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# Closing auctions: Nasdaq versus NYSE ☆

Narasimhan Jegadeesh[a,*], Yanbin Wu[b]

[a] Goizueta Business School, Emory University, Atlanta, GA 30322, USA
[b] Warrington College of Business, University of Florida, Gainesville, FL 32611, USA

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ABSTRACT

Closing auction volume steadily increased over the last decade, and it reached a peak of about 10% of the total trading volume in 2019. We examine the price impact and resiliency of closing auctions, and we compare closing auction liquidity in Nasdaq and the NYSE. The NYSE offers more depth. In both exchanges, it takes about 3–5 days for the temporary component of the price impact to fully dissipate. Trading strategies that exploit this price impact and its reversals are significantly profitable.



## 1. Introduction

The trading volume in closing auctions has grown significantly in recent years, increasing from about 3% of the trading volume in 2010 to about 10% in 2019. Closing auctions are the busiest time in the US equity market trading day, and they produce the day's most important price point for investors. The closing auction price is the most widely published reference price for mutual funds and for many exchange-traded products.

We examine closing auctions in detail, and we address the following research questions: How does closing auction volume relate to uninformed trades versus informed trades? What is the price impact of closing auction trades? How large are the permanent and temporary components of this price impact? How much time is required for the temporary component to dissipate? How does the cost of trade executions in closing auctions compare to executions made during trading hours?

We also compare the price impact of closing auctions in Nasdaq versus the NYSE. The primary difference between these exchanges is that Nasdaq's algorithms determine the closing price for each stock that maximizes trading volume, and it uses time priority to allocate shares

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* Corresponding author.
*E-mail address:* jegadeesh@emory.edu (N. Jegadeesh).

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against limit orders with the limit price equal to the closing price. In contrast, *designated market makers* (DMMs, formerly known as *specialists*) manage the NYSE's closing auction. The DMMs, as well as the floor brokers (collectively, *floor traders*) who place their orders directly with the DMMs, have more flexibility in placing and modifying on-close orders in the NYSE than off-exchange traders. Also, the NYSE uses a "parity/priority" rule that prioritizes limit orders from floor traders over limit orders from off-floor traders when there is an excess demand or excess supply at the closing price.[1]

The growing importance of closing auctions and the special treatment of floor traders have fueled questions about whether the NYSE model benefits investors or whether it mainly benefits floor traders. Nasdaq and the NYSE separately released their own research reports claiming that closing auctions perform better in their respective exchanges.[2] Additionally, a recent bulletin by the Congressional Research Service observes that the recent temporary shutdown of the NYSE trading floor has also "...intensified interest in an ongoing debate over the utility and necessity of the trading floor, which some characterize as an obsolete relic."[3]

We present a model to conceptually examine the relative merits of the closing auction processes in Nasdaq and the NYSE. Our model builds on Madhavan and Panchapagesan (2000) and adds key features of closing auctions. In our model, the exchanges announce closing auction order imbalances, and various categories of liquidity providers (LPs) compete to absorb them. The LPs in the Nasdaq setting are a homogeneous set of off-exchange traders. In the NYSE setting, these off-exchange LPs compete with the floor traders. Because of their special privileges, the floor traders have a competitive advantage over the off-exchange LPs. As a result, they displace some of the latter. Which of these systems provides better liquidity depends on whether the incremental market depth provided by the floor traders offsets the loss of depth due to the displacement of off-exchange LPs.

We first investigate the participation of informed and uninformed traders in closing auctions. As Kyle (1985) shows, informed traders adversely affect market depth while uninformed traders add depth. We find a positive correlation between proxies for uninformed trading, such as measures of arbitrage activities in exchange-traded funds (ETFs), fund flows into and out of index mutual funds, and closing auction volume. In contrast, we find a marginally negative relation between closing auction volume and the flows into and out of active mutual funds, which is a proxy for informed trading. We also find that the closing auction volume, as a fraction of total trading volume, significantly declines on the day before earnings announcements. Overall, these findings indicate that closing auctions attract uninformed traders, but informed traders are more likely to trade during trading hours than in closing auctions.

We then examine the price impact of closing auctions. We use closing auction data that Nasdaq and the NYSE disseminate in real time to their subscribers every few seconds until close, starting at 3:50 p.m. in Nasdaq and at 3:45 p.m. in the NYSE.[4] The information these exchanges disseminate for each stock includes total orders, total buy and sell orders, and order imbalances.

The evolution of order imbalances during this dissemination window in Nasdaq differs significantly from that in the NYSE. For instance, order imbalances in Nasdaq drop by about 80% immediately after the start of closing information dissemination, and they gradually decline thereafter. In contrast, the order imbalances in the NYSE remain virtually constant until 3:55 p.m., then they drop sharply when closing information starts including orders placed through floor brokers. Orders through floor brokers account for about 20% of the NYSE closing auction volume, while total new orders after the first dissemination of closing information account for only about 0.1% of the Nasdaq closing auction volume.

We next examine the price impact and resiliency of closing auctions. We find that the price impact in Nasdaq is 58% larger than in the NYSE during the 2010–2020 sample period. The price impact in Nasdaq is more than twice as large as in the NYSE in the second half of the sample period. Orders placed through floor brokers also comprise a larger fraction of closing auction volume in the second half of the sample period than in the first half.

We examine the time it takes for the temporary component of the price impact to fully dissipate, which is a measure of price resiliency. The temporary components of the price impact comprise about 85% in Nasdaq and about 62% in the NYSE, and they fully reverse over the next 3–5 days in both exchanges. The temporary component of the price impact in Nasdaq is larger, but both exchanges seem equally resilient. We consider trading strategies to evaluate the economic significance of the price impact and reversals. These strategies yield economically significant profits.

The NYSE closed floor trading during the second quarter of 2020 due to the COVID-19 pandemic, and this closure serves as a natural experiment to directly assess floor traders' contribution to the depth of the NYSE closing auctions. Contrary to our findings over the full sample period, the depth of closing auctions in Nasdaq was better than in the NYSE during the shutdown period. This evidence is consistent with the predictions of our model that competition from floor traders would displace at least some off-exchange LPs in the NYSE; therefore, Nasdaq would have more depth in the absence of floor traders.

During the shutdown, the NYSE's floor brokers had the ability to place orders individually through the electronic order book. Yet, the depth of Nasdaq's closing auction was better than that of the NYSE during this period. Therefore, the special privileges the floor brokers enjoy, and their

[1] See https://www.nyse.com/article/parity-priority-explainer?utm_source=navigation&utm_medium=nav&utm_campaign=tradenav

[2] See https://www.nasdaq.com/articles/are-designated-market-makers-really-better-in-stressed-markets-2020-04-16 and https://www.nyse.com/article/stocks-trade-better-on-nyse

[3] See https://sgp.fas.org/crs/misc/IN11447.pdf

[4] The time when the exchanges start to disseminate closing auction data varies over our sample period. Appendix A presents these times. The starting times are 3:50 p.m. in Nasdaq and 3:45 p.m. in the NYSE during most of our sample period. All times are Eastern Time.

ability to work collectively on the floor with the DMMs, is critical for NYSE's depth during normal operations.

Recent papers by Bogousslavsky and Muravyev (2020) and Hu and Murphy (2021) also study closing auctions. Bogousslavsky and Myravyev document that closing auction prices deviate from the midpoints of the final bid–ask spread quotes before closing auctions. They also examine several implications of their findings for issues such as ETF mispricing and put–call parity violations.

Hu and Murphy (2021) (hereafter *HM*) also compare closing auctions in Nasdaq and the NYSE as we do, but they conclude that "...closing auction market quality is significantly worse on NYSE than Nasdaq throughout the closing auction process." HM draw their inferences based on several metrics that differ from the metrics we use, and this leads them to a different conclusion. We discuss their metrics in more detail and explain why we reach different conclusions later in the paper, after we describe our empirical tests and results.

## 2. Closing auctions

Nasdaq and the NYSE conduct closing auctions for stocks listed on their respective exchanges in generally similar ways until near the end of trading hours. Nasdaq accepts market-on-close orders (MOCs) and limit-on-close orders (LOCs) starting some time before the market opens. Starting at 3:50 p.m., Nasdaq disseminates closing information that includes the number of paired orders, the number of imbalance shares, and the indicative clearing price. We refer to this feed as *closing information*.

Nasdaq does not allow new orders or cancellations/modifications of existing MOCs or LOCs after 3:55 p.m. LOCs may be entered until 3:58 p.m. Nasdaq also accepts imbalance-only orders (IOs) up to 4:00 p.m., which are limit orders at Nasdaq best bid or offer (BBO) price at close.[5] Any outstanding market orders at the end of regular trading are also cleared during closing auctions.

The NYSE also opens its order book for MOCs and LOCs before the market opens, then closes the order book at 3:45 p.m. (recently changed to 3:50 p.m.). It disseminates closing information starting at 3:45 p.m. (recently changed to 3:50 p.m.). After this time, traders are allowed to place MOCs and LOCs on its electronic order book only on the contra-side of *OI*. The NYSE also allows investors to place *closing offset* orders (COs) on any side, but they are executed only against the opposite side of the imbalance at close, and they can never add to the imbalance.

The main difference between the closing auctions in Nasdaq and the NYSE is the involvement of DMMs and floor brokers in the NYSE. Investors can place discretionary orders for execution at close, also known as closing *D-orders*, through floor brokers in the NYSE. D-orders can be placed or modified until 3:59:50 p.m., and they are included in the closing information only after 3:55 p.m.

Closing D-orders can be buy or sell orders regardless of the side of the order imbalance. DMMs can also buy or sell for their proprietary accounts. DMMs are obligated to manage the closing auction process, "...which includes setting the closing price at a level that satisfies all interest that is willing to participate at a price better than the closing auction price, and supplying liquidity as needed to offset any remaining auction imbalances that exist at the closing bell."[6]

The two exchanges also differ in how they allocate shares against on-close orders when there is excess demand or supply at the closing price. Nasdaq prioritizes allocations based on the time of order entry. In contrast, the NYSE uses a "parity/priority" rule that prioritizes on-close orders from the floor traders over similar orders placed through its electronic order book. According to the NYSE, this rule is designed to improve market liquidity.

## 3. A model of closing auctions: Nasdaq vs. the NYSE

This section presents a model to theoretically examine market liquidity in settings that broadly capture the features of closing auctions in Nasdaq and the NYSE. Our model builds on Madhavan and Panchapagesan (2000) (hereafter *MP*), and it incorporates the announcements of order imbalances (OIs) and subsequent bids in two settings. The first setting allows for bidding from any trader after the announcement of OIs, which is broadly similar to the Nasdaq procedure. The second setting also allows bidding by floor traders, as in the NYSE. We compare the market depths in these two settings.

As in MP, there are $N$ informed investors in an economy, and there is one risky asset traded in the economy. The informed investors have a negative exponential utility function $U_i(W_i) = -e^{\rho W_i}$, where $W_i$ and $\rho$ are investor $i$'s terminal wealth and risk aversion coefficient, respectively. The investor's initial wealth is composed of risky asset $e_i$ and $c_i$ in cash. The initial position $e_i$ is normally distributed with $E(e_i) = 0$ and $Var(e_i) = \sigma_e^2$. We normalize the risk-free interest rate to zero.

Investors share a common prior that the unknown terminal risky asset value is normally distributed with mean $\mu$ and precision $\omega$.[7] The terminal value of the stock $v$ is revealed on the terminal date. Informed investors receive a noisy signal $s$ about the terminal value, and $s$ is normally distributed with mean $v$ and precision $\psi$. Because we assume informed investors' priors and the signal are normally distributed, their posteriors are also normally distributed with mean $v_0$ and variance $\sigma^2$, and

$$v_0 \equiv E[v|s] = \mu\gamma + s(1-\gamma), \tag{1}$$

$$\sigma^2 \equiv Var[v|s] = (\omega+\psi)^{-1}, \tag{2}$$

where $\gamma = \omega/(\omega+\psi)$. With these assumptions, MP show that the informed investors' demand function $q_i^{inf}(p)$ is

$$q_i^{inf}(p) = \frac{1}{\rho\sigma^2}(v_0 - p) - e_i. \tag{3}$$

[5] Buy IOs execute only if closing prices are above the 4:00 p.m. *ask* price. Sell IOs execute only if closing prices are below the 4:00 p.m. *bid* price.

[6] See https://www.nyse.com/article/nyse-closing-auction-insiders-guide

[7] The *precision* is the inverse of the *variance*.

The aggregate demand of $N$ informed traders is

$$Q^{inf}(p) = N\lambda_{inf}(v_0 - p) - \sum_{i=1}^{N} e_i, \text{ where } \lambda_{inf} = \frac{1}{\rho\sigma^2}. \tag{4}$$

There is a continuum of noise traders in the economy who trade for exogenous reasons unrelated to the fundamental value of the asset. These noise traders place MOC orders. The MOC orders are aggregated, and $OI$ is the order imbalance from noise traders, which is normally distributed with $E[OI] = 0$. Because MOC orders are due to exogenous factors, $OI$ is uncorrelated with informed traders' signal $s$, and $OI$ does not convey any value-relevant information.

