NYSE Floor Shutdown and Market Quality into the Close*

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Abstract

The spread of Covid-19 forced the New York Stock Exchange (NYSE) to shut down its trading floor from March 23 through May 25, 2020, resulting in complete suspension of floor brokers' use of D-Orders, a special order type that enables investors to participate in the closing auction beyond 15:50. We investigate its impact on consolidated limit order books over the last 10 minutes into the close 15:50-16:00, the period in which floor brokers become a possible alternative execution channel for investors. Analyzing NYSE- and Nasdaq-listed stocks in the Russell 3000 index in matched-sample and machine learning (ML) approaches, we found that the floor closure had a limited impact on market quality overall: (a) our matched-sample analysis revealed that percentage quoted spread and consolidated displayed depth on average did not differ between the two groups; (b) our ML investigation uncovered that only a small fraction of the NYSE-listed sample stocks experienced wider percentage quoted spread and lower consolidated displayed depth, limited to the first few weeks of the shutdown.

JEL Codes: G12, G14

Keywords: NYSE floor shutdown, D-Orders, Floor brokers, Covid-19 pandemic, Machine learning.

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1. Introduction

In this paper, we study how the trading floor of the New York Stock Exchange (NYSE) affects quality of consolidated limit order books over the last 10 minutes into the close, 15:50–16:00. The NYSE is the only major U.S. stock exchange adopting a hybrid model that, in addition to the "standard" automated electronic trading, offers human-powered floor trading.[1] Among its unique features is Discretionary Order (D-Order, hereafter), a special order type only available for floor brokers in the closing auction process. All other orders for the closing auction must be submitted by and locked in at 15:50; floor brokers, acting on behalf of their clients, can enter, modify, and cancel D-Orders beyond the cutoff through 15:59:50, which effectively allows investors to participate in the closing auction for most of the last 10 minutes. Because of it, floor brokers, heading toward the end of the trading session, come into play as an alternative trading channel for NYSE-listed stocks against consolidated limit order books. This paper is focused on this market structure, attempting to unravel the structural relation between floor brokers and consolidated limit order books for 15:50–16:00 in the context of the Covid-19 closure.[2]

The initial wave of the Covid-19 spreading across the New York City area forced the NYSE to shut down its trading floor for about two months in the period of March 23 to May 22, 2020. During this period, all the floor employees, including floor brokers, moved to working remotely, and, most important, the use of D-Orders was completely halted. From an empirical perspective, this is a natural experiment involving a meaningful intervention to D-Orders' market structure, providing a reliable identification strategy for casual inference on its impact on related outcomes. Given that the role of D-Orders is essentially limited to the closing auction process, we restrict our analysis to 15:50–16:00, the period in which the presence of the NYSE trading floor, featured by D-Orders, becomes most relevant to consolidated limit order books for NYSE-listed stocks.

We look at the two most representative quote-based market quality measures in the market microstructure literature: percentage quoted spread and consolidated displayed depth, both measured at National Best Bids and Offers (NBBO) level. That is, in reflection of the U.S. stock market structure in which investors can trade NYSE-listed stocks on other exchanges, our analysis is focused on the market-wide impact of the floor closure. Importantly, we construct those two market quality measures only over 15:50–16:00 to correctly relate them to D-Orders during the regular trading session. Using a sample of NYSE- and Nasdaq-listed stocks built upon the Russell 3000 index constituents and taking the floor closure as treatment, we first look into average treatment effects on the treated (ATT) in a matched sample approach. To complement ATT results that can deliver only average implications, we further investigate individual stock-level treatment effects on the treated (ITT) in a machine learning (ML) approach of Chernozhukov, Wuthrich, and Zhu (2021).

Employing a similar matching strategy as Chung and Chuwonganant (2022), we construct a matched sample and estimate ATT of the floor closure in the matched difference-in-difference regressions. We found that for both percentage quoted spread and consolidated displayed depth, the floor closure had little impact over the last 10 minutes into the close. This result holds for three different sample periods starting from January, February or March 2020, showing robustness against likely effects of pandemic-

[1] The importance of the trading floor, particularly in closing auctions, can be found at the NYSE's website, describing that "The NYSE Trading Floor plays an important role in the closing auction, and interest represented via the floor currently contributes more than one-third of total Closing Auction volume." https://www.nyse.com/article/trading/d-order.

[2] Independent of the Covid-19 closure, 15:50–16:00 is special for both NYSE- and Nasdaq-listed stocks in that trading volume is highly concentrated on this interval. For our sample stocks, for instance, the last 10 minutes, only 2% of the trading hours, account for about 10% of aggregate trading volume, excluding opening and closing ones, over all of the pre-closure, the floor closure, and the floor reopening periods in January to June 2020.

driven turmoils in the U.S. market. Our regression analysis also covers the floor reopening period of May 26–June 30, 2020. We documented that the floor reopening period had no change in the market quality measures either. Our findings based on ATT differ from Brogaard, Ringgenberg, and Rösch (2021) and Chung and Chuwonganant (2022) who, using market quality measures constructed over the whole trading hours 09:30–16:00, find significant deterioration of market quality due to the floor closure. When we placed their versions of percentage quoted spread and consolidated displayed depth on our matched difference-in-difference regression model, we obtained similar results with our main results for the samples starting from either January or February 2020 but contrasting ones for the sample starting from March 2020. This might call into question the robustness of their results.

In the Synthetic Control Method (SCM) framework, analysis of ITT is based on comparison between observed outcomes and predicted counterfactuals over the treatment period, where counterfactuals are out-of-sample predicted from a ML model trained over the pre-treatment period. Important, regularization bias that arises in the course of model training irrespective of the treatment is corrected by cross-fitting. Further, a scale-free test-statistic on the treatment effect is obtained for each sample stock, making comparison of the test statistics in the cross-section meaningful. Looking into the distribution of the test statistics for NYSE-listed stock against Nasdaq-listed stocks over every three-week from the beginning of the floor closure, we found little difference between the two groups for both percentage quoted spread and consolidated displayed depth in most of the floor closure period as well as of the floor reopening period. The only exception was the first three-week of the floor closure period in which there were about 14% and 10% of the NYSE-listed stocks resulting in p-value less than 0.05 for percentage quoted spread and consolidated displayed depth, respectively, twice as much as the fractions in other three-week periods. Overall, we conclude that the empirical evidence from our ITT analysis by and large is consistent with ATT, supporting that the impact of the floor closure on market quality is limited.

There are several contemporaneous academic papers dealing with the Covid-19 floor closure in related contexts. Hu and Murphy (2020) assess closing auction market quality by looking at accuracy of indicative closing auction information in comparison between NYSE- and Nasdaq-listed stocks. Using data prior to the Covid-19 closure, they first reveal that indicative closing auction information on the NYSE is inaccurate relative to Nasdaq but its accuracy is improved as soon as D-Orders are incorporated into the pubic data feed. Focusing on the Covid-19 closure, they document improvement in accuracy of NYSE's closing auction information, brought by the absence of D-Orders. On the other hand, Jegadeesh and Wu (2022) uncover that closing auction in Nasdaq was better than in the NYSE during the floor closure period. They attribute it to the absence of floor brokers following their model prediction that displacement of off-exchange liquidity providers by floor brokers on the NYSE would lead to lower depth on the NYSE during the shutdown period. Meanwhile, Brogaard, Ringgenberg, and Rösch (2021) and Chung and Chuwonganant (2022) relate the Covid-19 shutdown with more general aspects of market quality. Based on a matched sample obtained from NYSE- and Nasdaq-listed stocks, they look into the effects of the floor closure on a variety of market quality measures, time-weighted averaged over the whole trading hours, 9:30–16:00. Overall, they both find that the shutdown of the trading floor undermines market quality.

This paper differs from all the studies above in one critical respect that our focus is on the last 10 minutes into the close 15:50–16:00, during which floor brokers start serving as a meaningful execution channel for investors. Notice that Hu and Murphy (2020) and Jegadeesh and Wu (2022) are interested in the on-exchange closing auction, a "local" event occurring only on listing exchanges. In addition, while Brogaard, Ringgenberg, and Rösch (2021) and Chung and Chuwonganant (2022) also look at market quality measures on consolidated limit order books, their measures cover the whole trading hours and are designed to study the importance of physical interactions of humans on the NYSE trading floor. In contrast, we pay little attention to physicality of the trading floor but to the privileged features of D-Orders, an unique market structure of the NYSE in the closing auction process.

