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

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ABSTRACT

In this paper we provide a novel method for the evaluation of the Rule 201 (US short sale restrictions) 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, magnet effect, overpricing, price efficiency, price discovery

JEL Classification: G14, G18

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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 among 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]

During the COVID pandemic, many countries in Europe imposed short selling restrictions (Bessler and Vendrasco (2022)). In contrast to what was done in Europe, in the U.S. no additional short sale restrictions were implemented in response to the pandemic. Instead, the US relied 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[2]), 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 well-functioning of the market. Such exemptions were not novel and had been commonly included in the past, when banning short

[1] In most cases such short selling bans include exceptions related to market-making and essential basic trading strategies, such as hedging and derivative trading.

[2] If the price also suffers a 10% drop in the next 24 hours, the restrictions are extended another 24 hours.

sales.[3]

The current paper provides an in-depth analysis of the immediate impact of the Rule 201 restrictions, both over the remainder of the day the Rule is implemented, and locally, around the time of the implementation. The analysis covers a broad set of variables to help identify the channel through which these restrictions operate. The objective is to provide additional insights to help understand the regulation, identify potential dimensions for improvement, and determine the potential value of this type of regulation for other markets.[4]

Our analysis covers a 2-year period (2016 and 2017) during which the US experiences a growing stock market and low overall uncertainty (VIX). What we find is that on the day of the price drop, the Rule 201 is effective in reducing selling pressure and slowing down price drops. Novel insights are that these effects are accompanied by increased liquidity and reduced informed trading, specially from trades with very short-term or no informational advantages. We also find changes in trading strategies that become more passive and/or reroute orders to dark venues. These results suggest that short sale regulation of this type is positive for the market, at least during the period of initial implementation.

A second and novel part of our analysis is the study of the local effects at the time of the introduction of the regulation. To identify the local effects we introduce a novel methodological tool in this literature, the concept of a pseudo-trigger for the control sample. This pseudo-trigger represents an event for the control sample equivalent to the event that triggers the application of the Rule 201 for the treated sample. Having this equivalent event for the control group provides a new way to estimate the hypothetical local effects in the

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

[4] EU Regulation No 236/2012 of the European Parliament and of the Council of 14 March 2012 allow similar rules in the EU but we have failed to find any country that implements them.

absence of the regulation. This method estimates local effects using contemporaneous data and serves as an alternative to using pre-regulation data (as in Hautsch and Horvath (2019) in the context of trade halts). The pseudo-trigger event in our study is a 9% price drop relative to the previous day's closing price. The objective is to evaluate the triggering mechanism in the Rule 201 regulation, and in particular, see if there are significant local effects associated with the triggering mechanism. Such effects are usually referred to as "magnet effects" in the literature. Our analysis shows that, during the minutes surrounding the event that triggers Rule 201 short-sale restrictions–a 10% price drop relative to the previous day's closing price–many microstructure variables differ significantly from their average levels. However, these differences are not due to a magnet effect of the regulation. In the control group, we observe the same significant differences in the variables surrounding the pseudo-event. Furthermore, we also find these significant differences in a separate sample which we construct as a placebo test for our analysis.

2 Related Literature and the Theory on Short-sale Restrictions

2.1 Related Literature

This paper contributes to the empirical literature on short-sale regulation, and the implementation of regulation using endogenous triggering rules. Empirical research of short-sale regulation centers primarily on three types of regulation: (i) The former US regulation on short sale restrictions (the uptick rule) and the associated short sale pilot program implemented to evaluate its effects (May 2, 2005 to August 6, 2007); (ii) the implementation and/or removal of nationwide bans on short sales, affecting either all stocks or a significant portion of traded stocks, in response to financial crises; and (3) the literature on the current US regulation, Rule 201, introduced in 2011 and still in effect today.

The results obtained in the first two groups of papers generally identify negative or insignificant effects of short-sale regulations, although there is some variation in the findings. The results from the majority of studies in the first group (studying the uptick rule and the associated short sale pilot) suggest that the removal of the uptick rule had modest effects on market quality and short-selling activity, with potentially more pronounced impacts on smaller stocks (see, Alexander and Peterson (2008), Diether et al. (2009), Grullon et al. (2015) or Fang et al. (2016)). Regulators reached a similar conclusion in the sense that following the conclusion of the pilot, effective July 3 2007, the restrictions on short sales imposed by the uptick rule were removed.

The recent set of papers on the implementation and/or removal of nationwide bans on short sales focuses on the ones surrounding the 2008 financial crisis. In the United States, the SEC implemented emergency measures, including a prohibition on short sales of financial stocks, and similar measures were implemented in many countries. Research on these restrictions yielded mixed results. Boulton and Braga-Alves (2010) observed stock overpricing at the announcement of the ban, followed by a significant price decline upon its expiration. Boehmer et al. (2013) found no significant effect on asset prices but noted substantial market quality degradation. In a broader context, Beber and Pagano (2013) examined similar bans across 30 countries, concluding that while these restrictions did not affect price levels, they increased volatility and slowed price discovery. Marsh and Payne (2012) looked at the UK ban on short sales for financial stocks, and found that it led to a deterioration in liquidity and market quality.

Overall, evidence from these papers suggests that short-sale bans generally resulted in poor market quality, decreased liquidity, and slower price discovery, while having limited or no positive impact on stock prices, except for the improvement in trade informativeness found in Kolasinski et al. (2013).

The third group of papers, the ones studying the Rule 201 restrictions and where the current paper belongs, can be separated into two blocks. The group consists of four key papers: Jain et al. (2012), Davis et al. (2017), Switzer and Yue (2019), and Barardehi et al. (2024).[5] The first block are the first three papers in this list and they identify no or negative effects of the regulation. 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 a 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. The latter two papers also do not go beyond 2012 in their analysis. Davis et al. (2017) focuses on price efficiency and conclude that it declines with the restrictions, as evidenced by an increase in price clustering, while Switzer and Yue (2019) document no effect on the main metrics of market quality. The key characteristic of these papers is that they exploit variation of the same stocks before vs after the creation of Rule 201, and the sample periods used are

[5] Nathan Halmrast's unpublished first chapter of his thesis, Halmrast (2015), also covers the regulation and provides similar results.

centered around February 2011. This was a period of significant uncertainty and volatility (following the 2008 US financial crisis and leading to, and including, the sovereign debt crisis in Europe). They also include significant heterogeneity in the stock-days under study in terms of the magnitude of the price drop–some stocks experiencing price drops exceeding 20% in one day. This complicates the identification of the causal effect of the regulation because, in general, the magnitude of the price drop has important consequences on key microstructure variables, such as volume, short-sales, returns, and return volatility which may be confounding the causal effect of the regulation. None of these three papers control for the magnitude of the price drop.

The second block includes only the most recent paper, Barardehi et al. (2024), and the current paper (and the original thesis Florindo (2021)). We share the concern for causal identification and the importance of the magnitude of the price drop. As those in the first block, Barardehi et al. (2024) uses data close to the implementation but with a longer sample period, from March 2011 to March 2013. In contrast with the papers in the first block, they include only stocks with similar price drops both as treated and control stocks (between 8% and 12%, plus/minus 2% around the threshold of 10% used to trigger the Rule 201 short-sale restrictions). They find the opposite effect, namely that the regulation is effective in reducing overall short-sale volume and reducing price declines, and that the effect on prices is not reversed after the removal of the restrictions.