### 3.1. Nasdaq and NYSE features

This subsection adds closing auctions to the model. We first introduce *liquidity providers* (LPs), who are uninformed traders competing to be counterparties to $OI$, as in Nasdaq closing auctions. We then introduce floor traders who compete with the LPs to absorb the $OI$. Floor traders differ from LPs because they have access to superior information, as we describe below. The addition of floor traders captures a feature of closing auctions in the NYSE. We then compare closing auction liquidity in these two settings.

### 3.2. Liquidity providers

The liquidity providers place LOCs after the announcement of closing information and compete to absorb the order imbalance. The LPs in our model are uninformed traders who seek to profit from the difference between the closing auction price and the fundamental value of the stock. For example, if there were a sell order imbalance, LPs offer to buy the stock at prices less than its fundamental value and the difference between the closing price and fundamental value is the LPs' compensation for providing liquidity.[8] The LPs also compete with the limit orders placed by the informed investors, which remain on the order book.

LPs also have a negative exponential utility function with the risk aversion coefficient $\rho$.[9] Because $OI$ conveys no value-relevant information, the LPs' demand curve is based on the uninformed prior distribution of $v$. An LP's demand curve is

$$q^{lp}(p) = \lambda_{lp}(\mu - p), \tag{5}$$

where $\lambda_{lp} = \frac{\omega}{\rho}$.

### 3.3. Designated market makers and floor brokers

DMMs have an obligation to maintain fair and orderly markets for the stocks assigned to them. The DMMs and the floor brokers who work with them in the NYSE have access to information that is not available to off-floor traders. The floor brokers can enter orders that are visible only to DMMs and not to NYSE's OpenBook data feed that transmits aggregate limit-order volume at every bid and offer price to off-exchange subscribers. DMMs also have access to additional information, including disaggregated data at the individual order level that includes price, size, and the names of the entering and clearing firms. The NYSE allows DMMs to share this disaggregated information with floor brokers in response to brokers' queries.

Additionally, the floor brokers tend to have long relationships with their clients, and they tend to have information about their clients' motives for trading. Benveniste et al. (1992) show that because DMMs have repeat relations with the floor brokers, DMMs would be able to incentivize floor brokers to truthfully reveal their information, and sanction those who are not truthful.[10] As a result, Benveniste et al. show that floor brokers truthfully reveal their information in equilibrium. Effectively, DMMs and floor brokers have a symbiotic relationship. They collectively have access to information not available to off-exchange traders.

Let $\delta$ denote the floor traders' information and let $\delta$ be normally distributed with mean $v$ and precision $\psi_\delta$.[11] The floor traders' posterior $p^*$ is

$$p^* \equiv E[v|\delta] = \mu\gamma_\delta + \delta(1 - \gamma_\delta), \tag{6}$$

$$\gamma_\delta = \frac{\omega}{(\omega + \psi_\delta)}, \text{ and} \tag{7}$$

$$Var(p^*|\delta) \equiv \sigma^2_{p^*} = (\omega + \psi_\delta).^{-1} \tag{8}$$

Suppose there are collectively $N_{ft}$ floor traders, and their utility function is represented by a negative exponential utility function with a risk aversion coefficient equal to $\rho$.[12] The floor traders' aggregate demand function is

$$Q^{ft}(p) = N_{ft} \times \lambda_{ft}(p^* - p), \text{ where } \lambda_{ft} = \frac{1}{\rho\sigma^2_{p^*}}. \tag{9}$$

[8] The difference between the closing auction price and the fundamental value depends on the side of the order imbalance. However, in the end, every buy order matches with a sell order. For example, starting with a sell order imbalance, the expected closing auction price would be less than the fundamental value. This difference between the fundamental value and the closing price is the compensation the noise traders pay the LPs for providing liquidity.

[9] We assume the same risk aversion for informed investors and LPs for notational convenience.

[10] The DMMs serve as the information nerve centers and facilitate floor brokers' execution of large orders. For example, if a floor broker representing a buying interest inquires about potential selling interest, the DMM may inform the broker of other parties who may have inquired about buying interest. The DMMs could also be the contra-side in their own proprietary account. The critical role that DMMs play in facilitating floor brokers' trades gives DMMs the leverage to incentivize floor brokers to be truthful.

[11] All informed investors, including floor brokers' clients, receive the same signal $s$. Therefore, $\delta$ is noise added to $s$ and the noise is due to factors such as the clients' initial endowment and any errors in the brokers' inferences about their clients' motives. Because informed investors directly observe $s$, they do not gain any additional information from floor traders' orders or from the eventual closing price.

[12] A floor broker is effectively a representative agent for their customers. We assume that $\rho$ for the representative agent is the same as that for all other agents for notational convenience. We also do not consider trades for exogenous reasons through floor brokers for notational simplicity.

*3.4. Price impact*

This section determines the closing auction prices and compares the price impacts of order imbalances with and without floor traders. We refer to the setting that includes LPs but not floor traders as *Nasdaq*, and we refer to the setting that includes both LPs and floor traders as *NYSE*, because these settings broadly capture the features of the closing auctions in the respective exchanges.

Let there be $K_{nasd}$ LPs in Nasdaq. Their aggregate demand curve $Q_{nasd}(p)$ is

$$Q_{nasd}(p) = Q^{inf}(p) + K_{nasd}q^{lp}(p) + OI. \tag{10}$$

The closing auction price $p_{nasd}$ is the price that clears the market, i.e., $Q_{nasd}(p_{nasd}) = 0$.

Let $K_{nyse}$ be the number of LPs in the NYSE. Because of competition from floor traders, $K_{nyse}$ could be different from $K_{nasd}$. The aggregate demand curve, including floor traders' demand, is

$$Q_{nyse}(p) = Q^{inf}(p) + K_{nyse}q^{lp}(p) + Q^{ft}(p) + OI. \tag{11}$$

The closing auction price $p_{nyse}$ is the price that clears the market, i.e., $Q_{nyse}(p_{nyse}) = 0$.

A large fraction of closing auction volume cross between traders who submit buy and sell orders, but the exchange plays an important role in clearing order imbalances. How does the liquidity of the Nasdaq system compare to that of the NYSE system? One important measure of liquidity is the price impact of *OI*. The price impact is the difference between the closing auction price and an appropriate reference price. The reference price could be the price just before the announcement of *OI* or the price after the trade when the price impact fully dissipates. The two measures of the price impact in our context are:

- Ex ante price impact $\equiv E[(p_j - \mu)|OI]$
- Ex post price impact $\equiv E[(v - p_j)|OI]$, and for $j = nasd \text{ or } nyse$

The ex post price in the model is the terminal value $v$.[13] The ex ante price is the price just before the *OI* announcement. The model does not determine an ex ante price because (a) there is no trade in our model before the *OI* announcement and (b) informed traders are initially exogenously endowed with some stocks. However, if the informed investors were not initially endowed with any risky asset, then the equilibrium pre-auction price is $\mu$. Therefore, $\mu$ is our ex ante reference price.

*Proposition 1. Under the model assumptions,*

$$E[(p_1 - \mu)|OI] = -E[(v - p_1)|OI] = \frac{OI}{\lambda_{nasd}}, \text{ and} \tag{12}$$

$$E[(p_{nyse} - \mu)|OI] = -E[(v - p_{nyse})|OI] = \frac{OI}{\lambda_{nyse}}, \tag{13}$$

where $\lambda_{nasd} = N\lambda_{inf} + K_{nasd}\lambda_{lp}$ and $\lambda_{nyse} = N\lambda_{inf} + K_{nyse}\lambda_{lp} + N_{ft}\lambda_{ft}$.

**Proof**: See Appendix B.

[13] We ignore any risk premium because the time horizon in our model is fairly short.

Eqs. (12) and (13) indicate that price impact is a linear function of *OI*. The closing auction depth is the order imbalance that results in a price impact of one dollar, which equals the inverse of the price impact. Therefore, the depths in Nasdaq and the NYSE equal $\frac{1}{\lambda_{nasd}}$ and $\frac{1}{\lambda_{nyse}}$, respectively. The depth per trader in the three categories are $\frac{1}{\lambda_{inf}}$, $\frac{1}{\lambda_{lp}}$, and $\frac{1}{\lambda_{ft}}$. Because a floor trader has more precise information than an LP, a floor trader provides more depth than an LP (i.e., $\frac{1}{\lambda_{ft}} > \frac{1}{\lambda_{lp}}$).

Which system offers more depth? Based on Eqs. (12) and (13) in Proposition 1, Nasdaq would have more depth if $K_{nasd} > (K_{nyse} + \frac{N_{ft}\lambda_{ft}}{\lambda_{lp}})$, and vice versa. Therefore, if all LPs who operate in the Nasdaq setting continue to operate in the NYSE setting, then the NYSE would be at least as deep as Nasdaq. However, because LPs incur fixed costs of operation (e.g., data subscription fees, infrastructure costs, personnel costs) in practice, some of them would likely exit when faced with competition from floor traders. If LPs incur a fixed cost of $\kappa$, then the number of LPs would adjust so that in equilibrium, the certainty equivalent of the expected profit per LP equals $\kappa$, as in Grossman and Miller (1988). The expected profit for LPs as a group is smaller when they compete against floor traders. Therefore, in equilibrium, there would be more LPs in Nasdaq than in the NYSE (i.e., $K_{nasd} > K_{nyse}$).

If floor traders can provide enough depth to offset the loss of depth due to the departure of some LPs, then $(K_{nyse} + \frac{N_{ft}\lambda_{ft}}{\lambda_{lp}}) > K_{nasd}$, and the NYSE would offer more depth, and vice versa. Because $K_{nasd}$ and $K_{nyse}$ depend on a number of unknown exogenous parameters, the question of which closing auction offers more depth can only be determined empirically. Nevertheless, because $K_{nasd} > K_{nyse}$, our model implies that LPs as a group provide more depth in Nasdaq than in the NYSE. We could empirically test this implication if floor traders were temporarily excluded from the NYSE. As it happens, the NYSE recently shut down its floor operations due to COVID-19, and this shutdown offers a natural experiment to test this implication.

## 4. Empirical tests and results

This section first presents the trajectory of closing auction volume in Nasdaq and in the NYSE over the last decade. We then examine the relation between closing auction volume and the participation of informed and uninformed traders. Next, we examine the price impact and resiliency of closing auctions, and we compare the liquidity in the two exchanges. We also examine the relative depths of closing auctions in these exchanges during the recent closure of the NYSE floor operations.

*4.1. Trend over time*

We use Trade and Quote (TAQ) data to compute both the daily trading volume and the closing auction volume. For Nasdaq- and NYSE-listed stocks, TAQ identifies closing auction trades with codes *M* and *6*, respectively. The dollar value of closing auction trades is the product of the number of shares traded and the closing auction price. Fig. 1

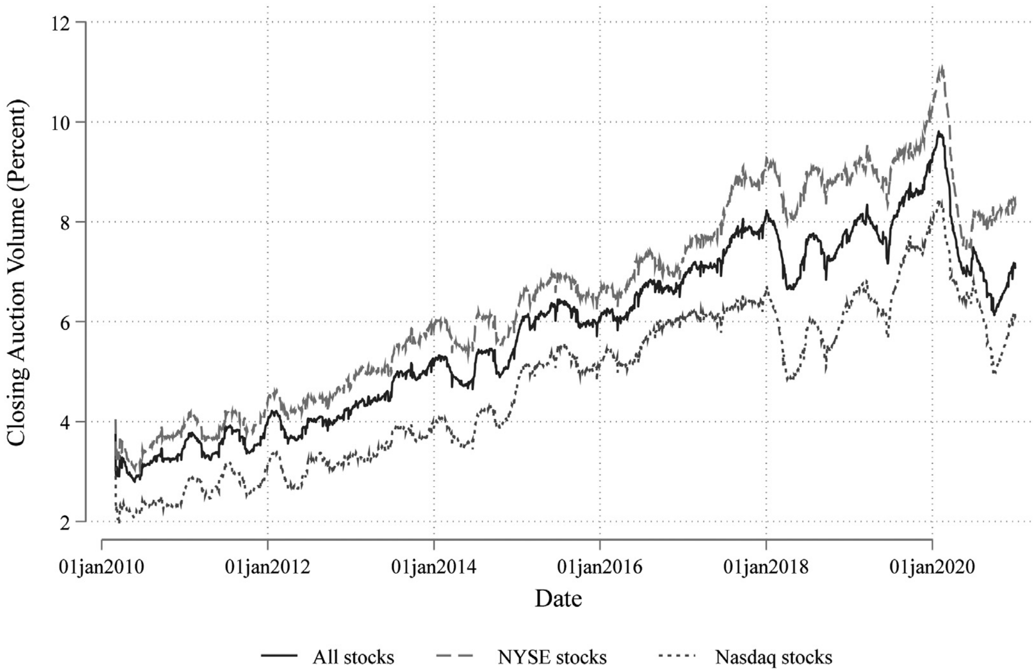


**Fig. 1.** Time-series trends in closing auction trading volume.
This figure presents the 90-day moving average of the total dollar volume of closing auction trades as a fraction of total trading volume for both NYSE stocks and Nasdaq stocks during the sample period of March 2010 to December 2020.

plots the total dollar volume of closing auction trades as a fraction of the dollar volume of all trades for all common stocks with non-zero closing auction volumes. Closing auction volumes steadily increase from about 3% in 2010 to a peak of about 10% in 2019, before declining to about 7% in 2020. This decline in 2020 occurred because the total daily trading volume significantly increased during the COVID-19 pandemic, but the closing auction volume did not grow as fast.[14] The closing auction volume in the NYSE is always greater than the contemporaneous closing auction volume in Nasdaq.