We believe the contribution of our paper is largely threefold. First, this paper contributes to a large literature focused on the NYSE's hybrid model. In particular, among two types of floor employees on the NYSE, designated market makers (DMMs) and floor brokers, the literature has focused primarily on the DMMs (e.g., Battalio, Jennings, and McDonald, 2021; Bessembinder, Hao, and Zheng, 2020; Clark-Joseph, Ye, and Zi, 2017; Bessembinder, Hao, and Zheng, 2015; Battalio, Ellul, and Jennings, 2007; Panayides, 2007). We add to it the role of floor brokers, especially for the last 10 minutes when their influence would likely be most evident. Second, our paper makes a contribution to the literature that looks into impacts of Covid-19 driven shocks on financial markets (e.g., Augustin et al., 2022; Bordo and Duca, 2022; He, Nagel, and Song, 2022; Neukirchen et al., 2022; Chakrabarty and Pascual, 2022; Berkman and Malloch, 2021; Caballero and Simsek, 2021; Cox and Woods, 2021; Demirgüç-Kunt, Pedraza, and Ruiz-Ortega, 2021; Ding et al., 2021; Duan et al., 2021; Dursun-de Neef and Schandlbauer, 2021; Goldstein, Koijen, and Mueller, 2021; Huber, Huber, and Kirchler, 2021; John and Li, 2021; Kargar et al., 2021; Levine et al., 2021; O'Hara and Zhou, 2021). Our paper offers an U.S. equity market microstructure perspective on the matter. Finally, our paper is among the initial works in market microstructure that employ a machine learning approach to empirical research (Kye, 2020; Ju, Kim, and Lim, 2019). Especially, we introduce how granularity of market microstructure data can translate into the casual inference framework that underlies a majority of empirical questions in the area.

The remainder of the paper is organized as follows. In Section 2, we provide an overview of the NYSE market structure, restricted to 15:50–16:00. In Section 3, we describe data used for analysis, define outcomes of interest, and detail the sampling procedure. In Section 4, we estimate the impact of the floor closure on market quality using a matched sample approach and do so with a machine learning approach in Section 5 that complements the preceding analysis. Finally, we discuss implication and limitation in Section 6 and conclude the paper in Section 7.

2. NYSE's Market Structure into the Close

The special role of floor brokers on the NYSE trading floor is most evident toward the end of the regular trading session. They serve as a sole alternative execution channel to limit order books beyond 15:50 by enabling investors to execute through the closing auction. With this regard, this section introduces the NYSE's market structure focused on 15:50–16:00 and provides what had changed in it during the floor closure period.

2.1. Trading on the NYSE for 15:50–16:00

Heading toward the end of the regular trading session, investors, in addition to trading on public limit order books, are given an alternative option for trading: the closing auction. On the NYSE, in particular, there are two ways of participating in the closing auction. The first is sending limit or market orders for the closing auction to brokerage firms, which are then processed in an automated manner, similar to the typical trading process in the continuous trading session on electronic limit order books. Alternatively, investors can direct their orders to a floor broker who then uses his or her discretion for execution at the close under a special arrangement with the NYSE. Importantly, under this arrangement, floor brokers, besides potential "soft" advantages of physical presence on the trading floor, possess structural advantages in the closing auction process brought by D-Orders, a special order type only available to floor brokers.

Table 1: Closing Auction Timeline on the NYSE

This table shows the closing auction timeline on the NYSE, drawn from the NYSE's website (https://www.nyse.com/article/nyse-closing-auction-insiders-guide). Market-On-Close (MOC) and Limit-On-Close (LOC) orders are standard limit and market orders, respectively, submitted for closing auctions.

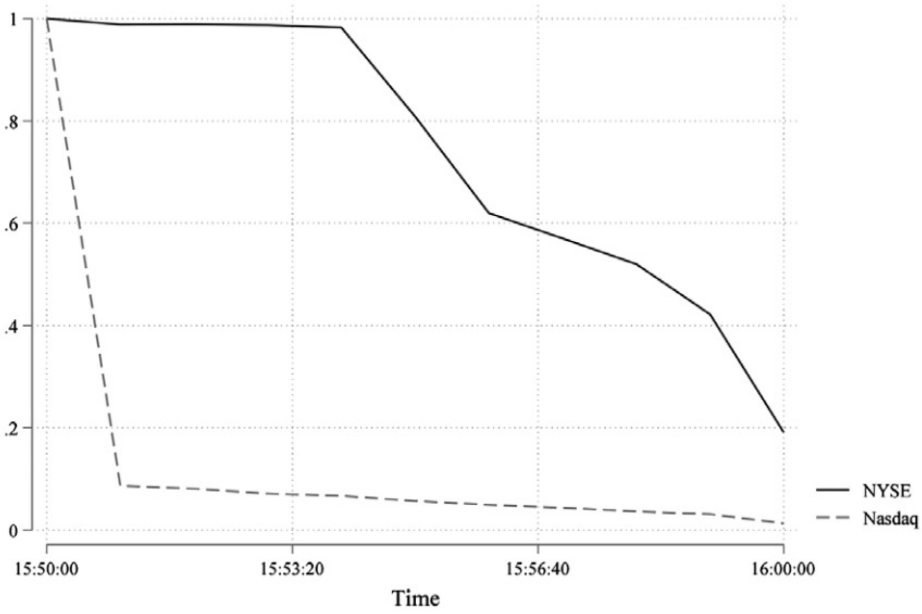
6:30 am	MOC/LOC orders can be entered.
2:00 pm	Imbalance information is published to Floor Brokers.
3:50 pm	Cutoff for MOC and LOC order entry, modification, and cancellation (except for legitimate error). Imbalance dissemination begins.
3:55 pm	Imbalance dissemination begins including Closing D-Orders at their discretionary price range.
3:58 pm	Cutoff for cancelling a MOC/LOC for legitimate error.
3:59:50 pm	Cutoff for Closing D-Order entry, modification and cancellation.
4:00 pm	Regular way trading ends and auction commences.

The NYSE's closing auction timeline in Table 1 hints, at least, two of them. First, unlike to a standard order type which must be submitted by 3:50 pm, D-Orders can be entered until the last 10 seconds of the regular trading session. That is, while investors employing standard order types have to make a final decision on order submission strategy 10 minutes before the close, floor brokers can wait until the last moments before making a decision. Furthermore, because of it, floor brokers can incorporate order imbalance information compiled by others, or "competitors," into their own order submission strategy, which is impossible to those who rely on standard order types.[3] In short, even excluding all presumable advantages of human interactions on the floor, floor brokers are in a better position to compete for execution at the close due to those structural advantages.

One important implication of Table 1 is that because floor brokers offer investors an opportunity to participate in closing auction via D-Orders for most of the last 10 minutes, liquidity on consolidated limit order books on the interval of 15:50–16:00 becomes more evidently interconnected with the NYSE trading floor. Figure 1 provides the evidence that floor brokers are actively involved in the closing auction process on that time interval. Starting from 15:55 pm, at which D-Orders are incorporated into order imbalance dissemination, order imbalance on the NYSE significantly decreases, and this change continues up until 10 seconds before the close. Thus, to those who want to execute their orders for the last 10 minutes of the regular session, the NYSE trading floor serves as an alternative trading channel, thereby influencing liquidity of consolidated limit order books.

[3] This structure differs from that of Nasdaq. On Nasdaq, there is no special order type, like D-Orders. Furthermore, order imbalance information is released at 3:50 pm, ahead of the cutoff time 3:55 pm (3:58 pm) for market (limit) orders. Thus, investors can make a decision of closing auction participation with knowledge of order imbalance information.

Figure 1: Evolution of Order Imbalance in 15:50–16:00



This figure, drawn from Panel C of Figure 2 in Jegadeesh and Wu (2022), shows the average buy-sell order imbalance (OI) for common stocks (CRSP share code 10 or 11), either NYSE- or Nasaq-listed, as a proportion of the OI at the time of the first closing information dissemination over April to December 2020. $OI_{i,t}$ for stock i at time t is defined as:

$$OI_{i,t} = \frac{C\_Buy_{i,t} - C\_Sell_{i,t}}{Total\ trade_{i,t}}$$

where C_Buy and C_Sell represent the number of buy and sell market orders (MOC) and implementable limit orders (LOC).

2.2. The Closure of NYSE Trading Floor

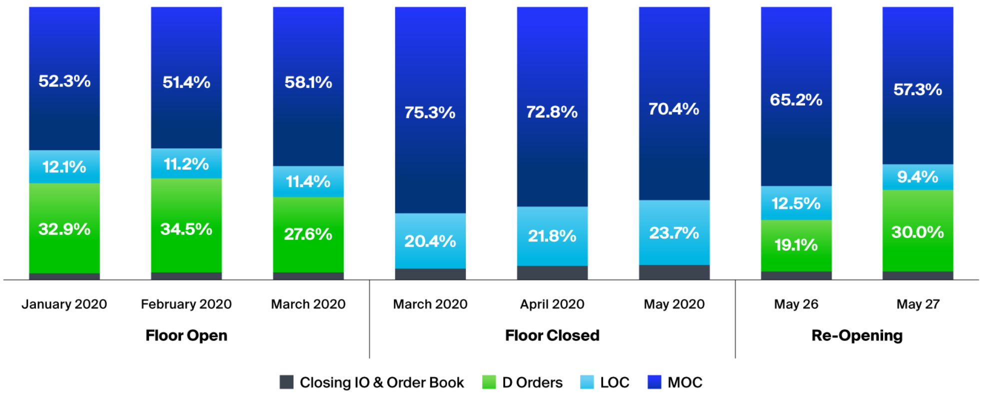
As a precautionary measure to contain the spreading of Covid-19 in the New York City area, the NYSE decided to shut down its trading floor. The floor closure started on March 23, 2020 and lasted for about two months until it was partially reopened on May 26, 2020. In this floor closure period, all the floor employees, DMMs and floor brokers, moved to working remotely.