Our study contributes to this literature in a number of ways, with a focus on the time immediately surrounding the event triggering the regulation. First, as in Barardehi et al. (2024) we find that the regulation is effective but using a different sample: we use a later period (2016-2017) with a growing stock market and much lower global uncertainty (measured using the VIX index).[6] Second, it expands the analysis to cover a broader and more detailed set of microstructure variables. This allow us to obtain additional insights on the channel through which the regulation operates. Thirdly, we incorporate the time surrounding the trigger event, that in Barardehi et al. (2024) is excluded from both the treated and control samples (Figure 7), and extend the methodology in a novel way to identify the causal effect of the mechanism triggering the implementation of the regulation.

The methodology we introduce applies more broadly, to the literature that studies endogenously triggered events which includes not just the Rule 201 restrictions but also other regulation such as circuit breakers and volatility stops (Madhavan (1992), Abad and Pascual (2007), Hsieh et al. (2009), and Hautsch and Horvath (2019)). These papers study the price dynamics around restrictions (usually trading halts) triggered by endogenous market events. As controls they use similar days (Abad and Pascual (2007)), or, when available, the same event prior to the introduction of the regulation (Hautsch and Horvath (2019)). We create a pseudo-trigger event that (at least in our sample) can act as an intraday event to act as control, and separate the local dynamics from the one generated by the regulation. By defining a pseudo-trigger event for the control group we are able to identify an event that matches the event triggering the regulation. This gives us a hypothetical event when the regulation is not introduced that we use to apply the diff-in-diff methodology using contemporaneous shocks, instead of relying on historical ones, as in Jain et al. (2012). Using contemporaneous events has the advantage that the time effects are subject to the same shocks happening that day,

[6] Comparing the distribution of the monthly VIX, the first and nine deciles (10% and 90% respectively) of the distribution for the monthly VIX between 02-2011 and 03-2013 are 14.3 and 30.0 respectively, while in our sample the corresponding VIX levels are 10.3 and 15.7. In addition, during our sample period, equity trading is to a large extent automated and Rule 201 has been fully integrated into trading as it have been in effect for over five years.

and are not biased by systematic unobservable differences in the sample periods. To avoid introducing a new bias from using a different threshold we use the placebo methodology to identify possible differences arising from the differences in the thresholds. In the placebo we compare changes for a (placebo) control sample surrounding an 8% pseudo-triggering event, with a (placebo) treated sample surrounding a 9% pseudo-triggering event. The results from the placebo diff-in-diff analysis finds the same systematic effects on the microstructure variables around the trigger events as in the original analysis, while it finds no significant differences between the placebo treated and control samples. This is significant evidence in favor of the validity of our approach. The effects that we find for the main analysisfind minimal differences due to the regulation. This is evidence of the absence of a significant magnet effect, and serves as a cautionary warning for the interpretation of simply looking at the differences before and after the event that do not include a control event. This is because the rules are implemented at times of significant market turbulence which will confound inferences from the analysis.

2.2 Short Selling Theories

From the theoretical point of view, the literature identifies four types of motivations behind short selling, each of which generate slightly different predictions on the effect of a ban on short sales. First, we find short selling behavior of the kind that makes headlines at times of financial crisis. We refer to short selling by traders running bear-raids and predatory trading strategies, Brunnermeier and Oehmke (2013). This kind of behavior is considered toxic and generates political pressure for short term bans like the ones observed after the

2008 crisis. These usually take the form of blanket bans on short trading, and the objective is to limit the negative and value-irrelevant price pressure from these strategies, improving market conditions and reducing the frequency of large negative price drops.

The second motivation for selling a stock short is to exploit information not (yet) reflected in prices. Traders that have negative information about a stock and want to profit from this information want to sell the stock. If they do not own the stock, they will sell the stock short, if possible. In this case, the effect of a short sale ban would be to limit the incorporation of negative information on the underlying asset into the stock price. This then reduces price informativeness, price efficiency, and generates overpricing (Miller (1977), Diamond and Verrecchia (1987), Boehmer and Wu (2012)), and future large price drops (Hong and Stein, 2003).

The third type of short-selling is as part of a more general market-making strategy with the aim of providing liquidity. A short selling ban would limit the ability of market-makers to manage their inventories (Beber et al., 2020) and provide liquidity in option markets (Battalio and Schultz, 2011). The result is lower market liquidity.

Finally, there is a fourth dimension to short-selling, which is the short-selling of regular traders that want to obtain liquidity in the presence of differences of opinion. Pessimistic traders and those with a short-term liquidity need may use short selling as a way to obtain liquidity (Diamond and Verrecchia (1987); Boehme et al. (2006)). Banning these trades reduces the volume coming from the more pessimistic traders, increasing frictions and reducing liquidity.

Because the Rule 201 ban is not an outright ban on all short sales, we build on the insights in Comerton-Forde et al. (2016), which provides a more nuanced analysis of short sales taking into account trader heterogeneity. Their analysis separates passive (buyer-initiated) short sales from aggressive (seller-initiated) short sales in a Glosten and Milgrom (1985) model. The most relevant insight for the analysis of the Rule 201 restrictions is that passive short sales are contrarian while aggressive short sales follow price declines. In terms of the specifics of the 201 Regulation, which we will see below, the predictions we obtain from Comerton-Forde et al. (2016), are that the regulation will not affect market makers. This contrasts with some of the predictions in the literature, as in Boehmer et al. (2008) for example. It also implies that the ban should essentially only affect aggressive short sellers, whether informationally motivated, toxic trading, or motivated by liquidity needs.

A final theoretical issue to consider is that, in general, trading restrictions of any kind tend to generate trade-reducing frictions. However, in the case of short-selling restrictions, these frictions could have a net positive side effect if they have a disproportionate effect on toxic trading strategies that are imposing unnecessary intermediation costs. By toxic trades we refer to those that execute aggressively 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. (2022)) and predatory trades (as in Brunnermeier and Oehmke (2013). A more detailed view of the channels through which the regulation operates will help evaluate whether the net effect of the friction is positive or negative from the regulator's perspective.

3 Institutional Setting

The Rule 201 shortsale 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.[7]

Once the security's price crosses the threshold, short sale restrictions come into effect. In particular, 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.[8]

The Rule 201 restrictions represent an innovation because the trigger condition is endogenously determined by the market price crossing the 10% threshold. 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.

4 Data & Methodology

4.1 Data

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, and we keep only those stock-events that are not preceded by another event on the same stock in the previous

[7] 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.

[8] Division of Trading and Markets: Responses to Frequently Asked Questions Concerning Rule 201 of Regulation SHO. Accessed: Sep 28, 2017.

24 hours.[9] Our period of study covers observations from January 2016 until December, 2017. 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).[10] 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 also drop stocks whose identifying information does not allow a merge with both CRSP and Daily TAQ.

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. The intraday TAQ data is the most comprehensive in terms of trade coverage, and we focus on data during the regular trading day while excluding the minutes closest to the daily open and close (from 9:40AM–3:50PM EST). Each transaction is timestamped at the millisecond and matched to the prevailing mid-point. TAQ transactions are classified into buyer-initiated (Aggressive Buys, AggB) or seller-initiated (Aggressive Sells, AggS) using the Lee-Ready (1991) algorithm.[11] Individual transaction level information for short sales is obtained from the main four data centers: FINRA monthly files (Nasdaq TRF, New York TRF, and the ADF files), NASDAQ group,

[9]https://www.phlx.com . In addition, we verify the time of the implementation by looking at the number of non-exempt aggressive short sales to avoid false or delayed implementation of the restrictions. We find that the rule is implemented as recorded, with some variation within the minute of implementation. This minute should be considered a time interval containing periods with and without the restrictions being in effect.