### *4.2. Informed and uninformed trades*

As our model describes, the LPs provide liquidity by taking the opposite sides of the *OI*, and the price impact is compensation for their service. An important factor that determines the price impact is the composition of informed versus uninformed traders in closing auctions. We first examine whether closing auctions attract uninformed traders, whose presence would dampen the price impact and improve liquidity. Specifically, we first examine whether closing auction volume is correlated with proxies for passive trading.

Informed traders also pool with uninformed traders to the extent that they could also benefit from a potentially smaller price impact.[15] However, the decision of informed traders about whether they should wait until close to trade would depend on a trade-off between a potentially smaller price impact and the rate of decay of the value of their information. For example, Holden and Subrahmanyam (1994) show that when risk-averse informed traders expect competition from other informed traders, they optimally execute their trades soon after they receive private information, and they do not wait until a later time to trade. We examine whether closing auction volume is also correlated with proxies for informed trading.

#### *4.2.1. Uninformed trades*

Exchange-traded funds (ETF) that track stock indexes comprise an important category of passive investors. The assets under management (AUMs) of ETFs increase or decrease over time when their designated authorized participants (APs) create or redeem ETF shares.[16] To create new shares, APs first buy the basket of stocks in the ETF portfolio and then sell (or short sell) ETF shares.[17] At the end of

[14] The average daily volume in 2020 was $10.9 billion, compared to about $7.0 billion in 2019.

[15] Admati and Pfleiderer (1988) show that uninformed investors pool their trades during periods of concentrated trading, and closing auctions fit this description. They also show that informed traders prefer to trade with uninformed traders in order to benefit from a smaller price impact. Budish et al. (2015) and the papers surveyed by Menkveld (2016) also present models in which uninformed traders migrate to batch auctions in order to avoid the cost of trading against high-frequency traders in continuous auctions.

[16] Authorized participants are large institutions such as Goldman Sachs, Bank of America, and Morgan Stanley. On average, each ETF has 38 authorized participants (see Antoniewicz and Heinrichs (2014) and Lettau and Madhavan (2018)).

[17] Our sample is composed of unlevered ETFs that hold underlying stocks, and our description applies to such ETFs. ETFs that invest in other financial instruments (e.g., bonds) or derivatives (e.g., futures and swaps) are not included in our sample.

the trading day, APs deliver the underlying basket to the ETF. In exchange, the ETF delivers its shares to the APs. APs and ETFs undergo the reverse process to redeem ETF shares.

APs profit from these creation and redemption activities when an ETF's net asset value (NAV) deviates from its market price. APs buy the underlying portfolio, then they either sell the ETF if it trades at a sufficiently large premium relative to its NAV to offset transaction costs, or they execute opposite trades if the ETF trades at a sufficiently large discount. APs settle these arbitrage trades directly with the ETF at the end of trading.

APs undertake such arbitrage activities whenever profitable trading opportunities arise during the trading day. In fact, the closing auction per se may not be particularly suitable to initiate such arbitrage trades. Because closing prices are not known at the time that MOC orders are placed, investors cannot predict whether the closing prices for ETFs (and their underlying stocks) will allow for arbitrage.

Closing auctions are particularly suitable for ETF convergence arbitrage traders who are not APs. These arbitrageurs could also initiate arbitrage trades during the trading day when profitable opportunities arise. Unlike APs, these arbitrageurs cannot settle trades directly with the ETFs. They can, however, close their arbitrage trades through offsetting orders for both ETFs and their holdings in closing auctions.

We construct two proxies for ETF arbitrage-related passive trades. One proxy, which we label *ETF_arb*, categorizes all closing auction trades of ETF shares as one leg of the arbitrage trades. The other leg consists of orders for the underlying basket of stocks. While all ETF arbitrage involves trading these two legs, not all ETF trades in closing auctions are necessarily parts of ETF arbitrage trades. Therefore, this proxy for ETF arbitrage potentially overstates ETF-arbitrage trades.[18]

Another proxy is the volume of daily ETF creation and redemption. As we discussed earlier, both APs and other ETF arbitrageurs seek to profit from the differences between the NAV and the market prices of ETFs. Therefore, we use creation and redemption as the second proxy for ETF arbitrage trades in closing auctions. We refer to this proxy as *ETF_cr*. We compute *ETF_cr* as the aggregate dollar value of stocks in the ETF units that are created or redeemed daily.

We compute both *ETF_arb* and *ETF_cr* using all domestic stock ETFs for which the necessary data are available. We start with all domestic stock ETFs (both active and inactive) traded on US exchanges in the Morningstar Direct database. We obtain holdings data for these ETFs from the Thomson-Reuters Mutual Fund Ownership database for each quarter, and we obtain daily creation and redemption data from Morningstar Direct.[19]

Our sample is composed of 713 unique ETFs from the CRSP sample that we could match with the other two data sources. Table 1 presents the number of ETFs in our sample at the end of each calendar year as well as their assets under management (AUM).[20] The number of ETFs increases from 199 in 2010 to 580 in 2020, and total AUMs increase from $351 billion to $2.639 trillion.

To estimate ETF arbitrage–related trades that are reversed in closing auctions, we first determine the closing auction trading volume for each ETF in our sample from the TAQ data. We compute $ETF\_arb_{i,t}$ for each stock as

$$ETF\_arb_{i,t} = \frac{\sum_{j=1}^{J_t} N_{j,t} S_{i,j,t}}{Dollar\ Volume_{i,t}}, \tag{14}$$

where $t$ is the date subscript, $J_t$ is the number of ETFs in the sample, $N_{j,t}$ is the number of shares of ETF $j$ traded in the closing auction, $S_{i,j,t}$ is the dollar value of stock $i$ held per unit of ETF $j$, and $Dollar\ Volume_{i,t}$ is the day's total dollar trading volume of the stock.[21] We compute $ETF\_cr_{i,t}$ analogously using creation and redemption data.

Panel B of Table 1 presents summary statistics for closing auction trading volume and the proxies for uninformed and informed trades. The average closing auction trading volume is $3.5 million, and its average proportion of the total trading volume is 8.16%. The average ETF-arbitrage volume is $147,036. On average, *ETF_arb* comprises 14% of the closing auction volume. The average daily ETF creation and redemption is $1.14 million (Table 1).

To examine the relation between ETF arbitrage and closing auctions, we run the following regression:

$$Closing\ Volume_{i,t} = \alpha + \beta \times ETF\_arb_{i,t} + \epsilon_{i,t}, \tag{15}$$

where $Closing\ Volume_{i,t}$ is the dollar value of stock $i$ traded in the closing auction divided by the total trading volume for that stock on day $t$. For ease of interpretation, all variables are normalized each day by subtracting the mean for that day and then dividing by the contemporaneous standard deviation of that variable. We also include day and stock fixed effects in the regression.

Column (1) of Table 2 presents the estimates of Regression (15) with *ETF_arb* as the independent variable. The slope coefficient on $ETF\_arb_{i,t}$ is 0.171, and the $t$-statistic is 29.46. Column (2) of Table 2 presents the estimates of a univariate regression using $ETF\_cr_{i,t}$ as the proxy for ETF arbitrage trading, and the result is similar. The slope coefficient on $ETF\_cr_{i,t}$ is 0.208, and the $t$-statistic is 47.58.

The next uninformed trading proxy uses daily fund flows for open-end mutual funds that track selected stock indexes. For the most part, these funds trade to invest fund inflows and to meet outflows, but they also trade to reinvest dividends. Although these funds can trade at any time of the day, they have an incentive to trade at closing auctions because flows from investors are priced at the NAV at close. We use fund flows into and out of index funds as the final proxy for uninformed trading. We obtain daily

[18] The convergence arbitrage traders could also close the positions during the day or make arrangements with the APs to swap their positions for a fee. These trades would not be included in *ETF_arb*.

[19] We match the ETFs on CRSP and Morningstar with their ticker symbols and CUSIP numbers.

[20] The total AUMs of the ETFs in our sample are, on average, about 80% of the ETFs in the CRSP database.

[21] We determine the number of shares of stock $i$ held by fund $j$ from the most recent quarterly holdings data from Thomson Reuters, then we multiply this by the stock price on day $t$ to compute $S_{i,j,t}$.

**Table 1**
Sample and summary statistics.
The table reports the summary statistics for the sample we use to construct proxies for informed and uninformed trades. Panel A reports the number of index ETFs, index mutual funds, active mutual funds, and their assets under management (AUM) for each year. Panel B reports the summary statistics for the closing auction trading volume and the proxies for ETF arbitrage trades at the stock–day level. *ETF_arb* is the sum of the closing auction ETF trades and the stock trades implied by the ETF trades. *ETF_cr* is the dollar value of stock trades that correspond to the creation and daily redemption of ETFs. We use Morningstar data to compute daily fund flows into index funds and actively managed funds. The sample period is from March 2010 to December 2020.

Panel A: ETF/Mutual fund sample

| | Index ETFs | | Index Mutual Funds | | Active Mutual Funds | |
|---|---|---|---|---|---|---|
| Year | # of Funds | AUM ($ billions) | # of Funds | AUM ($ billions) | # of Funds | AUM ($ billions) |
| 2010 | 199 | 350.9 | 109 | 214.7 | 1325 | 1436.2 |
| 2011 | 239 | 378.5 | 117 | 206.0 | 1389 | 1340.5 |
| 2012 | 248 | 477.6 | 122 | 234.4 | 1445 | 1469.0 |
| 2013 | 245 | 734.3 | 123 | 313.6 | 1506 | 1994.9 |
| 2014 | 269 | 908.0 | 125 | 314.1 | 1538 | 2081.6 |
| 2015 | 325 | 939.7 | 138 | 334.6 | 1598 | 2007.5 |
| 2016 | 364 | 1190.6 | 143 | 392.3 | 1644 | 2042.4 |
| 2017 | 435 | 1568.9 | 164 | 482.3 | 1725 | 2334.8 |
| 2018 | 474 | 1576.5 | 170 | 646.5 | 1754 | 2043.7 |
| 2019 | 513 | 2145.0 | 176 | 850.6 | 1791 | 2448.2 |
| 2020 | 580 | 2638.8 | 180 | 985.2 | 1802 | 2752.5 |

Panel B: Summary statistics

| Variable | Mean | Median |
|---|---|---|
| Closing Auction Vol($) | 3493,226 | 320,728 |
| Closing Auction/Total Trading | 8.16% | 5.11% |
| ETF_cr($) | 1135,126 | 165,723 |
| ETF_arb ($) | 147,036 | 12,427 |
| ETF_arb/Closing Auction | 14.25% | 2.93% |
| Index Fund Flows ($) | 193,983 | 21,974 |
| Active Fund Flows ($) | 696,524 | 107,694 |

**Table 2**
Closing Auction Volume and Uninformed and Informed Trading Proxies
The table presents estimates from panel regressions of daily closing auction trading volume on proxies for ETF arbitrage trades (ETF_arb), ETF creation and redemption (ETF_cr), index mutual fund trades (MF_index), active mutual fund trades (MF_active), and EAD_dummy, which equals 1 if the stock announces earnings after close on that day and 0 otherwise. The sample is composed of all common stocks (CRSP share code 10 or 11) except stocks priced less than \$5 on the previous day. The dependent variable is close auction trading volume divided by the total daily trading volume. All variables are standardized each day by subtracting the mean and dividing by the standard deviation. All models control for firm fixed effects and trading date fixed effects. Standard errors are double-clustered at the stock and day level, and *t*-statistics are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| ETF Arbitrage | 0.171*** | | | | | 0.080*** |
| | (29.46) | | | | | (13.21) |
| ETF Creation/Redemption | | 0.208*** | | | | 0.160*** |
| | | (47.58) | | | | (28.78) |
| Index Fund Flows | | | 0.009*** | | | 0.001 |
| | | | (3.30) | | | (0.07) |
| Active Fund Flows | | | | −0.001 | | −0.003* |
| | | | | (−0.58) | | (−1.68) |
| EAD_dummy | | | | | −0.111*** | −0.071*** |
| | | | | | (−31.38) | (−23.25) |
| *N* | 7751,912 | 7428,067 | 7390,806 | 7425,195 | 7754,754 | 7245,959 |
| Adj. $R^2$ | 0.225 | 0.247 | 0.196 | 0.211 | 0.207 | 0.248 |

flows for all domestic equity active and inactive passive mutual funds from the Morningstar Direct database. Based on the holdings data from the Thomson-Reuters Mutual Fund Ownership database for each quarter, our calculation of daily passive mutual fund flows is analogous to *ETF_cr.*

The number of stock index mutual funds in the sample increases from 109 in 2010 to 180 in 2020, with AUMs increasing from \$215 billion to \$985 billion. The average daily index fund flow is \$193,983. Table 2, Column (3) reports the estimates of Regression (15) modified with daily index fund flows as the independent variable. The slope coefficient is 0.009, and the *t*-statistic is 3.30. Therefore, closing auction volume is also significantly related to index fund flows.