NYSE's official documents related to the floor closure stress two aspects of it: (1) DMMs and floor brokers will work as usual but electronically; (2) floor-broker-only order types (i.e., D-Orders) will not be available—which later has been confirmed by the NYSE, as shown in Figure 2.[4]

Most important, this disclosure leads us to conclude that the only economically meaningful intervention, brought by the Covid-19 floor closure, is the suspension of the use of D-Orders and that other "regular" functions of the NYSE floor would likely remain intact, thanks to its transition to being fully electronic. In other words, we do not postulate that the absence of physical contacts due to switching over to remote working mode significantly impacts floor employees' capabilities of performing their routine jobs. This perspective contrasts Brogaard, Ringgenberg, and Rösch (2021) and Chung and Chuwonganant (2022) who consider physical proximity as essential to the floor's functioning.

[4]There are two versions of FAQ the NYSE posted on its website regarding the floor closure: "NYSE Group BCP Trading Floor Closure FAQ" (https://www.nyse.com/publicdocs/NYSE_Floor_Closing_FAQ.pdf) and "NYSE Trading Floor Closure FAQ" (https://www.nyse.com/publicdocs/NYSE_Floor_Closing_FAQ.pdf).

Figure 2: Closing Auction Order Type Usage on the NYSE



This figure, drawn from the NYSE's Data Insights page (https://www.nyse.com/data-insights/nyse-trading-floor-re-opening-improves-market-quality), shows percentages of usage of order types at the close in the context of the NYSE floor shutdown. Market-on-Close (MOC) is an unpriced order to buy or sell a security at the closing price; Limit-on-Close (LOC) is an order bound by the maximum price an investor is willing to buy, or the minimum price to sell, in the closing auction; D Orders are floor-broker-only order type.

3. Data

This section offers data description. We rely on three widely utilized data sets in market microstructure research, all of which are accessible via the Wharton Research Data Services (WRDS): TAQ, CRSP, and IID.[5] We employ TAQ quote data to compute percentage quoted spread and consolidated display depth at the National Best Bid and Offer (NBBO) level, time-weighted over the last 10 minutes into the close, 15:50–16:00. We use CRSP and IID to obtain stocks' characteristics and daily summaries of intraday trading. The whole sample period includes all the trading days in the period of December 2019–June 2020, excluding the four days on which the market-wide circuit breaker was activated, of which January–June 2020 is the main sample period for analysis and December 2019 serves as a reference month for construction of a matched sample between NYSE- and Nasdaq-listed stocks.[6]

3.1. Liquidity Measures for 15:50–16:00

We generate from scratch liquidity measures corresponding to 15:50–16:00 on each trading day in our main analysis period, January–June 2020. To be specific, for each stock in our sample, we first compute top-of-book liquidity information, based on NBBO, at every quote update on a given trading day from market-open to market-close from raw TAQ quote data. In this process, we put in place the Holden and Jacobsen filters to rule out withdrawn, stalled, or incomplete quote observations from the raw data.[7] After that, we take time-weighted average on the liquidity measures over every one minute interval starting from 15:50 through 16:00, generating 10 one-minute time-weighted liquidity measures

[5] IID refers to the Intraday Indicators by WRDS that contains daily stock market indicators computed from TAQ. It has, for example, a variety of time-weighted liquidity measures over each trading day, such as percentage quoted spread and consolidated displayed depth, etc.

[6] The market-wide circuit breaker is activated four times in March 2020: March 9, March 12, March 16, and March 18.

[7] Details of the Holden and Jacobsen filters, revised to serve for the nanosecond version of TAQ, can be found in their SAS code, which is available on the Prof. Holden's website: https://host.kelley.iu.edu/cholden.

at stocks-days level. We call it one-minute time-weighted inside-quote data. Important, averages of the 10 one-minute time-weighted liquidity measures on a given day deliver the daily version of them, time-weighted only over the last 10 minute. In later sections of empirical analysis, we will use both one-minute and daily versions but separately for different empirical strategies, which will be detailed in the subsequent section.

Figure 3: Example of One-Minute Time-Weighted Inside-Quote Data

	symbol	date	period	tw_pqsprd	tw_depth
0	A	20200102	15:50:00-15:51:00	1.5420	7.24680
1	A	20200102	15:51:00-15:52:00	1.1699	15.66770
2	A	20200102	15:52:00-15:53:00	1.1914	17.35795
3	A	20200102	15:53:00-15:54:00	1.1981	10.35320
4	A	20200102	15:54:00-15:55:00	1.4683	8.97815
5	A	20200102	15:55:00-15:56:00	1.2601	7.55025
6	A	20200102	15:56:00-15:57:00	1.2512	9.51025
7	A	20200102	15:57:00-15:58:00	1.2808	8.44590
8	A	20200102	15:58:00-15:59:00	1.1647	9.89610
9	A	20200102	15:59:00-16:00:00	1.4825	12.15815

This figure shows an example of one-minute time-weighted inside-quote data for stock ticker symbol `A` (Agilent Technologies, Inc.) on January 2, 2020. From the left to the right, **symbol**: security ticker symbols; **date**: date; **period**: one-minute time intervals; **tw_pqsprd**: time-weighted percentage quoted spread in basis points; **tw_depth**: time-weighted consolidated displayed depth in 100-share unit.

We consider two popular liquidity measures, percentage quoted spread and consolidated displayed depth. Percentage quoted spread at a given tick is defined as the national best bid price minus the national best offer price divided by the midquote of NBBO at the tick. Consolidated displayed depth at a tick is the sum of the bid depth at the national best bid price aggregated over exchanges on the national best bid and the ask depth at the national best offer price aggregated over exchanges on the national best offer divided by two. Figure 3 shows an example of one-minute time-weighted inside-quote data.

3.2. Sample Construction

We construct sample stocks from constituents of the Russell 3000 index that tracks the performance of the roughly 3,000 largest U.S.-traded stocks. It offers a natural choice of sample stocks that keep a high level of trading activities in daily stock market while representing the entire U.S. stock market comprehensively. We obtain the list of the index constituents for 2018–2019 and 2019–2020 cohorts from the FTSE Russell's website and take those as the starting point for sample construction.[8]

Table 2 summarizes the procedure for sample construction. We start with Russell 3000 constituents that maintain the index membership for two consecutive membership years in 2018–2019 and 2019–2020.[9] This is to exclude the stocks potentially affected by listing to or delisting from the index. From this initial set of stocks, we further remove the stocks that are not uniquely identifiable by a pair of `CUSIP`

[8]For detail, visit the FTSE Russell's website: `https://www.ftserussell.com`.

[9]The membership list for 2018-2019 is the one determined on July 1, 2019 and that for 2019-2020 on June 29, 2020.

Table 2: Sample Construction

Sampling Details	#Stocks (change)	Agg. Volume Shr. (%)
Russell 3000 index constituents, listed in both 2018-2019 and 2019-2020 membership years[a]	2,699 (-)	100.00
Exclusion of the stocks not uniquely identifiable with a pair of `CUSIP` and `TSYMBOL` in CRSP and of those switching listing exchanges in January - June 2020	2,692 (-7)	99.47
NYSE- or Nasdaq-listed stocks only, identified by `EXCHCD` $\in \{1,3\}$ in CRSP	2,665 (-27)	99.19
Common stocks only, identified by `SHRCD` $\in \{11,12,18\}$ in CRSP	2,635 (-30)	97.66
Deletion of stocks that drop out of data processing to generate one-minute time-weighted inside quote in 15:50-16:00[b]	2,617 (-18)	96.35

[a]The membership lists for the Russell 3000 index are available on the FTSE Russell website. The constituents for the 2018–2019 and 2019–2020 membership years are published on July 1, 2019 and June 29, 2020, respectively.
[b]Deleted stocks are mostly those having a few valid observations in quote data for 15:50-16:00 after the Holden and Jacobsen's filters are applied. The detail of the filtering rules can be found in their SAS code.

and `TSYMBOL` in CRSP as well as those that switch listing exchanges over in the period of January – June 2020. Next, we delete the stocks listed on other than the NYSE and Nasdaq and keep only common stocks, identified by `SHRCD` $\in \{11,12,18\}$ in CRSP. Finally, we drop 18 stocks that do not generate one-minute time-weighted inside quote-data properly with the Holden and Jacobsen filters. One of the Holden and Jacobsen filters imposes price range restriction on raw quote observations in TAQ, removing those not satisfying it in the first place.[10] Because of this, certain stocks on some days are left with very few quote observations, making computation of NBBO meaningless. For this reason, we delete such stocks, specifically those that have no, or a very small number of, observations for over two days in the period of January - June 2020 due to the filters and those that do not have any quote update for more than five one-minute intervals for 15:50–16:00 during January–Feburary 2020, the period when Covid-19 has not yet shaken the market significantly. In sum, our sample consists of 2,617 stocks with 1,255 NYSE-listed and 1,362 Nasdaq-listed that collectively account for 96.35% of aggregate share trading volume over the initial set of the Russell 3000 constituents in the period of January–June 2020.

