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Operate, not Amputate: Rule 201 as an Example of a Surgical Approach to Dealing with Toxic Short Selling

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ABSTRACT

In 2011 the SEC introduced Rule 201 aimed at striking a balance between limiting the threat of short sellers on price stability while interfering as little as possible with the provision of liquidity and the process of price discovery. In this paper we provide a novel evaluation of this Rule using over two years of intraday data, carefully matching restricted and control assets, and separating local effects around the implementation from those over the remainder of the trading day. We find that the Rule achieves its objectives: despite a 4% drop in volume, liquidity and volatility improve (the spreads fall by 7% and the range by 13%). Our analysis indicates that the restrictions achieve this by increasing the cost of short selling in a way that primarily affects toxic short sellers.
Keywords: Short sale bans, Rule 201, overpricing, price efficiency, price discovery

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1. Introduction

Short sale restrictions have a long history and are a significant point of contention in popular debates over stock market regulation, specially at times of generalized stock market price declines. The general consensus amongst regulators is that short selling is a necessary part of well-functioning markets but at times it can be a source of price instability. In the past, the most common regulatory approach can roughly be described as: allow short selling and intervene only at times where the risk of price instability is greatest, and do so by essentially forbidding short selling.[1] For example, in Spain short selling has been possible for a long time, but on March 12th, 2020, when the Covid crisis started, the regulator introduced a temporary ban on all short sales for a large subset of shares traded in the Spanish stock market. The ban was introduced for a month initially, and it was later extended until May 18th, 2020.[2]

In contrast no additional short sale restrictions where implemented in the U.S. in response to the pandemic, relying instead on the existing regulation introduced by the SEC during 2011. This, then novel, regulation, the Rule 201, established when, how, and how long to impose short sale restrictions, and is significantly different from other bans introduced in the past. In particular, this regulation differs in three key aspects: (i) it is triggered automatically by a market event (a price drop of 10% relative to the previous day's closing price), (ii) it lasts for a pre-defined and relatively short period of time (the rest of the trading day and the next 24 hours[3]), and (iii) it imposes short sale restrictions only on aggressive short sales, that is it forbids short sales at or below the best bid. In addition, it includes a list of conditions to exempt short sales that are deemed necessary for the

[1] Usually the short selling ban includes exceptions related to market-making and essential basic trading strategies, such as hedging and derivative trading.
[2] The ban applied to stocks that suffered a significant price drop on March 12th, 2020, which essentially covered the entire Spanish stock exchange. See Losada-Lopez and Martinez-Pastor (2020).
[3] If the price also suffers a 10% drop in the next 24 hours, the restrictions are extended another 24 hours.

well-functioning of the market–although such exemptions are not novel and have been commonly included in the past, when banning short sales.[4]

This paper provides a novel evaluation of the implementation of the Rule 201 restrictions to determine whether it provides a useful framework to deal with the risk of price instability from short sales while preserving their useful contributions to market functioning. The key novelty of our approach is the methodological approach focused on identification of the channel through which the 201 restrictions operate. Our identification strategy shares the approach of regression discontinuity analysis in carefully selecting similar treated and control samples so as to identify the causal effects of the ban, and uses and validates a pseudo-event for the control group to separate the effects of the Rule 201 restrictions from the large price drop that triggers it. To discipline the analysis we use a rich set of standard microstructure variables used in previous studies (with a single exception to capture the effect predicted in Hong and Stein (2003)), as we follow the predictions identified by the different theoretical models describing the channels by which the restrictions could operate. Furthermore, the analysis described in this paper is an (admittedly unintended) replication of a previous analysis done on a smaller sample [in anonymized]. [5]

This regulation compares favorably with the implementation of selective bans at the regulator's discretion such as those introduced in the past, e.g. the Spanish ban during the Covid crisis, or the US ban during the 2008 financial crisis. In particular, we find that the Rule 201 restrictions are a useful tool for preserving price stability while maintaining liquidity, and it achieves this by increasing the cost of short selling for toxic trades. This is in stark contrast with the results of temporary bans as documented in the existing literature. For example, Beber and Pagano (2013) find that the bans introduced during the financial crisis were detrimental to liquidity and failed to sustain prices.

[4] See `https://www.sec.gov/rules/final/2010/34-61595-secg.htm`.

[5] To ensure a disciplined replication approach we repeat all and only those analysis in [XXX-a previous working paper version available online and removed for anonymity] using the new expanded sample.

Our analysis provides a causal evaluation of the Rule 201 restrictions based on a carefully selected matched sample of asset-days over two years of trading (2016 and 2017).[6] The matching procedure controls for individual asset characteristics (industry, type of asset, time of day, size, price, volume, and the average quoted spread) as well as for the circumstances surrounding the application of the restrictions. The sample selects assets on both sides of the point of discontinuity defined by the price level that triggers the restrictions (a 10% price drop relative to the previous day's close). Our conclusions are based on a diff-in-diff analysis of the matched sample of assets that covers a wide range of variables measuring different market characteristics, including traded volume (segmented by short sales, aggressiveness, and venue), standard market quality measures (spreads, depth, volatility), algorithmic activity, and price informativeness.

The overall picture is that the Rule 201 restrictions primarily affect aggressive short sales, reducing price pressure, and allowing the price to rebound further than it would otherwise do. The reduction in aggressive sales is not compensated by an increase in trading on the ask, so that the restrictions also reduce volume overall. This is accompanied by an increase in price stability measured both in terms of the intra-minute price range and the standard deviation of returns over the remainder of the trading day. Liquidity also benefits from the restrictions. We observe improvements both in spreads and depth, which suggests that the primary channel of the effect of the regulation is through a reduction in informed/toxic trading.

We explore this channel by looking at different measures of price efficiency and price impact. We find mixed evidence as to the overall effect on informed trading that we interpret in terms of a partial reduction in informed trading together with a change in the mix in the half-life of the informed traders' informational advantage. We find that there appears to be an overall negative effect on informed trading using a novel measure for the presence of delayed negative information in prices, based on the likelihood of delayed price drops as proposed in Hong and Stein (2003). When looking at informational measures at shorter horizons we find that very short lived

[6] This sample period is selected according to data availability.

informational trading is reduced as measured in terms of very short term price impacts. On the other hand, we find that at longer horizons price efficiency appears to improve, as measured using the 5-minute price impact, and the 5- and 10-minute variance ratios. It appears that the regulations reduce informed trading overall and primarily affect those trades with short lived informational advantages. We find further evidence of this when looking at different measures of algorithmic activity. The results we find are consistent with a reduction in trades from toxic high-frequency algorithmic strategies.

1.1 Related Literature and Short-sale Restrictions

Our evaluation of the 201 Rule compares favorably with restrictions in the form of bans and the short sale regulation in the U.S prior to 2008: the short sale price test, also referred to as the uptick rule. A large number of studies look at the effect of short sale restrictions. Most of the theoretical contributions focus on the previous uptick rule and the short sale pilot introduced to study its effects (May 2, 2005 to August 6, 2007), while others look at the introduction and/or removal of bans on short sales. Among the papers that study the previous uptick rule and the short sale pilot, Alexander and Peterson (2008) finds that the removal of the restriction is beneficial for traders in terms of quicker order execution, while no reduction in market quality is observable. Diether et al. (2009a) report minor effects on intraday spreads, volatility and no significant changes in terms of daily metrics from the suspension of the uptick rule in the pilot. Grullon et al. (2015) on the contrary, finds significant reduction of investment and equity issues in the group of pilot stocks, a reduction attributed to the higher exposition to short selling. However, Fang et al. (2016) document the positive role of short sellers in terms of prevention of accounting fraud, helping asset prices to be more informative about the true situation of the firm. Other analyses conducted under this framework include a comparison of auditor fees related to the disciplining mechanism of short sellers (Hope et al., 2017), return predictability (Diether et al., 2009b) or voluntary disclosure of information (Clinch et al., 2019). Overall, the evidence from the short sale pilot concluded that suspending the short sale restrictions associated with the uptick rule generated greater benefits than costs. Following the pilot, effective July 3, 2007, the restrictions on short sales imposed by the uptick rule were removed.

Shortly after the pilot program and the removal of the uptick rule, the financial crisis of 2008 generated pressure on the SEC to act and undertake emergency actions, and a prohibition of short sales on financial stocks was introduced. Boulton and Braga-Alves (2010) find evidence of stock overpricing at the announcement of the restriction, with a significant price decline at the expiration of the emergency ban. In the same context, Boehmer et al. (2013) find no significant effect on asset prices, but a substantial market quality degradation from the ban. Kolasinski et al. (2013) argue that the short selling restrictions in the aftermath of the financial crisis acted as a filter, increasing the number of informed trades in the short seller population, yielding more efficient prices. As mentioned earlier, Beber and Pagano (2013) also study short selling bans during the crisis, the US ban as well as many others. They find that across different countries the bans have no effect on price levels but increase volatility and reduce market quality. Again, the evidence points to sale bans as a source of poor market quality with little gain, except for the change in the informativeness of trades found by Kolasinski et al. (2013).

Other studies look at short selling restrictions from alternative perspectives. For example, Saffi and Sigurdsson (2011) look at the effect of supply restrictions on short selling with data on the availability and costs of stocks for short sale. They find that limitations on short selling are related to delayed price discovery and reduced price efficiency. While others like Boehmer and Wu (2012) reach the same conclusions using the tick pilot.

Recent research on the true effects of Rule 201 is scarce. Jain et al. (2012) analyze the period immediately surrounding the implementation of the Rule and include only two months after February 2011 (the compliance date). They are unable to document any clear benefits of the SEC Rule 201 after comparing assets-days with price drop of less than 10% with those with smaller price drops, as well as with those with price increases (separating the latter two groups). They conclude that the 201 restrictions would have been ineffective in reducing price declines. Halmrast (2015) also finds no significant effect of the ban on stock prices. This paper excludes part of 2012, precisely the most volatile months, which are the ones for which assessing the effects of the ban is more interesting for market participants and regulators.

Also studying the 201 restrictions, Davis et al. (2017) find evidence of price clustering, a sign of price inefficiency, while Switzer and Yue (2019) document no effect on the main metrics of market quality. Both these two studies do not go beyond 2012 in their analysis. While Davis et al. (2017) use a difference (before vs after) design, Switzer and Yue (2019) introduce a differences-in-differences analyses that select as controls the same stocks that are affected by the Rule 201 but during days of significant price drops prior to the implementation of the regulation (before February, 2011). Instead, we use contemporaneous assets with similar characteristics as controls. Given the significant informational component we could expect from a price decline of 10% (or more) we believe there is potential for a better identification of the effects when the units of analysis share informational sets, which cannot be the case when the data for the treated unit and the control unit are separated by a very significant time difference.

In a very recent paper Barardehi et al. (2023) study Rule 201 using intraday data from March 2011 to March 2013, and also exploit the discontinuity generated by the 10% price drop to select assets in the sample, treating assets that had a price drop greater than 9% but did not reach the 10% trigger for Rule 201 as similar to those that triggered the Rule 201 restrictions but did not drop more than 11%.[7] However, they analyse the data over 65-minute bins and do not apply a threshold on the control assets.[8] In contrast, using

[7] They also consider assets with price drops within a wider bands: (-8%:-12%) and (-8.5%:-11.5%). Their paper focuses on the results for the widest band.

[8] The exact method is not clearly described in the paper. It appears to us that a control asset is selected if it experiences a return close to -10% during the 65 minute window in which the treated asset crossed the threshold. We base our conclusion on the following text: "Figure 7 illustrates the way in which we split up bins as well as the contrast between treatment and control observations. In the figure, we show a hypothetical treated stock (stock A) experiencing an intraday low return of -10% at noon (i.e., bin 3) on day t, with respect to the value at close of day $t-1$. The nine subsequent 65-minute bins ending at

1-minute aggregates and creating a threshold for the control assets allows us to study the hypothetical behavior of the assets around the threshold. Our methodological approach also differs from theirs in the ways we control for microstructure- and price-relevant asset characteristics. While their selection of the control sample is purely based on the price drop, and (in some specifications) include additional variable in the regressions to control for size, volume, etc, our control sample is selected by pairwise matching assets with a similar price drop in the same day and similar time of day. We also match assets on security type, industry, size, volume, price, and quoted spread.

In terms of insights, our analysis complements theirs. Their paper focuses on the effect of the 201 Rule on prices and short sales (reported to the FINRA-TRF–we also include those from NASDAQ-ICE, NYSE, and the CBOE groups). Our analysis provides a more precise estimation of the broad impact of the Rule on a large set of market microstructure variables (Depth in the LOB, differences between Exempt and Non-Exempt short selling, or HFT activity, among other variables), which allows us to study the channel through which the Rule 201 effects operate.

The rest of the article is organized as follows. Section 2 summarizes the institutional setting of Rule 201. Section 3 describes the theoretical background relating short selling restrictions with well known market variables. Section 4 details the data and the methodology we follow. Sections 5 and 6 present the main results and Section 7 concludes.

2. Institutional Setting

The short selling restrictions that are the focus of this paper refer to measures restricting short selling adopted by the Securities and Exchange Commission on February 26, 2010, and fully implemented by February 28, 2011. Hereinafter, we will refer to these restrictions as the **Rule 201**, but to be

the close on day $t+1$ comprise a treatment group observation. The figure also shows a hypothetical control stock (stock B) that experiences an intraday return of -9.9% at noon on day t. Our methodology contrasts trading outcomes over the subsequent nine bins for stock A with the matching nine bins for stock B." (Barardehi et al. (2023), p 16) precise, this new price/bid test is the result of a series of amendments to Rule 201 Regulation SHO.[9] Originally, this directive from the SEC removed all the previous price tests after the conclusions on the Pilot study that deemed short selling bans as ineffective.[10]

The Rule 201 ban prohibits the short selling of any security at or below the national best bid (NBB) if that security's price has fallen below a threshold of 10% relative to the last closing price for all but exempt short sales. On average, more than 95% of short sales for assets included in our analysis are non-exempt.[11] Once the trigger condition is met, short sale orders at or below the best bid are immediately prohibited for the asset for the remainder of the current trading day and the whole of the next one. The rule allows for the possibility of an activation on consecutive days. If this happens, the ban extends for an additional trading day after the last trigger. Trading centers are required to comply with the new regulation since February 28, 2011.[12]

The Rule 201 restrictions represent an innovation with respect to previous short sale restrictions. In contrast with most previous bans, the trigger condition is endogenously determined. Whether the prohibition is imposed or not depends on the behavior of the stock's price in the market. Most previous research has been based on regulations that were always active for all stocks (the pilot: uptick test for the NYSE and bid price test for Nasdaq, e.g. Diether et al. (2009a)), or provided (or lifted) blanket restrictions on short sales to a large number of, if not all, stocks (as documented for example in Beber and Pagano (2013)). Furthermore, Rule 201 acts as a temporary correction mechanism, that is automatically reverted shortly after its application, which contrasts with previous bans which were in force for much longer time periods.