Each of the three proxies that we use is a noisy measure of uninformed trading, as we discussed above. For example, trades for the creation and redemption of ETFs are not executed at closing auctions; however, we use them as measures of the potential arbitrage opportunities available during the day. Hence, they are potential indicators of the closing auction activities of other ETF arbitrageurs.[22] Noise in a proxy weakens the evidence of correlation, but the evidence shows significant correlations between each of the three noisy proxies for uninformed trading and closing auction volumes. Therefore, uninformed trades are a significant part of closing auction volumes.

### 4.2.2. Informed trades

We use trades by active funds as one proxy for informed trading because these funds trade stocks that they expect would beat their benchmarks. Active funds trade in response to fund inflows and outflows, and they also trade when they rebalance their portfolios. We do not observe their daily rebalancing trades, but we have data from Morningstar on their daily fund inflows and outflows. We use their fund flow data to construct a proxy for active trading.

Table 2 presents the summary statistics for our sample of active domestic equity mutual funds from Morningstar. The sample increases from 1325 funds with an aggregate AUM of \$1.436 trillion in 2010 to 1802 funds with an aggregate AUM of \$2.753 trillion in 2020. The average daily active fund flow is \$696,524 per stock. We compute daily flows into and out of each stock using a procedure similar to that for the index mutual funds. Table 2, Column (4) reports the estimates of Regression (15) modified with daily active fund flows as the independent variable. The slope coefficient is −.001, which is not statistically different from zero.

Our second proxy for informed trading is the closing auction volume on the day preceding earnings announcements. We expect more informed trading due to potential information leakage about the imminent news release on the day before earnings announcements. We obtain time-stamped earnings announcement dates from Compustat. We define the date on which earnings are announced after market close as *day 0*. The average trading volume on day 0 is about twice the average trading volume over the previous five days. This increase indicates that expected earnings announcements increase trading volume on day 0.

To examine the earnings announcement date (EAD) effect on closing auction volume, we run Regression (15) using the earnings announcement date dummy variable as the explanatory variable. Columns (5) and (6) of Table 2 present the regression estimates. The slope coefficient on the EAD dummy is −.111, with a $t$-statistic of −31.38. This significantly negative estimate indicates that *Closing Volume* significantly declines on day 0. The dollar closing auction volume on day 0 is about 35% higher than on the five previous days, but the ratio *Closing Volume* is smaller because the trading volume in the denominator almost doubles on day 0. Some of this increased trading volume potentially comes from informed trades, but our results indicate that a larger fraction of the increase occurs during trading hours.

Overall, the evidence in this subsection indicates that closing auction volume is significantly related to proxies for uninformed trades.[23] However, assets managed through passive strategies and closing auctions grew contemporaneously, so we do not draw any inference about the direction of causality from these results. Informed investors seem to trade relatively more during trading hours than in closing auctions, possibly because the value of their information is short-lived or because of their desire to get ahead of potential competition from other informed investors.

## 4.3. Order imbalances

This subsection examines order imbalances in closing auctions. We obtain information about on-close orders and order imbalances from Nasdaq and the NYSE for the March 2010 to December 2020 period. At the start of the sample period, Nasdaq and the NYSE began disseminating these data to their subscribers at 3:50 p.m. and 3:45 p.m., respectively. Nasdaq changed its start time to 3:55 p.m. on October 29, 2018, then changed it back to 3:50 p.m. on April 15, 2019. The NYSE changed its start time to 3:50 p.m. on April 1, 2019. The NYSE aggregates closing D-orders with other on-close orders starting at 3:55 p.m.

We compute the order imbalance as

$$OI_{i,t} = \frac{C\_Buy_{i,t} - C\_Sell_{i,t}}{Total\ trade_{i,t}}, \tag{16}$$

where *C_Buy* and *C_Sell* represent the number of buy and sell MOC orders and implementable LOC orders as reported by the exchanges.[24]

Table 3 presents the *OI* summary statistics at the time of first dissemination of closing information. Panel A presents the statistics for daily *OI*, and Panel B presents them for the absolute value of daily *OI*. The mean and median *OI* in Panel A are close to zero in both Nasdaq and the NYSE, which indicates that buyer-initiated and seller-initiated trades in closing auctions are about equal. The mean absolute *OI* is 1.48% in Nasdaq and 2.27% in the NYSE. The NYSE's larger absolute *OI* is consistent with its greater closing auction volume (Fig. 1).

Fig. 2 plots the trajectories of order imbalances during the closing auction dissemination window for both Nasdaq and the NYSE. The figure scales *OI* at each point in time by the *OI* as of the first dissemination for each stock, averaged across stocks each day and then across time. Panel

[22] Our untabulated results indicate that daily ETF creations and redemptions are correlated with differences between ETF price and contemporaneous intraday NAV (called the *indicative optimized portfolio value*, or IOPV) that ICE computes and disseminates on behalf of its ETFs, as required by the SEC. This result supports our hypothesis that *ETF_cr* is correlated with the availability of intraday arbitrage opportunities.

[23] Raillon (2019) documents that closing auction volume in developed countries in Europe ranges from 24% to 44% in 2019, which is greater than those in the US. Raillon indicates that one reason for this growth in Europe is that fund managers can more easily comply with their Trade & Cost Analysis and disclosure obligations under MiFID II when they trade in closing auctions. Our evidence suggests that passive funds are more likely than active funds to have shifted their trades to closing auctions after MiFID II came into effect.

[24] Our results are qualitatively similar when we use $C_{Buy} + C\_Sell$ in the denominator in place of *Total trade*. We use *Total trade* in the denominator because small differences between *C_Buy* and *C_Sell* could be unduly magnified if $C_{Buy} + C\_Sell$ is small.

**Table 3**
Distribution of Order Imbalances
The table presents the distributions of closing auction order imbalances in Nasdaq and the NYSE at the time of the first dissemination of closing information as a percentage of daily trading volume. Panels A and B report the summary statistics for order imbalances and for absolute the order imbalances, respectively. The sample is composed of NYSE- and Nasdaq–listed common shares (CRSP share code 10 or 11) and excludes stocks priced less than $5 on the previous day. The sample period is from March 2010 to December 2020.

Panel A: Order Imbalance

| | All Periods | | March 2010 to Dec 2015 | | Jan 2016 to Dec 2020 | |
|---|---|---|---|---|---|---|
| | NYSE | Nasdaq | NYSE | Nasdaq | NYSE | Nasdaq |
| Mean | 0.06% | 0.04% | 0.13% | 0.14% | −0.01% | −0.07% |
| Median | 0.02% | 0.00% | 0.06% | 0.00% | 0.00% | 0.00% |
| Std.Dev | 3.90% | 4.64% | 3.55% | 3.91% | 4.29% | 5.38% |

Panel B: Absolute Order Imbalance

| | All Periods | | March 2010 to Dec 2015 | | Jan 2016 to Dec 2020 | |
|---|---|---|---|---|---|---|
| | NYSE | Nasdaq | NYSE | Nasdaq | NYSE | Nasdaq |
| Mean | 2.27% | 1.48% | 2.03% | 1.33% | 2.57% | 1.66% |
| Median | 1.30% | 0.02% | 1.14% | 0.00% | 1.53% | 0.08% |
| Std.Dev | 3.17% | 4.40% | 2.92% | 3.68% | 3.43% | 5.12% |

A presents the trajectory for the subperiod from March 1, 2010 to October 31, 2018, when the dissemination windows start at 3:45 p.m. in Nasdaq and 3:50 p.m. in the NYSE. In Panel B, the sample periods are from November 1, 2018 to April 14, 2019 for Nasdaq and from November 1, 2018 to March 31, 2019 for the NYSE; and the dissemination windows start at 3:55 p.m. in Nasdaq and at 3:45 p.m. in the NYSE. In Panel C, the subperiods are from April 15, 2019 to December 2020 for Nasdaq and from April 1, 2019 to December 2020 for the NYSE; and the dissemination window starts at 3:50 p.m. in both exchanges.

In Nasdaq, *OI* declines to less than 20% within one minute after the exchange first disseminates closing information. In the NYSE, *OI* declines by less than 2% by 3:55 p.m., which is 5–10 min after the exchange starts disseminating closing information. Why do LPs place new closing orders much sooner in Nasdaq than in the NYSE? The LPs use *OI* information to place their orders, and Nasdaq uses time priority when there is excess demand or excess supply at closing prices. Therefore, LPs tend to place new on-close orders as soon as the closing information is first disseminated because later orders are less likely to be filled.

The NYSE's off-exchange LPs compete against better informed floor traders who can place closing D-orders in any direction. Therefore, the LPs are exposed to a winners' curse because they are more likely to have their orders filled when floor traders' orders are in the opposite direction than when they are in the same direction. The NYSE's parity/priority allocation rule likely exacerbates this winners' curse. The floor traders' orders are not included in the closing information until 3:55 p.m., hence we do not see a marked decline in *OI* until that time.

Fig. 3 presents the trajectory of total closing orders every minute, scaled by total closing orders at the time of the first *OI* information dissemination, and the sample periods in the three panels in this figure correspond to those in Fig. 2. In Nasdaq, the percentage of new on-close orders is less than 0.1% in all panels. In the NYSE, new orders rise to about 4% at 3:55 p.m., then they increase to about 17% at close in Panel A. The corresponding figures in Panel C, the most recent subperiod, are 18% and 44%, respectively.

Fig. 4 presents the time series of daily closing D-orders as a percentage of total closing orders at the time of the first closing information dissemination. Panel A presents the 90-day moving average during the 2010 to 2019 period, and Panel B presents the daily percentages in 2020. There are no closing D-orders from March 23, 2020, to May 25, 2020, because the NYSE closed its trading floor due to the COVID-19 pandemic. Closing D-orders increase from about 0% at the beginning of the sample period to a peak of about 50% in 2019, before declining to about 40% in 2020.

### *4.4. Price impact: Nasdaq vs. the NYSE*

The results in the last section indicate that floor traders are dominant in the NYSE closing auctions, and off-exchange LPs play only a minor role. How does the lack of competition from off-exchange LPs affect market liquidity? This subsection addresses this question.

The market learns about order imbalances when the exchanges first disseminate closing information, hence the price impact based on this information is incorporated into the stock prices at the time of first dissemination. We compute the ex ante price impact as the return from the time of first dissemination to close, which we denote as $R_{i,t}^{OI\_ann\ to\ close}$, where the subscripts denote stock $i$ and day $t$.

We examine the price impact in Nasdaq and the NYSE using the following regression:

$$R_{i,t}^{OI\_ann\ to\ close} = a + b \times OI_{i,t} + c \times (NasdaqDummy_{i,t} \times OI_{i,t}) + \boldsymbol{\gamma}'\boldsymbol{X}_{i,t}^{s} + \epsilon_{i,t}, \tag{17}$$

where $NasdaqDummy_{i,t} = 1$ if the stock is listed on Nasdaq, and 0 otherwise.[25] The slope coefficient $b$ is the price im-

[25] We obtain intraday prices at the time of the first closing information dissemination from TAQ. Due to potential errors in the TAQ intraday price

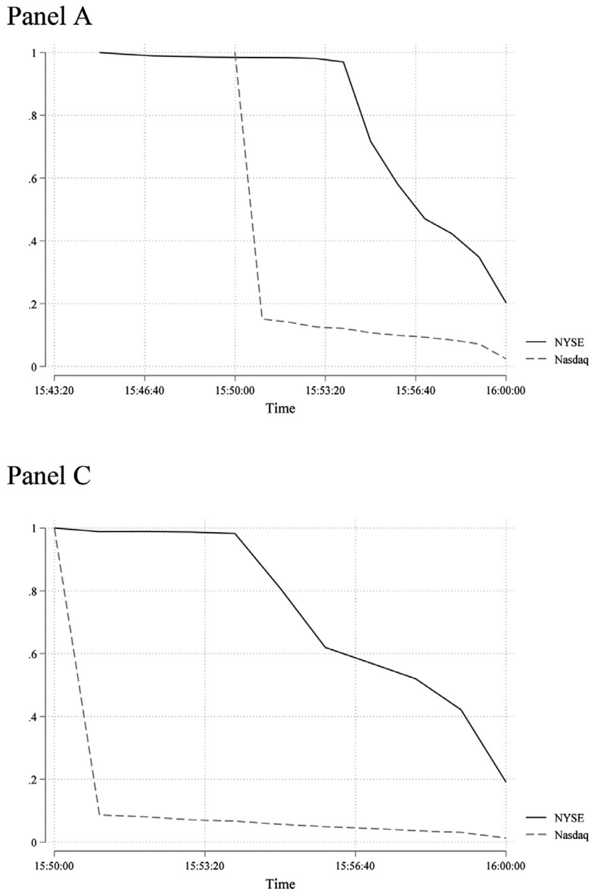


**Fig. 2.** Order imbalance trajectory during auction period.
This figure presents the average order imbalance (OI) as a proportion of the OI at the time of the first closing information dissemination. The sample periods in the three panels are; Panel A: March 1, 2010, to October 28, 2018, for both Nasdaq and the NYSE, Panel B: October 29, 2018, to April 14, 2019, for Nasdaq and October 29, 2018, to March 31, 2019, for the NYSE, and Panel C: April 15 to December 2020 for Nasdaq and April 1 to December 31, 2020, for the NYSE. The times of the first closing information dissemination are, Panel A: 3:50 p.m. in Nasdaq and 3:45 p.m. in the NYSE, Panel B: 3:55 p.m. in Nasdaq and 3:45 p.m. in the NYSE, and Panel C: 3:50 p.m. in both Nasdaq and the NYSE.

pact in the NYSE, $c$ is the differential impact in Nasdaq, and $b+c$ is the total price impact in Nasdaq. The variable $\boldsymbol{X^s_{i,t}}$ is the vector of the control variables, and we use it to account for cross-sectional differences in liquidity. We set the liquidity control variables as positive for stocks with buy imbalances and negative for stocks with sell imbalances to account for the directional asymmetry of the price impact of buy and sell imbalances.

