# Who Trades at the Close? Implications for Price Discovery and Liquidity* 

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#### Abstract

Closing auctions set daily closing prices for U.S. stocks and account for a striking $7.5 \%$ of daily volume in 2018 , up from $3.1 \%$ in 2010 . We study closing auctions in the new regime of record volume. Closing auctions appear to match volumes at low cost: closing prices typically match pre-close bid or ask prices, and price impact is lower than during continuous trading. Auction price deviations revert quickly and almost completely on average. Auction-to-intraday volume spikes on S\&P 500 additions and increases permanently afterwards, suggesting that closing volume is fueled directly and indirectly by the growth of indexing and ETFs.


JEL Classification Codes: G10, G12, G14
Keywords: Closing auction, passive investing, price pressure, liquidity

## 1 Introduction

U.S. equities closing prices are determined in a special call auction held at the listing exchange a few seconds after regular trading hours. The auction clears submitted orders to maximize executed volume in a single trade. Auction closing prices are essential. They are used to price mutual fund shares and derivatives, report performance by institutional investors, compute margin and settlement payments as well as asset value for exchange-traded funds (ETFs) and stock indices. Closing prices in CRSP and other databases are generally determined in these closing auctions. ${ }^{1}$

While the introduction of closing auctions in the late 1990s and early 2000s has been studied (for example, Pagano and Schwartz (2003)), relatively little trading occurred at the auction. Recently, however, the financial press reports that trading volume is shifting towards the end of the trading day and raises concerns about this trend. ${ }^{2}$ These concerns are fueled by occasional abnormalities at the close. For example, Figure 1 shows the price and volume of Tesla's stock on the day it joined the $\mathrm{S} \& \mathrm{P} 500$. On this day, the auction price deviated by as much as $3 \%$ from the preclose quote midpoint, with $\$ 150.8$ billion traded in the auction. Investors who bought Tesla in the auction lost $\$ 4.5$ billion since the auction price deviation entirely reversed overnight. Regulators are also concerned. In France, the Autorité des Marchés Financiers (AMF (2019)) identified the "concentration of transactions in the closing auction" as a new risk. "The associated risks are a deterioration in price formation and liquidity during trading sessions, not to mention the operational vulnerabilities at the end of the day given the volumes concentrated in the closing auction."

We examine the properties of end-of-day trading and especially the closing auction under the "new regime" of record volume at the close. Indeed, the closing auction has become a major trading mechanism. In 2018, $\$ 15.2$ billion are traded daily in the auction across U.S. stocks, which would make it the fifth largest equity market in the world by trading volume. ${ }^{3}$ Auction volume accounts for $7.48 \%$ of daily dollar volume on aggregate in 2018, up from $3.11 \%$ in 2010 . This contrasts to the $0.49 \%$ auction-to-total volume ratio upon Nasdaq's auction introduction in 2004 that Smith

[^1](2006) estimates. Contrary to auction volume, volume during $3: 30-\mathrm{to}-3: 55 \mathrm{pm}$ as a share of total volume declines between 2010 and 2018. Thus, volume migrates not just to the end of the trading day but to the last five minutes and especially the auction.

Does closing volume move prices? The closing price almost always deviates from the 4 pm closing quote midpoint, but this price deviation is small on average. The average (absolute) deviation is 8.1 basis points (bps), only slightly higher than the average half bid-ask spread of 7.6 bps . Indeed, the auction price matches the pre-close bid/ask price in $68.5 \%$ of cases. Even on S\&P 500 index rebalancing days, we find little evidence of abnormal price deviations at the auction relative to the volume traded. Hence, the closing auction appears to match a large volume cheaply on an absolute basis.

On a relative basis, we also find evidence that actual trading costs incurred by investors in the auction are lower than intraday. Absent account-level data, we resort to a simple price impact measure in the spirit of the Amihud (2002) ratio: the ratio of absolute midpoint return to volume. This illiquidity ratio is on average 0.89 over $3: 30-3: 45 \mathrm{pm}, 0.26$ over $3: 45-4: 00 \mathrm{pm}$, and 0.12 over 4pm-auction when adjusting the auction price for the half spread. The illiquidity ratio between $3: 45 \mathrm{pm}$ and the auction, without adjusting for the spread, is on average 0.18 . This interval accounts for the diffusion of auction imbalance information ahead of the auction.

Despite the auction matching large volume relatively cheaply, we identify and explore several potential concerns. First, although price deviations are typically small, we show that the auction price settles inside the bid-ask spread (i.e., bid $<$ auction price $<$ ask) in only $8.1 \%$ of cases. The minimum tick size is binding in $41.8 \%$ of all auctions and thus prevents closing prices from settling within the spread. To establish a causal link between tick size and auction price deviations, we show that closing price deviations increase sharply for small stocks right after their tick size is increased by the 2016 Tick Size Pilot Program. The binding tick size increases costs for liquidity takers and profits for liquidity providers. Half a tick is relatively modest on a single trade but becomes economically significant when applied to the tremendous volume executed in closing auctions. This raises a question about the optimal tick size in the closing auction.

Second, moving from the smallest price deviations to the other extreme, auction imbalances sometimes move prices beyond the spread and add "noise" to closing prices. Price deviations at the close exceed 63 bps in $1 \%$ of cases. Concentrated trading can lower costs and make prices more
efficient (Admati and Pfleiderer (1988)). In contrast, prices can deviate from fair values when riskaverse liquidity providers absorb large order imbalances (Grossman and Miller (1988); Hendershott and Menkveld (2014)). Consistent with uninformed price pressure, closing price deviations reverse almost fully overnight, even when adjusted for the half spread. For stocks with sufficient after-hours liquidity, one-third to one-half of the reversal occurs within the first half-hour after the close. This fast reversal is suggestive of imperfect liquidity provision in the auction. The rest of the reversal could compensate liquidity providers for bearing overnight risk.

Auction volume can contribute to price discovery when information about auction imbalance is disseminated before the auction. The NYSE and Nasdaq start to disseminate imbalance information at different time. We exploit this time difference to show that auction imbalance information contributes to price discovery, but the magnitude is not large enough to explain the low informativeness of closing price deviations. Furthermore, our main findings are robust across both NYSE and Nasdaq auction designs.

