-3.7524***	-0.2223
	(0.02)	(2.45)	(-0.11)	(-0.09)	(2.80)	(-5.77)	(-0.93)
Dollar trading volume	0.1371***	0.1773***	-0.0261**	0.0330*	0.1583***	-0.2781***	-0.1402***
	(15.70)	(18.62)	(-2.35)	(1.77)	(12.55)	(-11.28)	(-9.58)
Amihud illiquidity	14.7723***	17.8252***	5.5900***	10.3184***	16.3629***	-28.3833***	6.8530***
	(11.84)	(13.43)	(3.85)	(5.79)	(10.68)	(-8.53)	(4.70)
Observations	20,597	20,597	20,597	20,597	20,597	20,577	20,500
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.0735	0.108	0.00242	0.00624	0.0447	0.0168	0.0358

Table 7: Alternative Spoofing Definitions IV First Stage

Table 7 presents results for the following regression equation: $Spoofing_{it} = \beta_1 Post_t \times Treat_i + \beta_2 Amihud_{it} + \beta_3 Ret_{it} + \beta_4 Volume_{it} + \gamma_t + \zeta_i + \epsilon_{it}$, where $Spoofing_{it}$ is the standardized spoofing measure for stock i on day t. Columns 1, 2, and 3 measure $Spoofing_{it}$ with standardized attempted spoofs, percent of attempted spoofing order volume, and percent of genuine order trading volume, respectively. $Post_{it}$ is an indicator variable equal to 1 if the date t is on or after June 21, 2010, and $Treat_{it}$ is an indicator variable equal to 1 if stock i is not cross-listed on a U.S. exchange. $Amihud_{it}$ is the Amihud (2002) illiquidity measure, Ret_{it} is daily stock return, and $Volume_{it}$ is the dollar trading volume. We include stock and date fixed effects with γ_t and ζ_i, respectively and cluster standard errors by stock and day.

	(1) Attempted spoofing orders	(2) Percent of order volume associated with spoofing	(3) Percent of trading volume associated with genuine orders
Post × Treat	0.78***	0.77***	0.74***
	(4.41)	(4.18)	(4.84)
Amihud illiquidity	2.31	2.10	-0.59
	(1.05)	(0.90)	(-0.27)
Daily return	1.23*	0.95	0.40
	(1.75)	(1.31)	(0.50)
Dollar trading volume	0.06*	0.05	0.06*
	(1.78)	(1.34)	(1.92)
Observations	7,919	7,919	7,919
Stock FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Within R-squared	0.0597	0.0541	0.0544
F statistic	5.052	4.462	6.318

Table 8: Alternative Spoofing Definitions IV Second Stage

Table 8 presents results for the following regression equation: $\ln(MarketQuality_{it}) = \beta_1 \widehat{Spoofing}_{it} + \beta_2 Return_{it} + \beta_3 Volume_{it} + \gamma_t + \zeta_i + \epsilon_{it}$, where $MarketQuality_{it}$ is 1-minute return volatility, 5-minute return volatility, time-weighted quoted spread, volume-weighted effective spread, volume-weighted realized spread, variance ratio, or Hasbrouck (1993) pricing error σ. $\widehat{Spoofing}_{it}$ is the predicted standardized spoofing measure for stock i on day t from the first-stage IV regression. Panels A, B, and C measure $\widehat{Spoofing}_{it}$ with instrumented standardized attempted spoofs, percent of attempted spoofing order volume, and percent of genuine order trading volume, respectively $Return_{it}$ is the daily stock return, $Volume_{it}$ is log dollar trading volume, and $Amihud_{it}$ is the Amihud (2002) illiquidity measure. We include stock and date fixed effects with γ_t and ζ_i, respectively and cluster standard errors by stock and day. Panel A presents results for the 80-day window around the passage of Dodd-Frank, while Panel B presents results for the first 150 days in our sample.