We use the following variables as controls for liquidity:

- *Amihud measure*. The ratio of the previous day's absolute return divided by the dollar volume (expressed in $ millions).
- *Quoted spread*. The equal-weighted average of the quoted spread at the time of each transaction during the day.
- *Ln(Market cap)*. The natural log of market capitalization (in $ millions) at the end of the previous day.
- *1/Price*. The inverse of the stock's closing price on the previous day.

Previous studies that use one or more of these proxies for liquidity include Datar et al. (1998); Chordia et al. (2000); Amihud (2002); and Hasbrouck (2009). We also include firm fixed effects and day fixed effects when we fit the regression, and we compute standard errors that are double-clustered at the stock and day level.

Table 4 reports the estimates of Regression (5). It also presents estimates with selected subsets of the independent variables. The first column uses only *OI* as the independent variable to estimate the unconditional price impact. The slope coefficient ($t$-statistic) on *OI* is 2.555 (30.66). Therefore, *OI* has a significant price impact.

Column (2) in each panel presents the regression with *NadaqDummy* interacted with *OI* as an additional independent variable. The *OI* slope coefficient is 2.08, the interaction coefficient is 0.887, and both are statistically signifi-

data documented in the literature, we exclude observations when intraday returns are in the extreme 0.1% of the data range. We do not exclude any observations that use open and close prices from the CRSP Daily file to compute returns in our later analyses.

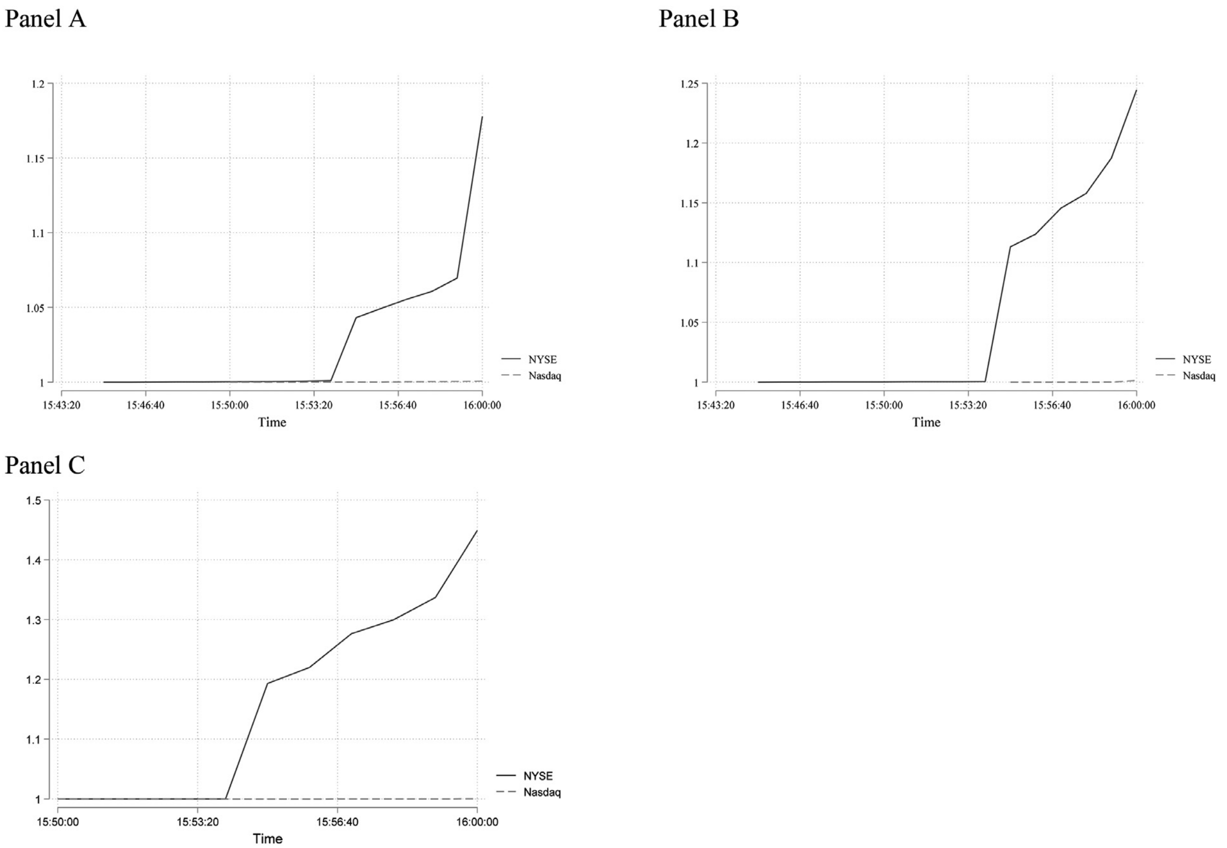


**Fig. 3.** Total closing auction order trajectory.
This figure presents total on-close orders as a proportion of total on-close orders at the time of the first dissemination of closing information. The sample periods in the three panels are, Panel A: March 1, 2010, to October 28, 2018, for both Nasdaq and the NYSE, Panel B: October 29, 2018, to April 14, 2019, for Nasdaq and October 29, 2018, to March 31, 2019, for the NYSE, and Panel C: April 15 to December 2020 for Nasdaq and April 1 to December 31, 2020, for the NYSE. The times of the first closing information dissemination are, Panel A: 3:50 p.m. in Nasdaq and 3:45 p.m. in the NYSE, Panel B: 3:55 p.m. in Nasdaq and 3:45 p.m. in the NYSE, and Panel C: 3:50 p.m. in both Nasdaq and the NYSE.

**Table 4**
Price response to closing auction order imbalance.
The table presents coefficients estimated from the following panel regression:
$R^{OI\_ann\ to\ close}_{i,t} = a + b \times OI_{i,t} + c \times (NadaqDummy_{i,t} \times OI_{i,t}) + \boldsymbol{\gamma}'\boldsymbol{X^s_{i,t}} + \epsilon_{i,t}$, where $R^{OI\_ann\ to\ close}_{i,t}$ is the return from the time of the first dissemination of closing information to close. $NadaqDummy_{i,t}$ is an indicator variable that equals 1 if the stock is listed on Nasdaq and 0 otherwise, and $\boldsymbol{X^s_{i,t}}$ is the vector of liquidity proxies (i.e., the lagged Amihud ratio, the intraday quoted spread, the inverse of the lagged stock price, and lagged log market capitalization) multiplied by the sign of the closing auction order imbalance (*Signed OI*). *Signed OI* equals +1 for stocks with buy order imbalances and −1 for stocks with sell imbalances at the first dissemination of closing information. The sample is composed of NYSE-listed and Nasdaq-listed common stocks (CRSP share code 10 or 11) and excludes stocks priced less than \$5 on the previous day. All models control for fixed effects for stocks and trading dates. See Appendix A for the time of the first dissemination of closing information in Nasdaq and the NYSE, which varies between 3:45 p.m. and 3:55 p.m. during the sample period of March 2010 to December 2020. Double-clustered standard errors at the stock and day level are used to compute the *t*-statistics presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | All Sample | | | Mar/2010 to Dec/2015 | | | Jan/2016 to Dec/2020 | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | (1) | (2) | (3) | (1) | (2) | (3) |
| *Closing Auction* $OI_{i,t}$ | 2.555*** | 2.080*** | 1.670*** | 3.094*** | 2.833*** | 2.383*** | 2.121*** | 1.469*** | 1.084*** |
| | (30.66) | (35.21) | (25.57) | (33.01) | (35.55) | (27.14) | (17.08) | (21.69) | (13.82) |
| $NadaqDummy_{i,t} \times OI_{i,t}$ | | 0.887*** | 0.979*** | | 0.483*** | 0.482*** | | 1.231*** | 1.458*** |
| | | (7.77) | (9.27) | | (4.00) | (4.00) | | (7.04) | (9.69) |
| $Signed\ OI_{i,t} * Amihud_{i,t}$ | | | −0.0247*** | | | −0.00616*** | | | −0.0532*** |
| | | | (−9.51) | | | (−4.30) | | | (−10.15) |
| $Signed\ OI_{i,t} * Quoted\ Spread_{i,t}$ | | | 0.0155*** | | | 0.00492** | | | 0.0220*** |
| | | | (9.00) | | | (2.21) | | | (9.78) |
| $Signed\ OI_{i,t} * \ln(Market\ Cap)_{i,t}$ | | | 0.00407*** | | | −0.000836 | | | 0.00442** |
| | | | (2.74) | | | (−0.44) | | | (2.12) |
| $Signed\ OI_{i,t} * 1/Price_{i,t}$ | | | 0.669*** | | | 0.647*** | | | 0.624*** |
| | | | (34.01) | | | (29.16) | | | (20.34) |
| Adj. $R^2$ | 0.190 | 0.191 | 0.198 | 0.251 | 0.251 | 0.259 | 0.157 | 0.159 | 0.166 |

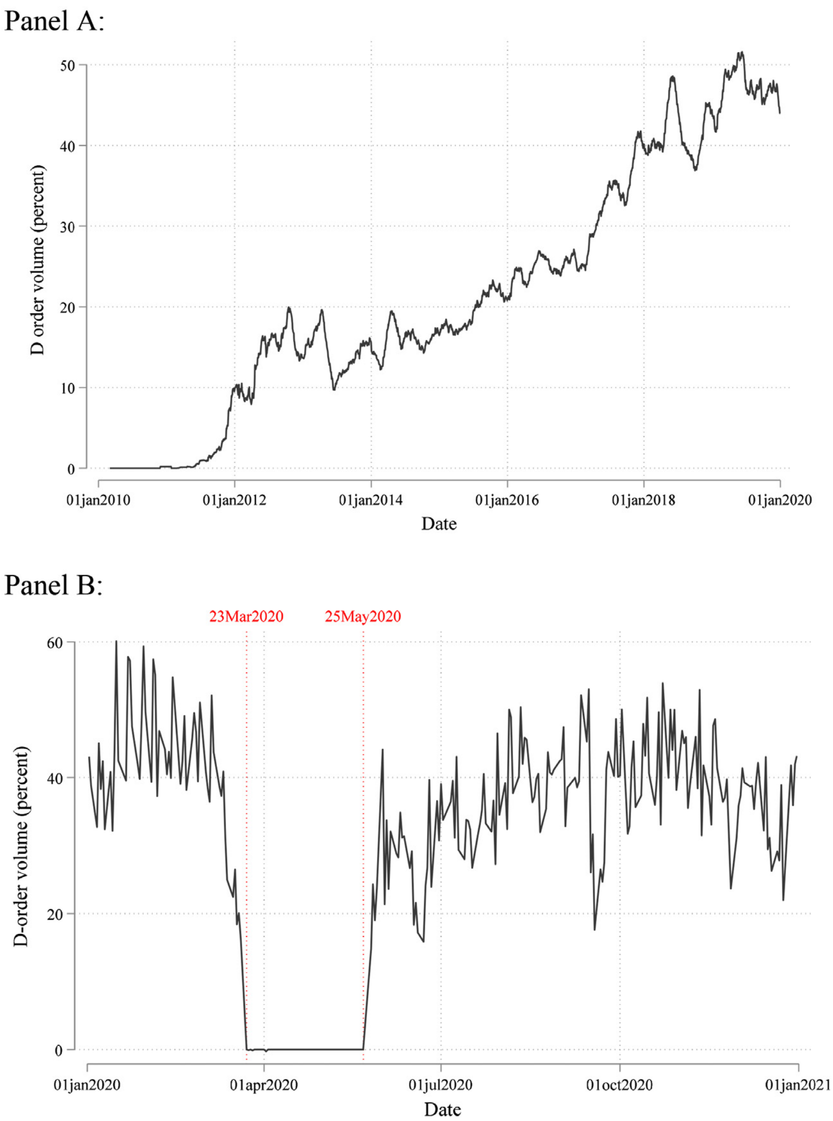


**Fig. 4.** Time-series Trend in D-orders in the NYSE.
Panel A presents the 90-day moving average of new on-close D-orders in the NYSE after the first dissemination of closing information as a percentage of closing auction volume at the time of the first closing order dissemination. Panel B presents the daily percentages for 2020. In this year, the NYSE shut down its trading floor due to COVID-19 from March 23, 2020, through May 25, 2020. On-close D-order volume is zero during this period. The time of the first closing information dissemination is 3:45 p.m. from March 2010 to March 2019, and 3:50 p.m. from April 2019 to December 2020.

cant. Therefore, the price impact is significantly larger in Nasdaq than in the NYSE. The results are similar when we add controls for liquidity.