[9] Also, a number of terms refer to these restrictions more or less precisely as the alternative uptick rule, Rule 201, Reg SHO, among others.
[10] Regulation SHO includes a pilot program in which from May 2, 2005 to August 6, 2007, pilot stocks were exempted from short sale price tests.
[11] Exempt short sales are normally part of a hedging trading strategy involving two highly correlated securities, such as different classes of a single company's common equity, two ETF's that track the same index, and so on.
[12] Division of Trading and Markets: Responses to Frequently Asked Questions Concerning Rule 201 of Regulation SHO. Accessed: Sep 28, 2017.

3. Theoretical Background

In general, the literature identifies three effects of short sale bans. First, short sale bans reduce selling pressure associated with toxic traders running bear-raids and predatory trading strategies. Brunnermeier and Oehmke (2013) defend the effectiveness of the bans in reducing predatory behavior on especially vulnerable assets, an argument that is often used by regulators when introducing such bans.[13] The main thrust of this argument is that short sales can be used to produce price drops that are not justified in terms of the underlying asset's value, and that by banning short sales these 'unnecessary' price drops and volatility could be eliminated.

The second effect is based on the opposing argument, that short sale bans limit the incorporation of negative information on the underlying asset into the stock price. By preventing investors from using short sales aggressively, the bans reduce the incorporation of this information into prices, reducing price informativeness, price efficiency, and generating overpricing (Miller (1977), Diamond and Verrecchia (1987), Boehmer and Wu (2012)). This could lead to the accumulation of negative news not being reflected in prices for a period of time, generating greater price instability, and future large price drops, Hong and Stein (2003).

The third effect is on liquidity, and it can be positive or negative. On the negative side, short selling bans limit the ability of market-makers to manage their inventories (Beber et al., 2020) and provide liquidity in option markets (Battalio and Schultz, 2011). Also, in the presence of differences of opinion, the short selling bans reduce the volume coming from the more pessimistic traders. These increased frictions reduce liquidity. In addition to these three main effects, regulation can have unintended consequences. By restricting short sales, the regulator may be blocking traders that have an urgent need

[13] Beber and Pagano (2013) and Beber et al. (2020) cite this argument used to protect financial institutions in the context of the subprime crisis and the eurozone crisis. For example, Spanish legislation explicitly establishes the possibility of introducing these bans to avoid 'disorderly price movements' which was used to justify a short sale ban in response to the Covid 19 crisis from March 12th 2020 to May 18th, 2020, see Losada-Lopez and Martinez-Pastor (2020). Shkilko et al. (2012) finds evidence that short sellers enhance price pressures but that long sellers are the primary drivers of price declines.

for financing unrelated to the fundamentals of the asset (Diamond and Verrecchia (1987)) thereby reducing trading opportunities. On the positive side, regulation may interfere with toxic traders that are imposing unnecessary intermediation costs, by for example aggressively executing against standing orders from market-makers that are not fast enough to cancel them as the price is falling (Cartea et al. (2015), Foucault et al. (2017), Aquilina et al. (2020)).[14] By imposing additional restrictions on such trading strategies, the Rule 201 could improve liquidity.

The combination of these effects generate ambiguous predictions. In terms of spreads, the reduction in informed trading helps reduce the costs of market-making and the bid-ask spread. Less informed trading and lower spreads (the cost of trading) may attract new trades that would otherwise not have taken place. On the other hand, increases in the transaction costs of market-making and the ban itself reduce volume by prohibiting some types of trades. In terms of volatility, reducing price pressure should reduce volatility however, limiting the incorporation of information into prices can lead to future price crashes and price instability (Hong and Stein, 2003).

Because of the specific circumstances of the Rule 201 restrictions, the predictions of the theoretical models we have seen so far need to be qualified. In particular, the restrictions imposed by the Rule are not imposed unconditionally, but rather, they are activated after a relatively rare market event: the asset's price drops by 10%. Secondly, these restrictions do not apply to all short sales, as some types of short sales related to market-making activities are exempted.[15] And finally, the restrictions do not impose a broad ban on short sales, but rather, they only restrict short sales at (or below) the National Best Bid (NBB), while allowing short sales to take place at higher prices. These specific properties of the Rule 201 restrictions imply that some of the general theoretical predictions may not be appropriate. For example, the negative effects on liquidity, namely increasing market-making frictions

[14] These traders are characterized by holding very low inventories (Kirilenko et al. (2017), Hoffmann (2014)) and hence are more likely to need aggressive short sales to snipe stale orders on the bid side when prices are falling, as is the case for assets under the Rule 201.
[15] See http://www.sec.gov/rules/final/2010/34-61595-secg.htm.

for liquidity providers, should be minimal as Rule 201 includes exemptions for market making short sales.

Comerton-Forde et al. (2016) provides a more nuanced analysis of short sales by separating passive (buyer-initiated) short sales from aggressive (seller-initiated) short sales in a Glosten and Milgrom (1985) model. They have three types of traders: liquidity traders, informed traders, and market-makers. Liquidity traders enter the market to liquidate an existing position, and hence they never use short sales. Informed and market-makers use short sales whenever they wish to sell but have no inventory. Because informed traders use aggressive orders and market-makers passive orders, aggressive short sales come from the informed and passive short sales from market-makers. Of the conclusions they draw from this model, the most relevant for us is that passive short sales are contrarian while aggressive short sales follow price declines. The predictions we obtain from Comerton-Forde et al. (2016), are that the regulation will not affect market makers (in contrast to what is predicted in Boehmer et al. (2008) for example), and that the ban should essentially only affect informationally motivated trades. The restrictions would not affect market makers for two reasons: first, market-makers have accumulated inventory as the price falls prior to the price drop triggering the restrictions so if they need to sell, they will sell long. And second, when market makers use short sales, they use them to sell passively (on the ask side), and hence even if they needed to use short sales they would not be affected by restrictions on short sale on the bid side. Thus, Comerton-Forde et al. (2016) anticipates that under the 201 restrictions price pressure on the stock will drop and the presence of informed traders will be reduced.

However, this theory does not incorporate the possibility of predatory trading or the dispersion of trading across multiple venues and instruments in the US's equity market. In particular it does not take into account that a trader that is restricted from making an aggressive short sale has a number of alternatives, other than cancelling the trade altogether. We may observe a change in the way informed traders operate, as they can try to execute their orders passively. This will increase their time until execution but lower transaction costs. Passive execution can be implemented in several ways:

one, by posting a visible limit order on the ask, saving on the spread and receiving a rebate instead of paying a fee; two, posting a hidden order inside the spread; and three, the order can be sent to a dark pool for midprice execution or to obtain a price improvement. Alternatively, traders may try to create synthetic positions, e.g. using options as suggested by Kolasinski et al. (2013). We expect traders affected by the restriction to pursue these alternative channels which we analyze via their consequent impacts on liquidity, and other microstructure variables.

4. Data & Methodology

We collect the data on Rule 201 bans from the Philadelphia Stock Exchange website, which publishes the list of stocks that trigger the circuit breaker on a daily basis. Our period of study covers observations from January 2016 until December, 2017.[16] We combine data from a number of sources: CRSP, TAQ trades and quotes, Total-View-ITCH, and transaction level short sales provided by FINRA, NASDAQ, NYSE-ICE, and BATS. We match CRSP and TAQ ticker symbols. We retain only common stocks (those with a CRSP share code equal to 11).[17] We require a minimum share price of $2 and at least 50 trades between market open and market close (in total between the NASDAQ and NYSE exchanges) for a stock-day to be included in our sample.

We use trade and quote level data between 9:40AM–3:50PM EST from Daily TAQ–as is common in the literature observations close to the opening and closing auctions are excluded. We obtain information on tick-by-tick prices, transaction sizes, and the exchange at which each transaction took place with millisecond time stamps from the Consolidated Trades Tape. We match each transaction to the mid-point of the prevailing best bid and offer prices at the end of the previous millisecond. We construct best national bid and offer prices at the millisecond frequency using the Consolidated Quotes

[16] https://www.phlx.com
[17] We exclude ETFs, ADRs, Certificates, companies incorporated outside the US, closed-end funds, and REITs.

Tape and NBBO files from the Daily TAQ database. We also drop stocks whose identifying information does not allow a merge with both CRSP and Daily TAQ. TAQ transactions are classified into buyer-initiated (Aggressive Buys, AggB) or seller-initiated (Aggressive Sells, AggS) using the Lee-Ready (1991) algorithm, based on the midpoint of national best quoted prices at the end of the millisecond prior to each transaction.[18]

Short sale information is obtained from four sources. For off-exchange short sales we use the FINRA monthly files which include all short sale transactions that are executed off-exchange and reported to the consolidated tape. We use all of the transactions reported via a FINRA Trade Reporting Facility (TRF). [19] The other sources of short sale data are the NASDAQ, NYSE-ICE, and BATS exchanges. BATS short sale information is posted on their website, while NASDAQ and NYSE-ICE have given us access to the short sale transaction level data for all short sales that took place on their exchanges.[20]

For more detailed variables (depth, messages, etc) we use Total-View-ITCH which is publicly available data from NASDAQ. The data is time-stamped to the millisecond and contain every message to post, or cancel a limit order, and messages that indicate the execution (partial or total) of a displayed or non-displayed (hidden) limit order. Although non-displayed orders are not visible in the data when they are submitted to the limit order book, one can see them (ex-post) if they execute against a marketable order.

Some of our variables are constructed using only NASDAQ data. This ensures the reliability of trade direction and allows us to study the mi-

[18] Chakrabarty et al. (2015) show that this algorithm performs well in modern markets. Nevertheless, there will be noise in this classification given the issues with the precision and coordination of timestamps in the TAQ as discussed in Conrad and Wahal (2020).

[19] FINRA posts the data on its website a week or so after the end of each month. It includes the ticker symbol, trade price, size, and other sale conditions, along with a time stamp to the nearest second. One additional field in this dataset is a condition code on whether the short sale is exempt from price tests. Our data includes all trades reported to the Nasdaq (Carteret) and New York (Mahwah) TRFs. The ADF files at FINRA (dated November 2016 until December 2017) contain no data.

[20] This data was provided by the exchanges as a courtesy to researchers. The exchanges include the NASDAQ exchanges: NASDAQ, BX, and PSX, and those of NYSE-ICE: NYSE, NYSE-ARCA, NYSE-AMEX.

crostructure conditions around the application of Rule 201 restrictions in detail (short sales affected and not affected, buys and sells, spreads, price impact, ...). NASDAQ is only one of the several exchanges that are open for trade in US cash equities. Although NASDAQ has gradually lost market share it remains as one of the dominant venues for trade and, in 2017, had an estimated market share of 20% (Cartea et al. (2015), 17.1% in our sample). Combining data from several sources allows us to provide a general overview of the effects of the Rule 201 restrictions while also providing additional analysis of market conditions for a key venue for which we have more detailed information.

One of the main challenges in analyzing the impact of Rule 201 is that it is triggered by a very unusual event, a 10% price drop relative to the previous day's close ("*the event*"). As we have discussed above, microstructure variables will be affected by these price movements, for example quoted spreads will be larger as market-makers accumulate inventory, so that the choice of a reference group to serve as counterfactual, as well as the choice of control variables, is very challenging but necessary. For example, Barardehi et al. (2023) select as reference group other assets that experience a similar price drop on the same day and at a similar time, and either do not control for other characteristics or include some of them, such as market capitalization, market-to-book, Amihud illiquidity, volatility, and market beta as control variables in a diff-in-diff regression. In contrast, we construct the reference group by selecting assets matched in terms of the price drop and asset characteristics to ensure a balance sample between treated and controls such that both have similar characteristics.

The first of these characteristics and key for selecting the reference group is the price drop. Short sale restrictions are triggered by a 10% price drop (relative to the previous day's close). We sample asset-days with a maximal price drop of between 9 and 11%, so that both treated and controls are assets that experience a similar price drop during the day. It also implies that our sample naturally selects assets whose prices do not experience continued price decreases after the event as well as excludes assets with relatively stable prices.[21] This is explained in greater detail below.

In our analysis we want to separate the general effects of the short sale restrictions from the specific circumstances surrounding the triggering event. However, as the event triggering the short sale restriction is a 10% price drop, we cannot use the exact same event for assets in the control group. Yet, because both the prices of the treated and controls rebound after entering the selection window, it is reasonable to assume that both groups of assets behave in a similar manner at price levels close to what will be their intraday minimum. Following this same logic we select a 9% price drop (which is 1% above the 10% minimum drop of any asset in the control selection window) as the (pseudo trigger) event. This event matches the 10% price drop trigger of the treated (which is also 1% above the 11% minimum drop of any asset in the treated selection window). We assume that absent the trading restrictions both groups of assets would have had similar market behaviour in the run up to the event and in the remaining trading day after the event.[22] To avoid events that occur very close to the opening and closing auctions we retain those with events between 9:45AM–3:45PM EST.

To ensure the control group represents a valid counterfactual sample we match treated and control asset-days along other key dimensions. We select treated and control candidates that satisfy the price drop condition on the same day, same time of day, and have the same share code.[23] We require that the event and the control stock in each pair are classified in the same

[21] Note that our restriction applies to treated and control samples alike, and is a necessary restriction as it is impossible to find control assets that suffer a 9% price drop and continue to experience further price drops without triggering the short sale restrictions.

[22] Florindo (2021) provides greater detail on the similarities between the price paths of assets with a similar price drop as those affected by the 201 Rule. Because our focus is to match assets of the key characteristics that are both theoretically and empirically robust determinants of intraday liquidity, we omit the test of parallel trends which may introduce additional bias to our choice of sample, see Kahn-Lang and Lang (2020): "parallel pre-trends is neither necessary nor sufficient for the parallel counterfactual trends condition to hold".

[23] We match assets with share code 11 – see footnote 17). For the time of day we divide the trading day intro three intervals: early trading (9:45-11:00), middle of the day (11:00-14:30), end of day trading (14:30-15:45). Recall that we drop asset-days that have an event too close to the market open, at 9:30, and the market close, at 16:00.

industrial group to account for potential unobservable sector-wide changes in the informational set.[24] We also exclude asset-days at which a volatility (LULD) halt is triggered.[25]

We also match treated and controls using standard dimensions (market capitalization, trading volume, the stock's average pre-event price, and the average quoted spread). The matching on the four variables is done by minimizing absolute differences in a score function constructed using all four variables. For each of the assets and each variable we keep the ranking of the asset in terms of the percentile in the population, so that each asset is characterized by a vector of four percentile values. We construct the matching score as the average absolute difference between the four percentile values of the treated and control assets, and keep the best control (smallest matching score) subject to the additional constraint that the average absolute difference is less than 10 (out of 100). This procedure leaves us with 954 closely matched pairs (1908 asset-days).

To check the matching procedure we first look at the price movements for the two groups of assets, treated and controls. In terms of total return (from the previous day's closing to the current day's closing) we find that there is a small significant difference that is driven by the intraday open-to-close return, which is to be expected from the difference between the maximal price drop between the two.[26] On Table 1 we analyze differences in our matching variables across treatment and control groups. We find the groups to be very similar, the t-tests find no significant differences between the two groups.[27]

[24] Classified by the 10 major groups according to their SIC.