Panel A: Attempted Spoofing Orders

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
$\widehat{Spoofing}$	0.1154***	0.0791**	0.0052	0.6155***	0.2404***	0.3377***	0.2643***
	(3.21)	(2.19)	(0.10)	(6.63)	(4.51)	(3.12)	(4.41)
Daily return	-0.2996	0.1149	0.0409	-0.4926	0.2689	-3.6581***	0.0156
	(-1.16)	(0.42)	(0.11)	(-0.80)	(0.81)	(-3.97)	(0.04)
Dollar trading volume	0.1182***	0.1561***	-0.0210	0.0173	0.1333***	-0.2892***	-0.1363***
	(10.48)	(12.77)	(-1.60)	(0.59)	(7.48)	(-7.78)	(-6.29)
Amihud illiquidity	10.7546***	14.4656***	1.7296	9.4178***	13.6569***	-32.1941***	2.2017
	(7.68)	(11.78)	(1.10)	(3.35)	(9.51)	(-6.12)	(1.04)
Observations	7,919	7,919	7,919	7,919	7,919	7,913	7,899
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	19.42	19.42	19.42	19.42	19.42	19.45	19.33

Panel B: Percent of order volume associated with spoofing

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
$\widehat{Spoofing}$	0.1179***	0.0808**	0.0054	0.6290***	0.2456***	0.3450***	0.2700***
	(3.19)	(2.16)	(0.10)	(7.40)	(5.03)	(3.14)	(4.32)
Daily return	-0.2695	0.1356	0.0422	-0.3317	0.3317	-3.5694***	0.0829
	(-1.03)	(0.50)	(0.12)	(-0.55)	(1.02)	(-3.87)	(0.20)
Dollar trading volume	0.1201***	0.1574***	-0.0210	0.0273	0.1372***	-0.2837***	-0.1319***
	(10.93)	(13.10)	(-1.60)	(0.95)	(8.02)	(-7.72)	(-6.23)
Amihud illiquidity	10.7743***	14.4791***	1.7305	9.5229***	13.6980***	-32.1433***	2.2457
	(7.62)	(11.74)	(1.10)	(3.46)	(9.83)	(-6.10)	(1.05)
Observations	7,919	7,919	7,919	7,919	7,919	7,913	7,899
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	17.47	17.47	17.47	17.47	17.47	17.51	17.40

Panel C: Percent of trading volume associated with genuine orders

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
$\widehat{Spoofing}$	0.1218***	0.0835**	0.0055	0.6498***	0.2537***	0.3566***	0.2789***
	(3.38)	(2.23)	(0.10)	(7.14)	(5.12)	(3.28)	(4.23)
Daily return	-0.2061	0.1790	0.0451	0.0061	0.4637	-3.3850***	0.2289
	(-0.79)	(0.66)	(0.13)	(0.01)	(1.37)	(-3.63)	(0.54)
Dollar trading volume	0.1179***	0.1559***	-0.0211	0.0157	0.1327***	-0.2901***	-0.1370***
	(10.41)	(12.81)	(-1.61)	(0.51)	(7.80)	(-8.20)	(-6.13)
Amihud illiquidity	11.0928***	14.6973***	1.7450	11.2216***	14.3612***	-31.2015***	2.9749
	(8.27)	(12.18)	(1.08)	(3.93)	(10.61)	(-6.14)	(1.43)
Observations	7,919	7,919	7,919	7,919	7,919	7,913	7,899
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	23.47	23.47	23.47	23.47	23.47	23.50	23.30

Table 9: Alternate First Stage IV Estimate Windows

Table 9 presents results for the following regression equation: $Spoofing_{it} = \beta_1 Post_t \times Treat_i + \beta_2 Amihud_{it} + \beta_3 Ret_{it} + \beta_4 Volume_{it} + \gamma_t + \zeta_i + \epsilon_{it}$, where $Spoofing_{it}$ is the standardized number of successful spoofing orders for stock i on day t, $Post_{it}$ is an indicator variable equal to 1 if the date t is on or after June 21, 2010, and $Treat_{it}$ is an indicator variable equal to 1 if stock i is not cross-listed on a U.S. exchange. $Amihud_{it}$ is the Amihud (2002) illiquidity measure, Ret_{it} is daily stock return, and $Volume_{it}$ is the dollar trading volume. We include stock and date fixed effects with γ_t and ζ_i, respectively and cluster standard errors by stock and day. Column 1 presents results for the 80-day window around the passage of Dodd-Frank, while column 2 presents results for the first 150 days in our sample.