Table 3 also presents the results for two roughly equal subperiods. The first subperiod is from March 2010 to December 2015, and the second subperiod is from January 2016 to December 2020. The *OI* coefficient in the univariate regressions in the first subperiod is 3.094, which is significantly larger than the coefficient of 2.121 observed in the second subperiod. The NYSE slope coefficient in the second subperiod is 1.469, which is roughly half that in the first subperiod. The Nasdaq price impact also declines from 3.316 (= 2.833 + 0.483) in the first subperiod to 2.700 in the second, but this decline is smaller. Fig. 4 shows the participation of floor traders in the NYSE's closing auctions increased in the second subperiod, which likely contributes to the improvement in the NYSE's depth. Overall, these results indicate that the closing auction is more liquid in the NYSE than in Nasdaq.

### *4.5. NYSE floor trading shutdown due to COVID-19: a natural experiment*

The NYSE closed its floor operations from March 23, 2020, to May 25, 2020, due to the COVID-19 pandemic. This closure serves as a natural experiment to examine closing auction depth with and without floor traders. Our model implies that during this period of suspended floor

**Table 5**
COVID-19 floor trading shutdown by the NYSE: a natural experiment.
The table presents coefficients estimated from the following panel regression:

$R^{OI\_ann\ to\ close}_{i,t} = a + b \times OI_{i,t} + c \times (NasdaqDummy_{i,t} \times OI_{i,t}) + d \times OI_{i,t} \times SDummy_{nasd} + e \times OI_{i,t} \times SDummy_{nyse} + \boldsymbol{\gamma}'\boldsymbol{X}^{s}_{i,t} + \epsilon_{i,t}$,

where $R^{OI\_ann\ to\ close}_{i,t}$ is the return from the time of first dissemination of closing information to close, and $NasdaqDummy_{i,t}$ is an indicator variable that equals 1 if the stock is listed on Nasdaq and 0 otherwise. $SDummy_{nasd}$ equals 1 for Nasdaq stocks during the shutdown period and 0 otherwise, and $SDummy_{NYSE}$ is defined analogously for NYSE stocks. The shutdown period is from March 23, 2020, to May 25, 2020. $\boldsymbol{X}^{s}_{i,t}$ is the vector of liquidity proxies (i.e., the one-day lagged Amihud ratio, the intraday quoted spread, lagged log market capitalization, and the inverse of the lagged stock price) multiplied by the sign of the closing auction order imbalance (*Signed OI*). *Signed OI* equals +1 for stocks with buy order imbalances and −1 for stocks with sell imbalances at the time of the first closing information dissemination. The sample is composed of NYSE-listed and Nasdaq-listed common stocks (CRSP share code 10 or 11) and excludes stocks priced less than $5 on the previous day. All models control for firm fixed effects and trading date fixed effects. The sample period is from April 2019 to December 2020, and the time of the first dissemination of closing information is 3:50 p.m. during this period. Standard errors are double-clustered at the stock and day level, and *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) |
|---|---|---|
| *Closing Auction* $OI_{i,t}$ | 1.508*** | 1.268*** |
| | (15.92) | (11.88) |
| $NadaqDummy_{i,t} \times OI_{i,t}$ | 1.171*** | 1.279*** |
| | (7.05) | (8.10) |
| $OI_{i,t} \times SDummy_{nyse}$ | 4.447*** | 4.340*** |
| | (11.25) | (10.98) |
| $OI_{i,t} \times SDummy_{nasd}$ | 0.794* | 0.788* |
| | (1.83) | (1.82) |
| $Signed\ OI_{i,t} * Amihud_{i,t}$ | | −0.055*** |
| | | (−12.20) |
| $Signed\ OI_{i,t} * Quoted\ Spread_{i,t}$ | | −0.00053 |
| | | (−0.13) |
| $Signed\ OI_{i,t} * \ln(Market\ Cap)_{i,t}$ | | −0.0135*** |
| | | (−5.00) |
| $Signed\ OI_{i,t} * 1/Price_{i,t}$ | | 0.206*** |
| | | (6.94) |
| Adj. $R^2$ | 0.236 | 0.241 |

trading, the NYSE would have less liquidity than Nasdaq because floor traders would displace at least some off-exchange LPs. Because this suspension is temporary, most of the displaced LPs would likely not invest the setup costs necessary to re-enter the market.

To examine price impacts during the shutdown period, we add the interaction terms $OI_{i,t} \times SDummy_{nasd}$ and $OI_{i,t} \times SDummy_{nyse}$ to Regression (17), where $SDummy_{nasd}$ equals 1 for Nasdaq stocks during the shutdown period, and 0 otherwise; and $SDummy_{nyse}$ is defined analogously for the NYSE stocks. Because closing auction depth increases over time, we fit the regression over a recent sample period. We choose the subperiod from April 1, 2019, to December 31, 2020 because the NYSE's dissemination window remained unchanged during this period.

Table 5 presents the regression results. In Column (1), the NYSE shutdown dummy interaction coefficient is 4.447. This coefficient is significantly positive, and it indicates that the closing auction price impact increased during this period. The Nasdaq shutdown dummy interaction coefficient is 0.794, which is significant at the 10% level. It is not clear why the Nasdaq price impact increases during this period. Perhaps the off-exchange LPs shifted some of their attention and resources to the NYSE closing auctions during this period, which may have adversely affected the depth in Nasdaq. The total price impact during the shutdown period in the NYSE is 5.955 (=1.508 + 4.447) and 3.473 (= 1.508 + 1.171 + 0.794) in Nasdaq. Therefore, Nasdaq's depth is better than the NYSE's during the temporary suspension of floor trading.

The significantly positive Nasdaq dummy coefficient in Table 5 indicates that the NYSE had more depth during this recent subperiod outside the shutdown, which is consistent with the results in Table 3 for the full sample period. We find similar results when we add the control variables to the regression.

The NYSE's floor brokers had the ability to individually place their customers' orders through the electronic order book during the shutdown. Yet the depth of Nasdaq's closing auction was better than the NYSE's during the shutdown. This evidence indicates that the better depth of the NYSE's closing auctions is due to its floor trader operations, which includes floor traders' ability to "work" their orders collectively on the floor as well as the other special privileges accorded to them.

### 4.6. Permanent and temporary components of the price impact

The price impact of *OI* has a permanent component due to the information content of *OI*, and a temporary component that constitutes compensation for LPs. This subsection estimates the permanent and temporary components of the closing auction price impact in the two exchanges using a two-stage IV regression. In the first stage, we fit Regression (17) without liquidity controls.[26] Let $\hat{R}^{OI\_ann\ to\ close}_{i,t}$ be the fitted value from this regression, which is an estimate of the price impact of closing auctions. We then fit the following regression separately for Nasdaq and NYSE stocks:

$$R_{i,t+j} = a_j + b_j \times \hat{R}^{OI\_ann\ to\ close}_{i,t} + \epsilon_{i,t+j}, \tag{18}$$

where $R_{i,t+j}$ is future returns.

Table 6 presents the estimates of Regression (18) with $j = overnight$ and days 1 through 5, where *overnight* is the return from the closing auction to the next day's opening. The overnight return slope coefficients are −0.430 in Nasdaq and −0.212 in the NYSE. Therefore, about 43% of the price impact is reversed overnight in Nasdaq, and 21% is reversed in the NYSE (Table 6).

The slope coefficients gradually increase in both exchanges. By $j = 5$, the coefficients are −0.848 in Nasdaq and −0.615 in the NYSE.[27] Therefore, about 85% of the price impact in Nasdaq is temporary compared to about 62% in the NYSE. These results indicate that the proportion

[26] We also obtain similar results when we use liquidity controls in the first-stage regression.

[27] In untabulated results, we find that the slope coefficients up to $j = 10$ are not significantly different from those at $j = 5$.

**Table 6**
Price impact and future returns.
Panels A and B present regression results for Nasdaq and NYSE stocks, respectively. In the first stage, we fit the regression of the return during the closing auction period on order imbalances, and the second stage regresses future returns from close to the period indicated in the column heading on the fitted value from the first stage. The table presents the second-stage regression results. All models control for firm and trading day fixed effects. The sample is composed of NYSE-listed and Nasdaq-listed common stocks (CRSP share code 10 or 11) and excludes stocks priced less than $5 on the previous day. The sample period is from March 2010 to December 2020. Standard errors are double-clustered at the stock and day level, and *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively..

| Panel A: Nasdaq | | | | | | |
|---|---|---|---|---|---|---|
| | $R_{i,overnight}$ | $R_{i,t,t+1}$ | $R_{i,t,t+2}$ | $R_{i,t,t+3}$ | $R_{i,t,t+4}$ | $R_{i,t,t+5}$ |
| $\hat{R}_{i,t}^{OI\_ann\ to\ close}$ | −0.430*** | −0.641*** | −0.744*** | −0.756*** | −0.818*** | −0.848*** |
| | (−82.03) | (−53.59) | (−43.63) | (−35.99) | (−33.69) | (−31.24) |
| N | 3673,317 | 3683,560 | 3681,005 | 3677,500 | 3674,014 | 3670,649 |
| **Panel B: NYSE** | | | | | | |
| | $R_{i,overnight}$ | $R_{i,t,t+1}$ | $R_{i,t,t+2}$ | $R_{i,t,t+3}$ | $R_{i,t,t+4}$ | $R_{i,t,t+5}$ |
| $\hat{R}_{i,t}^{OI\_ann\ to\ close}$ | −0.212*** | −0.389*** | −0.454*** | −0.512*** | −0.627*** | −0.615*** |
| | (−29.55) | (−24.26) | (−19.76) | (−18.09) | (−19.18) | (−16.84) |
| N | 3188,911 | 3189,115 | 3187,458 | 3185,276 | 3183,070 | 3181,914 |

of the price impact attributable to information is larger in the NYSE than in Nasdaq.

The speed of the decay of the temporary component measures price resiliency, which is another measure of market liquidity (see Kyle (1985)). The overnight coefficient in Nasdaq is about twice as large as in the NYSE. But, because Nasdaq's temporary component is a larger proportion of the price impact, this difference does not necessarily suggest that Nasdaq is more resilient. These temporary components require about five days to fully dissipate in both exchanges, and they appear to be equally resilient.

## 5. Economic significance: trading strategies

This section evaluates the economic significance of the price impact and reversals using two trading strategies. First, to examine the significance of the price impact on the day of auctions, we sort stocks into deciles based on order imbalances at the first dissemination of closing information. We take long and short positions in the deciles that have the largest and smallest order imbalances, respectively. We close out the positions in the closing auctions.

Table 7 presents the returns for all 10 decile portfolios. In Nasdaq, the equal-weighted raw returns on Deciles 1 and 10 are −13.44 bps and 16.89 bps, respectively. The returns increase monotonically from Decile 1 to Decile 10, and the difference between Decile 10 and Decile 1 returns are 30.34 bps. In the NYSE, the return is −11.12 bps for Decile 1 and 13.12 bps for Decile 10, with a difference of 24.79 bps. We present this set of strategies mainly to provide an economic perspective on the price impact. These strategies would be hard to execute in practice because prices tend to react quickly after the first announcement of closing information but Table 7 does not account for any price reaction after the announcement.

The next set of strategies evaluates the economic significance of return reversals. They take positions in the opposite direction from the order imbalances and hold these positions overnight or over the next few days. Table 7 presents the decile portfolio returns for the overnight strategy and for strategies that use holding periods of one and five days. The pattern of portfolio returns for longer holding periods is the opposite of the previous strategy, and it takes long positions in Decile 1 and short positions in Decile 10. These returns are monotonic across deciles, with a few exceptions.

The difference between Decile 1 and Decile 10 returns for the overnight holding period is 15.08 bps in Nasdaq and 5.09 bps in the NYSE, and the corresponding returns for 5-day holding periods are 40.49 bps and 18.58 bps, respectively. The larger profits in Nasdaq are due to both a larger price impact and larger price reversals.