[25] We keep assets in the Tick Pilot group but they only represent 5.5% of our sample.

[26] We test and reject that this difference is not driving our results using a placebo replication of our analysis comparing assets that experience a drop between 8 and 10% as described below.

[27] In a prior working paper version of the analysis we included the moments of the return distribution in the matching procedure, as we think these to be relevant variables. However, more matching variables can lead to less precise matching, so we decided to focus the matching on the primary theoretical factors that account for microstructure differences, namely industry, size, volume, price, and quoted spread. As can be seen on Table 1, this approach selects assets in our sample with similar return moments without explicitly including them in the matching procedure.

Our analysis estimates differences-in-differences in a joint panel OLS estimation with standard errors clustered by treated-control matched pair.[28] For the control group we define an equivalent trigger event to distinguish before from after the event. This trigger event is the first time the price hits 9%, which corresponds to a price 1% lower than the minimum for the day (10%) for the control group. As described earlier, we exclude data from the first and last 10 minutes of trading to avoid contamination from the opening and closing auctions.

We separate the circumstances surrounding the substantial price drop that is the triggering event from the effect of the short sale restrictions during the remainder of the day by including dummy variables for an 11 minute time window around the minute of the event (the *event window* that covers from five minutes before to five minutes after the event).[29] This time window also has the advantage that it allows us to compare the actual trigger event with the pseudo-trigger, and, in the placebo analysis, the behaviour around large price drops for groups of assets that are not affected by the short sale restrictions. In all cases we find that observed differences across samples are small, and yet the circumstances surrounding the event have statistically and economically important effects on microstructure variables that would otherwise confound the analysis of the Rule 201 restrictions (see Figure 1).

Our sample selection criterion, assets that experience a significant price drop, implies that we are observing assets that experience unusually high volatility days. In order to control for the effects of unrelated price movements on the variables of interest we introduce controls for the size of the movement in the price from the start to the end of the minute. We introduce these controls in the form of price movement fixed effects, by including dummies for within-minute price changes in the following 22 intervals: $(-\infty, -10\%]$, $(-10, -9\%]$, $\ldots$, $(9, 10\%]$, $(10\%, \infty)$. The resulting dummies

[28] Each pair of treated and control pairs is identified by the variable MatchID.

[29] The separation of the local from the general effects of the regulation is motivated by existing results in the literature that find that regulation triggered by market conditions, such as volatility halts or trading pauses, may be accompanied by specific market reactions, such as for example the magnet-effect (Abad and Pascual (2007), Goldstein and Kavajecz (2004), Sifat and Mohamad (2020)). These effects are considered in detail for the 201 restrictions below, in Section 6..

allow us to control for unusual trading conditions arising from large price moves that are not associated with the application of Rule 201. Large price movements have been associated with unusual volume and isolated toxic order flows (see Easley et al. (2012)).

The main specification of the panel data regression we run includes time-of-day fixed effects every half-hour, and is described by the following equation:

$$Y_{i,t} = \alpha_i + \beta_1\,Drop + \beta_2\,Drop \times 201Rule + \sum_{j=-5}^{5} (\delta_j T_{j,t} + \eta_j T_{j,t} \times 201Rule)$$
$$+ \sum_{j=1}^{13} \kappa_j H_j + \sum_{j=-10}^{11} \gamma_j Dum_{r_{i,t} \in [R_{j-1}, R_j]} + \varepsilon_{i,t}, \qquad (1)$$

where $Y_{i,t}$ denotes the variable of interest for asset-date i in minute t. We analyze a number of microstructure related variables described in Table 2 and defined in detail in section 1. of the Appendix. Our main parameters of interest are β_1 and β_2. The parameter β_1 captures the baseline effect of both treated and control assets after the large price drop that defines the triggering event. This event is either the application of the restrictions for the treated group, or the price dropping by 9% for the control stocks. The parameter β_2 captures the differential effect of the treated group, and, where statistically significant, the impact of the Rule 201 restrictions on the variable of interest.

The parameters $(\delta_j)_{j=-5}^{5}$ and $(\eta_j)_{j=-5}^{5}$ capture the transitory dimension in the minute of the event as well as the five minutes immediately surrounding the event, before and after. Like β_2, the η_j parameters capture the differential effect of the treated group, and hence the impact of the Rule 201 restrictions. The γ_j coefficients capture the fixed effects for the magnitude of the change in the price during the current minute, modelled as the 22 dummies ($Dum_{r_{i,t} \in [R_{j-1}, R_j]}$) described above. The coefficients α_i and κ_j capture the matched asset-day pair and the (half-hourly) time fixed effects, respectively.

We winsorize variables at the 0.5 and 99.5 per cent levels to limit the influence of outliers, and standardize most variables. We use standardization in order to avoid issues with the scaling of the variables and facilitate the interpretation of coefficients. The coefficients measure changes in the variables of interest in terms of standard deviations from the mean for each stock-day.[30] Variables like returns and market share, that are naturally comparable across assets, are not standardized.

5. Results

After analyzing the data, we find that it is consistent with Rule 201 restrictions reducing toxic and informed trading while preserving, even improving liquidity. In order to present the results in an orderly manner, we proceed by looking at the evidence on the effect of the 201 restrictions from the most direct effects to the more subtle ones, structured along the lines put forth by the different theories while at the same time testing the predictions and implications of these theories. Summary statistics for the main variables used in the analysis, as well as a summary of the economic significance of the results is included in Table 2.

We start by looking at short selling activity directly and find asymmetric effects on short sales. In Table 3 we find there is an overall reduction in short selling activity, which is driven by a reduction in non-exempt short sales, and we find a significant effect of an increase in the overall level of exempt short selling activity (coefficient β_2 in the columns under "ALL MARKETS" of Table 3).

This pattern is repeated when we look only at total exempt and non-exempt short sales on the NASDAQ stock exchange (unreported). Taking advantage of the precise signing of visible trades in the ITCH data we look at aggressiveness (columns "Passive SS NQ" and "Aggressive SS NQ" in Table 3) in NASDAQ. Consistent with the aim of Rule 201 to reduce price pressure with minimal impact on liquidity, we find a very significant decrease in aggressive non-exempt short sales. We also find a significant decrease in

[30] Moments are computed using the in-sample means and standard deviations. The use of the in-sample means is standard practice in all panels with fixed-effects, and the use of the in-sample standard deviation will, if anything, bias against finding significant differences, given that the sample stock-days have unusually high intraday volatility.

non-exempt passive short sales but of a significantly smaller magnitude. Rule 201 applies explicitly to non-exempt short sales on and below the bid. In the second to last column of Table 3 (labelled *NBB or lower*) we exploit the detail in our dataset to look at these short sales directly. Consistent with the application of the Rule, we find a very significant effect. In contrast, we also find a statistically and economically significant reduction in non-exempt passive short sales on and above the ask (in the last column of Table 3), which in principle should be unafffected.[31] Such a reduction in passive short sale activity could be accompanied by a worsening in market liquidity if such passive short sales are required for liquidity provision. Nevertheless, as proposed in Comerton-Forde et al. (2016) and discussed further below, passive short sale restrictions should have little effect on market making strategies, at least in the short term.

According to all the theories discussed above the reduction of aggressive short selling activity reduces sell volume and consequently downward price pressure on the treated assets. In terms of observables, this should translate into lower volume, smaller price drops, and greater returns. The evidence supports this. In Table 4 we observe a reduction in volume following the activation of the short sale restrictions suggesting that some traders are driven away from the market. We also see a decrease in price pressure in terms of lower aggressive sell trades and no significant changes in aggressive buys. Our analysis allows us to document that this reduction in price pressure would also have taken place without the regulation. The *Drop* (β_1) coefficients in Table 4 tell us that aggressive buys increase significantly and aggressive sales decrease (though not significantly) for all the assets in our sample, those affected by Rule 201 and those that are not affected by it (the same occurs on the NASDAQ stock exchange, Table 6). However, our design identifies the differential effect of the regulation. We find that Rule 201 has an additional impact on volume traded, reducing volume on both sides, but primarily by reducing aggressive sales. Our analysis allows us to disentangle the effect of regulation, and we find that the constraints increase

[31] In personal discussions with market-making traders, it was suggested that some brokers prefer to abstain from using short sales altogether to avoid any possible errors.

the reduction in aggressive sales by an order of magnitude (from -0.016 to $-0.11 = -0.016 - 0.094$). On the other hand, the Rule reduces the increase in buying pressure that comes after such a sharp (and in our sample, limited) price drop (Table 4) by half.

On Table 5, we look at whether this reduction in price pressure translates into greater returns. The starting point is the overall effect on all assets, the β_1 coefficient.[32] As predicted, the assets in our sample experience a price rebound after the event, that is consistent with the evidence in Florindo (2021), Jain et al. (2012), or Barardehi et al. (2023) that price drops of the magnitude needed to trigger the short sale restrictions tend to be followed by a price 'rebound'. The interaction coefficient does identify an additional statistically significant rebound (a smaller price drop) for the treated (Rule 201) assets. This suggests that the Rule 201 is effective, at least in the short run, not only in generating a reduction in sellers' price pressure, but that the reduced price pressure translates into a reduction in the stock's price drop.

The effect of the restrictions (the lower price drop) is consistent with the overpricing theories of Miller (1977) and Diamond and Verrecchia (1987) that predict that the removal of short sellers introduces an overpricing of assets, as the negative opinions on the stock (whether informed or uninformed) cannot be channelled through trading by short sellers.[33]

Beyond the effect on short sales, price pressure, and returns, further theoretical predictions, specially in terms of what happens to liquidity, depend on the motivation behind the trades that are affected by the short selling restrictions, and how the market reacts to the reduced presence of such trades. As we saw earlier, the model in Comerton-Forde et al. (2016) predicts no effect from the restrictions on market making as by the time the price hits the Rule 201 trigger, market makers will have accumulated a long position in the stock. Overall, the analysis of volume indicates that the restrictions

[32] Naturally, the return regression does not include return size dummies, only time fixed effects. The results are not affected if we exclude the time fixed effects. Also, this regression is computed with the actual returns and the variable is not standardized.

[33] Jones and Lamont (2002), Dechow et al. (2001) or Florindo et al. (2019) among many others provide evidence in favor of Miller's hypothesis.

affect informed short sales (Comerton-Forde et al. (2016), Diamond and Verrecchia (1987)), as well as short sales from uninformed liquidity demanding (Diamond and Verrecchia (1987)), and toxic (Brunnermeier and Oehmke (2013), Foucault et al. (2017)) traders.

Having found no evidence of a reduction in passive (market-making) short sales, there is no initial support for the theory that short selling restrictions generate frictions to market-makers that reduce liquidity as proposed in Boehmer et al. (2008) and others. To further confirm the lack of significant negative effects on market making activities, we also look at the effect of the restrictions on liquidity variables directly in Tables 7 and 8. The theories that do not focus on the direct frictions on market-making, generate implications for liquidity indirectly, via the effect of restrictions on the asymmetric information costs of providing liquidity. A theory such as that in Boehme et al. (2006) that argues that restrictions will primarily affect the uninformed liquidity short sellers, and do so negatively, logically predicts a worsening of market liquidity. On the other hand, theories that argue that the restrictions will primarily have a negative effect on toxic or informed short sellers predict an improvement in liquidity along the lines of Glosten and Milgrom (1985).

Table 7 describes the effect of the restrictions on spreads which point at an improvement in liquidity, which is also found though in a more limited way in depth measures. We observe that the quoted and effective spreads (on the NASDAQ exchange) decrease in the treated group but increase (Quoted) in the control one. The quoted spread as measured using the NBBO (TAQ data) shows the same result. Our interpretation is that in a context of worsening liquidity, the overall effect of the 201 restrictions is to improve liquidity. The lack of a negative effect on market-making discussed earlier is strengthened by the reduced price pressure and what appears to be a reduction in the level of informed trading volume and in the cost of adverse selection as measured by the quoted and effective spreads. We observe a similar but weaker pattern in the depth of the (NASDAQ) limit order book (LOB) in Table 8. Again, the 201 restrictions reverse the damage from the price drop to liquidity as measured by depth at the best offer (Ask) and at five cents from the best (Ask + 5c). The magnitude of the increase in depth for treated stocks more than compensates the decrease we observe in the control stocks. On the bid side and deeper into the LOB, at ten cents from the best, the evidence points to an statistically insignificant effect of the restrictions. This evidence that the restrictions improve liquidity both in terms of spreads (Table 7), and depth (Table 8) supports the theories that argue that the effect of the restrictions falls primarily on informed and toxic short sales.[34]

Other relevant dimensions of importance for regulators are volatility and price informativeness, and the evidence we find is consistent with the regulation primarily affecting informed trades. As discussed in the theory section, the short sale restrictions have a direct effect in reducing the impact of differences of opinion among those that trade. In terms of volatility we find a significant reduction in intra-minute price variation in Table 5, as well as in the standard deviation of 1 minute returns, Table 10. In Table 5 we can observe a clear difference in volatility between treated and control stocks: while there is a significant increase in volatility in the control assets after the price drop, the treated stocks experience a significant reduction in volatility which more than compensates the increase observed in control assets.[35] However, from the empirical point of view, the effect of smaller differences of opinion on volatility is confounded by the reduced volume that we have already documented in Tables 4 and 6. Lower volume is known to be associated with lower volatility (Jones et al. (1994) or Gallant et al. (1992)). And yet the effect we observe appears to be there after controlling for volume.[36]

[34] This is also consistent with the evidence in Barardehi et al. (2023) that uses an alternative matching and estimation procedure but find similar results for spreads and depth at the touch. They do not study depth deeper into the LOB.

[35] The joint effect on returns and volatility is interesting: the restrictions generate an increase in returns together with a decrease in volatility. Barardehi et al. (2023) finds similar results.

[36] Given our narrow window of observation we cannot estimate conditional volatility as in Jones et al. (1994) or Gallant et al. (1992). We introduce volume (contemporaneous and lagged) as a control variable in our panel estimation. In unreported results, we replicate equation 1 including Total (log) TAQ volume interacted with the diff-in-diff dummies, and

The implications for future price movements from the exclusion of traders that want to aggressively short sell the assets depends on how much information is in the excluded trades. Hong and Stein (2003) argues that removing informed traders via a short sale ban does not invalidate the information driving these trades. Limiting the ability of traders to incorporate this information into prices can lead to substantial price drops in the future. We look for evidence of this by looking at whether assets under the 201 restrictions suffer more frequent large price drops at later times. Lacking a standard measure for capturing these delayed price drops, we look at the distribution of overnight returns for the night after the restrictions come into effect (from the price at the close on the date the restrictions come into effect to the price at the open on the next trading day). We test for the presence of delayed incorporation of negative information into prices by testing whether the restricted assets are overrepresented in the lower tail of the distribution (bottom decile). The result of this novel test is that of the 190 assets in the tail, 82 are controls and 108 are treated assets (the difference in the distributions is significant with a p-value of 0.028 using a 1-sided Fisher's exact test). Thus we find evidence that the Rule 201 delays the incorporation of information into prices.