Price reversal suggests that auction volume could be driven to a significant extent by uninformed trading. We explore the determinants of auction volume. Intuitively, passive investors seek to trade at the auction price to minimize tracking error as they are benchmarked against closing prices for indices they track. A difference-in-difference analysis shows that ETF and passive mutual fund ownership are much more strongly associated with auction volume than with pre-auction volume, whereas active mutual fund ownership displays the opposite pattern. A $1 \%$ increase in passive mutual fund ownership is associated with a $3.7 \%$ increase in closing auction turnover but only with a $0.6 \%$ increase in $3: 55-4: 00 \mathrm{pm}$ turnover, all else equal. Moreover, auction volume spikes on index rebalancing days, option expiration days, and end-of-month days. In contrast, auction volume is lower on and around earnings announcements whereas pre-close volume is higher, which goes against the idea that informed trading drives auction volume.

Index funds and ETFs (especially leveraged ETFs) increase closing volume by rebalancing and through the creation and redemption process, but it is unlikely that their direct trading fully explains the economic magnitude of the closing volume increase. First, trend coefficients are positive and strongly significant for auction volume despite the inclusion of ETF ownership and passive ownership in our regression. Second, BlackRock (2020) estimate that ETF flows are too small to account for the increase in closing auction volume. Indexers, however, can attract other investors
who take advantage of the higher volume at the close. Consistent with this hypothesis, closing volume permanently increases by $20 \%$ (decreases by $15 \%$ ) relative to intraday volume after a stock is added to (deleted from) the S\&P 500 index, relative to control stocks.

We study potential spillovers from the auction to the rest of the day, which the AMF (2019) report is concerned about. We establish a correlation between the increase in trading at the close and potentially undesirable changes in the trading environment intraday. As investors cluster their trades at the close, intraday liquidity could deteriorate (Admati and Pfleiderer (1988); Foster and Viswanathan (1990)). We find that turnover in the first 15 minutes of trading drops by $22 \%$ on average for S\&P 500 stocks over our sample period. Liquidity worsens substantially: Effective spread increases by 10 bps , and market depth declines by $63 \%$. Open volatility increases after controlling for volatility during the day, and the price contribution of the open to the intraday return also increases. Hence, liquidity deteriorates and price discovery increases around the open over our sample period when closing volume increased substantially.

To conclude, we provide one application where correcting for price deviations at the close makes a difference. The put-call parity is one of the most basic and widely studied no arbitrage relationships. Prior research finds that the parity between the underlying stock and option prices is frequently violated. We show that many put-call parity violations disappear if the parity is computed with stock midquotes instead of closing prices, which is a standard approach. Daily option prices are as of 4 pm , but the closing stock price is from the auction shortly after 4 pm . This price mis-synchronization and the fact that closing price deviations fully revert overnight also fully explain why put-call parity violations predict next-day stock returns.

Overall, the results have potential policy implications. One concern with the current auction design is that the dominance of passive investors in the auction makes the closing price noisy, which undermines its role as a benchmark. We indeed find that the closing price occasionally deviates from the pre-close midquote and then fully reverses on average. Our results also help start the debate about optimal tick size in the auction and about the effect of concentrated trading at the close on intraday trading.

### 1.1 Related Literature

We contribute to several lines of research. Prior literature on equity auctions mostly focuses on the introduction of closing auctions. The evidence generally indicates that market quality mostly improves when a closing auction is introduced on Nasdaq and international exchanges in the late 1990s and early 2000s. ${ }^{4}$ In fact, Nasdaq introduced the closing cross following demand for more robust closing prices (Pagano, Peng, and Schwartz (2013)).

Contemporaneous papers by Jegadeesh and Wu (2022) and Hu and Murphy (2020) focus on comparing closing auctions on the NYSE and Nasdaq in recent years but reach opposite conclusions. Hu and Murphy (2020) show that information disseminated ahead of the auction is less accurate on the NYSE than Nasdaq. Jegadeesh and Wu (2022) find greater depth on the NYSE than on Nasdaq. Our main findings are robust across both auction designs. Jegadeesh and Wu (2022) also find that "it takes about 3-5 days for the temporary component of the price impact to fully dissipate." In contrast, we find that auction price deviations are small and reverse overnight. We reach different conclusions because their measure of price impact combines the last ten (fitfteen) minutes of continuous trading and the closing auction on Nasdaq (the NYSE), whereas our price deviation measure focuses exclusively on the auction. We discuss this distinction further after introducing our measure. We also provide distinct evidence on index inclusions/deletions and afterhours price moves as well as difference-in-difference analyses to rule out alternative explanations. Raillon (2020) studies closing auction volume and price formation for CAC 40 shares on Euronext Paris. In subsequent work, Comerton-Forde and Rindi (2021) examine increased closing auction activity in European markets and find "substantial differences between closing auction prices and prices set at the end of the continuous trading day." Unlike in the U.S., closing auctions in Europe occur with a substantial delay after the end of continuous trading.

A growing literature finds mixed evidence on how the growth of passive investing affects markets. Cushing and Madhavan (2000), Cheng and Madhavan (2009), Ben-David, Franzoni, and Moussawi (2018), Baltussen, van Bekkum, and Da (2019), Shum et al. (2016), and Tuzun (2013) provide evidence that more index investing can lead to higher volatility. However, in the context of leveraged

[^2]ETF rebalancing, Bessembinder (2015) and Ivanov and Lenkey (2018) argue that indexing should not significantly affect volatility. While our results do not directly contribute to this debate, they suggest that indexing improves liquidity at the close. Our results suggest that the auction can match a large volume cost-effectively in absolute terms, relative to the bid-ask spread, or relative to the Amihud (2002) ratio. Passive investing directly affects the market in the last five minutes of trading and especially the auction. It could also indirectly affects trading during the day by encouraging other investors to shift their trades towards the close.

Finally, this paper highlights the importance of the tick size for closing auctions and prices. ${ }^{5}$

## 2 Data

We study common stocks listed on the NYSE and Nasdaq with a price greater than $\$ 5$ and a market capitalization greater than $\$ 100$ million at the beginning of a month. Thus, we focus on the stock universe that is potentially accessible to institutional investors. Observations with a missing CRSP return are excluded. We obtain auction price and volume data from the Trade and Quote dataset (TAQ) over January 2010 to December 2018. Auction trades are reported with a special condition by the NYSE and Nasdaq. The procedure to identify auction trades and the relevant filters are detailed in Appendix B. Intraday returns and trading volumes are obtained from TAQ. Turnover is computed by dividing volume by shares outstanding obtained from CRSP.