[10]We exclude ETFs, ADRs, Certificates, companies incorporated outside the US, closed-end funds, and REITs.

[11]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).

NYSE-ICE group, and BATS group. FINRA and BATS short sale information is posted on their websites, 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.[12] More detailed variables (depth, messages, etc) are constructed using the Total-View-ITCH. Some of our variables are constructed using only NASDAQ data to ensure the reliability of trade direction.

4.2 Methodology

Methodologically, we control for heterogeneity in the magnitude of the price drop by selecting stock-events price drops of a magnitude similar to the cutoff price drop of 10%. This ensures that the shocks suffered by the stocks in our sample are inherently similar, except for the implementation of the Rule 201 restrictions. Thus, the selected control stocks serve as valid counterfactuals for what would have happened to the treated stocks on that day. We further control for observed heterogeneity by pairwise distance matching, and for local effects by constructing a pseudo-trigger for the control group.

Our approach uses recent data and we substitute the pre-regulation period with data from same day (matched) assets that experience similar price drops but did not trigger the restrictions as controls. Barardehi et al. (2024) follow a similar approach although they include all assets that experience a similar price drop on the same day as control group. They adjust for observed heterogeneity linearly, by introducing control variables in the regression.

Matching Price Drop: 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

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

day's close ("*the event*"). So the choice of a reference group to serve as counterfactual, as well as the choice of control variables, is very challenging but necessary. 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.

Selecting stock-days in this way naturally generates a selection bias. As is well-known in the literature, the selection procedure ensures that treated and control stock-days are very similar, but it also selects a sample that is not representative of the population as a whole. It prioritizes causal identification over estimation of the effect on the population.

Our sample of stock-days has the following properties: First, it excludes stocks with relatively stable prices. These do not enter our sample as they very rarely (if at all) experience the significant one day price declines required to be selected into the sample. Second, the size of the shock that stocks in our sample are exposed to is also limited, as we do not include stock-days with price drops greater than 11%.

Matching Event: One of the contributions of our analysis is the analysis of the circumstances immediately surrounding the implementation of the restrictions. These restrictions are implemented when the stocks price drop reaches a fixed 10% level. Control stocks never reach this level, hence we needed to identify an event that is similar to hitting the fixed 10% barrier, for the control group. We construct this event reasoning by analogy, and verify its validity empirically. The analogy is based on the sampling criterion. The sampling criterion for the treated group is based on two barriers: the stock's return on the day has to hit the 10% barrier but not reach the 11% barrier. Similarly, the treated group is selected using two barriers: the stock's return on the day has to hit the 9% barrier but not reach the 10% barrier. For the control group, the triggering event is a price drop that is (10%) 1% below the minimum price drop for the day (11%). For the treated group we define the analogous event, which we refer to as the pseudo-trigger: the price drop is (9%) 1% below the minimum price drop for the day (10%). The implied assumption is that absent the Rule 201 trading restrictions both the treated and control groups would experience similar market behavior both in the run up to the triggering event and, more broadly, for the remainder of the trading day. We check this assumption empirically, as described in Section 7). Furthermore, these test also validate the similarity across shocks within the selected sample stock-days.

Matching Assets: We control on observables in a flexible way by matching treated and control asset-days along other dimensions of relevance for the stock's market behavior during the day of interest. We have already selected treated and control candidates that experience similar price drops on the same day. We further strengthen the match by imposing exact matching on the same time of day for the triggering event, and on the stock's type (same share code).[13] We further require that the event and the control stock in each matched pair are classified in the same industrial group to account for potential unobservable sector-wide changes in the informational set.[14] To avoid confounding effects from other regulatory events

[13]We match assets with share code 11 – see footnote 10). 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.

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

we exclude stock-days at which a volatility (LULD) halt is triggered.[15]

We also match treated and controls using standard dimensions of relevance for microstucture studies (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).

The Matched Sample: 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.[16] 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. As our analysis is focused on the immediate impact of the regulation we limit the horizon of our analysis to intraday market variables during the remainder of the trading day, while

[15] We keep assets in the Tick Pilot group but they only represent 5.5% of our sample. The Tick Pilot was implemented for a subset of small cap stocks from September 2016 to September 2018, and increased the tick size from 1 to 5 cents. The effects are studied in a number of papers, see Penalva and Tapia (2021).

[16] 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.

markets are open. A detailed analysis of the closing auction, overnight trading, next day trading, and trading after the Rule 201 restrictions are lifted are beyond the scope of this paper. Barardehi et al. (2024) study of the overall effectiveness of Rule 201 restrictions.

Econometric Estimation: Our analysis estimates differences-in-differences in a joint panel OLS estimation with standard errors clustered by time-of-day and treated-control matched pair.[17] The implementation of the diff-in-diff analysis is based on two dummy variables (and their interaction): *Rule201* which identifies treated (=1) and control (=0) stock-days, and *Drop* which identifies the period before (=0) and after (=1) the implementation of the Rule 201 restrictions. The variable *Drop* for the control group is based on the pseudo-trigger event described earlier (the first time the stock price hits 9%). The interaction of these two dummies captures the average causal effect of the regulation on our sample stock-days.

Local Effects: We separate the circumstances surrounding the substantial price drop that is the triggering event from the broader 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).[18] Our choice of time window for the event allows us to compare the actual trigger event and the pseudo-trigger. Additionally, in the placebo analysis, it allows us to identify market conditions around significant price declines for asset groups unaffected by short sale restrictions. Across all samples, the differences we observe are minor. However,

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

[18]The motivation to analyze separately the local, event specific, changes and the broader 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

market conditions around the event display significant changes in microstructure variables both statistically and economically (refer to Figure 1 and Section 6 for further details). We estimate the local effects in the same regression with the average post implementation effects to provide a consistent estimation of the dynamic effects of the implementation of the restrictions. Including the local effect estimation with the average effect estimation provides a better estimate of the coefficients of the control variables, specially the fixed effects that control for the magnitude of price movements, reducing confounding around the time of the implementation. It also provides a consistent separation of the local and average effects of the implementation of the restrictions.

Controls for Large Price Movements: 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: $(-\infty, -10\%]$, $(-10, -9\%]$, …, $(9, 10\%]$, $(10\%, \infty)$. The resulting dummies allow us to control for unusual trading conditions arising from large price moves that are not associated with the application of Rule 201, and which have been associated with unusual volume and isolated toxic order flows (see Easley et al. (2012)).[19] Naturally, these dummies are not included when the return variable appears on the LHS.

Regression Equation: The main specification of the panel data regression we run also

[19]These "return fixed effects" remove differences that may arise if differences in the distribution of shocks introduces biases in the estimation. The results are robust to excluding these controls.

includes time-of-day fixed effects every half-hour, and is described by the following equation:

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

where $Y_{i,t}$ denotes the variable of interest for asset-date i in minute t. We analyze a number of microstructure related variables defined in detail in section A of the Appendix. Our main parameters of interest are β_1 and β_2. The parameter β_1 captures the baseline effect on 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 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, modeled 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.

Outliers: 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 to 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.[20] Variables like returns and market share, that are naturally comparable across assets, are not standardized.