Following this line of enquiry on the effect of the restrictions on price informativeness we consider different measures and find mixed results. Less informed trades should lower price informativeness, while a reduction in toxic order flow would have no direct effect on price informativeness. However, a reduction in toxic order flow would increase liquidity and lower transaction costs, which may attract traders that had stayed out of the market because of the lower liquidity. If these new traders have long-term information they would generate an improvement in the overall informational content of prices. We find that the results on the impact on price informativeness varies depending on the estimation method and time horizon. When we look

the lagged Total (log) TAQ volume as controls. From the resulting regression results we obtain that the lower volatility under the 201 restrictions, is primarily due to the change in the positive relationship between volume and volatility after the event. In particular, this relationship is weaker after the event and not significantly different between treated and control assets.

at price impact directly we find a reduction at the shortest, 100ms and 1min, horizons in Table 9, as well as an increase at the longest, 5min, horizon. In Table 10 we look at the autocorrelation of 1 minute returns and the Amihud illiquidity ratio (both of which can be interpreted as measures of price impact (Goyenko et al. (2009))). We find no significant increase in the former and a decrease in the latter (statistically significant when measured over 1min intervals). On the other hand, also in Table 10, the Variance Ratios (at 5 and 10 minutes) are lower suggesting an improvement in price efficiency for treated stocks at longer horizons. This is also partly supported by an increase in price impact for the treated at the 5 minute horizon (Table 9).

Results on price impact are not in line with those in the study of the 201 rule in Davis et al. (2017). They measure price impact of the short sale restrictions from Rule 201 over a 5 minute horizon and find that the price impact is lower while the Rule 201 restrictions are in effect. However, there are some important methodological differences between our analysis and the one in Davis et al. (2017). First, they analyze all events during 2012, thus they are estimating an average treatment effect (ATE) for all the treated. Also, their ATE is estimated relative to the price impact for the same asset using the five days before and the five days after the Rule 201 restrictions. In contrast to our analysis, they do not address identification, which we do via the pairing of carefully selected treated and control assets experiencing a similar price drop at around the same time, as well as via the definition of the intraday event for the control assets.

To interpret our results, we connect them with the analysis so far. We started with the reduction in the order imbalance in Tables 4 and 6. The reduced price pressure is accompanied by lower price volatility, as well as lower price impact over short horizons (consistent with Saffi and Sigurdsson (2011)), but also by an increase in liquidity. Together, these results suggest that the regulation primarily excludes aggressive short sellers and reduces the overall level of toxic order flow. At the same time we observe an increase in price impact at the longest, five minute, horizon, as well as a reduction in variance ratios, which suggests that a second effect of Rule 201 is to change the mix of informational trades, increasing the relative importance of information at longer time horizons. This is a possibility that was partially identified in Kolasinski et al. (2013). They argue that the short sale ban during the crisis acted as a filter for less sophisticated short sellers, and thereby increased the relative presence of sophisticated investors and the informativeness of prices. In our case, the relative increase in sophisticated traders with long-lived information is accompanied by a reduction in sophisticated ones with short-lived, speed-sensitive information (it is possible that unsophisticated short sellers also leave the market, but we cannot identify this effect in our data).[37] From what we have seen so far, it appears that as short sale restrictions come into effect the reduction in aggressive sell volume comes primarily from aggressively informed traders with short-lived information.

Short lived information trades are usually associated with toxic high-frequency order flow arising from high-frequency traders or HFTs. This view of HFTs as damaging to liquidity is found in the existing literature (Cartea et al. (2019), Aquilina et al. (2020), or Brogaard et al. (2017)). This is not to say that all HFTs are toxic traders. Other papers emphasize that another subset of algorithmic traders provide liquidity Menkveld (2013), Brogaard et al. (2014). We have argued that liquidity providers should not be affected, and we do observe an increase in liquidity, so that if we observe changes in algorithmic activity it should come from the toxic HFTs.

To gauge the impact of the regulation on HFT we turn to measures of algorithmic activity. In Table 11, we observe clear differences between control and treatment assets in measures of algorithmic activity: the total number of messages (Messages), fleeting orders (PC100), and trade-to-order ratios (T2O) separately for the bid and ask sides of the LOB. These measures go in the same direction: HFTs reduce their activity once the ban is active. This is consistent with the increase in short term price impact we saw earlier

[37] The argument used in Kolasinski et al. (2013) is that more sophisticated investors can bypass the restriction by using alternative trading strategies such as options. This argument also supports the weaker effect of the restrictions on long-lived information trades who also can take advantage of these alternative trading strategies. In contrast, informed algorithmic trades that require aggressive liquidity taking to exploit short-term price inefficiencies would be more affected by the restrictions, hence changing the mix of informational trades, as hypothesized.

if the restrictions have a disproportionate impact on algorithmic activity that has very short lived information that damages liquidity, e.g. snipping algos. Fewer toxic orders make other market participants less eager to rapidly cancel standing visible limit orders, which would be reflected in longer queues at the best prices, smallers quoted spreads, and lower price impact in the short term, which is consistent with everything we have found so far.

Thus, the exclusion of aggressive short sales appears to exclude toxic HFTs. Other informed traders, with more long-lived informational advantages and hence more patient, may be less affected. This is because they can continue to sell short using less aggressive orders at prices above the bid, as well as using less time sensitive alternative trading strategies (as proposed in Kolasinski et al. (2013)). Such a change in the term structure of information in the market would explain the patterns we observe in the term structure of price impact. If we turn to the gains for passive trading in terms of realized spreads, in Table 12, we see the same pattern. Fewer toxic HFTs is consistent with the observed increase in the realized spread at the shortest horizon. On the other hand, the proposed relative increase in the informational content from the remaining long sales and less aggressive short sellers is consistent with the observed reduction in realized spreads as the horizon lengthens.

As we have said earlier the 201 restrictions only apply to (non-exempt) short sales at the bid, so that short selling may continue to occur via less aggressive strategies, and in the highly fragmented US equity market these may be reflected in changes in trade flows across different venues. In the theoretical discussion we proposed that the restrictions will encourage traders with aggressive short sale orders to reconfigure their execution strategy. We have seen that some traders may leave the market (lower sell volume in Tables 4 and 6). Others may reconsider turning aggressive into passive short sales. We find some evidence of this in Table 8, as depth at the ask increases. Others may consider rebate chasing (Chao et al. (2018), Comerton-Forde et al. (2019)). To test this, on Table 13, we repeat the diff-in-diff analysis on market shares for three groups: the asset's primary exchange ("QuotingX"), dark pools ("FINRA"), and lit pools with inverted fee schedules

("Inverted", taker-maker exchanges BATY, NASDAQ-BX, EDGE-A.).[38] In terms of volume we see no significant differences between the changes in the market share of the quoting exchange and that of the inverted fee ones, and hence no evidence of rebate chasing.[39] Other traders may choose to execute their orders in less transparent ways, both as hidden orders in organized exchanges, or by moving trades to off-exchange venues. Contrary to this, we find a small but significant drop in hidden orders (Table 6). However, we do find significant volume shifting into off-exchange venues in Table 13. There we see that the market share of treated stocks (specially sale volume) in the quoting exchange (NYSE and NASDAQ) falls and that of dark pools (FINRA) increases significantly for both sales and purchases. This could be explained by short sellers seeking execution at less aggressive prices, e.g. at midprice venues, and driving more liquidity to these venues.

In conclusion Rule 201 in addition to lead to a decrease in selling pressure and increased liquidity, appears to increase the cost of aggressive short positions, driving some traders out, and others to dark pools. It also appears to reduce trading based on very short-lived informational advantages, increase liquidity, and increase the relative weight of longer-lived informational trades, with a mixed effect on intraday price informativess, as well as leading to an overall delay in the incorporation of negative information into prices.

6. Endogenous Triggers and the Magnet Effect

In this section we briefly explore the dynamics of the main variables around the event. We look at the minute in which the restrictions come into effect, the minutes immediately surrounding it, and the general dynamics, before and after the event.

[38] The TAQ dataset reports trading reported to regular exchanges from those reported to FINRA. The volume reported to FINRA is between 40-60% of the asset's total daily volume and comes from dark trading venues: ECNs, internal broker crossings, etc.

[39] The market share of inverted fee venues mirrors the changes in the market share of the quoting exchange, but with smaller, sometimes insignificant, coefficients.

One of the main characteristics of the Rule 201 restrictions is that they are rule-based, that is, they are activated by a market event described by a pre-defined rule: when the asset's price reaches a price level that is 10% lower than the previous day's market closing price. As the restrictions are activated by market events, they are endogenous to market circumstances. This type of triggering event has been used in other contexts to activate circuit-breakers or volatility stops, and has been studied, among others in Miller (1989), McMillan (1990), Madhavan (1992), Abad and Pascual (2007), Hsieh et al. (2009), and Hautsch and Horvath (2019). The literature focuses on the presence or absence of a "magnet effect". By magnet (or gravitational) effect we understand that the possibility of triggering a rule-based event leads to the accumulation of actions prior to the event that accelerate the activation of the rule. For example, in the context of a rule-based volatility stop, as the price approaches the level at which market trading is going to be stopped, traders accelerate their execution schedules, thereby increasing trade and pushing the price towards the limit defined by the rule. In the context of the Rule 201 short sale restrictions, the magnet effect would be an increase in aggressive non-exempt short sales as the price approaches the price limit that triggers the ban.

Our matched sample allows us to do a diff-in-diff of the price drop that triggers the 201 Rule relative to a similar price drop that does not trigger it, thereby identifying the specific effects of the rule-based component of the Rule. We find no evidence of a statistically significant effect of the Rule 201 restrictions. What we do find is that the event that triggers the Rule 201 does have an impact on markets, but this impact is present both for the Rule 201 stocks and the control group. The minute in which the price drop crosses the threshold price (which is close to the day's minimum for both treated and control stocks) is associated with three key effects: (i) an increase of short selling activity; (ii) an increase in volume (TAQ and NASDAQ); and, (iii) an increase in HFT and Algorithmic activity. All of these are accompanied by an increase in the demand for liquidity in the form of larger spreads and smaller depth (on the ask).

Tables 3-12 describe the effects during the minute in which the event is triggered: row “Event Minute (δ_0)” includes the coefficient for the baseline effect on all assets on the minute the event is triggered (the actual implementation of the restrictions for the treated group, and the price drop of 9% for the controls); row “Event Minute $\times$ 201 (η_0)” is the coefficient for the interaction term of the minute of the event with the treatment indicator. For the interested reader we have created an internet appendix where we replicate the tables in the main paper and add the coefficients for each of the five minutes before and after the event (we refer to these tables in brackets when we refer to the minutes surrounding the event minute). The effects of the price drop are described by the δ_0 coefficient, while the (mostly insignificant) differential effect is described by the η_0 one.

7. Discussion of Methodology

Our identification strategy is based on the argument that the control group is a valid representation of the counterfactual behavior of the treated assets in the absence of the Rule 201. This argument has two components to it. The first is common to all regression discontinuity identification strategies, namely that the assets that are on either side of the event that triggers the treatment (the Rule 201 restrictions) are essentially identical. The difference between having experienced a 10% price drop relative to the closing price the previous day and not having experienced it is essentially a matter of exogenous noise in the price process. The second is that from the microstructure perspective and absent the Rule 201 restriction, the event that triggers the 10% price drop for the treated groups is equivalent to a 9% price drop for the control group.

We reinforce the first component of the argument by selecting the assets in the control group to be a close match to the assets in the treated group. As described in greater detail above, we match each treated asset with a similar one in terms of asset type (ordinary share), industry, size, volume, price, and quoted spread. In addition we also match the time of day of the triggering event.

In terms of the second component, we cannot identify the validity of the equivalence between the event for the treated and for the control solely from comparing the two samples, treated and control. To address this we run a placebo analysis. If the first component of our argument is valid, then assets on either side of the event we use to define the control group, a 9% price drop relative to the previous day's closing price, are essentially the same. Thus we define those assets that experience a 9% price drop but do not fall more than 10% as the treated group in the placebo analysis, the P-treated group. Similarly, assets that experience an 8% price drop relative to the previous day's closing price but do not fall more than 9% form the control group in the placebo analysis, the P-control group. As with the main analysis, we construct the sample for the placebo analysis by matching each asset in the P-treated group with an asset in the P-control group following the exact same procedure as for the main analysis. Furthermore, if the second component of our argument is valid then the 8% price drop is to the P-control group, the same type of event as the 9% price drop is to the P-treated group.

We repeat the regressions we run in the main analysis. If our argument is correct and we had an unlimited amount of data, the coefficients for the post-event (β_1) and the minutes surrounding the event (δ_ts) would be exactly the same as in the main analysis, and the interaction dummies with the Rule 201 restrictions (β_2 and the η_ts) would all be zero. Our data is not unlimited, but the resulting comparison of coefficients provide strong evidence that our hypotheses are valid. As illustration we choose the five key microstructure variables in our analysis: asset return, volatility (intra-minute difference between midprice high and low), quoted spread, volume on the bid side, and short sales affected by the restrictions (non-exempt short sales on or below the bid price). In Figure 1 we plot the coefficients β_1 and δ_ts for these five variables.

In Figure 1a we see the return dynamics up to and following the event. The β_1 coefficient (to the left of the dashed vertical line) are positive and we find no appreciable difference between the placebo and the experiment (xt201). The δ_ts, on the right of the dashed vertical line, describe a large price drop up to the minute after the event which is followed by low positive returns in the subsequent minutes.[40] The confidence intervals suggest no significant differences between placebo and experiment. Turning to short sales, in Figure 1b we observe no significant average difference before and after the event (the β_1 coefficients are not significantly different from zero), and a gradual increase in non-exempt short sales growing with the return decrease up to minute one and dropping to zero. Again there appears to be no statistically significant differences between the coefficients from the placebo and experiment.

The pattern observed in short sales is repeated for volume (on the bid) in Figure 1c: no significant differences on average before and after the event, increasing in the minutes running up to the event, up until minute one, and decreasing to zero. Again, no significant differences appear between the placebo and the experiment. The dynamics around the event are also roughly the same for volatility, Figure 1d, although we do observe higher volatility on average after the event. This difference is larger in the placebo, though the difference is not quantitatively very large and with so many coefficients it could be due to noise in the estimation. Finally, quoted spreads, in Figure 1e, are greater after the event, and we see that the average increase appears immediately after the peak price increase, in minute two. Again, there are no statistically significant differences between the placebo and the experiment.

These patterns are also observed in the remaining variables in this study, and in particular, differences between the β_1 and δ_t coefficients are not statistically significant. The control variables behave in the same way in the experiment and the placebo. However, when looking at the treated (the P-treated in the placebo), the coefficients are very different. We have described those for the treated in the main analysis above. Those for the P-treated are easy to summarize: they are statistically indistinguishable from zero. Thus, from the placebo analysis we conclude that there is strong evidence that the research design identifies the causal effects we are interested in, an does so separately identifying the effect of the large price drop from the effect of the Rule 201 restrictions.

[40] Minute zero corresponds to the minute that contains the event.