Panel B of Table 7 also presents abnormal returns estimated using the single-factor model

$$R_{i,t} = \alpha_i + \beta_i \times R_{mkt,t} + \epsilon_{i,t}, \tag{19}$$

where $R_{mkt,t}$ is the market return. We use SPY, the ETF that tracks the S&P 500, as a proxy for the market. We assume that the risk-free rate is zero because our holding periods are short, and weekly interest rates are close to zero during our sample period. Therefore, $\alpha_i$ is the abnormal return.

Panel B presents extreme decile abnormal returns as well as the differences between them for both equal-weighted and value-weighted portfolios. The differences between the abnormal returns of the extreme decile portfolios are almost the same as the corresponding differences in raw returns in Panel A, which indicates that the extreme portfolios have about the same market risk. The value-weighted returns are smaller than the equal-weighted returns in both exchanges, and this evidence indicates that large firms experience smaller price impacts and reversals than small firms. All these trading strategies lead to larger profits in Nasdaq than in the NYSE.

The second set of strategies replicates possible strategies that closing auction LPs follow, and they estimate the compensation LPs receive for providing liquidity. They can also be implemented by other traders by opening positions with MOCs on the opposite side of *OI* after the

**Table 7**
Trading strategies based on closing auction order imbalances.
The Panel A reports raw returns (in basis points) for portfolios formed based on closing auction order imbalances (OIs) for both Nasdaq-listed stocks (Left Panel) and Nasdaq-listed stocks (Right Panel) at the time of the first closing information dissemination. Robust *t*-statistics based on Newey–West (1987) corrected standard errors with 12 lags are reported in parentheses. The sample is composed of Nasdaq- and NYSE-listed common stocks (CRSP share code 10 or 11) and excludes stocks priced less than \$5 on the previous day. Stocks are sorted into deciles based on OIs at the time of the first dissemination of closing information. Decile 1 and Decile 10 are the deciles of stocks with the largest sell and buy OIs, respectively. Panel A reports equal-weighted returns for various holding periods. $R_{i,t}^{OI\_ann\ to\ close}$ is the return from the time of the first dissemination of closing information to close. The other columns show returns from close on day t to the date indicated by the second superscript on returns in the column heading. Panel B reports the market-model alpha with SPY as the market proxy. EW is for equal-weighted portfolios, and VW is for value-weighted portfolios. The sample period is from March 2010 to December 2020.

Panel A

| | Nasdaq | | | | NYSE | | | |
|---|---|---|---|---|---|---|---|---|
| OI Decile | $R_{i,t}^{OI\_ann\ to\ close}$ | $Ret_t^{overnight}$ | $Ret_t^{t,\ t+1}$ | $Ret_t^{t,\ t+5}$ | $R_{i,t}^{OI\_ann\ to\ close}$ | $Ret_t^{overnight}$ | $Ret_t^{t,\ t+1}$ | $Ret_t^{t,\ t+5}$ |
| 1 | −13.44 | 12.16 | 20.02 | 47.09 | −11.12 | 6.24 | 10.96 | 33.85 |
| | (−25.36) | (8.56) | (7.59) | (8.61) | (−15.90) | (4.09) | (4.21) | (6.06) |
| 2 | −4.11 | 10.60 | 16.99 | 44.71 | −7.21 | 5.45 | 10.10 | 33.21 |
| | (−9.01) | (6.56) | (5.80) | (7.00) | (−8.56) | (3.46) | (3.82) | (5.81) |
| 3 | −1.77 | 9.79 | 13.87 | 32.38 | −4.94 | 5.05 | 8.04 | 31.33 |
| | (−2.92) | (4.35) | (3.69) | (3.80) | (−9.97) | (3.17) | (3.02) | (5.34) |
| 4 | −1.39 | 6.58 | 5.55 | 43.44 | −2.07 | 5.33 | 8.18 | 31.64 |
| | (−2.04) | (2.59) | (1.25) | (4.46) | (−2.32) | (3.29) | (3.05) | (5.29) |
| 5 | 0.16 | 6.74 | 6.36 | 26.33 | 18.07 | 5.50 | 7.43 | 31.51 |
| | (0.29) | (3.28) | (1.76) | (3.24) | (1.04) | (3.42) | (2.77) | (5.23) |
| 6 | 1.77 | 5.25 | 3.80 | 32.22 | 3.06 | 4.83 | 5.33 | 30.16 |
| | (2.88) | (2.36) | (0.96) | (3.73) | (3.32) | (2.99) | (1.97) | (4.99) |
| 7 | 2.57 | 3.89 | 1.31 | 18.96 | 5.81 | 4.19 | 4.84 | 28.89 |
| | (3.78) | (1.55) | (0.27) | (1.94) | (3.92) | (2.60) | (1.81) | (4.84) |
| 8 | 3.53 | 5.46 | −4.19 | 15.20 | 6.50 | 2.88 | 2.61 | 24.30 |
| | (6.87) | (2.63) | (−1.12) | (1.95) | (7.24) | (1.80) | (0.98) | (4.10) |
| 9 | 6.50 | 3.45 | −3.31 | 15.15 | 17.43 | 2.25 | 1.17 | 20.98 |
| | (14.75) | (2.10) | (−1.15) | (2.54) | (1.87) | (1.41) | (0.44) | (3.61) |
| 10 | 16.89 | −2.93 | −8.40 | 6.61 | 13.12 | 0.45 | −1.31 | 15.27 |
| | (28.73) | (−2.04) | (−3.04) | (1.19) | (20.95) | (0.30) | (−0.50) | (2.74) |
| Decile 10–1 | 30.34 | | | | 24.79 | | | |
| | (40.02) | | | | (48.69) | | | |
| Decile 1–10 | | 15.08 | 28.42 | 40.49 | | 5.79 | 12.27 | 18.58 |
| | | (28.89) | (23.63) | (16.86) | | (16.69) | (13.76) | (10.14) |

Panel B

Nasdaq

| | $Ret_t^{3:45\ to\ close}$ | | $Ret_t^{overnight}$ | | $Ret_t^{t,\ t+1}$ | | $Ret_t^{t,\ t+5}$ | |
|---|---|---|---|---|---|---|---|---|
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | −13.66 | −13.14 | 9.34 | 5.53 | 14.87 | 10.10 | 21.52 | 21.69 |
| | (−25.72) | (−28.90) | (16.55) | (10.57) | (11.78) | (9.28) | (4.35) | (6.53) |
| 10 | 16.78 | 14.12 | −5.76 | −2.22 | −13.84 | −7.69 | −18.96 | −5.22 |
| | (18.80) | (18.66) | (−10.78) | (−3.86) | (−9.01) | (−6.14) | (−3.40) | (−1.53) |
| 10–1 | −30.44 | −27.25 | 15.11 | 7.75 | 28.70 | 17.80 | 40.48 | 26.92 |
| | (−26.30) | (−28.63) | (20.73) | (9.27) | (16.55) | (9.98) | (11.52) | (7.47) |

NYSE

| | $Ret_t^{3:45\ to\ close}$ | | $Ret_t^{overnight}$ | | $Ret_t^{t,\ t+1}$ | | $Ret_t^{t,\ t+5}$ | |
|---|---|---|---|---|---|---|---|---|
| | EW | VW | EW | VW | EW | VW | EW | VW |
| 1 | −11.46 | −3.98 | 3.13 | 2.10 | 5.43 | 4.09 | 5.54 | 6.79 |
| | (−14.62) | (−2.23) | (7.21) | (5.31) | (5.00) | (5.27) | (1.28) | (3.02) |
| 10 | 12.95 | 8.64 | −2.64 | −1.01 | −6.93 | −2.24 | −12.92 | −4.59 |
| | (15.02) | (4.31) | (−6.26) | (−2.27) | (−5.62) | (−2.34) | (−2.73) | (−1.56) |
| 10–1 | −24.83 | −12.90 | 5.76 | 3.11 | 12.36 | 6.33 | 18.46 | 11.39 |
| | (−22.38) | (−9.66) | (13.47) | (5.60) | (9.64) | (4.84) | (8.07) | (4.41) |

first closing information dissemination and closing them out with market-on-open orders the next day or MOCs on subsequent days. Table 7 reports gross profits, but traders who implement the strategies would also incur transaction costs including exchange fees and shorting-selling costs.[28]

## 6. Price impact: closing auctions vs. regular trading hours

Investors can choose to trade in closing auctions or trade during trading hours. How does the cost of trading in closing auctions compare to the cost during regular trading hours?

One measure of the cost of trading during regular hours is the *half spread*, which is the difference between the midpoint of quoted spreads and either the ask price (for buy orders) or the bid price (for sell orders). Box et al. (2021, Table VI) report that the average half spread is about 6.2 bps, which is the trading cost for orders smaller than or equal to the quote depth.

The price impact for larger orders would be outside the spread, and they would depend on order size. For instance, Breen et al. (2002) find that the price impact varies with the size of the order and with other firm characteristics such as market cap, price, and inclusion in the S&P 500 Index. For our purposes, we will consider the price impact of an average stock traded on the NYSE. Breen et al. (2002, p. 473) report that their estimates imply a proportional price impact of 17.9 bps for a 1000-share trade. Breen et al. also note that the estimates in Glosten and Harris (1988) and in Hasbrouck (1991) imply a slightly larger price impact for a similar trade.

For closing auction trades, the price impact for each decile is the absolute value of returns for that decile that we report in Table 7. For example, Decile 10 stocks experience the largest price impact, which is 16.89 bps in Nasdaq and 13.12 bps in the NYSE. During the second half of the sample period, the largest price impacts are 17.12 bps in Nasdaq and 11.22 bps in the NYSE.

To facilitate the comparison of price impacts during trading hours and closing auctions, Table 8 presents *OI* as a percentage of daily trading volume, the average dollar value, and the number of shares in each decile when closing information is first disseminated. The average *OI* in the extreme deciles is about 5.4% of the daily trading volume in Nasdaq and 6.2% in the NYSE. The *OI* per stock in Decile 10 is 24,317 shares in Nasdaq and 76,000 shares in the NYSE. Even in this decile, investors on the same side as the *OI* face a smaller price impact than the estimates in Breen et al. (2002) for a trade of only 1000 shares.[29] The price impacts in the other deciles are significantly smaller, although they all show imbalances greater than 1000 shares. Also, the price impact is a cost for trades in the same direction as the *OI*, but a profit for trades in the opposite direction. Even if closing auction trades are in the extreme deciles and in the same direction as the *OI*, they entail significantly smaller execution costs than trades during trading hours (Table 8).

## 7. Results in perspective

This section places our results in perspective within the literature and discusses the implications of our evidence. Bogousslavsky and Muravyev (2020) document that (a) closing auction prices deviate from the midpoints of the last BBO quotes of the day and (b) these deviations are corrected overnight. Bogousslavsky and Myravyev also examine the implications of their findings for the mispricing of options and the longer horizon predictability of stock returns. We examine the price impact of closing auction order imbalances starting from the time when the market first receives the information about order imbalances. Our measure of the price impact starting with the first disclosure of the information gives us a more complete picture to address the issues in our paper.

HM also examine closing auction quality in Nasdaq and the NYSE. They conclude that "... closing auction market quality is significantly worse on NYSE than Nasdaq throughout the closing auction process" (Hu and Murphy, 2021, p. 2). The metrics that HM use to assess closing auction market quality differ from the metrics we use to assess the liquidity of closing auctions. Two of the metrics that HM use to draw their inferences are the average absolute differences between (a) the indicative closing prices during the closing information dissemination window and the actual closing price and (b) the indicative paired volume and actual paired volume at close. HM find that both these metrics are larger in the NYSE than in Nasdaq.

Both exchanges compute indicative prices and paired volumes based on on-close orders (MOCs, LOCs, IOs/COs) as of the time of closing information dissemination. As Fig. 2 shows, new on-close orders after the beginning of *OI* dissemination is less than 0.1% in Nasdaq but more than 20% in the NYSE, on average. The different results reported by HM are likely explained by the evidence that NYSE traders submit more closing orders during the dissemination window than Nasdaq traders, and it is not clear how these metrics capture closing auction quality.

Another metric that HM use is the absolute deviation between the midpoints of the last BBO prices and the closing auction price as defined by Bogousslavsky and Muravyev (2020). HM find larger absolute differences in the NYSE, and they find evidence of larger overnight reversals in the NYSE than in the Nasdaq. HM find no further reversals after the market opens the next day.

Our measure of price impact is return from the time of first dissemination of closing information to close. Markets

[28] Both Nasdaq and the NYSE charge fees of between \$0.00085 and \$0.0027 per share, depending on the type of closing order and the time of entry. Because the fees are calculated per share, the percentage fee depends on the share price, and they are less than 1 basis point for a \$30 share. See http://nasdaqtrader.com/Trader.aspx?id=PriceListTrading2 and https://www.nyse.com/publicdocs/nyse/markets/nyse/NYSE_Price_List.pdf for fee schedules.