We use the end-of-day midquote reported by CRSP, which matches with the 4 pm midquote from TAQ for $95.80 \%$ stock-days. Observations with a crossed quote are excluded. The differences are small, and our results are quantitatively similar whether we use the CRSP or TAQ midquote. We prefer the CRSP midquote to be consistent with our use of the CRSP closing price. For the same reason, we use the CRSP closing price to compute the price deviation at the close (instead of the TAQ auction price). The CRSP and TAQ closing prices match in $98.95 \%$ of cases. The differences are small and concentrated over 2010 to part of 2014. The match rate is greater than $99.99 \%$ after 2014. Our results are quantitatively similar if we use the TAQ auction price instead of the CRSP closing price and robust to using only the second half of the sample.

[^3]We compare the auction price to both the CRSP daily closing price and midquote and exclude observations for which the absolute difference between the CRSP price/midquote and the auction price is greater than $10 \%$ of the price/midquote. This filter excludes 76 observations, which appear to be data errors. We also exclude days with early closures from the sample. Our final sample contains $5,720,876$ stock-day observations allocated across 1,887 NYSE-listed stocks ( $47.59 \%$ of all observations) and 2,946 Nasdaq-listed stocks ( $52.41 \%$ of all observations). Among NYSE- (Nasdaq)listed stocks, $99.18 \%$ ( $96.01 \%$ ) of stock-day observations have a valid auction price.

We retrieve institutional ownership data from the 13F filings reported in the Thomson Reuters database and compute active and passive mutual fund ownership. A mutual fund is classified as passive if the $R^{2}$ of a regression of the fund's holdings-implied returns on the Fama-French three factors is greater than $95 \%{ }^{6}$ ETF ownership is obtained from the CRSP mutual fund database for 2010 and 2011, and from ETF Global from 2012 to 2018.

## 3 Price deviations at the close

We briefly review the remarkable growth in closing volume before comprehensively studying its effect on closing prices. Closing auction volume is large, has increased tremendously relative to total volume, and behaves differently from intraday volume. Figure 2 plots the trends in the fraction of aggregate daily dollar volume executed intraday and around the close. The fraction of daily volume executed intraday (9:30am-3:30pm) decreases over our sample period (top plot). The fraction of volume in the last five minutes of trading increases from $4.6 \%$ in 2010 to about $5.2 \%$ in 2018 and varies in a narrow range (middle plot). In contrast, the fraction of aggregate daily volume executed in the auction increases significantly from $3.1 \%$ in 2010 to $7.5 \%$ in 2018 (bottom plot). Auction volume regularly spikes from the baseline level to reach about $15-20 \%$ of daily volume.

Table 1 confirms that the aggregate volume results in Figure 2 hold for an average stock and across size quintiles. Auction volume is $5.69 \%$ of total daily volume for an average stock-day. The last five minutes ( $3: 55 \mathrm{pm}$ to $4: 00 \mathrm{pm}$ ) and the preceding 25 minutes ( $3: 30 \mathrm{pm}$ to $3: 55 \mathrm{pm}$ ) account for $6.96 \%$ and $10.90 \%$ of total daily volume. The auction volume share changes little across size quintiles, from $5.67 \%$ for large firms to $6.06 \%$ for small firms. Similarly, the pre-close volume has

[^4]no clear pattern. ${ }^{7}$ The auction volume share is similar across size groups despite smaller stocks having more days without an auction, which is consistent with Madhavan (1992). Madhavan (1992) predicts that auctions are more important for thinly-traded stocks since the pooling of trades reduces adverse selection. Consistent with this intuition, the auction volume share is similar across size groups despite smaller stocks having more days without an auction. Nevertheless, our results suggest that a minimum amount of trading activity is required to make an auction viable.

Does this "new regime" of massive volume make closing auction prices "noisier"?

### 3.1 How large are closing price deviations?

To study how prices deviate at the close, we define the absolute deviation as

$$
\begin{equation*}
\text { deviation }=\left|\log \left(p_{\text {auc }} / p_{4: 00}\right)\right|, \tag{1}
\end{equation*}
$$

where $p_{\text {auc }}$ is the auction price and $p_{4: 00}$ is the quote midpoint at 4 pm . We use the 4 pm midquote merely as a benchmark and do not imply that investors can trade at it. An alternative to (1) is to start the return with the first disclosure of auction imbalance information (3:45pm on the NYSE and 3:50pm on Nasdaq), as in Jegadeesh and Wu (2022). We use the deviation between last midquote and auction price to avoid contamination from new information released during continuous trading. This allows us to cleanly investigate auction-driven price moves. Anticipated price moves are, however, impounded through the dissemination of imbalance information, which we discuss in Section 3.2. Therefore, the two measures provide complementary information.

Panel (a) of Table 2 reports the distribution of closing price deviations for the entire sample and across size quintiles. While deviations can be large occasionally, they are small most of the time. Auction price deviations are 8.12 bps on average and range from 20.6 bps for small stocks to 2.66 bps for large stocks. The distribution has positive skewness. In $5 \%, 1 \%$, and $0.1 \%$ of stock-days closing prices deviate by more than $0.26 \%, 0.63 \%$, and $1.95 \%$, respectively. ${ }^{8}$

[^5]On a relative basis, we also find evidence that actual trading costs incurred by investors in the auction are lower than intraday. Absent account-level data, we resort to a simple benchmark based on public data. In the spirit of the Amihud (2002) ratio, we compute the ratio of absolute return to share volume for the auction and other periods near the end of the day. ${ }^{9}$ Panel (b) of Table 2 reports descriptive statistics for these ratios. The average ratio is about two times lower in the auction (Column (1)) than over 3:30pm-3:45pm (Column (2)), consistent with auction trades incurring relatively low costs. The average ratio is even lower between 3:45pm and 4:00pm (Column (3)) than in the auction: 0.263 vs 0.421 . Returns are, however, measured midpoint-to-midpoint for continuous trading but midpoint-to-price for the auction. We therefore compute the auction illiquidity ratio with the auction price that is adjusted for the half-spread by adding (subtracting) half the spread for trades made below (above) the 4 pm midpoint. Column (4) shows that the average "spread-adjusted" auction return-to-volume ratio is only 0.124 , which is lowest among all intervals considered. This supports a lower cost of trading in the auction than intraday. As we discuss below, many auctions execute at the best bid or ask as of the end of continuous trading. Finally, Column (5) shows that the return-to-volume ratio is on average much lower over the last 15 minutes of trading including the auction than over $3: 30 \mathrm{pm}$ to $3: 45 \mathrm{pm} .{ }^{10}$