5 Rule 201 Restrictions: Effectiveness and Mechanism

In this section we present the results of the effects of the Rule 201 restrictions on the main market variables for the rest of the day after their implementation. The results are presented in the following sequence: First, we look at the effectiveness of the restrictions by looking at their direct impact on short sales, volume, and price pressure. After establishing the significance of the restrictions, the second step is to test the validity of different theories by examining their predicted impact on key market microstructure variables. This allows us to identify the channels through which the net effect of the restrictions have a greater impact on trading behavior and market quality. In a third step, we look at additional variables that complement the analysis and are of interest to regulators at the end of the Section. Additional details and variables are included in the Internet Appendix. Summary statistics for the main variables used in the analysis, as well as a summary of the economic significance of the results are included in the Internet Appendix.

5.1 Are the Restrictions Effective?

We start by looking at short selling activity during the remainder of the day directly (Table 2). We find that Rule 201 negatively affects both aggressive and passive (non-exempt)

[20]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.

short sales. On the other hand, exempt short sales increase but not enough to compensate the effect on exempt short sales.

The reduction in short sales is accompanied by lower volume (Table 2), and in particular, aggressive sell volume, thereby reducing downward pressure on prices. We also document that for the assets in our sample this phenomenon would have happened in the absence of the 201 Rule as well: aggressive buys increase significantly and aggressive sales decrease (though not significantly) for all the assets in our sample. However, our design identifies the differential effect of the regulation: the Rule 201 has an additional impact on volume traded, reducing volume on both sides, but primarily by reducing aggressive sales: Rule 201 increases the reduction in aggressive sales by an order of magnitude (from $\beta_1 = -0.016$ to $\beta_1 + \beta_2 = -0.016 - 0.094 = -0.11$ see Table 2), and reduces the increase in buying pressure from aggressive buys by half.

On Table 2, we look at whether this reduction in price pressure translates into greater returns (bigger price rebound). As expected, the price of the assets in our sample recover partially after the event, consistently with the evidence in Florindo (2021), Jain et al. (2012), and Barardehi et al. (2024). We find that this rebound lasts for the remainder of the trading day and is greater in the treated group.

Combining these results, we find that Rule 201 is effective in reducing sellers' price pressure during the remainder of the day, which leads to a slowdown in the stock price decline. Despite the rule's narrow scope–it only bans short sales at or below the best bid–and its various exemptions, the restrictions have a significant effect on short-selling, downward price pressure on prices, and returns on the day of implementation.

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5.2 The Effect on Trading Strategies and Market Quality: Testing the Theoretical Models

Beyond its effectiveness in reducing price pressure, we are interested in how the restrictions affect trading and market quality. We appeal to existing theories, that differ on the motivation behind the trades that are affected by the restrictions, and how the market reacts to the reduced presence of such trades.

The model in Comerton-Forde et al. (2016) argues that market makers use short-sales only passively and primarily after price increases that leave them without an inventory in the affected stocks. In principle, Rule 201 will not affect market-makers directly as passive sales on the ask side are unaffected. Furthermore, because the Rule 201 is triggered after a significant price decline, market makers providing liquidity will have accumulated a long position in the stock and will no longer have a need to short-sell, even if they wanted to sell aggressively.

To confirm that market making activities are not affected we look at measures of market-making activity, depth and spreads, in Table 3, where we find an improvement in both. Quoted and effective spreads decrease, while the effect on depth measures is significant on the Ask side. In particular, the decrease in depth at the best offer (Ask) and at five cents from the best (Ask + 5c) is reversed in the treated group. On the Bid side we find no difference between treated and controls. Thus, we find that overall market-making activity increases, improving liquidity. Furthermore, these results are inconsistent with the models that argue that short-selling restrictions will have a significant effect on short sales from uninformed liquidity demanding traders (Diamond and Verrecchia (1987); Boehme et al.

(2006)). A significant reduction in uninformed liquidity demanding trades would reduce the amount of uninformed trading, increasing the expected cost of market-making, and leading to the opposite effect: higher spreads and less depth.

This leaves two types of theories as possible explanations: those that look at informed short sales (Comerton-Forde et al. (2016), Diamond and Verrecchia (1987)), and those that look at toxic (Brunnermeier and Oehmke (2013), Foucault et al. (2017)) traders as candidates for affected trades. Lower trading from these participants reduces the cost of market-making, and is consistent with the observed results.

A key difference between toxic short-sellers and informed ones is the informational content of their trades. Hong and Stein (2003) points out that removing informed traders via a short sale ban does not invalidate the information driving these trades, just delays the incorporation of the information into prices, and leads to substantial future price drops. As a possible way to capture this 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). As the short sale restrictions do not apply outside of regular trading hours, overnight traders can build short positions.[21] 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). This

[21] As the NBBO is disseminated only during regular trading hours (https://www.finra.org/investors/insights/extended-hours-trading), the short-selling restriction cannot be implemented.

evidence supports the hypothesis that the Rule 201 has a significant effect on informed short sales.

Traditional measures of price informativeness (price impact, Amihud, autocorrelation, and variance ratios) provide mixed results. The impact of Rule 201 on price informativeness varies depending on the estimation method and time horizon. In Table 3 we find a reduction in the price impact component in effective spreads at the shortest, 100ms and 1min, horizons, and an increase at the longest, 5min, horizon. In Table 4 we look at two other measures related to the information content in prices (Goyenko et al. (2009)): the autocorrelation of 1 minute returns and the Amihud illiquidity ratio. We find no significant increase in the former and a decrease in the latter (statistically significant when measured over 1 min intervals). We also consider variance ratios in Table 4, and find lower Variance Ratios (at 5 and 10 minutes) which are associated with an improvement in price efficiency. These results suggest that the 201 Rule favors traders with longer lived informational advantages (beyond 5 minutes), to the detriment of traders with shorter lived informational advantages (less than one minute) and moves some informed trades outside regular trading hours.

Thus, what we find is that a net effect of the Rule 201 restrictions is to delay the incorporation of information into prices, reducing informed trading (as put forth in Comerton-Forde et al. (2016), Diamond and Verrecchia (1987)). But, the impact is greater on toxic trades, whether they have a very short lived informational advantage (Foucault et al. (2017)), or none at all (Brunnermeier and Oehmke (2013)), than on longer lived informational trades. Our evidence on overall price efficiency is mixed, with improvements in the long-term variance ratio accompanied by greater overnight price drops.

We look for further evidence along these lines by looking at measures of HFT activity, as these trades are (at least in part) associated with toxic order flow in a number of theoretical and empirical studies (Cartea et al. (2019), Aquilina et al. (2022), or Brogaard et al. (2017)). Consistently with our interpretation of the effects on informational trades, we find, in Table 3, that measures of algorithmic activity decline once the ban is active.

5.3 Further Supporting Evidence and Results

The evidence suggests that the impact of the Rule 201 restrictions is consistent with a significant decline in informed trading, which is stronger on toxic trades with shorter lived or no informational content, including trades from HFTs. We hypothesize that patient traders with long-lived informational advantages may be less affected because they can continue to sell short using less aggressive orders. We propose two reasons for this. One, the restrictions do not apply to (passive) short sales at prices above the bid. Two, investors acting on long-lived information will be sufficiently sophisticated to employ alternative non-short contrarian strategies, for example using derivatives or pairs trading (as proposed in Kolasinski et al. (2013)).