Table 3 provides descriptive statistics for the sample stocks. The average market cap of NYSE-listed stocks is \$16.7 billion and that of Nasdaq-listed stocks is \$9.32 billion.[11] Both groups have skewed distributions of market cap, carrying more of small stocks but fewer of large stocks in value. We see similar distributions for price level with averages \$71.77 and \$54.27 for NYSE- and Nasdaq-listed stocks, respectively. Overall, NYSE-listed stocks are larger in both market cap and price level than Nasdaq-listed stocks.

For all the three sub-periods of January–June 2020, our main analysis period, NYSE-listed stocks have

[10]For example, "If the quoted spread is greater than \$5.00 and the bid (ask) price is less (greater) than the previous midpoint - \$2.50 (previous midpoint + \$2.50), then the bid (ask) is not considered."
[11]Market cap is computed based on the number of outstanding shares and closing prices on Jan 2, 2020, the first trading day of our main sample period, from CRSP.

Table 3: Descriptive Statistics

This table shows descriptive statistics. Market cap and price are computed from the number of outstanding shares and closing prices on the first trading day of the main sample period. In addition, panel-data means are reported for percentage quoted spread and consolidated displayed depth, based on the daily version that takes time-weighted average only over 15:50-16:00 on each sample day.

	Obs.	**Mean**	**Std. Dev**	**25 Pct**	**Median**	**75 Pct**
First Trading Day: January 2, 2020						
Market Cap ($B)						
NYSE	1,255	16.17	41.58	1.29	3.80	11.54
Nasdaq	1,362	9.32	61.62	0.40	1.11	3.29
Price ($)						
NYSE	1,255	71.77	138.46	20.04	42.86	84.40
Nasdaq	1,362	54.27	110.50	15.03	29.94	58.58
Pre-Closure Period: January 2 - March 20, 2020 (51 trading days)						
Percentage Quoted Spread (bps)						
NYSE	64,005	11.53	19.44	3.47	6.11	11.97
Nasdaq	69,462	35.26	79.49	6.14	13.08	32.65
Consolidated Displayed Depth (100 shrs)						
NYSE	64,005	48.83	264.31	4.17	7.24	21.60
Nasdaq	69,462	28.90	165.20	3.54	5.38	11.16
Floor Closure Period: March 23 - May 22, 2020 (44 trading days)						
Percentage Quoted Spread (bps)						
NYSE	55,152	20.31	28.58	6.89	12.53	23.56
Nasdaq	59,859	55.59	104.31	11.62	23.48	51.79
Consolidated Displayed Depth (100 shrs)						
NYSE	55,152	38.26	209.45	3.80	6.26	17.04
Nasdaq	59,859	20.99	98.95	3.39	4.90	9.40
Reopening Period: May 26 - June 30, 2020 (26 trading days)						
Percentage Quoted Spread (bps)						
NYSE	32,630	13.82	21.51	4.84	8.21	14.68
Nasdaq	35,412	39.09	77.38	8.29	15.27	35.13
Consolidated Displayed Depth (100 shr)						
NYSE	32,630	45.96	221.41	4.20	7.04	19.46
Nasdaq	35,412	25.06	126.21	3.48	5.23	10.23

lower percentage quoted spread and larger consolidated displayed depths than does Nasdaq-listed stocks, consistent with the stock composition in terms of market cap. Also, it appears that the two groups have a similar trend of time-series of the market quality measures on average: market quality worsens from the pre-closure period to the floor closure period but improves from the floor closure period to the following reopening period. This reveals an empirical challenge in drawing a causal relation between market quality deterioration and the floor closure for NYSE-listed stocks, as Nasdaq-listed stocks, unlikely to be affected by the NYSE floor closure, also experience declines of market quality during the trading-floor closure period. That is, worsening market quality for NYSE-listed stocks in the floor-closure period can simply be a reflection of market-wide time effects, unrelated to the floor closure.

4. Matched-Sample Analysis

This section introduces an empirical strategy, focused on estimation of average effects of the NYSE floor closure on NYSE-listed stocks, or ATT. To estimate ATT, we rely on a matched-sample approach, which is widely adopted in empirical finance and by the papers looking into the Covid-19 closure in a related context (e.g., Brogaard, Ringgenberg, and Rösch, 2021; Chung and Chuwonganant, 2022).

4.1. Empirical Method

Based on the sample base constructed in the previous section, we match one NYSE-listed stock with one Nasdaq-listed stock that is in the same first two-digit North American Industry Classification System (NAICS) code and is closest on average market cap, average share trading volume, average closing price, and average volatility over December 2019, one month before the main sample period of analysis. Those are the same matching characteristics chosen by Chung and Chuwonganant (2022). We also use the same matching score function as them, defined for NYSE-listed stock i and Nasdaq-listed stock j in the same NAICS code as:

$$MatchingScore_{ij} = \sum_{k=1}^{4} \left[\frac{\bar{x}_k^i - \bar{x}_k^j}{(\bar{x}_k^i + \bar{x}_k^j)/2} \right]^2 \tag{1}$$

where $\bar{x}_k$ represents the four matching characteristics stated above.[12]

We first calculate the matching score (1) on every possible pair for NYSE-listed stock i and then assign to it Nasdaq-listed stock j that achieves the minimum of (1) over other Nasdaq-listed candidates. If Nasdaq-listed stock j is the minimizer for multiple NYSE-listed stocks, we assign it to NYSE-listed stock i whose matching score is the smallest among other NYSE-listed stocks having j as the minimizer. We then recalculate (1) for the leftover NYSE-listed stocks and repeat the above procedure until they find one-to-one match from the remaining Nasdaq sample. In the end, we obtain 726 pairs ($726 \times 2 = 1{,}452$ stocks) successfully matched in the process from the initial sample base.

Table 4 shows panel-data averages and standard deviations of the matching characteristics for the NYSE and Nasdaq groups along with normalized difference between the two groups by four sub-periods.[13] From the table, we can confirm that our matched sample is well-constructed, achieving a high-level of similarity on average throughout the whole sample period. Further, small magnitudes of normalized difference for all the matching characteristics suggest that a linear regression approach for ATT estimation is reasonable (see Imbens and Wooldridge, 2009, p. 24).

For estimation of ATT of the floor closure, we consider the following panel-data linear regression model, built on the matched-sample difference-in-difference framework:

$$Y_{it} = \beta_1 FloorClosure_t \times NYSE_i + \beta_2 FloorReopen_t \times NYSE_i + X_{it}'\gamma + c_i + d_t + e_{it} \tag{2}$$

where Y_{it} is a market quality measure for stock i on day t, time-weighted only over 15:50–16:00;

[12] We use as a volatility measure `ivol_q` in IID that computes NBBO quote-based second-by-second sample variances.

[13] Imbens and Wooldridge (2009, p. 24) suggest that normalized difference is a better measure than t-statistics in evaluating significance of differences in covariates between treatment and control groups as it is not overstated by sample size. They propose to use 1/4 as a rule-of-thumb cutoff for evaluation, exceeding which linear regression methods are likely to be sensitive to model specification.