To gain additional insights, we decompose the (absolute) auction price deviation into quoted half spread and closing spread deviation:

$$
\begin{equation*}
\mid \text { deviation } \mid=\text { half spread }+ \text { spread deviation, } \tag{2}
\end{equation*}
$$

where the half spread is defined as $\log \left(p_{\text {ask }} / p_{4: 00}\right)$ if $p_{\text {auc }} \geq p_{4: 00}$ and $\log \left(p_{4: 00} / p_{\text {bid }}\right)$ otherwise. Spread deviation is $\log \left(p_{\text {auc }} / p_{\text {ask }}\right)$ if $p_{\text {auc }} \geq p_{4: 00}$ and $\log \left(p_{\text {bid }} / p_{\text {auc }}\right)$ otherwise. In words, the spread deviation is defined as the difference between the absolute auction price deviation and the quoted half spread at the end of continuous trading. Aside from fees and commissions, a small liquidityconsuming trade pays in general half the bid-ask spread as it consumes liquidity at the best bid or

[^6]ask. A closing auction trade may, however, execute within the spread or beyond the spread. For example, a large buying (selling) imbalance in the auction may cause the closing auction price to be above (below) the best ask (bid) at the end of continuous trading, resulting in a positive spread deviation. Though there is no spread in the auction, it is of interest to evaluate the extent to which it is the case

Table 3 reports the distribution of half spread and spread deviation. If the auction is like a regular small trade, then the price deviation from the midquote will only reflect half the spread. The average auction half spread is 7.56 bps , while spread deviation is only 0.55 bps . The average absolute deviation of 8.1 bps is thus only slightly higher than the average half spread. For large stocks, the half-spread and spread deviation are about equal: 1.47 and 1.19 bps . In line with theories of price impact (e.g., Grossman and Miller (1988); Kyle (1985)), Section IA.B in the Appendix shows that spread deviation at the close increases with volatility and auction volume (which we expect to be correlated with auction imbalance).

Figure 3 plots a histogram of auction absolute dollar deviation divided by the half spread at 4:00pm. Remarkably, only $1.8 \%$ of all auctions execute at the midpoint and as few as $8.1 \%$ settle within the bid-ask spread. As many as $68.5 \%$ of auctions execute at exactly the best bid or ask. The spread binds mostly due to the minimum tick size, which binds for $42 \%$ of all auctions. A binding tick size could benefit continuous trading if it promotes liquidity at the best bid and ask. It is unclear to which extent this benefit apply to the auction since the auction aggregates liquidity supply and demand at a single point in time. Furthermore, dark pools regularly match large volumes within the spread, even when the tick size is binding (e.g., Kwan, Masulis, and McInish (2015)). The same could be implemented in closing auctions and would perhaps be less controversial as auctions do not compete directly (i.e., time wise) with the continuous market. On the other hand, absent the minimum tick size, liquidity providers could disengage from the auction. Our results raise a question about the optimal tick size for closing auctions.

To establish a causal link between tick size and closing price deviations, we use the 2016 Tick Size Pilot program. The Pilot program increased the tick size for a sample of small stocks. Figure 4 plots and compares the cross-sectional daily median absolute auction deviation among small and large stocks. Closing price deviations increased sharply for small stocks after the Tick Size Pilot started. The discontinuity in price deviations coincides exactly with the start of the Pilot. In
contrast, price deviations declines over the sample period among large stocks despite the large increase in auction volume. ${ }^{11}$

A deviation of half a tick seems relatively modest but becomes economically significant once multiplied by the large volume executed in closing auctions. Assuming that the auction price deviation reverses, which we show formally in Section 3.2, a back-of-the-envelope calculation indicates that this friction increases the aggregate costs of taking liquidity at the close by up to $\$ 3$ billion in 2018. This number is obtained by multiplying the $\$ 15.2$ billion average daily auction volume in 2018 by the average half spread of 7.6 bps times 252 trading days.

Auction price deviations are small on average, but the case of TSLA in Figure 1 shows that the auction price can substantially deviate from the pre-close midquote. How far do closing prices deviate when closing volume is extremely large and one-sided? We test the resiliency of closing auctions under extreme conditions by using S\&P 500 additions and deletions. Our sample period includes 207 S\&P 500 rebalancing events ( 122 additions and 85 deletions). ${ }^{12}$ For index additions, the day prior to the official inclusion date is the event day since passive funds must rebalance on that day to minimize tracking error. We refer to this day as the event day for simplicity. Since the results are similar for additions and deletions, we study them jointly.

For each event (addition/deletion), we include the rebalancing day as well as the prior two months to control for baseline values. We divide the last 30 minutes of trading into six five-minute intervals and add the auction. For each interval, we measure $\log$ turnover and volatility. Volatility is measured as the absolute ( $\log$ ) return in each interval to match our definition of the auction deviation. We then regress turnover and volatility on event fixed effects, indicators for the five-minute intervals over the last 30 minutes of trading (excluding the $3: 30-35 \mathrm{pm}$ indicator) and the auction, an event day indicator ( SP (join/exit)), and interactions between the five-minute/auction and event day indicators. In this difference-in-difference analysis, the coefficient on Auction*SP(join/exit) measures how much turnover increases at the auction on rebalancing days relative to the prior two months, in excess of the same difference in turnover at $3: 30-35 \mathrm{pm}$. Focusing on intraday relative variation controls for changes in visibility from S\&P 500 membership.