	(1) Spoofing orders	(2) Spoofing orders
Post × Treat	0.71***	1.03***
	(3.47)	(4.64)
Amihud illiquidity	3.71	0.77
	(1.37)	(0.37)
Daily return	1.24	0.82
	(1.18)	(1.26)
Dollar trading volume	0.21***	0.18***
	(4.15)	(5.17)
Observations	6,298	12,527
Stock FE	Yes	Yes
Date FE	Yes	Yes
Within R-squared	0.0375	0.0748
F statistic	5.633	8.539

Table 10: Alternate Timing Second-stage IV Estimates

Table 10 presents results for the following regression equation: $\ln(MarketQuality_{it}) = \beta_1 \widehat{Spoofing}_{it} + \beta_2 Return_{it} + \beta_3 Volume_{it} + \gamma_t + \zeta_i + \epsilon_{it}$, where $MarketQuality_{it}$ is 1-minute return volatility, 5-minute return volatility, time-weighted quoted spread, volume-weighted effective spread, volume-weighted realized spread, variance ratio, or Hasbrouck (1993) pricing error σ. $\widehat{Spoofing}_{it}$ is the predicted standardized number of successful spoofing orders for stock i on day t from the first-stage IV regression, $Return_{it}$ is the daily stock return, $Volume_{it}$ is log dollar trading volume, and $Amihud_{it}$ is the Amihud (2002) illiquidity measure. We include stock and date fixed effects with γ_t and ζ_i, respectively and cluster standard errors by stock and day. Panel A presents results for the 80-day window around the passage of Dodd-Frank, while Panel B presents results for the first 150 days in our sample.

Panel A: 80-day Window

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
$\widehat{Spoofing}$	0.1219***	0.0782*	0.0771	0.5316***	0.2267***	0.3939***	0.2188***
	(3.05)	(1.95)	(1.34)	(4.77)	(3.82)	(2.77)	(3.12)
Daily return	-0.1227	0.2516	0.0170	-1.3009*	-0.0845	-3.0271***	-0.0373
	(-0.47)	(0.84)	(0.04)	(-1.76)	(-0.23)	(-2.86)	(-0.08)
Dollar trading volume	0.0981***	0.1437***	-0.0302	-0.0551	0.0948***	-0.3263***	-0.1657***
	(6.91)	(10.36)	(-1.49)	(-1.42)	(4.22)	(-6.61)	(-6.07)
Amihud illiquidity	9.1553***	13.3020***	1.3687	10.3636***	13.2209***	-32.5564***	2.4464
	(6.26)	(11.14)	(0.75)	(2.74)	(8.15)	(-5.42)	(1.06)
Observations	6,298	6,298	6,298	6,298	6,298	6,292	6,278
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	12.05	12.05	12.05	12.05	12.05	12.08	12.01

Panel B: First 150 Days of Sample

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
$\widehat{Spoofing}$	0.0882***	0.0548**	-0.0029	0.4574***	0.1838***	0.2617***	0.1883***
	(3.30)	(2.01)	(-0.07)	(7.07)	(4.78)	(3.61)	(4.39)
Daily return	-0.1558	0.3079	-0.0974	-0.4809	0.5314*	-3.9939***	-0.4440
	(-0.74)	(1.36)	(-0.34)	(-1.07)	(1.96)	(-5.00)	(-1.54)
Dollar trading volume	0.1179***	0.1626***	-0.0184	-0.0382*	0.1227***	-0.3547***	-0.1604***
	(11.65)	(14.01)	(-1.45)	(-1.71)	(7.73)	(-11.73)	(-9.71)
Amihud illiquidity	12.5235***	15.7704***	3.5335***	8.6786***	13.6187***	-30.6996***	4.8014***
	(11.02)	(12.88)	(2.78)	(4.91)	(9.35)	(-7.03)	(2.88)
Observations	12,527	12,527	12,527	12,527	12,527	12,519	12,490
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	21.50	21.50	21.50	21.50	21.50	21.51	21.33