Table 4: Summaries of Matched Sample

This table shows

	Market Cap ($B)	Volume (1,000 shrs)	Price ($)	Volatility (bps)
Matching Period: December 2 - 31, 2019				
NYSE	10.27	1249	59.88	2.43
	(30.57)	(3047)	(73.24)	(4.14)
Nasdaq	8.96	1241	59.28	2.97
	(23.51)	(3112)	(70.01)	(4.03)
Norm. Diff.	0.0340	0.0019	0.0059	-0.0936
Pre-Closure Period: January 2 - March 20, 2020				
NYSE	9.99	1765	58.34	2.98
	(29.75)	(4870)	(74.57)	(4.22)
Nasdaq	9.02	1754	58.43	3.63
	(24.38)	(4864)	(74.07)	(4.81)
Norm. Diff.	0.0254	0.0016	-0.0008	-0.1020
Floor Closure Period: March 23 - May 22, 2020				
NYSE	8.14	2266	46.56	5.18
	(25.07)	(6683)	(65.39)	(7.07)
Nasdaq	8.15	2058	50.40	5.91
	(23.48)	(5824)	(72.16)	(7.52)
Norm. Diff.	-0.0002	0.0235	-0.0395	-0.0713
Reopening Period: May 26 - June 30, 2020				
NYSE	9.24	2322	53.88	3.30
	(27.57)	(7175)	(73.22)	(5.29)
Nasdaq	9.31	2173	59.05	3.83
	(26.22)	(7956)	(84.83)	(5.65)
Norm. Diff.	-0.0019	0.0139	-0.0461	-0.0681

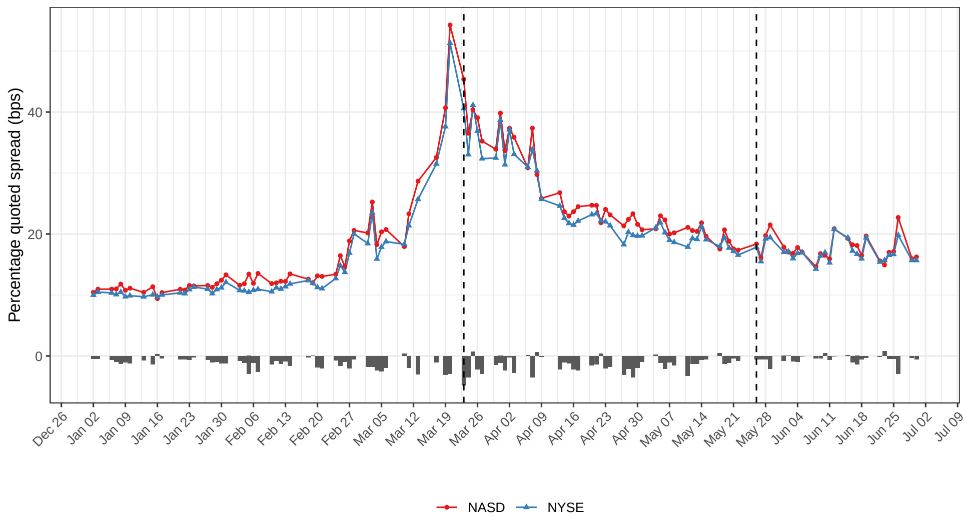
$FloorClosure_t$ and $FloorReopen_t$ are dummy variables indicating the periods of the closure and reopening of the NYSE trading floor, respectively; $NYSE_i$ is a dummy variable taking 1 if stock i is NYSE-listed and 0 otherwise; X_{it} is a vector of controls composed of matching characteristics; c_i and d_t are stock and day fixed effects; e_{it} is an error term whose variance is assumed to vary at stock-day level. Here parameters of interest are β_1 and β_2 that capture the floor closure effect and floor reopening effect, respectively.

4.2. Results

Before discussing estimation results of (2), we first go over graphical findings of cross-sectional averages of market quality measures over the pre-closure, floor closure, and floor reopening periods, as shown in Figure 4. On top of that, we want to stress that the NYSE and Nasdaq group appear to have a common trend for both outcomes in the pre-closure period, supporting that our empirical strategy written in a difference-in-difference form is well-founded. Overall, there is no conspicuous change of difference in the outcomes between the NYSE and Nasdaq group across the three sub-periods, and it would hint that the floor closure and its reopening have little impact on the consolidated limit order book for the last 10 minutes into the close, a short window when floor brokers are most influential and active in trading process.

Figure 4: Time Series of Cross-sectional Averages

A. Percentage quoted spread time-weighted over 15:50-16:00



B. Consolidated displayed depth time-weighted over 15:50-16:00

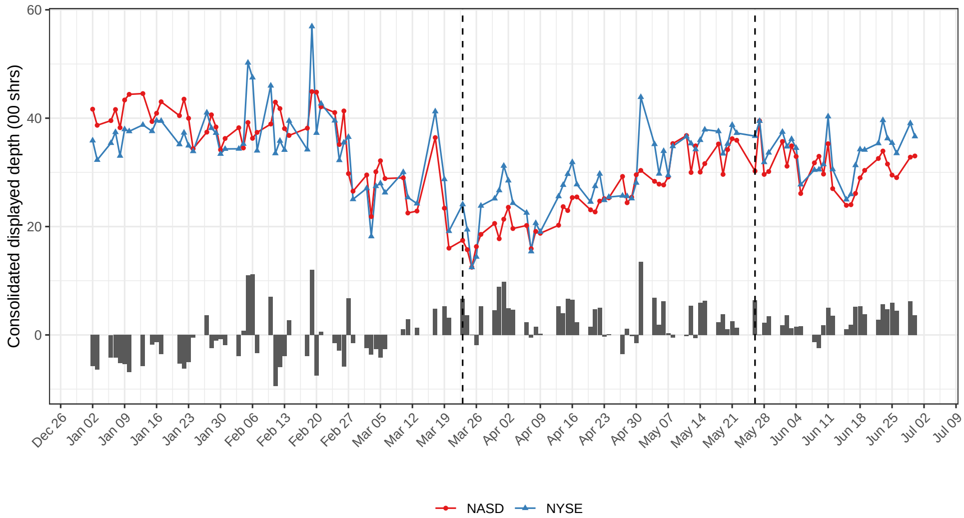


Table 5 reports the estimation result of (2), where we also consider the two market quality measures from IID data, time-weighted over the whole trading hours 09:30-16:00. Taking into account possible confounding effects of the Covid-19-driven uncertainty beginning from late February in 2020, we vary the starting date of estimation sample and see how results change in respond to it.

Most important, the results show that the floor closure and its reopening overall have insignificant effects on both market quality measures for the last 10 minutes into the close, regardless of choice of the starting date of estimation sample. While those time-weighted over the whole hours also appear to be little impacted by the floor closure and its reopening, there is one case that the floor closure significantly increases percentage quoted spread at 5% level, as seen in model **M3** estimated with the sample beginning with March 2020. We believe this supports our view that market quality measures time weighted over the whole trading hours would not properly capture activities of floor brokers, whose influence is mostly

Table 5: Regression Results

This table shows estimation results of (2). Outcomes of interest are percentage quoted spread (bps) and consolidated displayed depth (100 shrs), time-weighted over either 09:30-16:00 or 15:50-16:00. We consider three estimation samples having different starting dates: January 2, February 3, and March 2, 2020. $NYSE_i$ is a dummy variable indicating NYSE-listed stocks. $FoorClosure_t$ and $FloorReopen_t$ are dummy variables indicating the floor closure period (March 23 - May 22, 2020) and the following reopening period (May 26 - June 30, 2020), respectively. Market cap ($MarketCap_{it}$), closing price ($Price_{it}$), and share trading volume ($Shr.Volume_{it}$) are drawn from CRSP data. $Volatility_{it}$ is square root of NBBO quote-based second-by-second variance (`ivol_q`), delivered by IID data. Standard errors clustered by stocks and days are reported in parentheses.

	M1 From Jan. 2, 2020		**M2** From Feb. 3, 2020		**M3** From Mar. 2, 2020	
	09:30-16:00	15:50-16:00	09:30-16:00	15:50-16:00	09:30-16:00	15:50-16:00
	Percentage Quoted Spread (bps)					
$\text{NYSE}_i \times \text{FloorClosure}_t$	0.8691	-0.2165	1.4979	0.0472	3.1846*	0.5682
	(0.7928)	(0.6258)	(0.8210)	(0.5485)	(1.2672)	(0.5261)
$\text{NYSE}_i \times \text{FloorReopen}_t$	0.3642	0.3632	1.0488	0.6703	2.7872	1.2301
	(0.6116)	(0.4858)	(0.7512)	(0.4975)	(1.4015)	(0.7224)
log(Market Cap_{it})	-2.0855**	-0.8137	-1.3776	-0.7645	0.8826	-0.4177
	(0.7206)	(0.6062)	(0.8647)	(0.6852)	(1.1853)	(0.8417)
log(Shr. Volume_{it})	-4.3594***	-1.6664***	-4.6318***	-1.6961***	-6.1507***	-2.2985***
	(0.4300)	(0.3221)	(0.4593)	(0.3483)	(0.4827)	(0.3903)
Volatility_{it} (bps)	3.9482***	2.0379***	3.6619***	1.8073***	3.3014***	1.5395***
	(0.3318)	(0.2287)	(0.3423)	(0.2349)	(0.3876)	(0.2585)
$1/\text{Price}_{it}$	-4.0287	25.0673*	-2.6145	22.6557*	-1.8399	15.8918
	(9.2004)	(9.7181)	(9.6999)	(10.1655)	(9.9348)	(9.8197)
Adjusted R^2	0.8187	0.7303	0.8246	0.7377	0.8324	0.7413
	Consolidated Displayed Depth (100 shrs)					
$\text{NYSE}_i \times \text{FloorClosure}_t$	1.4985	-0.3161	2.7041	0.1340	5.7356*	0.8288
	(1.6026)	(1.3222)	(1.6320)	(1.1531)	(2.3994)	(1.0650)
$\text{NYSE}_i \times \text{FloorReopen}_t$	1.4942	0.9818	2.8042	1.5238	5.8733*	2.2677
	(1.2445)	(1.0368)	(1.4992)	(1.0598)	(2.6949)	(1.5018)
log(Market Cap_{it})	-2.7314*	-1.2627	-1.5285	-0.9565	1.9804	0.1178
	(1.0926)	(0.9316)	(1.2682)	(1.0295)	(1.6160)	(1.1969)
log(Shr. Volume_{it})	-6.3232***	-2.4649***	-6.6274***	-2.4620***	-8.5623***	-3.2778***
	(0.7319)	(0.5662)	(0.7520)	(0.6003)	(0.7749)	(0.6627)
Volatility_{it} (bps)	3.6741***	1.9158***	3.4106***	1.6923***	3.0747***	1.4315***
	(0.3327)	(0.2331)	(0.3404)	(0.2375)	(0.3856)	(0.2595)
$1/\text{Price}_{it}$	-21.0694*	18.2911	-16.4677	17.8666	-9.7419	14.7359
	(9.8408)	(10.5565)	(10.3018)	(11.1081)	(10.6241)	(10.9557)
Adjusted R^2	0.7915	0.7045	0.7969	0.7121	0.8045	0.7154
Stock Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