[^7]Table 4 reports the results. Only the SP (join/exit) coefficient and its interactions are reported to save space. Auction volume increases by more than $3,000 \%$ on addition/deletion days relative to $3: 30-35 \mathrm{pm}$ volume (first column). End-of-day volatility also increases on event days (second column). The absolute auction deviation increases by about $21 \mathrm{bps}(=14.96+6.20)$. For comparison, the auction deviation is about 3 bps in the pre-event two-month window. A 21 bps increase is large relative to the baseline but moderate in economic terms given the extraordinary auction volume on rebalancing days. In fact, the auction price deviation interaction coefficient becomes statistically insignificant when controlling for turnover (last column). Hence, given the tremendous volume executed in the auction, absolute deviation between the auction price and the 4:00pm midquote is not abnormal on S\&P 500 addition/deletion days. This alleviates some of the concerns about auction robustness under extreme conditions and is consistent with Barclay, Hendershott, and Jones (2008), who show that the consolidation of order flow in the opening auction improves price efficiency on witching days.

The time between the end of continuous trading and the auction provides an additional measure of auction operational risk. Section IA.C in the Internet Appendix analyzes the distribution and determinants of this quantity. We do not find much evidence of auction operational risk. Auctions on NASDAQ are automated and are conducted within 45 seconds of the close in $99.9 \%$ of cases with a median time of 0.2 seconds. Auctions on NYSE take a median time of 122.3 seconds and may have delays, but we do not find a strong correlation with high-volume days or rebalancing days.

Overall, the results in this section suggest that the auction can match a large volume costeffectively in absolute terms, relative to the bid-ask spread, or relative to the Amihud (2002) ratio.

### 3.2 Do closing price deviations reflect information or noise?

Do auction prices deviate from the 4 pm midquote because information is incorporated through trading or because of price pressure? Deviations caused by new information should be permanent, whereas deviations caused by price pressure should reverse. We test this prediction by studying
how the overnight return depends on the auction price deviation:

$$
\begin{equation*}
\log \left(p_{9: 45, t+1} / p_{\text {auc }, t}\right)=a+b \log \left(p_{\text {auc }, t} / p_{4: 00, t}\right)+e_{t} \tag{3}
\end{equation*}
$$

where $p_{9: 45, t+1}$ is the midquote price on the next day at 9:45am, $p_{\text {auc }, t}$ is the auction price, and $p_{4: 00, t}$ is the midquote price at $4: 00 \mathrm{pm}$. The next-day price is adjusted for stock splits and dividends. We use the midquote 15 minutes after the open to avoid noisy and unreliable quotes over the first minutes of trading (e.g., Bogousslavsky (2021)). Some specifications control for the return over $3: 55 \mathrm{pm}$ to 4 pm .

The coefficient for price reversal, $b$, should be zero if auction price deviations are fully efficient and -1 if they are entirely due to price pressure. Panel (a) of Table 5 shows that the reversal coefficient is -0.85 , or $85 \%$ of the deviation is reversed by the next morning. For large and small stocks, $110 \%$ and $85 \%$ of the price deviation is reversed (reported in Table IA. 6 in the Internet Appendix). The reversal is complete if we control for the 3:55-4:00 price change (part of the the $4: 00$-auction price change is due to the reversal from the previous five minutes). Thus, price deviations are mainly due to price pressure and not new information. In contrast, only $19 \%$ of the last five-minute return is reversed the next morning; i.e., the 4 pm midquote change is mostly efficient. The auction price stands out relative to the pre-close price, which further suggests that auction volume differs from pre-close volume.

We confirm that the reversal is not driven by a mechanical bounce effect. As shown above, the auction price deviation often equals half the closing bid-ask spread. We adjust the reported auction price by adding (subtracting) half the spread for trades made below (above) the 4 pm midpoint and then estimate (3) using this spread-adjusted auction price. The reversal coefficient becomes closer to -1 after this adjustment: -0.95 for the full sample, and -0.97 and -0.98 for large and small stocks in Table IA.6. The last column of Table 5 restricts the sample to the top $1 \%$ of auctions with largest spread deviation (i.e., spread deviation greater than 19.70 bps as shown in Panel (b) of Table 3). In this sample, about $66 \%$ of the spread deviation reverses overnight. Hence, a substantial part of large deviations reverts in less than a day. For robustness, we interact indicators for NYSE-listing with returns to test whether the reversal differs between NYSE and Nasdaq auctions. For large stocks, the reversal is similar across them. For small stocks, the reversal is lower for NYSE stocks
but still exceeds $60 \%$ even when adjusted for the bid-ask bounce.
Overall, most of the auction price deviation reverses overnight, whether adjusted for the bid-ask bounce or not and whether we consider NYSE or Nasdaq auctions. ${ }^{13}$

Price reversal is consistent with liquidity provision ahead of the overnight period. Risk-averse liquidity providers require compensation to hold inventories during the overnight period due to its low liquidity and high price jump risk. Price reversal could also be consistent with imperfect liquidity provision in the auction due to "segmentation." Exchanges have an "effective monopoly" over the official closing price for their listed securities. A closing auction for Coca-Cola's stock organized on the Nasdaq does not set the official daily closing price for Coca-Cola because CocaCola is listed on the NYSE. Thus, investors who want execution at the official closing price must trade in the auction. ${ }^{14}$

This segmentation has several implications for liquidity provision in the auction. First, exchange fees net of rebates are likely higher to trade in the auction than in the continuous market (Hu and Murphy (2020)). Exchange fees are charged on both sides of an auction trade, whereas a rebate is generally issued to a trader who places a liquidity-providing order during regular trading. This increases the cost of providing liquidity in the auction relative to continuous trading. Second, trading in the auction is subject to more uncertainty than during regular hours. Kim and Trepanier (2019) argue that liquidity providers face queuing uncertainty in the closing auction, which makes them less willing to absorb imbalances. Liquidity providers should thus require higher compensation, leading to greater reversal (Grossman and Miller (1988)).

We examine after-hours trades to disentangle among the two hypotheses. Overnight risk predicts that reversal occurs mostly overnight. Segmentation suggests that reversal may occur faster than overnight. We compute after-hour returns from volume-weighted average prices between 4:10$4: 20 \mathrm{pm}, 4: 20-4: 30 \mathrm{pm}$ and $4: 30-4: 40 \mathrm{pm}$, and estimate the following regression:

$$
\begin{equation*}
r_{\mathrm{auc}-\tau}=a+b * r_{4: 00-\mathrm{auc}}+e \tag{4}
\end{equation*}
$$

[^8]where $\tau$ is 4:20 pm, 4:30 pm , and 4:40 pm. ${ }^{15}$ Because after-hours trading is illiquid, only large stocks that traded within this period are included, or about one third of all large stocks for the first twenty-minute window. Panel (b) of Table 5 shows that the price reverts halfway to the pre-close midquote in just twenty minutes after the close. If the after-close window is expanded to forty minutes, half of large stocks traded in this window, and the reversal coefficient is still close to one-half. The results are not affected by the bid-ask bounce (shown in Table IA. 8 in the Internet Appendix) and are similar if we add controls such as market capitalization, volatility, and volume.