8. Conclusions

Between 2010 and 2011 the SEC went beyond broad bans and generic restrictions, and designed and implemented market-driven, short lived, and targeted restrictions on short sales, collectively referred to as the Rule 201. In this paper we have provided a novel evaluation of the effects of these short sale restrictions using a solid theoretical framework, two years of intraday data, a broad gamut of market microstructure indicators, and a careful identification strategy that separately identifies the effects of the Rule 201 restrictions and those of the large price drop that triggers it.

We find that within our window of analysis the regulation achieves its objectives: liquidity improves in lit venues and prices become more stable. We find evidence that the regulation achieves this by reducing downward price pressure, and the toxicity of order flow in these venues, without imposing significant burdens on market making strategies. This is accompanied by a movement of short sale volume from lit exchanges to dark pools and a reduction in overall volume. The incorporation of negative information appears to be partially reduced, though price informativeness improves at longer (5-minute) horizons, possibly as a result of a change in the mix of informed trading.

Our analysis is consistent with the regulation generating costs for short selling that are concentrated on toxic short sales. This short selling appears to come primarily from two sources. The first is uninformed short sellers whose toxicity comes primarily from the accumulated price pressure already present on the asset at the time of the trigger. We hypothesize that these traders either withdraw or significantly reduce their desired short positions. The second type of affected short selling appears to come from strategies with very-short lived informational advantages. These are present in general, and are toxic in the sense described in Foucault et al. (2017). However, the restrictions remove them from the bid side of the book, lowering the cost of liquidity provision. In contrast, informed traders with longer-lived information appear to be less affected and increase their relative importance. Market making activity is unaffected in the sense that overall liquidity benefits from the restrictions. We conclude that the Rule 201 restrictions set a new standard for effective actions to deal with toxic short selling strategies for assets facing large price declines.

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Tables and Figures

Table 1 - Treated vs Controls

The table reports the t-tests of differences between the matching variables for the treatment and control groups, as well as daily returns. Daily return is the return from the previous market close to the current day's market close, the overnight return is the return from the previous market close to the current day's market open, and the intraday return is the return from the current day's market open to the current day's market close.

	Control	Treated 201	Difference	t-stat	p-value
Market Capitalization ('000) (in logs)	12.15	12.14	-0.008	0.106	0.916
Volume (log dollars)	13.1	13.06	-0.033	0.367	0.714
Price	8.3	8.45	0.151	-0.324	0.746
Quoted Spread† (cents)	6.80	7.42	-0.62	-1.299	0.903
Moments of daily returns: standard deviation	12.26	9.2	-3.058	1.618	0.106
Moments of daily returns: skewness	0.44	0.41	-0.035	0.465	0.642
Moments of daily returns: kurtosis	6.96	6.58	-0.38	1.171	0.242
Return (daily)	-5.93	-6.66	-0.73	4.339	0.000
Return (overnight)	-0.97	-1.08	-0.114	0.95	0.342
Return (intraday)	-4.95	-5.57	-0.62	3.041	0.002

† The *QuotedSpread* variable includes three very large outliers. The t-test in this table is done without these outliers. Including the outliers does not change the qualitative results but provides highly distorted values of the sample statistics–these are available upon request.

Table 2 - Descriptive Statistics and Economic Significance

The table reports the descriptive statistics of the main variables and the economic significance of the estimated effects of the Rule 201. The reported statistics are computed from the intraday means and standard deviations used to standardized the variables. The column labelled $Mean$ reports the average across assets of the in-sample average of the intraday variables, while the column labelled Std reports the average across assets of the in-sample standard deviations of the intraday variables. The coefficients correspond to the diff-in-diff interaction coefficient (β_2) in Equation 1 from Tables 4-10. The economic significance for standardized variables is obtained by adding the product of the coefficient and the mean standard deviation (Std) of the variable to the mean value of the variable, ($Mean$). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

Variable	Mean	Std	Coef.	Ec. Effect	201 level	Ec. Effect %
Total short sales (All)	4.658	2.953	-0.099***	-0.29	4.37	-6.3%
Total short sales (NQ)	2.388	2.679	-0.170***	-0.46	1.93	-19.1%
Not-Exempt Total SS (NQ)	2.307	2.634	-0.233***	-0.61	1.69	-26.6%
Not-Exempt SS at the bid (NQ)	0.751	1.650	-0.371***	-0.61	0.14	-81.5%
Total Volume (TAQ, log 000s $)	6.009	2.814	-0.076***	-0.21	5.80	-3.6%
Volume AggB (TAQ, log $)	4.638	2.933	-0.043**	-0.13	4.51	-2.7%
Volume AggS (TAQ, log $)	5.063	2.942	-0.094***	-0.28	4.79	-5.5%
Range † (bps, intraminute)	0.403	0.559	-0.353***	-0.35	2.45	-12.6%
StDev 1min †	0.387	0.260	-0.032**	-0.03	0.37	-7.9%
Quoted Spread (NASDAQ, bps)	140.8	86.99	-0.114***	-9.92	130.88	-7.0%
Depth Ask (NASDAQ best, log $)	7.401	0.837	0.217***	0.18	7.58	2.5%
Depth Bid (NASDAQ best, log $)	7.410	0.947	0.039	0.04	7.45	0.5%
Price Impact 100ms	2,240	3,119	-0.187***	-0.58	1.66	-26.0%
AR1 1min †	0.133	0.107	-0.011	-0.01	0.12	-8.3%
VR 5min †	0.180	0.326	-0.038	-0.04	0.14	-21.1%
Amihud 5min †	2.571	7.455	0.009	0.01	2.58	0.4%
Messages Bid	48.11	39.56	-0.208***	-8.23	39.88	-17.1%
PC100 Bid	7.754	8.678	-0.192***	-1.67	6.09	-21.5%
T2O † (bid side)	4.674	13.27	-0.058	-0.06	4.62	-1.2%
Realized Spread 100ms	2,084	4,198	0.062**	0.26	2.34	12.5%
Volume AggS† (FINRA %)	38.4	37.34	0.079***	0.08	38.48	0.2%
Volume AggS† (QuotingX %)	21.70	28.55	-0.804***	-0.80	20.90	-3.7%

† These variable are winsorized but not standardized as their magnitudes are readily interpretable and comparable across different assets.

Table 3 - Short Selling Activity

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are different metrics of short selling activity. Data for the ALL MARKETS analysis is provided by FINRA, CBOE, NYSE-ICE, and NASDAQ groups, and aggregated. In the first three columns we report results for all markets depending on how trades are marked: non-exempt, exempt and total (the sum of both). Subsequent columns use data only for the NASDAQ stock exchange. In the following four columns we separate total short-sales into passive (Passive SS NQ) and aggressive (Aggressive SS NQ) for all short-sale trades that are successfully matched with trades in the NASDAQ stock exchange. Trades are classified into buys and sells using the Lee-Ready algorithm, Lee and Ready (1991)). We separately analyze these aggressive and passive short sales based on whether they are exempt or not. In the final two columns, we separate non-exempt short sales into two groups: those at or below the national best bid (those forbidden by Rule 201, with some exceptions), and those at or above the ask (clearly passive short sales). Excluded from these two columns are non-exempt short sales with a reported price inside the NASDAQ spread, as for these the classification into aggressive buys and sells is very noisy. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

	ALL MARKETS			Passive SS NQ		Aggressive SS NQ		Non-exempt NQ	
	Non-exempt	Exempt	Total	Non-exempt	Exempt	Non-exempt	Exempt	NBB (or lower)	NBO (or higher)
Drop (β_1)	0.051***	-0.017*	0.040***	0.052***	-0.007*	0.028**	-0.011**	0.006	0.020*
Drop × 201 (β_2)	-0.132***	0.069***	-0.099***	-0.067***	0.187***	-0.264***	0.218***	-0.371***	-0.199***
Event Minute (δ_0)	0.170***	0.122***	0.194***	0.015	0.036	0.120***	0.039	0.150**	0.149***
Event Minute × 201 (η_0)	0.015	-0.070	0.003	-0.017	-0.020	0.094	0.008	0.102	0.042
Fixed Effects									
Price Δ	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asset-Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (30')	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	709,352	709,352	709,352	707,868	707,868	707,868	707,868	707,868	707,868
R-squared	0.029	0.016	0.034	0.017	0.013	0.053	0.013	0.056	0.056
# Events	1,912	1,912	1,912	1,908	1,908	1,908	1,908	1,908	1,908

Table 4 - TAQ Volumes

The table reports the coefficients from the estimation of the model described in equation 1. The table reports our results on trading activity defined as the record of transactions in the Trade and Quote (TAQ) Database. Our variables of interest ($Y_{i,t}$) are the (log) total dollar volume obtained by aggregating all (regular) trades in the TAQ dataset for asset i in minute t. *AggB* (*Ask*) reports the results considering orders classified as aggressive buy orders (Buyer Initiated Transactions). *AggS* (*Bid*) reports the results considering only aggressive sell orders (Seller Initiated Transactions), and *Total* reports the results for the total number of transactions, regardless of their type. Orders are classified as aggressive buy and sell using Lee and Ready (1991). All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

LOG VOLUME (All markets)	AggS (Bid)	AggB (Ask)	Total
Drop (β_1)	-0.016	0.092***	0.035**
Drop × 201 (β_2)	-0.094***	-0.043**	-0.076***
Event Minute (δ_0)	0.435***	0.272***	0.413***
Event Minute × 201 (η_0)	-0.080	-0.003	-0.067
Fixed Effects			
Price Movement Magnitude	Yes	Yes	Yes
Asset-Day	Yes	Yes	Yes
Time (30' Bins)	Yes	Yes	Yes
Observations	707,497	707,497	707,497
R-squared	0.080	0.051	0.079
# Events	1,907	1,907	1,907

Table 5 - Returns and Volatilities

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are Returns and Range (Volatility). *Return* (*bps*) reports the results for stock returns, where $Y_{i,t}$ is $Return_{i,t}$, defined as the asset one-minute return for asset i in minute t and is calculated as the log difference between the midprice at the end of minute t and the beginning of minute t. *Range* reports the results for our measure of volatility, where $Y_{i,t}$ is $Range_{i,t}$, calculated as the difference between the highest minus the lowest midprice during the minute, normalized by the average of the two. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

STOCK PRICE: VOLATILITY & RETURN	Return (bps)	Range
Drop (β_1)	5.821***	0.030**
Drop × 201 (β_2)	0.734***	-0.032***
Event Minute (δ_0)	-26.730***	0.123***
Event Minute × 201 (η_0)	-2.130	-0.016
Fixed Effects		
Price Movement Magnitude	No	Yes
Asset-Day	Yes	Yes
Time (30' Bins)	Yes	Yes
Observations	707,868	707,868
R-squared	0.009	0.335
# Events	1,908	1,908

Table 6 - NASDAQ Volume (Visible vs. Hidden)

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the (log) dollar volume in the NASDAQ market obtained by aggregating trades in the ITCH dataset for asset i in minute t. Orders are separated into *visible* and *hidden* depending on whether the trade-initiating order executes against a visible (*visible*) or non-visible (*hidden*) standing order. Visible trades are classified as buy or sell orders according to the reported side of the order book of the matching limit order. *AggB* (*Ask*) reports the results considering only orders classified as aggressive buy orders (Buyer Initiated Transactions). *AggS* (*Bid*) reports the results considering only aggressive sell orders (Seller Initiated Transactions) and *Total* reports the results for the total number of transactions, regardless of their type. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

VOLUME	Visible AggS (Bid)	Visible AggB (Ask)	Visible Total	Hidden Total
Drop (β_1)	0.001	0.018***	0.019**	0.009*
Drop × 201 (β_2)	-0.031***	-0.011*	-0.043***	-0.013**
Event Minute (δ_0)	0.102***	0.040*	0.137***	0.006
Event Minute × 201 (η_0)	0.000	-0.007	-0.013	0.056*
Fixed Effects				
Price Movement Magnitude	Yes	Yes	Yes	Yes
Asset-Day	Yes	Yes	Yes	Yes
Time (30' Bins)	Yes	Yes	Yes	Yes
Observations	707,868	707,868	707,868	707,868
R-squared	0.021	0.013	0.014	0.003
# Events	1,908	1,908	1,908	1,908

Table 7 - Effective and Quoted Spreads

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are $QSp_{i,t}$, $EffSp_{i,t}$ and $QSp_{NBBO,i,t}$. $QSp_{i,t}$ is the time-weighted quoted spread calculated with ITCH database (NASDAQ). $EffSp_{i,t}$ is the volume-weighted effective spread calculated with ITCH database (NASDAQ). $QSp_{NBBO,i,t}$ is the time-weighted quoted spread calculated with the NBBO of the TAQ database. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

SPREADS	QSp	$EffSp$	QSp_{NBBO}
Drop (β_1)	0.148***	0.035*	0.194***
Drop × 201 (β_2)	-0.114***	-0.157***	-0.146***
Event Minute (δ_0)	0.089***	0.015	0.134***
Event Minute × 201 (η_0)	-0.067	0.010	0.011
Fixed Effects			
Price Movement Magnitude	Yes	Yes	Yes
Asset-Day	Yes	Yes	Yes
Time (30' Bins)	Yes	Yes	Yes
Observations	707,868	287,593	704,751
R-squared	0.150	0.130	0.109
# Events	1,908	1,908	1,907

Table 8 - Depth

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the LOB depth $DX_{i,t}$, calculated as the sum of the total US dollar value resting on the LOB within $X \in \{0, 5, 10\}$ cents away from the best bid and ask, for asset i and time-weighted over minute t. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

DEPTH	Bid	Bid-5c	Bid-10c	Ask	Ask+5c	Ask+10c
Drop (β_1)	-0.059*	-0.180***	-0.213***	-0.091***	0.003	0.016
Drop × 201 (β_2)	0.039	-0.019	-0.047	0.217***	0.089**	0.041
Event Minute (δ_0)	0.092*	0.067	0.041	0.164***	0.042	0.003
Event Minute × 201 (η_0)	-0.017	-0.041	-0.094	-0.020	-0.019	-0.046
Fixed Effects						
Price Δ	Yes	Yes	Yes	Yes	Yes	Yes
Asset-Day	Yes	Yes	Yes	Yes	Yes	Yes
Time (30')	Yes	Yes	Yes	Yes	Yes	Yes
Observations	707,868	707,868	707,868	707,868	707,868	707,868
R-squared	0.012	0.026	0.024	0.024	0.046	0.029
# Events	1,908	1,908	1,908	1,908	1,908	1,908

Table 9 - Price Impact

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the intra-minute volume weighted average price impact for asset i, $PI_{i,t}$. The price impact for the transaction at time $t' \in [t, t+1)$ is computed as $D_{t'}(m_{t'+\Delta} - m_{t'})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $m_{t'}$ is the prevailing midquote at time t', and $m_{t'+\Delta}$ the prevailing midquote at time $t+\Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible trades are available from the ITCH dataset. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

PRICE IMPACT	100ms	1min	5min
Drop (β_1)	0.057***	0.054***	0.005
Drop × 201 (β_2)	-0.187***	-0.033**	0.034**
Event Minute (δ_0)	0.127**	0.522***	0.140**
Event Minute × 201 (η_0)	-0.251***	-0.017	-0.033
Fixed Effects			
Price Δ	Yes	Yes	Yes
Asset-Day	Yes	Yes	Yes
Time (30')	Yes	Yes	Yes
Observations	287,593	287,593	287,593
R-squared	0.088	0.082	0.028
# Events	1,908	1,908	1,908

Table 10 - Liquidity and Price Efficiency

The table reports our results on intraday volatility, variance ratios and Amihud liquidity from the estimation of the equation:

$$Y_{i,t} = \alpha_{P(i)} + \beta\, Drop + \gamma\, Rule201 + \xi\, Drop \times 201Rule + \varepsilon_{i,t}$$

Our sample is divided into two periods: before ($t = 0$), and after ($t = 1$) the event. Our variables of interest ($Y_{i,t}$) are $StDev\ 1min$, $AR1\ 1min$, $VR\ Xmin$, and $Amihud\ Xmin$. $StDev\ 1min$ measures the standard deviation of 1-minute midpoint returns for asset i, over period t. $AR1\ 1min$ measures the autocorrelation of 1-minute midpoint returns for asset i, over period t. $VR\ Xmin$ is one minus the variance ratio of midpoint returns measured every X minutes relative to the 1-minute midpoint returns for asset i, over period t. $Amihud\ Xmin$ measures the log of the average Amihud illiquidity ratio of absolute midpoint returns (in %) measured every X minutes relative to the volume over that same time interval for asset i, over period t. The variable $Drop$ is an indicator of the period after the event ($t = 1$), and $Rule201$ an indicator of whether i belongs to the treated group, i.e. whether the event triggers short selling constraints. The resulting observations are winsorized at the 1 and 99 percentile levels. The regression is a standard difference in difference regression (Stata: didregress command) with standard errors clustered by match-id (the identifier that identifies a pair of treated and control assets). Differences in sample sizes appear as matched pairs of assets are included only if they have at least 5 observations with which to compute each per period variance (at least five before, and five after the event).