To evaluate the first channel we look at the gains for passive trading in terms of realized spreads, in Table 5, where the results are consistent with our hypothesis. We find an increase in realized spreads at short horizons, consistent with a decline in short-lived informational and toxic trades. On the other hand, at longer horizons realized spreads decline.

Another effect of traders switching from aggressive to passive short sales is lower volume, as passive short selling eliminates the need for additional intermediation trades from market makers (see Cartea and Penalva (2012)). We find lower volume, Table 2. As this is also consistent with increased trading frictions and costs from the restrictions, we also look at depth, in Table 3. Consistent with the shift to passive trading, we find more depth at the ask.

In terms of the second channel, most of these assets do not have liquid derivatives, so we look for evidence of changes in equity execution strategies. Comerton-Forde et al. (2019) propose that short sellers may consider rebate chasing in response to the 201 Rule restrictions. To test this we look for evidence of changes in routing strategies in the market shares of different trading venues on Table 5, where we separate venues into the asset's primary exchange ("QuotingX") and lit pools with inverted fee schedules ("Inverted").[22] We do not find support for re-routing to inverted fee venues, as there is no significant differences between the changes in the market share of the quoting exchange and that of the inverted fee ones.[23]

We also look for changes in the transparency of trading strategies by looking at both hidden volume in organized exchanges, and shifts to off-exchange venues (such as those with mid-point execution). For trading off-exchange we use the total volume marked "FINRA" in the TAQ data.[24] Surprisingly, on-exchange transparency improves: we find a small but significant drop in hidden volume (Table 5). But, we do find a significant shift in the percentage of trades executed off-exchange (Table 5) as the market share of the quoting exchange falls while that of dark pools (FINRA) increases significantly. Surprisingly, on-exchange transparency improves: we find a small but significant drop in hidden volume. But,

[22]Inverted (taker-maker) exchanges are BATY, NASDAQ-BX, EDGE-A.

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

[24]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.

we do find a significant shift in the percentage of trades executed off-exchange (Table 5) as the market share of the quoting exchange falls (though not significantly) while that of dark pools (FINRA) increases significantly.

Finally we consider effects of the regulation on other dimensions of importance for regulators, namely volatility. The evidence we find is consistent with the effects we have found for liquidity: an improvement of market conditions associated with a reduction in informed and toxic trades.

In terms of volatility, fewer informational and toxic trades will lead to lower risks for passive orders, so we expect bid-ask prices to be less sensitive to market events, and less volatile. We find this when we look at intra-minute price variation in Table 5, and the standard deviation of 1 minute returns, Table 4. As we have documented a drop in volume, which is known to be associated with lower volatility (Jones et al. (1994) or Gallant et al. (1992)), we extend our baseline analysis with additional controls for volume changes, and the reduction in volatility persists.[25] In addition to the variables discussed, as a robustness check we include in the Internet Appendix additional variables that look at the same microstructure dimensions using different proxies and variables. Further robustness tests (changing the sample, sampling windows, ...) are available upon request.

In conclusion, we find that Rule 201 is effective in reducing selling pressure and slowing down price drops over the remaining trading day. We also find that this is accompanied by

[25]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 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.

increased liquidity and reduced informed trading, specially from trades with very short-term or no informational advantages. Furthermore, these results align with traders adopting more passive strategies or redirecting order flow to dark venues.

6 The Local Impact: Endogenous Triggers and the Magnet Effect

In this section we look at the dynamics of the main variables around the minutes immediately before and after the activation of the restrictions for the presence of a magnet effect. We start by looking at market quality and separate the local effects for the whole sample (treated and controls together, the δ parameters in Equation 1), from those specific to the Rule 201 restrictions (the η parameters), using our novel methodology that includes the pseudo-event for the control group. What we find is that there is a significant magnet effect but not due to the Rule 201 restrictions. The event with a magnet effect is the event as defined broadly, namely that the stock's price hits the upper price barrier that is used to determine the sampling window (8% for the controls, and 9% for the treated). Prices drop quickly up to and past the barrier and then experience a partial rebound. Additional effects are also observed in the key microstructure variables (volume, volatility, spreads, etc). Nevertheless, we find no evidence of a significant additional magnet or gravitational effect associated specifically with the triggering of the Rule 201 restrictions.

The analysis of local effects is included as tables in the Internet Appendix, where we summarize the overall effects of the Rule 201 restrictions discussed in the previous section

(Tables 2-5). The rows are those corresponding to the overall effects on the top of the tables (δ) and the those due to the restrictions (η). For example: "Event Minute (δ_0)" is the coefficient for the baseline effect for both treated and control stocks on the minute the event is triggered; while "Event Minute $\times$ 201 (η_0)" is the coefficient for the interaction term of the minute of the event with the treatment indicator.

The Internet Appendix includes these two rows plus the equivalent coefficients for each of the five minutes before and after the event (and we refer to these tables in brackets when we refer to the minutes surrounding the event minute). In the main text, and in order to assist the reader, we present the essential information graphically in Figure 1. Nevertheless, this figure contains a significant amount of information, some of which we will use only in the next section.

Figure 1 is divided into five subfigures, one for each of the key variables: the asset's return, volatility (intra-minute difference between the highest midprice and the lowest midprice normalized by the average of the two), quoted spread, and volume and short sales affected by the restrictions, namely volume on the bid side and non-exempt short sales on or below the bid price. In total, each subfigure includes 12 pairs of coefficients, separated by a dashed line. These coefficients displayed in this figure capture average effects in the variable of interest (without distinguishing treated and control, the β_1 and δ parameters) and not the interactions (β_2, η). We exclude these coefficients to avoid additional clutter. Nevertheless, visualizing them is relatively uninteresting as for the most part they are statistically insignificant.

The coefficients on Figure 1 are displayed in pairs as they correspond to two analysis. The coefficients in blue (on the left labeled *xt201*) correspond to the main analysis, and the other (in red on the right) correspond to the placebo analysis we discuss in the next section. Each subfigure splits the coefficients into two groups using a dashed line. The coefficients to the left of the dashed line are the baseline coefficients capturing the average effects for the remainder of the day. These coefficients are the baseline effects for the whole sample (β_1), without distinguishing between treated and control groups, which we have not discussed in previous sections where we focused exclusively on the relative differences between the treated and control groups.

The coefficients to the right of the dashed line describe the local effects we want to discuss in this section. In particular, we have the coefficients of the 11 (pairs of) δ_t dummies. Each δ_t coefficient corresponds to the dummy for each one of the minutes around and including the triggering event: five minutes before, the minute of the event, and five minutes after the event.

What we can see in the Figure 1 is that there are significant changes in market conditions surrounding the immediate triggering of the restrictions both for the Rule 201 stocks and the control group. Also, the peak effects are observed in the minute following the triggering event.

Firstly, Figure 1a illustrates how the triggering event occurs in the context of a significant local price drop. The effect of this event on returns does not last past the first minute after the price drop. In the following minutes, returns for all assets are close to zero but significantly positive, implying a partial price rebound. These local price dynamics suggest that prices around the trigger event are not purely random and include a certain degree of momentum for all groups, both negative before and positive after. This suggests a novel hypothesis, namely that there is a magnet effect. However this magnet effect is not due to the Rule 201 trigger as it is present for all the stock days in our sample, both treated and controls. The magnet effect we find is a magnet effect of the event as defined broadly for all the stock-days in our sample, namely that the stock's price hits the upper price barrier that is used to determine the sampling window (8% for the controls, and 9% for the treated).