Table 11: Buy vs Sell Spoofing Orders

Table 11 presents results for the following regression equation: $\ln(MarketQuality_{it}) = \beta_1 \widehat{Spoofing}_{it} + \beta_2 Return_{it} + \beta_3 Volume_{it} + \gamma_t + \zeta_i + \epsilon_{it}$, where $MarketQuality_{it}$ is 1-minute return volatility, 5-minute return volatility, time-weighted quoted spread, volume-weighted effective spread, volume-weighted realized spread, variance ratio, or Hasbrouck (1993) pricing error σ. $\widehat{Spoofing}_{it}$ is either the standardized number of buy or sell spoofing orders predicted from the first stage IV regression described in Table 5. $Return_{it}$ is the daily stock return, $Volume_{it}$ is log dollar trading volume, and $Amihud_{it}$ is the Amihud (2002) illiquidity measure. We include stock and date fixed effects with γ_t and ζ_i, respectively and cluster standard errors by stock and day. Panel A presents results for spoofing buy orders and Panel B presents results for spoofing sell orders.

Panel A: Spoofing Buy Orders

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
$\widehat{Spoofing}$	0.2014***	0.1380**	0.0092	1.0743***	0.4195***	0.5893***	0.4565***
	(3.08)	(2.11)	(0.10)	(5.48)	(4.19)	(2.93)	(4.05)
Daily return	-1.1658**	-0.4783	0.0015	-5.1122***	-1.5349*	-6.1947***	-1.9454**
	(-2.43)	(-1.04)	(0.00)	(-2.99)	(-1.83)	(-4.44)	(-2.30)
Dollar trading volume	0.0998***	0.1435***	-0.0219	-0.0810*	0.0949***	-0.3431***	-0.1790***
	(7.23)	(10.33)	(-1.39)	(-1.84)	(4.19)	(-7.51)	(-6.72)
Amihud illiquidity	10.8080***	14.5022***	1.7320	9.7027***	13.7682***	-32.0400***	2.3089
	(7.94)	(12.19)	(1.10)	(2.98)	(9.18)	(-6.00)	(1.06)
Observations	7,919	7,919	7,919	7,919	7,919	7,913	7,899
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	15.93	15.93	15.93	15.93	15.93	15.96	15.98

Panel B: Spoofing Sell Orders

	(1) 1-minute volatility	(2) 5-minute volatility	(3) Quoted spread	(4) Effective spread	(5) Realized spread	(6) Variance ratio	(7) Hasbrouck σ
$\widehat{Spoofing}$	0.1588***	0.1088**	0.0072	0.8470***	0.3308***	0.4646***	0.3618***
	(3.23)	(2.21)	(0.10)	(5.59)	(4.16)	(3.06)	(4.02)
Daily return	0.2884	0.5177	0.0676	2.6438**	1.4936***	-1.9369	1.3606**
	(0.87)	(1.65)	(0.20)	(2.30)	(3.06)	(-1.62)	(2.12)
Dollar trading volume	0.1001***	0.1437***	-0.0219	-0.0795**	0.0955***	-0.3424***	-0.1782***
	(7.72)	(10.40)	(-1.40)	(-2.05)	(4.48)	(-8.42)	(-7.03)
Amihud illiquidity	10.2575***	14.1252***	1.7070	6.7667**	12.6217***	-33.6547***	1.0499
	(7.42)	(11.66)	(1.11)	(2.31)	(8.90)	(-6.40)	(0.49)
Observations	7,919	7,919	7,919	7,919	7,919	7,913	7,899
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-statistic	18.20	18.20	18.20	18.20	18.20	18.23	18.16