explicit around the close. In sum, we conclude that on average the floor closure and its reopening have limited impact on market quality for NYSE-listed stocks in comparison to Nasdaq-listed stocks in our matched sample, suggesting that the consolidated limit order book can well absorb trading interests in the last minutes that otherwise would be directed to floor brokers.

5. Machine Learning Approach

This section illustrates a ML-based empirical strategy targeting to estimate floor closure effects at the individual stock level. Using Nasdaq-listed stocks as a donor pool, we examine possibility of asymmetric effects of the floor closure for NYSE-listed stocks, which, if exists, would not be well-captured in the ATT framework because of being averaged out. To this end, we employ Chernozhukov, Wuthrich, and Zhu (2021, CWZ, henceforth), and so much of this section is a summary of it.

5.1. Empirical Method

A short description of the empirical strategy is the following: (a) applying CWZ, a high-dimensional version of the SCM, to every NYSE-listed stock in the parallel manner as well as to every Nasdaq-listed stock and (b) running placebo studies, investigating how the distribution of estimates for NYSE-listed stocks are different from that for Nasdaq-listed stocks, where the Nasdaq group is assumed to be unaffected by the floor closure, serving as a donor pool. Because the estimation procedure is the same for all stocks, we will focus on estimation for one prototypical stock i in our initial sample, constructed in Table 2.[14]

Let $i = 0, 1, 2, \cdots, N$ denote the cross-sectional universe of $N + 1$ stocks, in which $i = 0$ indicates a stock potentially affected by the floor closure and $i = 1, 2, \cdots, N$ point to N Nasdaq-listed stocks, those unaffected by the floor closure. Further let $t = 1, 2, \cdots, T$ denote the sample periods, where the floor closure begins at $t = T_0 + 1$ so that there are T_0 pre-closure periods and $T_1 \equiv T - T_0$ floor-closure periods. For each stock, $Y^N_{i,t}$ denote the potential outcome to be realized when the floor remains open. For stock $i = 0$, $Y^I_{0,t}$, $t > T_0$ denotes the potential outcome to be realized under the floor closure. Then, $\alpha_{0,t} \equiv Y^I_{0,t} - Y^N_{0,t}$ for $t > T_0$ defines the floor-closure effect for stock $i = 0$ in period $t > T_0$. The parameter of interest here is its time-series average τ_0, which we call ITT:

$$\tau_0 = \frac{1}{T_1} \sum_{t=T_0+1}^{T} \alpha_{0,t} \tag{3}$$

Importantly, counterfactuals $\{Y^N_{0,t}\}_{t>T_0}$ of $\alpha_{0,t}$ in (3) is unobservable, known as the *fundamental problem of the casual inference*.[15] Following the SCM's idea, CWZ exploits a cross-sectional predictive relation between $i = 0$ and $i \neq 0$, assumed to be in a linear structure:

$$Y^N_{0,t} = \mu + \sum_{i=1}^{N} w_i Y^N_{i,t} + u_{0,t}, \quad \mathbb{E}[u_t] = 0 \tag{4}$$

where μ and $w = (w_1, w_2, \cdots, w_N)$ are an intercept and coefficients characterizing the cross-sectional predictive relation, and $u_{0,t}$ is a stationary error term. As in a traditional SCM model, we employ pre-closure data $t = 1, 2, \cdots, T_0$ to estimate μ and w first and then impute the counterfactuals using the outcomes for unaffected stocks over $t = T_0 + 1, \cdots, T$. Unlike to a typical setup of the SCM having

[14]When estimation is applied to Nasdaq-listed stock i, everything remains the same except that the predictor set changes from all Nasdaq-listed stocks to all Nasdaq-listed stocks but stock i.

[15]See Holland (1986).

small N relative to T_0, however, CWZ tackles a high-dimensional setup of N way larger than T_0 by means of regularization, in addition to a bias-correction strategy based on sample splitting.

To be specific, let $H_1 \cup H_2 \cup \cdots \cup H_K \subseteq \{1, 2, \cdots, T_0\}$ be the K consecutive non-overlapping blocks of the pre-closure period in equal size. Further, let H_k denote the k-th block and $H_{(-k)} \equiv \{1, 2, \cdots, T_0\} \setminus H_k$ the rest of the pre-closure period. Then, the Lasso regression on (2) with only the sample corresponding to $H_{(-k)}$ solves the following penalized least squares problem:

$$\min_{\mu, w} \sum_{t \in H_{(-k)}} \Big(Y_{0,t} - \mu - \sum_{i=1}^{N} w_i Y_{i,t} \Big)^2, \quad s.t. \quad \sum_{i=1}^{N} |w_i| \leqslant Q \tag{5}$$

where $Q > 0$ is a predetermined constant.[16] Let $\hat{\mu}_{(k)}$ and $\hat{w}_{(k)} \equiv (\hat{w}_{1,(k)}, \hat{w}_{2,(k)}, \cdots \hat{w}_{N,(k)})$ be the resulting estimates of the Lasso regression. Then, the bias-corrected estimator of τ_0 with respect to block k is defined as:

$$\hat{\tau}_k = \frac{1}{T_1} \sum_{t=T_0+1}^{T} \big(Y_{0,t} - \sum_{i=1}^{N} Y_{i,t} \hat{w}_{i,(k)} \big) - \frac{1}{|H_k|} \sum_{t \in H_k} \big(Y_{0,t} - \sum_{i=1}^{N} Y_{i,t} \hat{w}_{i,(k)} \big) \tag{6}$$

The first term represents the average out-of-sample prediction error over the floor-closure period, which would consist of closure effects and a *bias component*, inherently embedded due to regularization in the Lasso regression. The second term is also the average out-of-sample prediction errors but over H_k, a part of the pre-closure period, which would then only contain the bias component. Thus, taking difference between them removes the bias component.

The final estimator of τ_0 is the average of such estimators, defined as:

$$\hat{\tau}_0 = \frac{1}{K} \sum_{k=1}^{K} \hat{\tau}_k, \tag{7}$$

and a related test statistics $\mathbb{T}_K$ for the null hypothesis $H_0 : \tau_0 = c$ for some constant c is given by:

$$\mathbb{T}_K = \frac{\sqrt{K}(\hat{\tau}_0 - c_0)}{\hat{\sigma}_{\hat{\tau}}}, \quad \hat{\sigma}_{\hat{\tau}} = \sqrt{1 + \frac{Kr}{T_1}} \sqrt{\frac{1}{K-1} \sum_{k=1}^{K} (\hat{\tau}_k - \hat{\tau})^2}, \quad r = \min\{[T_0/K], T_1\} \tag{8}$$

where $\mathbb{T}_K$ follows a t-distribution with $K - 1$ degree of freedom asymptotically.

Note that while an asymptotic distribution for test statistics $\mathbb{T}_K$ is known, it depends on K, the number of blocks to be used for bias correction. Importantly, there is no definite rule suggested on choice of K in CWZ, even as it can result in different conclusions. For example, it is possible that estimated effects appear to be statistically significant with $K = 3$ but not with $K = 4$, as seen in an empirical example of CWZ. Thus, rather than relying on this asymptotic distribution, we adopt a placebo-test approach following the conventional SCM, comparing estimates for NYSE-listed stocks with those for Nasdaq-listed stocks with the same K in place.