Exploring this idea further along other dimensions, on Figure 1b we look at non-exempt short sales. What we find is that accompanying the price drop there is a gradual increase in short sales. These higher than average short sales do not disappear, but continue to be positive past the time when average returns have become positive.

We observe a pattern similar to the one observed in the affected short sales when looking at the measure of volume that is affected by the regulation directly (the one on the bid), and volatility in Figures 1c and 1d. Volume on the bid and volatility increase with the price drop. We find differences after the change in price dynamics. In the case of volume, after the peak price changes, volume returns to normal levels. On the other side, volatility drops but it does so gradually and by the end of our observation window (of five minutes) has not returned to normal levels.

Finally, quoted spreads, in Figure 1e, display a distinctly different dynamics. The level of the quoted spreads is higher than usual during the price drop, but this level does not change significantly during the price drop. However, following the price drop there is a shift, the level increases further and stays higher than during the price drop for the remainder of our observation window.

Overall, we find evidence of significant and meaningful changes in the key variables of interest once the price hits the triggers, the lower barrier defining the sampling window (9% for the control and 10% for the treated sample). But we find no evidence of a significant magnet effect for the Rule 201 restrictions. The price barrier defining the trigger defines a price that is close to the day's minimum for both treated and control stocks, and coincides with higher than usual price declines, short selling activity, volume, volatility, and quoted spreads. Beyond the immediate effects at the time of crossing the trigger price, we find subsequent (small) positive returns that are not accompanied by a reversal in the other variables. Volume, short sales, and volatility gradually return to normal levels. The reaction in volume is quicker than in short sales, and volatility is the slowest one. Quoted spreads on the other hand display a significantly different pattern. Not only do spreads not return to normal but they become wider, suggesting that the pressure on liquidity following the price decline leaves a significant negative impact on liquidity provision, both for treated and control stocks alike, that lasts the length of our observation window, but also for the remainder of the day. One thing we want to emphasize is that these price barrier do not define tradable events. We, as the econometrician, select the sample based on the whole day's price information and hence the price barrier, and the associated effects, are a feature of the sampling strategy used for identification. An important feature that we document for the sampling procedure of the identification strategy, and is distinct from the causal effect of the introduction of the regulation.

The causal effect of the restrictions is identified by the differential effect between treated and control stocks, captured by η_0, which we find is (mostly) insignificant.[26] This then implies that the magnitude of the effects surrounding the triggering event is not statistically

[26]The Internet Appendix includes all the interaction coefficients. There are a few significant coefficients, as one would expect from running such a large number of regressions and that many coefficients. The only effect we highlight is a slight slow down of exempt short sales in the run up to the trigger for the Rule 201 restrictions, which is partially offset 4-5 minutes afterwards (relative to the baseline average effect, which captures the significant drop for the remainder of the day when the restrictions are in place).

different for treated and control groups, hence not driven by the triggering of the Rule 201 restrictions.

7 The Identification Strategy

As outlined in the Methodology section, 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. In this section we first validate the sampling procedure. Then we look at the diff-in-diff method. The usual validation tests for diff-in-diff analysis can either be direct tests of the parallel trends assumption or use a placebo analysis. The first is difficult to implement with intraday data, as there is a natural discontinuity surrounding the regular trading day.[27] We use the second approach, a placebo test.

In terms of sampling, the key assumption used to select our sample is that the treatment and control assets are essentially identical, at least based on what information is available to us. Our sampling procedure achieves this matching each stock-day with the closest stock-day. The one-to-one matching ensures balance in the observed covariates. The matching on observables takes care of both the stock and the day, by matching on the general properties of the stock (the financial instrument), as well as on the circumstances of the stock on that day.

To control for the general characteristics of the stock, we have matched treatment and control stocks on the usual microstructure dimensions (market capitalization, volume, price, and quoted spread). The validity of the matching between stocks is standard in the empirical

[27] Florindo et al. (2019) includes a daily analysis with the same selection criteria. The parallel trends test on the daily data is satisfied in their sample.

microstructure papers. If anything, our matching procedure is more precise by including liquidity and trading activity (quoted spreads and volume), when most matchings are done using market capitalization, and industry (O'Hara et al., 2018).

The sampling criteria used to select the stock-days in the treatment and control samples is that the stock experiences a price drop of around 10% relative to the closing price the previous day. We argue that the difference between experiencing a price drop between 10 and 11% and drop between 9 and 10% are essentially random, and that the observed differences between treatment and control stocks is driven entirely by the Rule 201 restrictions. The previous analysis of the local effects already points to the insignificance of the local differences between the two groups surrounding the triggering event. To identify the local effects of the trigger, the 10% price drop, we have created a pseudo-trigger for the control group at the first time the stock price crosses the 9% price drop threshold. As we argued in the methodology section, we consider these two events as equivalent for our sampled stock-days, as they define thresholds relative to the maximum price drop used for inclusion in the treatment or control stock-day groups.

To address the validity of our arguments, we run the placebo analysis, comparing our pool of control stocks (those with a maximum price drop that is between 9 and 10%) to matched stocks on days with a maximum price drop that is between 8 and 9%. The first group we label as the P-treated, and the second group as the P-control group. We create the pseudo-trigger for the P-control group using the same logic as for the P-treated, that is, we use the moment the price enters the sampling window (8% price drop) for the first time as the pseudo-trigger of the P-control group. We then repeat the regressions we run in the main analysis comparing the P-treated with the P-control groups. The resulting comparison of coefficients provide strong evidence in favor of the validity of our identification assumptions as well as for the presence of a specific microstructure event for our sample assets at the time of the (pseudo) trigger.

We focus the presentation on the five key variables used to discuss the local effects, and compare the coefficients for the placebo and the main analysis on Figure 1. The results with all the coefficients and t-statistics are available upon request. Figure 1 includes the average post event coefficient (on the left of the dashed lines) and the local effects, to the right, in pairs. Each pair of coefficients is made up of the coefficient of the main analysis on the left (in blue) and the same coefficient in the placebo analysis on the right (in red).

Overall, in the placebo analysis we find significant local effects around the pseudo-trigger for both groups, and no significant differences between the P-treated and P-control groups. The local effects around the event replicate the ones in the main analysis we have described in the previous section: there are significant changes leading and including the price decline around the price barrier defining the trigger event. These changes are followed by a reversal in all variables but the quoted spread, and at different speeds. Changes in quoted spreads suggest a significant and persistent negative impact on liquidity for the remainder of the day. However, we find no statistically significant differences in the coefficients comparing the two groups, either in the main post-event coefficients, or in the local effects.

Therefore, the conclusion from the placebo analysis is that there is strong evidence that the research design identifies the causal effects we are interested in, an does so while separately identifying the effect of the large price drop from the effect of the Rule 201 restrictions. Furthermore, the sampling procedure identifies a significant microstructure event at the first time the selected assets' price crosses the price barrier used to define the lower bound of the sampling window. In the previous section we characterized these effects as a feature of the sampling procedure. We want to emphasize that there is no a priori theoretical or statistical reason why the first time the price of an asset crosses this threshold should be of particular significance, specially across the three different sample groups we have studied (P-controls, controls/P-treated, and treated groups). Although interesting, studying the phenomenon further goes beyond the scope of this paper, so having documented the phenomenon we leave its study for future research.