VARIABLES	StDev 1min	AR1 1min	VR 5min	VR 10min	Amihud 1min	Amihud 5min
Drop	-0.064***	0.0077	0.042**	0.006	-0.361***	-0.358***
$Drop \times Rule201$	-0.035***	0.0007	-0.045*	-0.079**	-0.172*	-0.004
Constant	0.428***	0.1287***	0.170***	0.246***	0.253***	-0.814***
Fixed Effects						
Matched Pair	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,808	3,788	3,752	3,672	3,780	3,724

Table 11 - Algorithmic Activity

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are $Messages_{i,t}$ $PC100_{i,t}$ and $T2O_{i,t}$. $Messages_{i,t}$ is the number of messages for asset i during minute t including posting, cancelling, and execution of visible limit orders on the corresponding side of the order book (bid and ask). $PC100_{i,t}$ is number of limit orders that are posted and subsequently cancelled within 100ms for asset i during minute t. $T2O_{i,t}$ is the trade-to-order ratio computed as the number of executed visible limit orders as a percentage of messages for asset i during minute t. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

ALGORITHM ACTIVITY	Messages (Bid)	Messages (Ask)	PC100 (Bid)	PC100 (Ask)	T2O (Bid)	T2O (Ask)
Drop (β_1)	0.100***	0.007	0.075***	0.010	-0.829***	0.535***
Drop × 201 (β_2)	-0.208***	-0.105***	-0.192***	-0.131***	-0.058	0.321**
Event Minute (δ_0)	0.374***	0.589***	0.200***	0.291***	0.418	-0.798***
Event Minute × 201 (η_0)	-0.017	-0.108	-0.119*	-0.129*	0.106	0.053
Fixed Effects						
Price Δ	Yes	Yes	Yes	Yes	Yes	Yes
Asset-Day	Yes	Yes	Yes	Yes	Yes	Yes
Time (30')	Yes	Yes	Yes	Yes	Yes	Yes
Observations	707,868	707,868	707,868	707,868	529,803	545,467
R-squared	0.108	0.162	0.044	0.091	0.039	0.031
# Events	1,908	1,908	1,908	1,908	1,908	1,903

Table 12 - Realized Spreads

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the intra-minute volume weighted average realized spread $RS_{i,t}$. The realized spread for the transaction at time $t' \in [t, t+1)$ is computed as $D_{t'}(p_{t'} - m_{t'+\Delta})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $p_{t'}$ is the trade price and $m_{t'+\Delta}$ the prevailing midquote at time $t + \Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible trades are available from the ITCH dataset. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

REALIZED SPREAD	100ms	1min	5min
Drop (β_1)	-0.013	-0.032**	0.008
Drop × 201 (β_2)	0.062**	-0.037**	-0.071***
Event Minute (δ_0)	-0.109*	-0.523***	-0.150**
Event Minute × 201 (η_0)	0.241***	-0.058	0.035
Fixed Effects			
Price Δ	Yes	Yes	Yes
Asset-Day	Yes	Yes	Yes
Time (30’)	Yes	Yes	Yes
Observations	287,593	287,593	287,593
R-squared	0.021	0.046	0.019
# Events	1,908	1,908	1,908

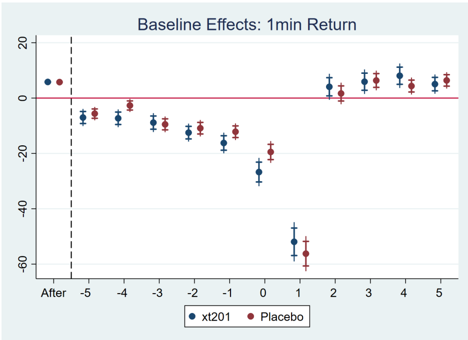
Table 13 - Share Volumes

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are standardized transacted share volume provided by FINRA and TAQ classified into three groups $QuotingX_{i,t}$, $FINRA_{i,t}$ and $Inverted_{i,t}$. $QuotingX_{i,t}$ stands for the market share of total volume traded on the asset's quoting exchange, obtained from the TAQ dataset for asset i in minute t as a percentage of total volume. $FINRA_{i,t}$ stands for the market share of total volume traded outside official exchanges as reported in the TAQ dataset under the FINRA moniker for asset i in minute t as a percentage of total volume. $Inverted_{i,t}$ stands for the market share of total volume traded on the markets with inverted fee structure. $AggB$ (Ask) reports the results considering only orders classified as aggressive buy orders (Buyer Initiated Transactions). $AggS$ (Bid) reports the results considering only aggressive sell orders (Seller Initiated Transactions) and $Total$ reports the results for the total number of transactions, regardless of their type. Orders are classified as aggressive buy and sell using Lee and Ready (1991). All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

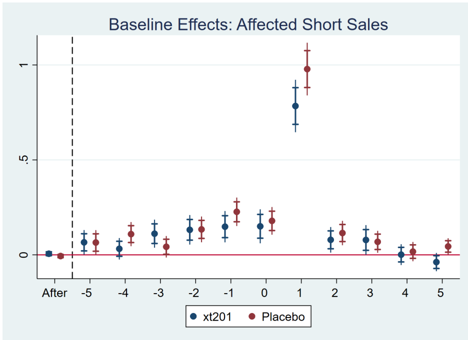
MARKET	QuotingX			FINRA			Inverted		
SHARE	AggS (Bid)	AggB (Ask)	Total	AggS (Bid)	AggB (Ask)	Total	AggS (Bid)	AggB (Ask)	Total
Drop (β_1)	0.009	-0.005	-0.008	-0.004	0.023**	0.033***	-0.004	0.006	0.001
Drop $\times$ 201 (β_2)	-0.028**	-0.024*	-0.019	0.033***	0.079***	0.066***	-0.035***	0.025**	-0.004
Event Minute (δ_0)	-0.073**	-0.061*	-0.100***	0.097***	0.118***	0.146***	-0.048	-0.066**	-0.040
Event Minute $\times$ 201 (η_0)	0.015	0.102**	0.109**	-0.024	-0.098**	-0.107**	-0.015	0.035	-0.012
Fixed Effects									
Price Δ	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Asset-Day	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time (30')	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	707,497	707,497	707,497	707,497	707,497	707,497	707,497	707,497	707,497
R-squared	0.002	0.012	0.008	0.002	0.012	0.009	0.003	0.008	0.007
# Events	1,907	1,907	1,907	1,907	1,907	1,907	1,907	1,907	1,907

Fig. 1 - Comparisons of Coefficients.

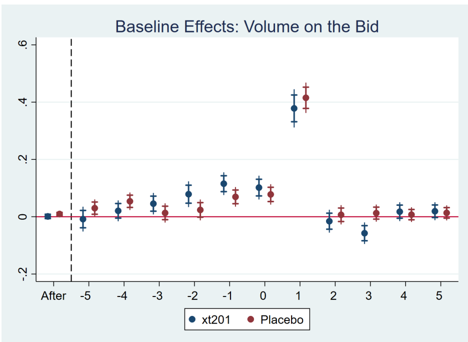
These graphs describe the differences in the coefficients between the experiment and the placebo. The coefficients are the baseline coefficients for the joint regression: $After$ is the average effect for the period after the event, and coefficient numbered $i\{-5,\ldots,5\}$ are the coefficients for the minutes surrounding the event, $t-i$. The vertical line represents the 95 percent confidence interval. The horizontally marked intervals represent the 83 percent confidence interval, which is suggested as a visual proxy for tests of differences in mean between the coefficients, as proposed in Goldstein and Healy (1995).



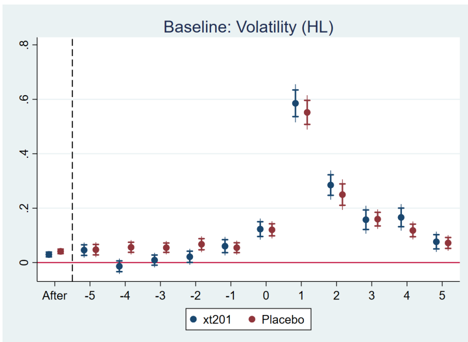
(a) One minute returns.



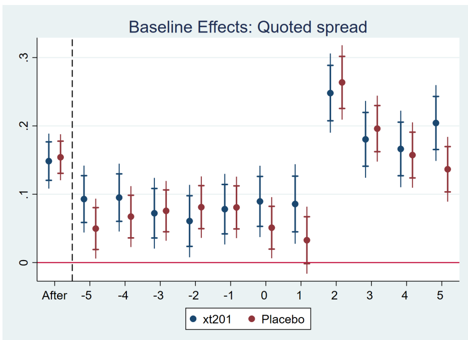
(b) Short sales at or below the bid



(c) Volume on the ask



(d) Volatility (high minus low)



(e) Quoted spread

Appendix

1. Variable Definitions

Our variables are defined as follows:

- *Market Capitalization* (in logs): log of the product of the number of shares outstanding and the asset's price (source: CRSP daily).
- *Volume* (log dollars): log of the product of the number of shares traded and the asset's price (source: CRSP daily).
- *Price*: asset's closing price.
- *Moments of daily returns*: *standard deviation*: standard deviation of the asset's daily returns of the past 40 trading days (source: CRSP daily).
- *Moments of daily returns*: *skewness*: skewness of the asset's daily returns of the past 40 trading days (source: CRSP daily)
- *Moments of daily returns*: *kurtosis*: kurtosis of the asset's daily returns of the past 40 trading days (source: CRSP daily)
- $Return_{i,t}$. One-minute asset return for asset i in minute t is calculated as the log difference between the midprice at the end of minute t and the beginning of minute t.
- $Range_{i,t}$. The range of price movement for asset i during minute t is calculated as the difference between the highest minus the lowest midprice during the minute, normalized by the average of the two.[41]
- $TAQVolume_{i,t}$. The (log) total dollar volume obtained by aggregating all (regular) trades in the TAQ dataset for asset i in minute t. Orders are classified as aggressive buy and sell using Lee and Ready (1991).[42]
- $\text{FINRA}^{SS}_{i,t}$. Off-exchange short selling activity for asset i in minute t measured as the log dollar total volume of the sum of trades reported as short sales to the TRF and published by FINRA on their website. Short sales are reported as *Exempt*, $Non - Exempt$, and $Total$ (the sum of the exempt and non-exempt).
- $\text{NASDAQ}^{SS}_{i,t}$. Short selling activity for asset i in minute t measured as the log dollar total volume of trades reported as short sales to the NASDAQ group exchanges. Short sales are reported as *Exempt*, $Non - Exempt$, and $Total$ (the sum of the two).
- $\text{CBOE}^{SS}_{i,t}$. Short selling activity for asset i in minute t measured as the log dollar total volume of trades reported as short sales to the BATS group exchanges. Short sales are reported as *Exempt*, $Non - Exempt$, and $Total$ (the sum of the two).
- $QuotingX$. The market share of total volume traded on the NASDAQ or NYSE exchange as reported in the TAQ dataset for asset i in minute t as a percentage of total volume.

[41] This variable is normalized in different ways in the literature. As we are working with intervals containing substantial price drops we use the arithmetic average of the two (highest and lowest) to avoid biasing the measure in any direction.
[42] For more details on the effectiveness of the Lee-Ready algorithm see Chakrabarty et al. (2012).

- $FINRA_{i,t}$. The market share of total volume traded outside official exchanges as reported in the TAQ dataset under the FINRA moniker for asset i in minute t as a percentage of total volume.
- $NASDAQVolume_{i,t}$. The (log) dollar volume obtained by aggregating trades in the ITCH dataset for asset i in minute t. Orders are separated into *visible* and *hidden* depending on whether the trade-initiating order executes against a visible (*visible*) or non-visible (*hidden*) standing order. Visible trades are classified as buy or sell orders according to the reported side of the order book of the matching limit order.
- $Quoted_{i,t}$. Quoted spread for asset i is the time-weighted (by millisecond) average, over minute t, of $(a_{t'} - b_{t'})/m_{t'}$ where $a_{t'}$ is the best ask, $b_{t'}$ the best bid, $m_{t'}$ the midprice, and t' indexes observations within a minute (source: ITCH).
- $Effective_{i,t}$. Effective spread for asset i is the intra-minute volume weighted average effective spread. The effective spread for the transaction at time t' is computed as $2\,D_{t'}(p_{t'} - m_{t'})/m_{t'}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $p_{t'}$ is the trade price and $m_{t'}$ the prevailing midquote (prior to an execution). Trade directions for visible traders are available from the ITCH dataset and do not need to be estimated. Hidden trades are classified using Lee-Ready (source: ITCH).
- $QuotedNBBO_{i,t}$. Quoted spread for asset i is the time-weighted (by millisecond) average, over minute t, of $(a_{t'} - b_{t'})/m_{t'}$ where $a_{t'}$ is the best ask, $b_{t'}$ the best bid, $m_{t'}$ the midprice, and t' indexes observations within a minute (source: TAQ).
- $Ask_{i,t}$. Depth at the Ask for asset i is calculated as the sum of the total US dollar value resting on the LOB within $X \in \{0, 5, 10\}$ cents away from the best ask, time-weighted over minute t (source: ITCH).
- $Bid_{i,t}$. Depth at the Bid for asset i is calculated as the sum of the total US dollar value resting on the LOB within $X \in \{0, 5, 10\}$ cents away from the best bid, time-weighted over minute t (source: ITCH).
- $Messages_{i,t}$. Number of messages for asset i during minute t. These include posting, canceling, and execution of visible limit orders on the corresponding side of the order book e.g. bid and ask (source: ITCH).
- $PC100_{i,t}$. Number of limit orders that are posted and subsequently canceled within 100ms for asset i during minute t (source: ITCH).
- $T2O_{i,t}$. Trade-to-order ratio computed as the number of executed visible limit orders as a percentage of messages for asset i during minute t (source: ITCH).
- $RS_{i,t}$. Realized spread for asset i is the intra-minute volume weighted average realized spread. The realized spread for the transaction at time t' is computed as $D_{t'}(p_{t'} - m_{t'+\Delta})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $p_{t'}$ is the trade price and $m_{t'+\Delta}$ the prevailing midquote at time $t + \Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible traders are available from the ITCH dataset and do not need to be estimated. Hidden trades are classified using Lee-Ready (source: ITCH).
- $PI_{i,t}$. Price Impact for asset i is the intra-minute volume weighted average price impact. The price impact for the transaction at time t' is computed as $D_{t'}(m_{t'+\Delta} - m_{t'})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an

aggressive buy and -1 for a sale), $m_{t'}$ is the prevailing midquote at time t', and $m_{t'+\Delta}$ the prevailing midquote at time $t+\Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible traders are available from the ITCH dataset and do not need to be estimated. Hidden trades are classified using Lee-Ready (source: ITCH).