This "fast reversal" is hard to explain with overnight risk and therefore lends (indirect) support to the segmentation hypothesis. That being said, the results also suggest that overnight risk is an important driver of auction price deviations. Anecdotally, about half of the auction price deviation reversed right after the auction in the case of Tesla (Figure 1), with the rest of the reversal occurring overnight.

Reversal of closing price deviation indicates that the closing price can be noisy. This noise undermines the closing price's role as a benchmark for performance attribution and derivatives settlement. Price deviations are also strongly positively correlated so that the price noise is in part systematic (see Footnote 8). We evaluate the auction's performance and highlight several features that could be further studied with proprietary auction data feeds, which we do not have. It is hard for us to suggest a better alternative mechanism because we do not observe the counterfactual.

While exploring whether this price reversal implies a profitable trading strategy is interesting, we do not have the detailed transaction costs data necessary for such an analysis. First, to follow this strategy, an investor must anticipate whether to buy or sell in the auction. Second, closing price deviations go rarely beyond the pre-auction bid or the ask prices, and thus transaction costs likely eat most of profits. Finally, for the liquidation price, trading is thin outside of regular trading hours, making it hard to properly assess transaction costs.

In the rest of this section, we provide additional results on the information content of closing pricing deviations using alternative methodologies. We use the weighted price contribution (WPC) to measure price discovery (e.g., Barclay and Hendershott (2003)). To compute WPC, we divide the $3: 30 \mathrm{pm}-9: 45 \mathrm{am}$ period into five-minute intervals and measure how much each interval's return

[^9]contributes to the total return over 3:30pm-9:45am. For each day, WPC for interval $k$ is defined as
\[

$$
\begin{equation*}
\mathrm{WPC}_{k}=\sum_{i=1}^{N}\left(\frac{\left|r_{i, 3: 30-9: 45}\right|}{\sum_{j=1}^{N}\left|r_{j, 3: 30-9: 45}\right|}\right)\left(\frac{r_{i, k}}{r_{i, 3: 30-9: 45}}\right), \tag{5}
\end{equation*}
$$

\]

where $r_{i, 3: 30-9: 45}$ is the ( $\log$ ) return of stock $i$ from $3: 30 \mathrm{pm}$ to $9: 45 \mathrm{am}$ on the next day, $r_{i, k}$ is the return over interval $k$ (for instance, between 3:50 and $3: 55 \mathrm{pm}$ ), and $N$ the number of stocks in the sample on that day. ${ }^{16}$ Panel (a) of Figure 5 plots WPC estimates computed across stocks in the bottom and top size quintiles. The closing auction return contributes little to price discovery since its price contribution is about ten times lower than the contribution of other periods with similar volume. The results are similar for all size categories with the auction having slightly higher WPC for smaller stocks as reported in Table IA.9. The auction's WPC drops to zero when the auction price is adjusted for the spread (Table IA.9). Thus, the auction price only conveys information to the extent that it takes place at the pre-close ask or bid.

The above results do not imply that auction volume is completely uninformative since exchanges release information about order imbalance ahead of the auction. As the market learns about these imbalances, prices move to reflect this information. The NYSE (Nasdaq) starts releasing imbalance information at $3: 45 \mathrm{pm}(3: 50 \mathrm{pm})$ over most of our sample period. If the imbalance is informative, price informativeness should increase at $3: 45 \mathrm{pm}(3: 50 \mathrm{pm})$ for NYSE (Nasdaq) stocks to reflect the increased information flow.

To study how dissemination of auction imbalance affects price discovery, we estimate a difference-in-difference regression. WPCs for every five-minute interval between $3: 30 \mathrm{pm}$ and $4: 00 \mathrm{pm}$ and the auction price deviation are averaged each day separately for NYSE and Nasdaq stocks and for each size quintile. These WPCs are regressed on an intercept, a NYSE indicator, indicators for each interval after 3:35pm, and NYSE-interval interaction indicators. These last indicators test for changes in WPC while controlling for fixed differences in WPC between different five-minute intervals at the end of the day and for fixed differences in WPC between NYSE and Nasdaq stocks. For instance, the NYSE and $3: 45 \mathrm{pm}-3: 50 \mathrm{pm}$ interaction allows us to test whether NYSE stocks experience a change between their $3: 45-50 \mathrm{pm}$ WPC and their $3: 30-35 \mathrm{pm}$ WPC in excess of the

[^10]change in WPC of Nasdaq stocks between the same intervals. For this test, the sample stops in September 2018 since Nasdaq switched its dissemination time to 3:55pm in October 2018.

Panel (b) of Figure 5 shows that disseminated auction imbalance contains some information. WPC increases for NYSE stocks when the NYSE starts to disseminate imbalance information at 3:45pm, which is not explained by a concurrent increase in the WPC of Nasdaq stocks. The opposite holds true at $3: 50 \mathrm{pm}$ when the Nasdaq starts to disseminate imbalance information. The full results are reported in Table IA.10. However, the economic magnitudes appear small. First, Panel (a) of Figure 5 shows that WPCs are stable over 3:30-4:00pm for large stocks, which is inconsistent with order dissemination playing a major role for price informativeness. Second, Panel (b) of Figure 5 suggests that the auction volume price contribution is approximately $1 \%(0.5 \%)$ for small (large) stocks, which is less than half of the price contribution between $3: 30 \mathrm{pm}$ and $3: 35 \mathrm{pm}$. Market participants could learn about imbalances for Nasdaq from observed imbalances for NYSE stocks. We cannot rule out this spillover concern, but a comparison of raw NYSE and Nasdaq WPC suggests that this channel, if it exists, is economically small.

In summary, auction volume contributes to price discovery but is less informative than volume over other intervals, especially for large stocks.