8 Conclusions

Between 2010 and 2011, the SEC moved beyond sweeping bans and generic restrictions, introducing Rule 201—a set of dynamic, market-driven, and precisely targeted short sale restrictions. In this paper, we deliver a novel and rigorous evaluation of Rule 201's short-term impact, by introducing a pseudo-event to match the event triggering the short sale restrictions. Leveraging a robust theoretical framework, two years of intraday data, and the novel identification strategy, we disentangle the immediate effects of Rule 201 from those of the significant price drops that trigger its activation. We also use a comprehensive set of market microstructure indicators that allow us to identify the channels through which the restrictions have the greatest impact on trading behavior and market quality.

We find that within our window of analysis the regulation achieves its objectives: liquidity improves 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, and price informativeness improves at longer (5-minute) horizons, possibly as a result of a change in the mix of informed trading. Furthermore, we find that 10% price drop that triggers the restrictions occurs under unusual market circumstances. However these circumstances are not caused by the regulation, as we also find them in both the control and placebo groups.

Our analysis is consistent with the regulation generating costs for short selling that are felt most strongly by toxic strategies. 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. Our evidence suggests that these traders either withdraw or significantly reduce their desired short positions. The second source of affected short selling appears to be strategies with very-short lived informational advantages. These are continuously present in markets, and are toxic in the sense described in Foucault et al. (2017). However, our evidence suggests that the restrictions remove them from the bid side of the book, lowering the overall cost of liquidity provision. In contrast, our analysis suggests that traders shorting the stock based on longer-lived information appear to be less affected and that their relative importance in price setting increases. Market making activity is unaffected in the sense that overall the net effect of the restrictions lead to improved liquidity. We conclude that in terms of immediate impact, the Rule 201 restrictions set a new standard for effective actions to deal with toxic short selling strategies for assets facing large price declines. A possible modification to consider is to replace the current uniform 10% cutoff by an asset's volatility dependent trigger.

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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 - Rule 201: Effectiveness

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, volume, and returns. Short-sale data for the ALL MARKETS analysis is provided by FINRA, CBOE, NYSE-ICE, and NASDAQ groups, and aggregated. All variables are standardized by the in-sample mean and standard deviation for each asset-day. * As returns are naturally comparable across assets, they are not standardized. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

Variable	Mean	St dev	Post Event (β_1)	Diff-in-Diff (β_2)	% change	Observations	R-squared
Passive NE SS	1.05	1.89	0.052***	-0.067***	-12.0%	707,868	0.017
Aggressive NE SS	1.96	2.49	0.028**	-0.264***	-33.6%	707,868	0.053
Non-Exempt SS	2.31	2.63	0.030***	-0.233***	-26.6%	707,868	0.048
Exempt SS	0.25	0.93	-0.018***	0.300***	112.8%	707,868	0.019
Short Sales (Total)	2.39	2.68	0.023*	-0.170***	-19.1%	707,868	0.051
Log Sell Volume (TAQ)	5.05	2.94	-0.016	-0.094***	-5.5%	707,497	0.080
Log Buy Volume (TAQ)	4.62	2.93	0.092***	-0.043**	-2.7%	707,497	0.051
Log Volume (Total, TAQ)	6.02	2.82	0.035**	-0.076***	-3.6%	707,497	0.079
Return (bps)*	-1.18	44.69	5.821***	0.734***	73 bps	707,868	0.009

Table 3 - Market Quality and Informativeness

The table reports the coefficients from the estimation of the model described in equation 1. All variables are standardized by the in-sample mean and standard deviation for each asset-day. * As trade-to-order ratios are naturally comparable across assets, they are not standardized. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

Variable	Mean	St dev	Post Event (β_1)	Diff-in-Diff (β_2)	% change	Observations	R-squared
Quoted Spread (bps)	140.80	86.99	0.148***	-0.114***	-7.0%	707,868	0.150
Effective Spread (bps)	4.43	3.05	0.035*	-0.157***	-10.8%	287,593	0.130
Depth (bid)	7.41	0.95	-0.059*	0.039	0.5%	707,868	0.012
Depth (L5, bid)	9.22	0.66	-0.180***	-0.019	-0.1%	707,868	0.026
Depth (ask)	7.40	0.84	-0.091***	0.217***	2.5%	707,868	0.024
Depth (L5, ask)	9.22	0.66	0.003	0.089**	0.6%	707,868	0.046
Price Impact (100ms)	2.24	3.12	0.057***	-0.187***	-26.0%	287,593	0.088
Price Impact (1 min)	3.18	4.91	0.054***	-0.033**	-5.1%	287,593	0.082
Price Impact (5 mins)	3.77	7.81	0.005	0.034**	7.0%	287,593	0.028
Messages (bid)	48.11	39.56	0.100***	-0.208***	-17.1%	707,868	0.108
PC100 (bid)	7.75	8.68	0.075***	-0.192***	-21.5%	707,868	0.044
Trade-to-order (bid)*	4.14	11.80	-0.829***	-0.058	-1.4%	529,803	0.039
Trade-to-order (ask)*	3.16	9.09	0.535***	0.321**	10.2%	545,467	0.031

Table 4 - 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 $AR1\ 1min$, $VR\ Xmin$, and $Amihud\ Xmin$. $AR1\ 1min$ 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. $\ln Amihud\ Xmin$ 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 differences in sample sizes occur because we include a matched pair of assets only if it has at least 5 observations with which to compute each per period variance (at least five before, and five after the event).

Variables	Post Event	Diff-in-Diff	Constant	Observations
AR1 (1min returns)	0.00769	0.00071	0.129***	3,788
ln Amihud (1 min)	-0.361***	-0.172*	0.253***	3,780
VarR (1:5 mins)	0.042**	-0.045*	0.170***	3,751
VarR (1:10 mins)	0.006	-0.079**	0.246***	3,673

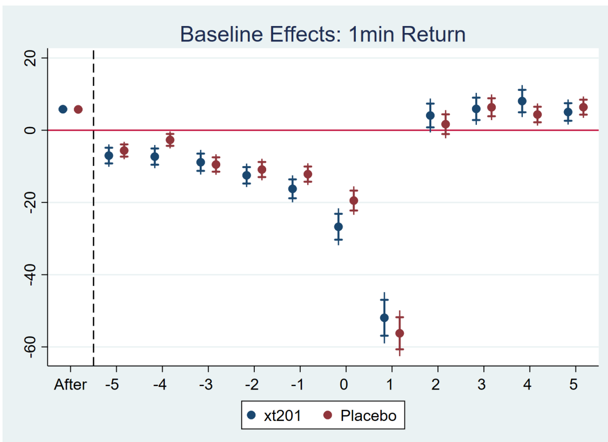
Table 5 - Further Results

The table reports the coefficients from the estimation of the model described in equation 1. All variables are standardized by the in-sample mean and standard deviation for each asset-day. * The volatility measure used is naturally comparable across assets, so it is not standardized. All models include standard errors clustered by treated-control matched pair and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