- $StDev1_{i,k}$. The volatility of one-minute midprice returns over period $k \in \{0, 1\}$, where $k = 0$ is before the event and $k = 1$ is after the event (source: ITCH).
- $AR1_{i,k}$. The auto-correlation of one-minute midprice returns $corr(r_{i,t}, r_{i,t-1})$ over period $k \in \{0, 1\}$, where $k = 0$ is before the event and $k = 1$ is after the event (source: ITCH).
- $VR_{i,k}$ $n$min. n minute variance ratio of asset i over period $k \in \{0, 1\}$, where $k = 0$ is before the event and $k = 1$ is after the event. The variance ratio is one minus the ratio of the sample variance of the $n-$minute returns divided by n times the sample variance of the one minute returns during period t (source: ITCH).
- $Amihud_{i,k}$ $n$min. Is the log of the average Amihud illiquidity measure for asset i over period $k \in \{0, 1\}$, where $k = 0$ is before the event and $k = 1$ is after the event. Amihud illiquidity is measured every n minutes as the absolute return over the n minutes divided by the total dollar volume during those n minutes (source: ITCH).

2. Internet Appendix

Table A.1 - Short Selling Activity

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are different metrics of short selling activity. Data for the ALL MARKETS analysis is provided by FINRA, BATS, NYSE-ICE, and NASDAQ groups, and aggregated. In the first three columns we report results for all markets depending on how trades are marked: non-exempt, exempt and total (the sum of both). Subsequent columns use data only for the NASDAQ stock exchange. In the following four columns we separate total short-sales into passive (Passive SS NQ) and aggressive (Aggressive SS NQ) for all short-sale trades that are successfully matched with trades in the NASDAQ stock exchange. Trades are classified into buys and sells using the Lee-Ready algorithm, Lee and Ready (1991)). We separately analyze these aggressive and passive short sales based on whether they are exempt or not. In the final two columns, we separate non-exempt short sales into two groups: those at or below the national best bid (those forbidden by Rule 201, with some exceptions), and those at or above the ask (clearly passive short sales). Excluded from these two columns are non-exempt short sales with a reported price inside the NASDAQ spread, as for these the classification into aggressive buys and sells is very noisy. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

	ALL MARKETS			Passive SS NQ		Aggressive SS NQ		Non-exempt NQ	
	Non-exempt	Exempt	Total	Non-exempt	Exempt	Non-exempt	Exempt	NBB (or lower)	NBO (or higher)
Drop (β_1)	0.051***	-0.017*	0.040***	0.052***	-0.007*	0.028**	-0.011**	0.006	0.020*
T-5	0.054	0.070**	0.089***	0.042	0.029	0.064*	0.027	0.066*	0.092**
T-4	0.088***	0.046	0.085***	-0.004	0.030	0.048	0.006	0.032	0.041
T-3	0.099***	0.088***	0.100***	0.011	0.012	0.171***	0.109*	0.112**	0.176***
T-2	0.155***	0.077**	0.175***	0.075*	0.004	0.098**	0.029	0.132***	0.111**
T-1	0.272***	0.189***	0.303***	0.063*	-0.012***	0.205***	0.077	0.148***	0.215***
Event Minute (δ_0)	0.170***	0.122***	0.194***	0.015	0.036	0.120***	0.039	0.150**	0.149***
T+1	0.589***	0.471***	0.648***	0.548***	0.074*	1.046***	0.208***	0.784***	1.141***
T+2	0.204***	0.129***	0.225***	0.333***	0.001	0.262***	0.024	0.079*	0.280***
T+3	0.133***	0.093**	0.163***	0.119**	-0.001	0.078*	0.056	0.078*	0.097**
T+4	0.167***	0.092***	0.194***	0.173***	0.027	0.174***	0.037	0.001	0.176***
T+5	0.046	0.081**	0.068**	0.039	-0.005	0.078*	0.009	-0.038	0.081*
201 Rule Interactions									
Drop × 201 (β_2)	-0.132***	0.069***	-0.099***	-0.067***	0.187***	-0.264***	0.218***	-0.371***	-0.199***
T-5 interaction	0.046	0.025	0.013	0.004	-0.015	0.060	0.008	0.028	0.037
T-4 interaction	-0.031	-0.001	-0.019	0.035	-0.014	0.058	0.064*	0.040	0.092*
T-3 interaction	-0.011	-0.058	-0.022	0.005	-0.010	-0.099	-0.082	-0.073	-0.097
T-2 interaction	-0.087*	-0.009	-0.082*	-0.060	0.056	-0.007	0.024	0.040	-0.019
T-1 interaction	-0.128***	-0.089*	-0.150***	-0.031	0.046**	-0.022	-0.028	0.028	-0.028
Event Minute × 201 (η_0)	0.015	-0.070	0.003	-0.017	-0.020	0.094	0.008	0.102	0.042
T+1 interaction	0.040	-0.120*	0.023	-0.008	0.041	0.169	0.237**	0.213*	0.138
T+2 interaction	0.067	-0.078	0.050	-0.110	0.080	0.054	0.096	0.038	0.039
T+3 interaction	0.126***	-0.061	0.094*	-0.025	0.053	0.160**	0.099	-0.020	0.159**
T+4 interaction	-0.006	-0.061	-0.024	-0.082	0.062	-0.019	0.053	0.054	-0.021
T+5 interaction	0.143***	-0.055	0.129***	0.069	0.046	0.062	0.001	0.138***	0.043
Observations	709,352	709,352	709,352	707,868	707,868	707,868	707,868	707,868	707,868
R-squared	0.029	0.016	0.034	0.017	0.013	0.053	0.013	0.056	0.056
# Events	1,912	1,912	1,912	1,908	1,908	1,908	1,908	1,908	1,908

Table A.2 - TAQ Volumes

The table reports the coefficients from the estimation of the model described in equation 1. The table reports our results on trading activity defined as the record of transactions in the Trade and Quote (TAQ) Database. Our variables of interest ($Y_{i,t}$) are the (log) total dollar volume obtained by aggregating all (regular) trades in the TAQ dataset for asset i in minute t. $AggB$ (Ask) reports the results considering orders classified as aggressive buy orders (Buyer Initiated Transactions). $AggS$ (Bid) reports the results considering only aggressive sell orders (Seller Initiated Transactions) and $Total$ reports the results for the total number of transactions, regardless of their type. Orders are classified as aggressive buy and sell using Lee and Ready (1991). All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

LOG VOLUME (All markets)	AggS (Bid)	AggB (Ask)	Total
Drop (β_1)	-0.016	0.092***	0.035**
T-5	0.231***	0.180***	0.243***
T-4	0.191***	0.069*	0.187***
T-3	0.200***	0.128***	0.226***
T-2	0.248***	0.157***	0.246***
T-1	0.326***	0.258***	0.315***
Event Minute (δ_0)	0.435***	0.272***	0.413***
T+1	1.225***	0.818***	1.083***
T+2	0.462***	0.363***	0.453***
T+3	0.240***	0.227***	0.292***
T+4	0.246***	0.346***	0.334***
T+5	0.140***	0.259***	0.233***
201 Rule Interactions			
Drop × 201 (β_2)	-0.094***	-0.043**	-0.076***
T-5 interaction	-0.075	-0.044	-0.089*
T-4 interaction	0.009	0.016	0.008
T-3 interaction	0.006	0.022	-0.014
T-2 interaction	-0.014	-0.015	-0.046
T-1 interaction	-0.044	-0.050	-0.038
Event Minute × 201 (η_0)	-0.080	-0.003	-0.067
T+1 interaction	0.012	0.081	0.013
T+2 interaction	-0.021	0.001	-0.002
T+3 interaction	0.158***	0.039	0.089
T+4 interaction	-0.021	-0.098*	-0.081
T+5 interaction	0.040	-0.121*	-0.057
Observations	707,497	707,497	707,497
R-squared	0.080	0.051	0.079
# Events	1,907	1,907	1,907

Table A.3 - Returns and Volatilities

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are Returns and Range (Volatility). *Return* (*bps*) reports the results for stock returns, where $Y_{i,t}$ is $Return_{i,t}$, defined as the asset one-minute return for asset i in minute t and is calculated as the log difference between the midprice at the end of minute t and the beginning of minute t. *Range* reports the results for our measure of volatility, where $Y_{i,t}$ is $Range_{i,t}$, calculated as the difference between the highest minus the lowest midprice during the minute, normalized by the average of the two. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

STOCK PRICE: VOLATILITY & RETURN	Return (bps)	Range
Drop (β_1)	5.821***	0.030***
T-5	-7.020***	0.046**
T-4	-7.307***	-0.014
T-3	-8.862***	0.009
T-2	-12.484***	0.021
T-1	-16.224***	0.060***
Event Minute (δ_0)	-26.730***	0.123***
T+1	-51.930***	0.585***
T+2	4.081	0.285***
T+3	5.918**	0.157***
T+4	8.069***	0.166***
T+5	5.047**	0.076***
201 Rule Interactions		
Drop × 201 (β_2)	0.734***	-0.353***
T-5 interaction	-0.174	-0.014
T-4 interaction	3.034	0.044*
T-3 interaction	-0.719	0.019
T-2 interaction	3.172	0.005
T-1 interaction	1.280	-0.008
Event Minute × 201 (η_0)	-2.130	-0.016
T+1 interaction	-2.992	0.030
T+2 interaction	3.636	-0.017
T+3 interaction	0.300	0.043
T+4 interaction	-2.065	-0.020
T+5 interaction	2.906	0.004
Observations	707,868	707,868
R-squared	0.009	0.335
# Events	1,908	1,908

Table A.4 - NASDAQ Volume (Visible vs. Hidden)

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the (log) dollar volume in the NASDAQ market obtained by aggregating trades in the ITCH dataset for asset i in minute t. Orders are separated into *visible* and *hidden* depending on whether the trade-initiating order executes against a visible (*visible*) or non-visible (*hidden*) standing order. Visible trades are classified as buy or sell orders according to the reported side of the order book of the matching limit order. *AggB* (*Ask*) reports the results considering only orders classified as aggressive buy orders (Buyer Initiated Transactions). *AggS* (*Bid*) reports the results considering only aggressive sell orders (Seller Initiated Transactions) and $Total$ reports the results for the total number of transactions, regardless of their type. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

VOLUME	Visible AggS (Bid)	Visible AggB (Ask)	Visible Total	Hidden Total
Drop (β_1)	0.001	0.018***	0.019**	0.009*
T-5	-0.008	0.037*	0.038	0.024*
T-4	0.021	0.037*	0.042	-0.013
T-3	0.046*	0.012	0.040	-0.014
T-2	0.079***	0.051**	0.097***	0.045**
T-1	0.115***	0.054**	0.140***	0.024
Event Minute (δ_0)	0.102***	0.040*	0.137***	0.006
T+1	0.378***	0.179***	0.498***	0.139***
T+2	-0.016	0.088***	0.079**	0.028
T+3	-0.057**	0.065***	0.009	0.007
T+4	0.018	0.052**	0.065**	-0.004
T+5	0.019	-0.001	0.005	-0.023
201 Rule Interactions				
Drop × 201 (β_2)	-0.031***	-0.011*	-0.043***	-0.013**
T-5 interaction	0.016	-0.001	-0.006	-0.003
T-4 interaction	-0.016	-0.008	-0.004	0.007
T-3 interaction	-0.003	-0.001	0.008	0.028
T-2 interaction	-0.020	-0.056*	-0.042	-0.060**
T-1 interaction	-0.048	-0.031	-0.057	0.010
Event Minute × 201 (η_0)	0.000	-0.007	-0.013	0.056*
T+1 interaction	0.070	0.007	0.071	-0.002
T+2 interaction	0.034	-0.014	0.031	0.005
T+3 interaction	0.062*	-0.002	0.055	0.004
T+4 interaction	-0.033	-0.006	-0.026	0.022
T+5 interaction	-0.039	0.027	0.013	0.056**
Observations	707,868	707,868	707,868	707,868
R-squared	0.021	0.013	0.014	0.003
# Events	1,908	1,908	1,908	1,908

Table A.5 - Effective and Quoted Spreads

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are $QSp_{i,t}$, $EffSp_{i,t}$ and $QSp_{NBBO,i,t}$. $QSp_{i,t}$ is the time-weighted quoted spread calculated with ITCH database (NASDAQ). $EffSp_{i,t}$ is the volume-weighted effective spread calculated with ITCH database (NASDAQ). $QSp_{NBBO,i,t}$ is the time-weighted quoted spread calculated with the NBBO of the TAQ database. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

SPREADS	Quoted	Effective	Quoted NBBO
Drop (β_1)	0.148***	0.035*	0.194***
T-5	0.093***	0.036	0.118***
T-4	0.095***	0.053	0.107***
T-3	0.072**	-0.059	0.104***
T-2	0.061*	0.013	0.106***
T-1	0.078**	-0.024	0.088**
Event Minute (δ_0)	0.089***	0.015	0.134***
T+1	0.086**	0.288***	0.106***
T+2	0.248***	0.204***	0.267***
T+3	0.180***	0.230***	0.219***
T+4	0.166***	0.200***	0.145***
T+5	0.204***	0.098*	0.161***
201 Rule Interactions			
Drop × 201 (β_2)	-0.114***	-0.157***	-0.146***
T-5 interaction	-0.044	-0.023	-0.011
T-4 interaction	-0.043	-0.036	0.016
T-3 interaction	-0.030	-0.001	0.004
T-2 interaction	-0.048	-0.002	-0.008
T-1 interaction	-0.046	0.031	0.040
Event Minute × 201 (η_0)	-0.067	0.010	0.011
T+1 interaction	0.050	0.056	0.086
T+2 interaction	0.099*	0.131*	0.091
T+3 interaction	0.128**	-0.026	0.087
T+4 interaction	0.119**	0.006	0.122*
T+5 interaction	0.061	0.007	0.108*
Observations	707,868	287,593	704,751
R-squared	0.150	0.130	0.109
# Events	1,908	1,908	1,907