[16] In empirical analysis, we solve the Lagrangian form of the problem (5):

$$\min_{\mu, w} \sum_{t \in H_{(-k)}} \Big(Y_{0,t} - \mu - \sum_{i=1}^{N} w_i Y_{i,t} \Big)^2 + \lambda \sum_{i=1}^{N} |w_i|$$

with tuning parameter λ obtained from the standard 10-fold cross-validation over the full sample. This is motivated by the fact that λ and Q has a one-to-one mapping.

In our estimation, time index t indicates an one-minute segment, and blocks, $H_1, H_2, \cdots, H_K$, correspond to the last K three-weeks in the pre-closure period. We also set $t = T_0+1, T_0+2, \cdots, T$ as one-minute segments over one given three-week in either the floor-closure periods or floor-reopening periods and run estimation for every three week one-by-one over floor-closure and floor-reopening periods, i.e., τ_0 represents ITT over one chosen three-week in either the floor-closure periods or floor-reopening periods. The three week as estimation interval is chosen to ensure that we are given enough observations from one-minute time-weighted inside quote data over 15:50-16:00, which is crucial to make Lasso-regularization meaningful in our high-dimensional setup with $N \approx 1,350$.

5.2. Results

Investigation into ITT regarding the floor closure is based on comparison of the distributions of the test statistics between the NYSE and Nasdaq placebo group. In this approach, the distribution for Nasdaq-listed stocks offer falsification results that play a role similar to the null distribution in the standard econometric framework.

Figure 5: Distribution of Test Statistics: Percentage Quoted Spread

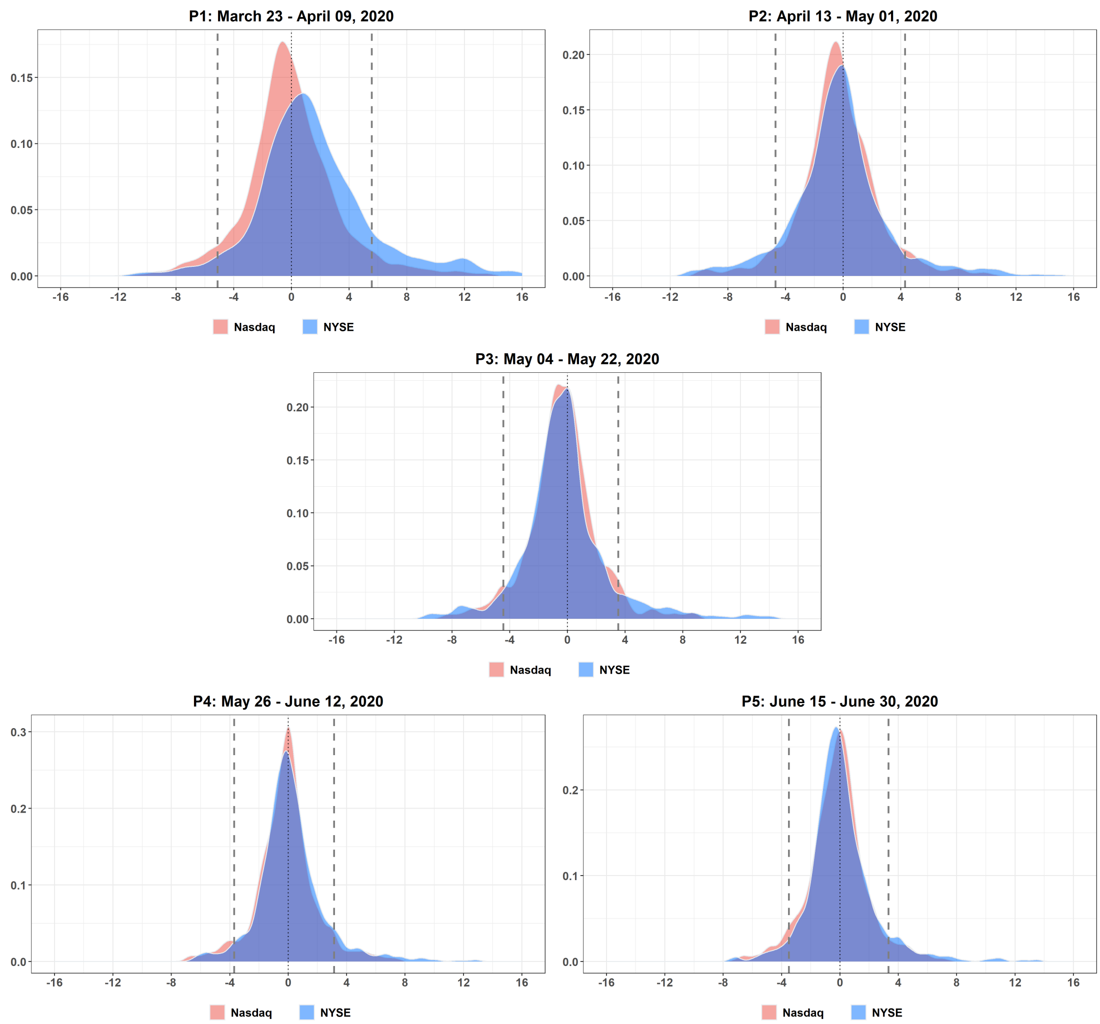


Figure 5 shows the distributions for percentage quoted spread by five sub-periods divided by three weeks starting from March 23 through June 30, 2020, where the first three sub-periods correspond to the floor closure period and the remaining two sub-periods to the floor reopening period. It appears that there is no conspicuous difference in the distributions of the test statistics between the NYSE and Nasdaq groups in our sample except **P1**, the first three weeks of the floor closure beginning from March 23 through April 9. However, even in **P1**, a majority of NYSE-listed stocks are indistinguishable from the placebo group, depicting that increases in percentage quoted spread for NYSE-listed stocks in our sample are limited to a small number of them, which in fact takes only about 14% of the NYSE-listed sample stocks.

Figure 6: Distribution of Test Statistics: Consolidated Displayed Depth

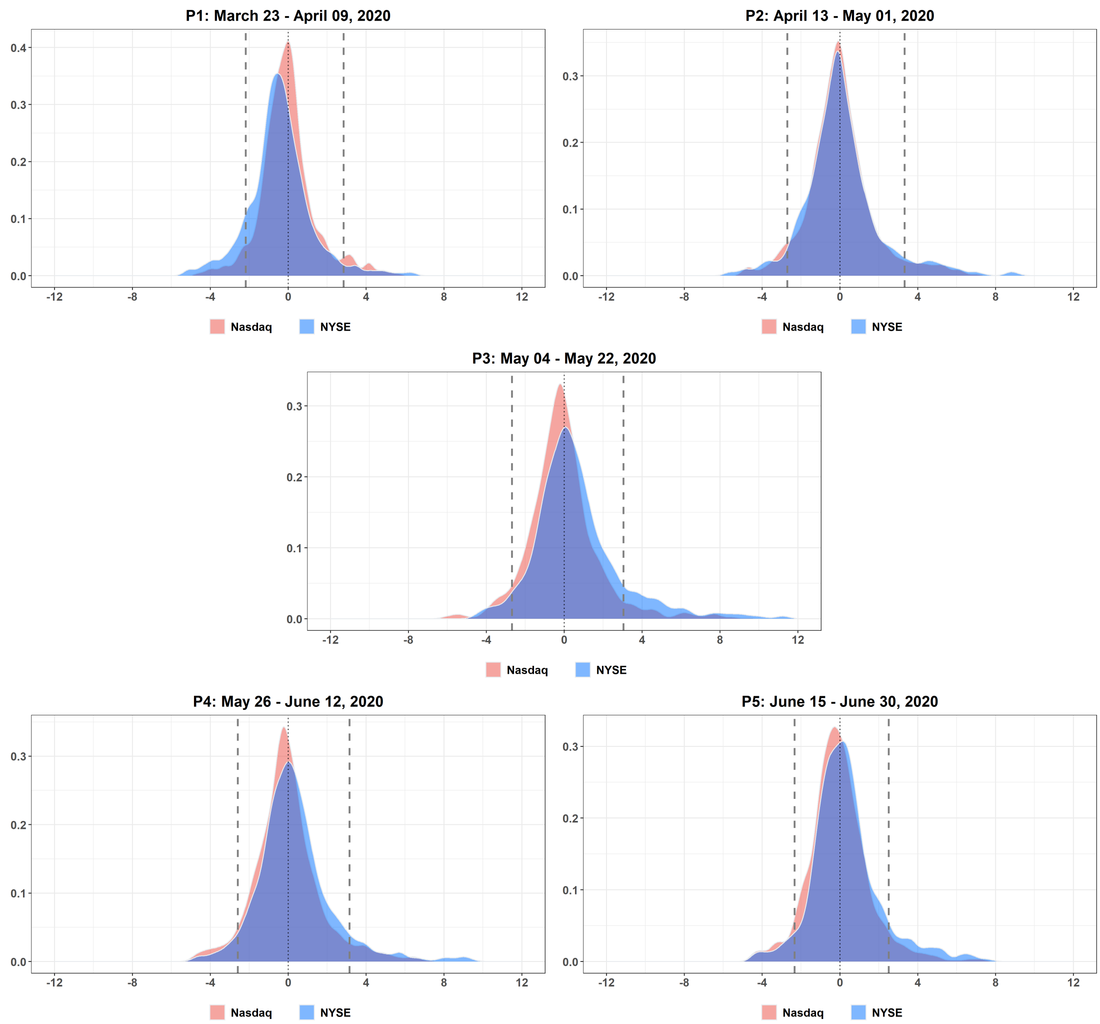


Figure 6 shows the results for consolidated displayed depth. The figures here overall paint a similar story to percentage quoted spread. There is no noticeable difference in the distributions between NYSE- and Nasdaq-listed stocks as a whole while there is weak evidence that some NYSE-listed stocks may experience decreases in consolidated displayed depth in the first three weeks of the floor closure, which amounts to merely 10% of the NYSE-listed sample stocks.