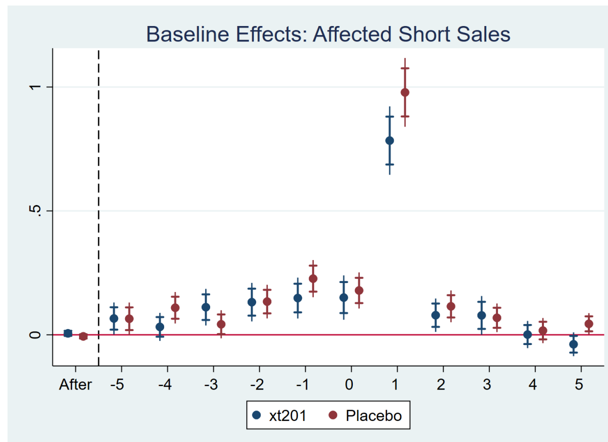
Variable	Mean	St dev	Post Event (β_1)	Diff-in-Diff (β_2)	% change	Obs	R-squared
RSpread (100 ms)	2.08	4.20	-0.013	0.062**	12.5%	287,593	0.021
RSpread (1 min)	1.11	5.41	-0.032**	-0.037**	-18.0%	287,593	0.046
RSpread (5 mins)	474.10	7.97	0.008	-0.071***	-0.1%	287,593	0.019
QuotingX	20.63	25.72	-0.008	-0.019	-2.4%	707,497	0.008
Inverted	10.64	18.96	0.001	-0.004	-0.7%	707,497	0.007
FINRA	41.28	35.36	0.033***	0.066***	5.7%	707,497	0.009
Hidden Volume	6.51	1.18	0.009*	-0.013**	-0.2%	707,868	0.003
Volatility (HL)*	0.34	0.60	0.030***	-0.032***	-9.3%	707,868	0.335

Figure 1 - Comparisons of Coefficients.

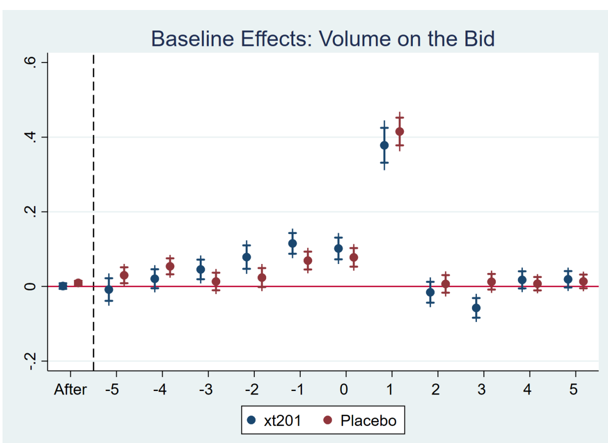
These graphs describe the differences in the coefficients between the experiment and the placebo. The coefficients are the baseline coefficients for the joint regression: $After$ is the average effect for the period after the event, and coefficient numbered $i\{-5, \ldots, 5\}$ are the coefficients for 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).



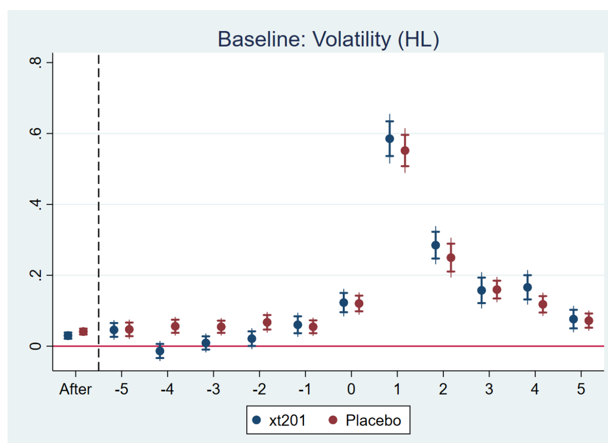
(a) One minute returns.



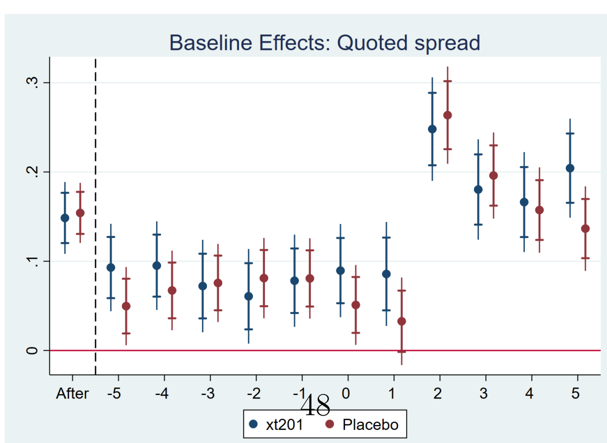
(b) Short sales at or below the bid



(c) Volume on the ask



(d) Volatility (high minus low)



(e) Quoted spread

Appendix

A 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.
- *Quoted Spread* (*cents*). Quoted spread for asset i is the time-weighted (by millisecond) average, over minute t, of $(a_{t'} - b_{t'})$ where $a_{t'}$ is the best ask, $b_{t'}$ the best bid measured in cents, and t' indexes observations within a minute (source: ITCH).
- *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.
- *Passive/Aggressive NE SS*. *SS* refers to short sales (log dollar volume reported as short sales). Short sales are reported as *Exempt* $[NE]$, $Non-Exempt$, and *Total* (the sum of the exempt and non-exempt). *Aggressive* short sales are short sale trades classified as aggressive sell orders using Lee and Ready (1991).[28] *Passive* short sales are short sale trades classified as aggressive buy orders using Lee-Ready.
- *Log Buy* (*Sell*) *Volume* : log of the dollar value of trades classified as aggressive buy (sell) orders using Lee and Ready (1991) (source: TAQ).
- *Quoted Spread*. 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 Spread*. 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

[28]For more details on the effectiveness of the Lee-Ready algorithm see Chakrabarty et al. (2012).

-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).

- *Depth* (*ask*) [(bid)]. Depth at the ask [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 ask [bid], time-weighted over minute t (source: ITCH).

- $Price\ Impact$. 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).

- $Messages$ (*bid*). Number of messages for asset i during minute t on the bid side of the LOB. These include posting, canceling, and execution of visible limit orders on the bid side of the NASDAQ order book (source: ITCH).

- $PC100$ (*bid*). Number of limit orders that are posted and subsequently canceled within 100ms on the bid side of the NASDAQ LOB for asset i during minute t (source: ITCH).

- $Trade{-}to{-}order$ (*bid*) [(ask)]. Trade-to-order ratio computed as the number of executed visible limit orders as a percentage of messages for asset i during minute t on the corresponding side of the LOB (source: ITCH).

- $AR1$. 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).

- *ln Amihud* 1 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 minute as the absolute return over the one minute divided by the total dollar volume during that minute (source: ITCH).

- *RSpread*. 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).

- *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.

- *Inverted*. The market share of total volume traded on inverted fee venues as reported in the TAQ dataset as a percentage of total volume. These venues are: NASDAQ-Boston exchange, EDGE-A, and BATS-Y.

- $FINRA$. 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.

- $Hidden\ Volume$. The (log) total dollar volume obtained by aggregating all hidden trades on the NASDAQ exchange.

- $Volatility(HL)$. 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.[29]

[29]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.

B 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 and time (half-hourly). 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	1,908	1,908	1,908	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 and time (half-hourly). 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 and time (half-hourly). 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 and time (half-hourly). 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 and time (half-hourly). 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 and time (half-hourly). 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 and time (half-hourly). 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 and time (half-hourly). 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 and time (half-hourly). 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 and time (half-hourly). One, two and three stars represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

MARKET SHARE	QuotingX			FINRA			Inverted		
	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
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