Table A.6 - Depth

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the LOB depth $DX_{i,t}$, calculated as the sum of the total US dollar value resting on the LOB within $X \in \{0, 5, 10\}$ cents away from the best bid and ask, for asset i and time-weighted over minute t. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

DEPTH	Bid	Bid-5c	Bid-10c	Ask	Ask+5c	Ask+10c
Drop (β_1)	-0.059*	-0.180***	-0.213***	-0.091***	0.003	0.016
T-5	0.145***	0.042	0.050	0.086**	0.091**	0.077*
T-4	0.132***	0.035	0.048	0.065	0.082*	0.069*
T-3	0.083*	0.047	0.040	0.115***	0.107**	0.080*
T-2	0.084*	0.003	0.034	0.143***	0.078*	0.062
T-1	0.082*	0.013	0.040	0.159***	0.065	0.045
Event Minute (δ_0)	0.092*	0.067	0.041	0.164***	0.042	0.003
T+1	0.247***	0.261***	0.228***	0.211***	0.010	-0.034
T+2	0.082*	0.142***	0.082*	0.082*	-0.045	-0.047
T+3	0.067*	0.116**	0.053	0.020	-0.043	-0.083*
T+4	0.050	0.094**	0.058	-0.005	-0.041	-0.113**
T+5	0.038	0.091*	0.055	0.001	-0.088**	-0.123***
201 Rule Interactions						
Drop × 201 (β_2) interaction	0.039	-0.019	-0.047	0.217***	0.089**	0.041
T-5 interaction	-0.097*	0.024	-0.061	-0.031	-0.067	-0.075
T-4 interaction	-0.098	0.039	-0.047	-0.038	-0.087*	-0.097*
T-3 interaction	-0.025	0.025	-0.047	-0.066	-0.114*	-0.106*
T-2 interaction	-0.060	0.033	-0.043	-0.074	-0.048	-0.068
T-1 interaction	-0.021	0.036	-0.056	-0.054	-0.035	-0.075
Event Minute × 201 (η_0)	-0.017	-0.041	-0.094	-0.020	-0.019	-0.046
T+1 interaction	-0.065	-0.055	-0.072	-0.239***	-0.125**	-0.112*
T+2 interaction	-0.055	-0.089	-0.059	-0.144**	-0.141**	-0.136**
T+3 interaction	-0.032	-0.087	-0.051	-0.078	-0.121**	-0.086
T+4 interaction	-0.055	-0.056	-0.047	-0.029	-0.096*	-0.044
T+5 interaction	-0.041	-0.085	-0.049	-0.056	-0.055	-0.038
Observations	707,868	707,868	707,868	707,868	707,868	707,868
R-squared	0.012	0.026	0.024	0.024	0.046	0.029
# Events	1,908	1,908	1,908	1,908	1,908	1,908

Table A.7 - Price Impact

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the intra-minute volume weighted average price impact for asset i, $PI_{i,t}$. The price impact for the transaction at time $t' \in [t, t+1)$ is computed as $D_{t'}(m_{t'+\Delta} - m_{t'})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $m_{t'}$ is the prevailing midquote at time t', and $m_{t'+\Delta}$ the prevailing midquote at time $t+\Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible trades are available from the ITCH dataset. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

PRICE IMPACT	100ms	1min	5min
Drop (β_1)	0.057***	0.054***	0.005
T-5	0.040	0.019	0.151*
T-4	-0.059	0.017	0.347***
T-3	-0.082*	0.007	0.575***
T-2	-0.046	-0.033	0.342***
T-1	0.015	0.357***	0.315***
Event Minute (δ_0)	0.127**	0.522***	0.140**
T+1	0.051	-0.010	-0.149***
T+2	-0.033	0.038	0.099*
T+3	0.160***	0.135**	0.187***
T+4	0.088*	0.097*	0.116*
T+5	0.007	-0.027	-0.039
201 Rule Interactions			
Drop × 201 (β_2)	-0.187***	-0.033**	0.034**
T-5 interaction	-0.133*	-0.037	0.073
T-4 interaction	0.099	0.134*	0.054
T-3 interaction	0.046	-0.010	-0.163
T-2 interaction	-0.015	0.148*	-0.014
T-1 interaction	-0.076	-0.245***	-0.097
Event Minute × 201 (η_0)	-0.251***	-0.017	-0.033
T+1 interaction	0.148**	0.027	-0.048
T+2 interaction	0.213***	0.051	-0.007
T+3 interaction	0.043	0.013	-0.142
T+4 interaction	0.040	-0.020	-0.027
T+5 interaction	0.090	0.057	0.049
Observations	287,593	287,593	287,593
R-squared	0.088	0.082	0.028
# Events	1,908	1,908	1,908

Table A.8 - Algorithmic Activity

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are $Messages_{i,t}$ $PC100_{i,t}$ and $T2O_{i,t}$. $Messages_{i,t}$ is the number of messages for asset i during minute t including posting, cancelling, and execution of visible limit orders on the corresponding side of the order book (bid and ask). $PC100_{i,t}$ is number of limit orders that are posted and subsequently cancelled within 100ms for asset i during minute t. $T2O_{i,t}$ is the trade-to-order ratio computed as the number of executed visible limit orders as a percentage of messages for asset i during minute t. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

ALGORITHM ACTIVITY	Messages (Bid)	Messages (Ask)	PC100 (Bid)	PC100 (Ask)	T2O (Bid)	T2O (Ask)
Drop (β_1)	0.100***	0.007	0.075***	0.010	-0.829***	0.535***
T-5	0.151***	0.242***	0.106**	0.083**	0.176	-0.464*
T-4	0.025	0.103**	0.014	0.015	0.876	-0.608**
T-3	0.067*	0.202***	0.010	0.050	1.383**	-1.074***
T-2	0.145***	0.252***	0.088*	0.132***	0.488	-0.424*
T-1	0.276***	0.392***	0.139***	0.256***	1.346**	-0.043
Event Minute (δ_0)	0.374***	0.589***	0.200***	0.291***	0.418	-0.798***
T+1	1.670***	1.908***	1.066***	1.460***	6.873***	0.517*
T+2	0.510***	0.641***	0.392***	0.331***	0.055	-0.342
T+3	0.249***	0.359***	0.182***	0.195***	0.338	-0.290
T+4	0.218***	0.271***	0.242***	0.154***	-0.410	0.457
T+5	0.091**	0.143***	0.058	-0.004	-0.500	0.306
201 Rule Interactions						
Drop × 201 (β_2)	-0.208***	-0.105***	-0.192***	-0.131***	-0.058	0.321**
T-5 interaction	-0.121**	-0.164***	-0.137**	-0.048	0.166	0.608
T-4 interaction	0.043	0.056	-0.001	0.034	-0.188	0.100
T-3 interaction	0.005	-0.008	0.008	0.019	-0.376	0.893***
T-2 interaction	-0.056	-0.047	-0.089	-0.043	0.690	-0.276
T-1 interaction	-0.070	-0.107	-0.064	-0.150**	-0.663	-0.187
Event Minute × 201 (η_0)	-0.017	-0.108	-0.119*	-0.129*	0.106	0.053
T+1 interaction	0.060	0.067	0.192	0.074	-1.913*	-0.256
T+2 interaction	-0.089	-0.136*	-0.107	-0.059	-0.263	0.233
T+3 interaction	0.001	-0.079	-0.014	-0.005	-0.283	0.065
T+4 interaction	-0.015	-0.047	-0.112*	0.010	0.117	-0.710
T+5 interaction	0.049	0.010	0.026	0.129**	0.878	-0.688
Observations	707,868	707,868	707,868	707,868	529,803	545,467
R-squared	0.108	0.162	0.044	0.091	0.039	0.031
# Events	1,908	1,908	1,908	1,908	1,908	1,903

Table A.9 - Realized Spreads

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are the intra-minute volume weighted average realized spread $RS_{i,t}$. The realized spread for the transaction at time $t' \in [t, t+1)$ is computed as $D_{t'}(p_{t'} - m_{t'+\Delta})/m_{t'+\Delta}$, where $D_{t'}$ is the direction indicator for the trade at t' (+1 for an aggressive buy and -1 for a sale), $p_{t'}$ is the trade price and $m_{t'+\Delta}$ the prevailing midquote at time $t+\Delta$, where Δ is a pre-specified period of time. We consider three values for Δ, namely 100ms, 1 minute, and 5 minutes. Trade directions for visible trades are available from the ITCH dataset. All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

REALIZED SPREAD	100ms	1min	5min
Drop (β_1)	-0.013	-0.032**	0.008
T-5	0.014	-0.001	-0.158*
T-4	0.073	0.008	-0.392***
T-3	0.106*	-0.031	-0.641***
T-2	0.074	0.057	-0.339***
T-1	-0.001	-0.376***	-0.356***
Event Minute (δ_0)	-0.109*	-0.523***	-0.150**
T+1	0.146***	0.145***	0.239***
T+2	0.174***	0.039	-0.072
T+3	-0.021	-0.049	-0.145**
T+4	0.031	-0.009	-0.070
T+5	0.061	0.069	0.066
201 Rule Interactions			
Drop × 201 (β_2)	0.062**	-0.037**	-0.071***
T-5 interaction	0.104	0.033	-0.070
T-4 interaction	-0.099	-0.159*	-0.041
T-3 interaction	-0.116*	0.021	0.172
T-2 interaction	-0.001	-0.167*	-0.012
T-1 interaction	0.052	0.252***	0.114
Event Minute × 201 (η_0)	0.241***	-0.058	0.035
T+1 interaction	-0.110*	-0.020	0.054
T+2 interaction	-0.085	0.007	0.050
T+3 interaction	-0.031	-0.016	0.134
T+4 interaction	-0.042	0.017	0.018
T+5 interaction	-0.082	-0.069	-0.067
Observations	287,593	287,593	287,593
R-squared	0.021	0.046	0.019
# Events	1,908	1,908	1,908

Table A.10 - Share Volumes

The table reports the coefficients from the estimation of the model described in equation 1. Our variables of interest ($Y_{i,t}$) are standardized transacted share volume provided by FINRA and TAQ classified into three groups $QuotingX_{i,t}$, $FINRA_{i,t}$ and $Inverted_{i,t}$. $QuotingX_{i,t}$ stands for the market share of total volume traded on the asset's quoting exchange (CRSP), obtained from the TAQ dataset for asset i in minute t as a percentage of total volume. $FINRA_{i,t}$ stands for the market share of total volume traded outside official exchanges as reported in the TAQ dataset under the FINRA moniker for asset i in minute t as a percentage of total volume. $Inverted_{i,t}$ stands for the market share of total volume traded on the markets with inverted fee structure. $AggB$ (Ask) reports the results considering only orders classified as aggressive buy orders (Buyer Initiated Transactions). $AggS$ (Bid) reports the results considering only aggressive sell orders (Seller Initiated Transactions) and $Total$ reports the results for the total number of transactions, regardless of their type. Orders are classified as aggressive buy and sell using Lee and Ready (1991). All variables are standardized by the in-sample mean and standard deviation for each asset-day. All models include standard errors clustered by treated-control matched pair. One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

MARKET SHARE	QuotingX AggS (Bid)	QuotingX AggB (Ask)	QuotingX Total	FINRA AggS (Bid)	FINRA AggB (Ask)	FINRA Total	Inverted AggS (Bid)	Inverted AggB (Ask)	Inverted Total
Drop (β_1)	0.009	-0.005	-0.008	-0.004	0.023**	0.033***	-0.004	0.006	0.001
T-5	-0.070**	0.001	-0.036	0.074**	0.032	0.075**	-0.031	-0.042	-0.083***
T-4	-0.033	-0.052*	-0.048	0.095***	0.065*	0.097**	-0.060*	-0.012	-0.064*
T-3	-0.053*	-0.020	-0.062*	0.111***	0.063*	0.114***	-0.025	-0.070***	-0.061*
T-2	-0.069**	-0.074**	-0.062*	0.065**	0.063*	0.073**	-0.033	-0.005	-0.038
T-1	-0.040	-0.013	-0.049	0.028	0.037	0.040	-0.055**	-0.007	-0.029
Event Minute (δ_0)	-0.073**	-0.061*	-0.100***	0.097***	0.118***	0.146***	-0.048	-0.066**	-0.040
T+1	0.025	0.220***	0.212***	-0.037	-0.118***	-0.136***	-0.114***	-0.037	-0.097***
T+2	0.018	-0.011	-0.008	0.040	0.107***	0.073*	-0.048	-0.062**	-0.051
T+3	-0.025	-0.028	-0.068**	0.073**	0.029	0.063*	-0.063**	-0.053**	-0.069**
T+4	-0.022	-0.037	-0.049	0.039	0.056*	0.066*	-0.056*	-0.034	-0.081***
T+5	-0.017	-0.029	-0.034	0.049	0.017	0.050	-0.046	-0.061**	-0.060*
201 Rule Interactions									
Drop × 201 (β_2)	-0.028**	-0.024*	-0.019	0.033***	0.079***	0.066***	-0.035***	0.025**	-0.004
T-5 interaction	0.021	-0.013	-0.014	0.030	0.005	0.024	0.010	0.034	0.049
T-4 interaction	0.004	0.098**	0.073	-0.064	-0.041	-0.060	0.004	0.031	0.031
T-3 interaction	0.044	-0.007	0.031	-0.076*	-0.021	-0.056	-0.029	0.052	0.011
T-2 interaction	0.030	0.056	0.014	0.007	0.006	0.034	0.006	-0.002	0.024
T-1 interaction	0.072*	-0.019	0.024	0.011	0.027	0.050	-0.010	-0.033	-0.052
Event Minute × 201 (η_0)	0.015	0.102**	0.109**	-0.024	-0.098**	-0.107**	-0.015	0.035	-0.012
T+1 interaction	0.162***	0.075	0.119**	-0.083*	-0.089**	-0.083*	0.022	-0.076*	-0.034
T+2 interaction	0.027	0.039	0.045	0.004	-0.081*	-0.034	-0.005	0.041	0.014
T+3 interaction	0.050	0.073	0.096*	0.003	-0.020	0.013	0.025	-0.008	-0.006
T+4 interaction	0.035	0.017	0.058	0.008	-0.053	-0.018	0.017	0.014	0.021
T+5 interaction	-0.007	0.097**	0.056	-0.015	-0.083*	-0.057	-0.025	0.035	-0.018
Observations	707,497	707,497	707,497	707,497	707,497	707,497	707,497	707,497	707,497
R-squared	0.002	0.012	0.008	0.002	0.012	0.009	0.003	0.008	0.007
# Events	1,907	1,907	1,907	1,907	1,907	1,907	1,907	1,907	1,907