### 3.3 Who trades at the close?

Auction price deviations exhibit much stronger reversal than returns in the last five minutes of trading. What leads to this discrepancy? Is volume more "uninformed" at the close? In this section, we shed light on these questions by studying the properties of auction volume.

We estimate a panel regression where auction turnover is regressed on proxies for potential reasons to trade at the close. We contrast the auction turnover results to similar regressions with intraday (9:30am-3:30pm) and pre-close turnovers (3:55-4:00pm) as dependent variables. We control for same-day changes in turnover that may not be specific to the auction by including intraday turnover, defined as volume on the same day divided by total number of shares outstanding. We also control for volatility (the average absolute return over the past five days including the current day), lagged return, market capitalization, and month-of-the-year and day-of-the-week seasonalities. Stock fixed effects control for time-invariant stock-specific factors. To facilitate interpretation, we use the logarithm of each variable except for the lagged return, trend variables, and indicator
variables. Results change little if these regressions include the lagged dependent variable.
These regressions provide several sets of results reported in Table 6 , which we discuss in turn. As expected, higher intraday turnover is associated with higher auction and pre-close turnovers: a $0.32 \%$ increase in auction turnover for a $1 \%$ increase in intraday turnover. Trend variables are measured in years and imply that auction turnover increases by about $10 \%$ per year. Pre-close turnover has a trend of about $6.1 \%$ per year, and intraday turnover stays roughly unchanged.

Why do investors trade at the close? Passive investors strive to minimize tracking error by trading in the auction since they are usually benchmarked against closing auction prices. We proxy for indexing with ETF ownership and passive mutual fund ownership and contrast them with active mutual fund ownership. We control for market capitalization to distinguish the effect of institutional ownership from size. Russell index rebalancing days (Friday in late June) highlight how passive investors trade as approximately $\$ 9$ trillion in assets are benchmarked to the Russell U.S. Indices. Other proxies for institutional rebalancing include indicators for beginning- and end-of-the-month, last day of the quarter, option expiration (third Friday of a month). We contrast them with indicators for the day before, the day of, and the day after an earnings announcement that capture periods with presumably higher informed trading.

ETF ownership is highly significant for auction turnover but its effect on pre-close turnover is only half as large in Table 6. Similarly, passive mutual fund ownership is strongly associated with auction turnover but only marginally so with pre-close turnover. In contrast, active mutual fund ownership is positively associated with pre-close turnover even after controlling for size and intraday turnover but does not affect auction turnover. If anything, the point estimate is negative.

To further contrast the effects of passive and active ownership, Figure 6 plots the elasticity of turnover to ETF, passive, and active mutual fund ownership for each five-minute interval between $3: 30 \mathrm{pm}$ and the auction. The ETF ownership elasticity of turnover gradually increases through the end of trading and spikes at the close. It is five times greater for auction turnover than for 3:30-3:35pm turnover. The pattern for passive ownership is even more remarkable: The volume elasticity remains roughly flat and close to zero before spiking in the auction. In contrast, active mutual fund ownership elasticity increases gradually but drops at the auction. These results have a difference-in-difference interpretation. The first difference compares the auction with the pre-close, and the second difference compares ETF and passive ownership with active ownership.

More formally, we estimate a two-step difference-in-difference specification. In the first step, turnover elasticities relative to active mutual fund, passive mutual fund, and ETF ownership are estimated for each stock over the sample period. These elasticities are estimated separately for auction turnover and turnover in every five-minute interval from $3: 30 \mathrm{pm}$ until 4 pm with the same set of control variables as in Table 6. In the second step, elasticities are regressed on indicators for time-of-day, ownership type, and interactions between time-of-day and ownership type. We find that ETF and passive mutual fund elasticities are significantly larger than for active mutual fund ownership in the auction relative to the intervals before. This holds true when we only compare 3:55-4:00pm with the auction, or when we focus separately on small and large stocks as reported in Table IA. 11 in the Appendix. ${ }^{17}$

Since ETFs do not trade once a day at their NAVs, the benchmarking motive is not as obvious as for passive mutual funds. Several strategies can contribute to the strong link between ETF ownership and auction turnover. First, leveraged ETFs rebalance daily at the close to maintain their leverage ratio. Though they often use derivatives, their counterparties hedge with the underlying stocks (Cheng and Madhavan (2009)). Second, ETFs are often traded to hedge market risk intraday, and these hedges are closed at the end of the day. The arbitrage activity then translates to extra volume in the underlying stocks. Third, some ETF arbitrageurs may use the closing auction to complete arbitrage trades that were initiated earlier during the day. Finally, ETF ownership could proxy for trading by investors who pool their trades at the close.

Auction and pre-close turnovers are $904 \%$ and $119 \%$ higher for an average stock on Russell index rebalancing days. ${ }^{18}$ The changes in auction and pre-close turnovers should be interpreted as beyond what is predicted by intraday turnover, which we control for in Table 6. Intraday turnover is not significantly higher on index rebalancing days (right column). In summary, index funds rebalance in the last five minutes of trading and especially at the auction. This behavior is consistent with minimizing tracking error.

Other calendar effects confirm that institutional rebalancing contributes to closing volume. Auction and pre-close turnovers are $138 \%$ and $38 \%$ higher on the last day of the month, while

[^11]intraday turnover is unchanged. Institutional investors report their portfolio and are benchmarked with month-end prices, which encourages them to trade at the close to minimize tracking error. Etula et al. (2020) show that many institutional investors accommodate inflows in the first days of the month. Indeed, turnover tends to be higher in all periods on the first day of the month but especially so at the auction. Auction turnover is $89 \%$ higher on option expiration days, while pre-close and intraday turnovers increase mildly. Option market-makers and other option investors, who hedge their positions in the underlying, unwind the delta-hedge right after options expire at the close. Auction turnover is between $5 \%$ and $10 \%$ higher in months marking a quarter-end, but auction turnover does not increase significantly on the last day of the quarter beyond the last day of the month increase.

Prior work suggests that informed trading is more likely around earnings announcements (e.g., Lee, Mucklow, and Ready (1993)). Intraday turnover increases by $22 \%$ to $96 \%$ around earnings announcement days in Table 6. Pre-close turnover increases substantially beyond what is predicted by higher intraday turnover. In contrast, auction turnover is virtually unchanged on those days when controlling for intraday turnover. This suggests that informed trading relative to uninformed trading is not significantly higher in the auction.