[29] The model presented by Breen et al. implies a linear relation between proportional price impact and order size. The price impact of a buy order of 943 shares (= 1,000 × 6.89 ÷ 17.9) equals 16.89 bps during regular trading hours. This would equal the price impact of a Decile 10 buy order in the same direction as the *OI* in closing auctions.

**Table 8**
Closing Auction Order Imbalance
This table reports descriptive statistics of closing auction order imbalances across deciles of portfolios based on closing auction order imbalances (OIs). Stocks are sorted into deciles based on OIs at the time of the first dissemination of closing information. The sample is composed of NYSE-listed and Nasdaq-listed common stocks (CRSP share code 10 or 11) and excludes stocks priced less than $5 on the previous day. Decile 1 and Decile 10 are the deciles of stocks with the largest sell and buy OIs, respectively. For each decile, the table presents OI as a% of total daily trading volume, the dollar value, and the number of shares of OI per stock. The sample period is from March 2010 to December 2020.

Panel A: Nasdaq.

| OI Decile | OI as a% of daily volume | Dollar value of OI per stock | Number of shares of OI per stock |
|---|---|---|---|
| 1 | −5.44% | 1111,469 | 24,735 |
| 2 | −1.39% | 657,969 | 11,782 |
| 3 | −0.82% | 450,980 | 7680 |
| 4 | −0.39% | 237,121 | 4423 |
| 5 | −0.07% | 113,679 | 2630 |
| 6 | 0.16% | 160,847 | 3615 |
| 7 | 0.55% | 321,041 | 6522 |
| 8 | 0.87% | 473,002 | 8795 |
| 9 | 1.55% | 707,849 | 13,166 |
| 10 | 5.31% | 1116,130 | 24,317 |

Panel B: NYSE

| OI Decile | OI as a% of daily volume | Dollar value of OI per stock | Number of shares of OI per stock |
|---|---|---|---|
| 1 | −6.10% | 3759,691 | 77,801 |
| 2 | −2.42% | 1788,426 | 36,755 |
| 3 | −1.36% | 1141,555 | 24,774 |
| 4 | −0.69% | 741,843 | 17,049 |
| 5 | −0.18% | 517,155 | 12,660 |
| 6 | 0.29% | 517,289 | 13,312 |
| 7 | 0.80% | 766,912 | 18,767 |
| 8 | 1.48% | 1188,530 | 26,761 |
| 9 | 2.56% | 1786,307 | 37,515 |
| 10 | 6.25% | 3694,436 | 76,032 |

rationally expect that order imbalances impact prices and the price reaction at the time of first closing information dissemination includes the expected price impact conditional on the information disseminated at that time. Therefore, our measure captures the full price impact including this expected component. Our estimate of price impact is larger in Nasdaq than in the NYSE. Also, the temporary component of the full price impact only partially reverses overnight, and we observe further reversals over the next three to five days.

How could Nasdaq improve the quality of its closing auctions? The evidence in Figs. 2 and 3 indicate that Nasdaq LPs enter new closing orders soon after the closing information is first disseminated, and there is little activity afterwards. This pattern of order submissions is likely due to Nasdaq's time priority rule. Under this rule, later orders are less likely to be filled, hence traders also have less incentive to collect and use new information to place later orders. Also, on-close orders entered after 3:50 p.m. in Nasdaq cannot be canceled or modified. Therefore, traders who enter on-close orders soon after the first dissemination of closing information must also account for the risk that their orders are more likely to be filled when the information revealed between 3:50 p.m. and close moves against them.

In contrast, the NYSE floor traders can enter orders up to 10 s before 4:00 p.m., hence they are less exposed to such an adverse selection problem. As Eq. (5) shows, the slope of the demand function is inversely related to the price risk, and the closing price risk faced by the Nasdaq LPs at 3:50 p.m. is larger than risk the NYSE floor traders face at 4:00 p.m. This difference likely reduces Nasdaq's depth.

Nasdaq's structure does not allow for replicating the NYSE's parity/priority model with floor traders, but Nasdaq should look for other ways to increase its depth. Presumably, Nasdaq's rule that on-close orders submitted after 3:50 p.m. may not be canceled or modified seeks to encourage LPs to submit their on-close orders early and thereby decrease uncertainty about market clearing prices at close. This rule also guards against any price manipulation strategies that could involve traders strategically placing early on-close orders that they intend to eventually cancel.

Nasdaq should consider relaxing this rule and allowing LPs to enter or modify their orders until seconds before 4:00 p.m. Under such a rule, LPs would effectively face a smaller price risk even if they enter their orders earlier than 3:50 p.m. to reserve their place in line. To address potential concerns about closing price uncertainty and price manipulation strategies, Nasdaq could experiment with this rule for only a select few actively traded large-cap stocks.

Nasdaq should also experiment with expanding its *qualified market maker* (QMM) program by adding incentives for providing liquidity in closing auctions. The QMM program currently pays Nasdaq market makers for meeting certain thresholds for quoting at the National BBO during trading hours. Perhaps this program could be expanded to include incentives for absorbing a threshold level of order imbalances in closing auctions.

## 8. Conclusion

Trading volume in closing auctions has significantly increased in recent years. We examine various aspects of closing auctions, including their growth and their relation to proxies for informed and uninformed trades. We find that closing auction volume is correlated with several proxies for uninformed trading, such as the creation and redemption of ETFs, a measure of ETF arbitrage activities, and fund flows into and out of index mutual funds. In contrast, we find a marginally negative relation between closing auction volume and active fund flows, which is a proxy for informed trading. We also find a significantly negative relation between closing auction volume on the trading day before earnings announcements. Overall, these findings indicate that closing auctions attract uninformed traders, but informed traders seem to prefer to trade during trading hours, perhaps to capitalize on their information before its value decays.

We also examine the depth and resiliency of closing auctions, and we compare the performance of closing auctions in Nasdaq and the NYSE. The auctions in these two exchanges have many common features, but NYSE floor brokers and designated market makers enjoy special privileges. For example, these floor traders can enter or modify their closing orders until 10 seconds before 4:00 p.m., but the deadline for other traders is 10 min earlier. Additionally, the NYSE follows a "parity/priority" rule that prioritizes allocations to floor traders when there is excess demand or supply at the closing auction price. In contrast, Nasdaq accords the same privileges to all traders. We present a model to conceptually compare the merits of these two systems.

We find that the price impact of closing auction order imbalances in the NYSE is smaller than in Nasdaq. Why does the NYSE have better depth when its preferential treatment of floor traders may discourage competition from off-exchange traders? We find that floor traders are significantly more active after the first dissemination of closing information than the off-floor LPs in Nasdaq. For example, the new on-close orders that Nasdaq traders submit after the first dissemination of closing information is less than 0.1% of the closing auction volume, but the new on-close orders that the NYSE floor traders submit is about 20%. The model by Benveniste et al. (1992) shows that floor traders have access to information that is unavailable to off-floor traders, and this informational advantage is likely one factor that contributes to the more active role they play. Our model shows that better informed traders offer more depth when they are couterparties to order imbalances.

The closure of the NYSE floor operations from March 23, 2020, through May 25, 2020, due to the COVID-19 pandemic brought renewed attention to the relative merits of the systems used by Nasdaq versus the NYSE. In published reports, both Nasdaq and the NYSE claim that their own system is superior, and they present evidence that includes metrics related to closing auctions during the closure of the trade floor. We find that the depth of closing auctions was better in Nasdaq than in the NYSE during the closure.

How can we reconcile this evidence with our findings that the depth was better in the NYSE during periods of normal operations? Our model shows that floor traders displace some competition from off-floor traders who provide liquidity. Therefore, Nasdaq was able to provide better liquidity than the NYSE's remaining off-floor traders when floor trading was halted. This evidence also indicates that the NYSE closing auctions have better depth because of the floor traders.

We find that about 85% of the price impact in Nasdaq is temporary, compared to about 62% in the NYSE. This evidence indicates that closing auction trades in the NYSE convey more value-relevant information than in Nasdaq. We also find that about three to five days are required for the temporary components of the price impact to fully dissipate in both Nasdaq and the NYSE.[30]

To assess the economic significance of this price impact, we consider a trading strategy that buys the decile of stocks with the largest buy imbalances and sells the decile with the largest sell imbalances at the time of the first *OI* dissemination. This strategy earns 30.34 bps in Nasdaq and 24.79 bps in the NYSE. The strategy that takes the opposite position at close, and closes the position at five days, earns 40.49 bps in Nasdaq and 18.58 bps in the NYSE. This is equivalent to annualized profits of about 21% and 10%, respectively. These are the ex post profits that liquidity providers earn if they hold their positions for five days, and their annualized profits are larger if they liquidate their positions sooner.

Our results indicate that the price impact of trades during closing auctions is generally smaller than trades made during trading hours. Therefore, it is unclear why far more trades occur during trading hours than in closing auctions. Traders who have time-sensitive information could find it advantageous to trade during trading hours and not wait until closing time. However, as Grossman and Stiglitz (1980) show, informed traders alone cannot sustain an active market. Therefore, some of the trades during trading hours must be made by uninformed investors who perhaps mistakenly believe that they have useful information. One avenue for future research would be to determine why an overwhelming majority of trades occur during trading hours as opposed to closing auctions.

## Appendix A

[30] Our evidence that stocks in ETF portfolios are more actively traded than others, together with the closing auction price impact and its reversal, could partly explain the evidence in Ben-David et al. (2018) that ETFs increase the non-fundamental volatility of stocks in their portfolios.

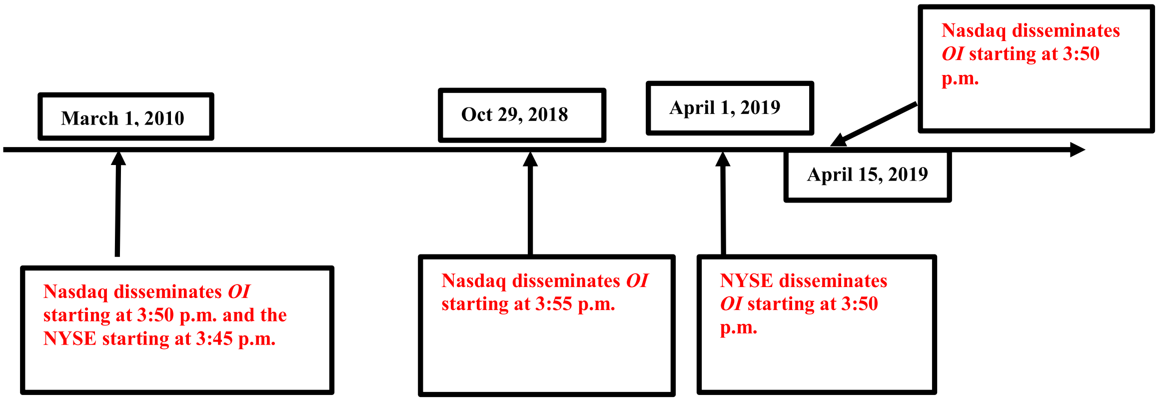


**Fig. A.1.** Time of first closing information dissemination.
This figure presents the time of the first order imbalance (OI) information dissemination during the March 2010 to December 2020 sample period.

## Appendix B

*Proof.* **of Proposition 1:** From Eqs. (4), (5), and (10), we obtain

$$Q_{nasd}(p) = N\lambda_{inf}(v_0 - p) - \sum_{i=1}^{N} e_i + K_{nasd}\lambda_{lp}(\mu - p) \ + OI. \tag{B.1}$$

We set $Q_{nasd}(p_{nasd}) = 0$, where $p_{nasd}$ is the Nasdaq closing auction price. We solve Eq. (B.1) to obtain

$$p_{nasd} - \mu \ = \frac{N\lambda_{inf}(v_0 - \mu) - \ \sum_{i=1}^{N} e_i + OI}{\lambda_{nasd}}, \tag{B.2}$$

where $\lambda_{nasd} = N\lambda_{inf} + K_{nasd}\lambda_{lp}$.

Taking expectations on both sides yields the first part of Eq. (12) because the expectations of the other terms on the right-hand side equal zero. Therefore,

$$E[p_{nasd} - \ \mu|OI] = \frac{OI}{\lambda_{nasd}} \ . \tag{B.3}$$

The other part of Eq. (12) (i.e., $-E[(v - p_1)|OI] = \frac{OI}{\lambda_{nasd}}$) follows because $E[v] = \mu$.

Using Eqs. (4), (5), (9), and (11), and setting $Q_{nyse}(p_{nyse}) = 0$, we obtain

$$[p_{nyse} - \ \mu|OI] = \frac{N\lambda_{inf}(v_0 - \mu) + N_{ft} \times \lambda_{ft}(p^* - \mu) - \ \sum_{i=1}^{N} e_i + OI}{\lambda_{nyse}}, \tag{B.4}$$

where $\lambda_{nyse} = N\lambda_{inf} + K_{nyse}\lambda_{lp} + N_{ft} \times \lambda_{ft}$. We prove Eq. (13) in Proposition 1 analogously.

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