Table 6 reports related numerical results, presenting the inverse-variance weighted average of estimates of ITT for NYSE-listed stocks in quintile groups sorted on the test statistics, along with average test statistics within the groups. It shows that only group 5 has a larger average test statistics than the 95th percentile of the test-statistics of the placebo group but except for the first three-week period of the floor closure (**P1**), it is barely larger than that. While an increase in percentage quoted spread in group 5 is more than a 2 basis points (bps) in the first three weeks of the closure (**P1**), it is around 1 bp in the rest of the floor closure period (**P2** and **P3**), delivering economically negligible magnitude of the effects. Looking through all the rest of the groups, it becomes clearer that impacts of the floor closure are limited on percentage quoted spread. The results for consolidated displayed depth, reported in panel B in the table, also reveal that reductions in consolidated displayed depth over the closure period (**P1**, **P2**, and **P3**) are not widespread nor economically meaningful. During the floor reopening period (**P4** and **P5**), the average estimates of ITT on either percentage quoted spread or consolidated display depth mostly remain small in magnitude, and the average test statistics also convey that those are similar to the placebo group as a whole. In sum, the results of ITT analyses are overall consistent with the ATT results drawn from the matched-sample analysis in the previous section but hint that there could be a small group of the NYSE-listed stocks negatively affected by the floor closure over the initial few weeks of the floor closure.

6. Discussion

To evaluate possible deterioration of market quality over 15:50–16:00 due to the Covid-19 closure, we first investigated ATT in a matched-sample approach and then employed a ML approach to tackled the question at more disaggregated level. Given our empirical setup that enables us to achieve a close match between NYSE- and Nasdaq-listed stocks as a group, the former would result in highly reliable estimates but only in the sense of average effects in the cross-section. On the other hand, the latter can describe a broader aspect, the distribution of treatment effects, but rather less reliably because its key intermediate step of estimation involves an array of predictions. Because of it, we believe the combination of them offsets the weakness of each.

Importantly, either approach in use, we reached the same conclusion: the floor closure had no significant impact on both percentage quoted spread and consolidated displayed depths for the last 10 minutes, the interval during which floor brokers are presumably most influential with D-Orders to investors. We interpret it as showing the absence of the alternative execution channel does not overwhelm liquidity on consolidated limit order books.

Notice that our analysis only look at quote-based liquidity measures. This is to ensure we are given enough observations for ML estimation. Combined with a short window of the last 10-minute for analysis, it makes us incapable of investigating trade-based market quality measures credibly, such as realized spread or effective spreads, which are among the market quality measures studied by Chung and Chuwonganant (2022) and Brogaard, Ringgenberg, and Rösch (2021), who focus on average impacts over the whole trading hours. Thus, admittedly, it would be a limitation of our paper.

However, from the perspective that floor brokers serves as an alternative execution channel to consolidated limit order books, the two quote-based measures considered in this paper, percentage quoted spread and consolidated displayed depth, would be the one that is most evidently affected by availability of floor brokers. Given that we document no impact of the floor closure on them, we conjecture that it also would have had a limited impact on other market quality measures during the floor closure period.

Table 6: Individual Stock-Level Treatment Effects on the Treated in Quintile

This table summarizes estimates of ITT for NYSE-listed stocks in quintile groups sorted by the test statistics over five three-week sub-periods beginning from March 23 through June 30, 2020. The inverse-variance weighted average is taken on estimates of ITT within each group, i.e., $\sum_i w_i \hat{\tau}_i / \sum_i w_i$ with $w_i = 1/\text{Var}(\hat{\tau}_i)$. Also, the simple average test statistics within the groups are reported along with quantiles of the test statistics for Nasdaq-listed stocks at the lower and upper 5% level. **P1**, **P2**, and **P3** are three three-week sub-periods of the floor closure from March 23 through May 22, 2020, and **P4** and **P5** are two three-week sub-periods of the floor reopening from May 26 through June 30, 2020.

Quintile Groups	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	$[Q^{nasd}_{5\%}(\hat{\mathbb{T}}_i), Q^{nasd}_{95\%}(\hat{\mathbb{T}}_i)]$
A. Percentage Quoted Spread (bps)						
P1	-0.8618	-0.0696	0.3425	0.6892	2.3704	
$\overline{\mathbb{T}}_g = N_g^{-1}\sum_i \hat{\mathbb{T}}_i$	-3.21	-0.32	1.15	2.95	8.54	[-5.12, 5.57]
P2	-0.6533	-0.6457	-0.1119	0.2496	1.0739	
$\overline{\mathbb{T}}_g = N_g^{-1}\sum_i \hat{\mathbb{T}}_i$	-4.66	-1.48	-0.30	0.80	4.55	[-4.69, 4.30]
P3	-1.1500	-0.8392	-0.3117	0.1875	1.1587	
$\overline{\mathbb{T}}_g = N_g^{-1}\sum_i \hat{\mathbb{T}}_i$	-3.92	-1.38	-0.38	0.56	4.10	[-4.44, 3.53]
P4	-0.7807	-0.3631	-0.0206	0.1446	0.7811	
$\overline{\mathbb{T}}_g = N_g^{-1}\sum_i \hat{\mathbb{T}}_i$	-2.55	-0.77	-0.03	0.82	3.51	[-3.70, 3.15]
P5	-0.4958	-0.5835	-0.0789	0.3690	0.8864	
$\overline{\mathbb{T}}_g = N_g^{-1}\sum_i \hat{\mathbb{T}}_i$	-2.60	-0.89	-0.14	0.71	3.45	[-3.50, 3.33]
B. Consolidated Displayed Depth (100 shrs.)						
P1	-0.5592	-0.4587	-0.1868	0.0618	0.4475	
$\overline{\mathbb{T}} = N_g^{-1}\sum \hat{\mathbb{T}}_i$	-2.56	-1.06	-0.48	0.13	1.82	[-2.18, 2.85]
P2	-0.7024	-0.2273	-0.0272	0.1860	0.6168	
$\overline{\mathbb{T}} = N_g^{-1}\sum \hat{\mathbb{T}}_i$	-2.29	-0.74	-0.09	0.60	3.01	[-2.70, 3.33]
P3	-0.6452	-0.2278	0.1142	0.4059	0.9642	
$\overline{\mathbb{T}} = N_g^{-1}\sum \hat{\mathbb{T}}_i$	-1.86	-0.46	0.29	1.19	4.13	[-2.68, 3.05]
P4	-0.7494	-0.2923	0.0653	0.3732	0.9426	
$\overline{\mathbb{T}} = N_g^{-1}\sum \hat{\mathbb{T}}_i$	-1.93	-0.58	0.12	0.89	3.24	[-2.59, 3.15]
P5	-0.8339	-0.2432	0.0641	0.3477	1.0257	
$\overline{\mathbb{T}} = N_g^{-1}\sum \hat{\mathbb{T}}_i$	-1.79	-0.56	0.11	0.81	2.98	[-2.33, 2.51]

7. Conclusion

This paper investigates the Covid-19 shutdown of the NYSE trading floor. We study the impact of the shutdown on market quality for the last 10 minutes into the close 15:50–16:00, when floor brokers become most useful as an alternative trading channel for investors. Looking at the Russell 3000 index constituents either NYSE-listed or Nasdaq-listed, we find that the impact of the floor closure on market quality is limited. Those results are supported by empirical evidence at both the individual stock level and aggregate level. We conclude that the absence of the floor brokers has no harm on market quality over 15:50–16:00, when gauged on percentage quoted spread and consolidated displayed depth.

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