Overall, auction volume is strongly associated with proxies of uninformed and liquidity-driven trading, in contrast to pre-close and intraday volumes. Thus, circling back to question raised at the beginning of this section, volume appears to be "more uninformed" at the close than pre-close, which is consistent with the evidence from reversal tests.

### 3.4 Liquidity begets liquidity

Importantly, while index funds and ETFs affect closing volume directly by rebalancing (especially for leveraged ETFs), their direct trading is unlikely to fully explain the increase in closing volume. First, Table 6 shows that the trend coefficients are positive and strongly significant for auction turnover despite the inclusion of ETF ownership and passive mutual fund ownership in the regression. Second, only $5 \%$ of trading in individual U.S. stocks is attributable to ETF flows according to a report by BlackRock (2020). A possible explanation is that other investors could be attracted by higher uninformed volume at the close. To shed light on this, we study auction volume following S\&P 500 addition and deletion events. Intuitively, we expect trading activities of index funds to
be mostly concentrated on the event date. A "large" change in closing auction volume relative to intraday volume beyond the event date would lend support to the idea that other investors move their trades to the auction.

We focus on the sample of S\&P 500 additions and deletions in Table 4 and define the closing volume ratio as the logarithm of closing auction share volume divided by intraday (9:30am-3:30pm) share volume. For each S\&P 500 rebalancing event and date, we compare the volume ratio for a treated stock with an average ratio across three control stocks. Control stocks are matched based on the listing exchange and the 60-day average closing volume ratio computed 60 days prior to the event. We require each added/deleted stocks to have at least 30 valid observations before and after the event, which restricts the sample to 113 additions and 66 deletions.

Figure 7 plots the average closing volume ratio for additions (top plot) and deletions (bottom plot) from 60 days prior to 120 days after the event. Five days before and after the event are excluded to give investors time to adjust. Added/deleted stocks and control stocks are similar pre event. However, the closing volume ratio increases (decreases) substantially for added (deleted) stocks relative to control stocks. Figure 7 shows that the volume shift is immediate and remains apparent 120 days after the event. Table 7 reports formal statistical tests: The increase is about $20 \%$ for added stocks ( $t$-statistic of 6.86) and the decrease is about $15 \%$ for deleted stocks ( $t$-statistic of -4.50) relative to control stocks. A plausibly exogenous increase (decrease) to passive mutual fund ownership therefore leads to a large and permanent increase (decrease) in closing volume relative to intraday volume. This economically large change suggests that index investors affect auction volume not only directly but also indirectly through the investor ecosystem that they create.

Do changes in institutional ownership explain why auction turnover remains persistently higher than intraday turnover following S\&P 500 additions? Table IA. 12 in the Internet Appendix shows that, as expected, ETF ownership and passive mutual fund ownership increase following S\&P 500 additions. These variables, however, do not explain the increase in auction turnover. This further supports the view that volume from other investors is attracted to the auction.

The results in Figure 7 and Table 7 suggest a "liquidity begets liquidity" effect that can explain several puzzling facts that we document. Auction volume increases strongly over our sample period, but Figure 4 shows no strong trend in the average price deviation over our sample period for both small and large stocks. If anything, large stocks' price deviations trend down. At the same time,
absolute auction price deviation increase with turnover (Table IA.2).
As uninformed order flow migrates to the close, traders who can choose when to trade during the day can decide to shift their trades towards the close to benefit from the increased liquidity at that time. In models such as Admati and Pfleiderer (1988) and Foster and Viswanathan (1990), discretionary liquidity traders optimally cluster their trades in the same period to reduce adverse selection costs. This clustering leads to increased volume and liquidity around the close.

The liquidity begets liquidity effect explains several of our findings. First, while passive mutual fund ownership and ETF ownership are both associated with trading volume around the close, they do not account for all of the increase in volume. Table 6 shows that the trend coefficients are positive and significant for auction volume despite the inclusion of passive mutual fund ownership and ETF ownership in the regression. This observation suggests that other traders shift their trades to the close and provide liquidity. Second, this increase in liquidity provision around the close explains the flat and declining price deviations in Figure 4. Nonetheless, on any given day, an unexpected increase in auction imbalance moves the auction price away from the 4:00pm midquote (see Table IA. 2 in the Internet Appendix, where volume proxies for imbalance). Intuitively, liquidity supply is imperfect at short horizons but adjusts over long horizons (e.g., Duffie (2010)).

The liquidity begets liquidity effect predicts that as trades migrate towards the close, volume and liquidity will decrease at other times of the day (Admati and Pfleiderer, 1988; Foster and Viswanathan, 1990). We test this prediction on another key period of the day-the open-and examine volume, liquidity, volatility, and price discovery in the first 15 minutes of trading (9:30am9:45am). The sample includes only large stocks that are traded over the full sample to make the stocks comparable with each other. The final sample includes 333 stocks, $92 \%$ of them are in the S\&P 500. We estimate panel regressions of (log) turnover, dollar-weighted percentage effective spread, and time-weighted depth on stock fixed effects, day and month indicators, calendar year indicators, and control variables (stock price, market capitalization, and volatility). Calendar year indicators capture the trend in the dependent variable, which is our focus.

Panel (a) of Figure 8 reports the percentage change in turnover at the open and at the auction each year relative to 2010. ${ }^{19}$ Over the sample period, auction turnover increases by about $100 \%$ but

[^12]open turnover decreases by around $25 \%$. This decrease is statistically significant at all conventional levels.

Liquidity deteriorates substantially at the open over the sample period. As shown in Panel (b), effective spread increases and depth decreases significantly, which indicates an unambiguous decline in liquidity at the NBBO. The magnitudes are economically large. Effective spread increases by more than $40 \%$. This corresponds to about 10 bps , which is substantial for S\&P 500 stocks. Depth at the best quotes declines by around $60 \%$. Related to these results, Upson and Van Ness (2017) report that spreads do not follow a U-Shape over the trading day anymore, with a lower spread at the close. Jiang, Wu, and Yao (2022) associate this change with trends in passive investing. They do not examine variations in liquidity at the open, though they document an improvement in liquidity around the close that supports the liquidity begets liquidity effect.

Yueshen, Zamojski, and Zhang (2022) find that trade informativeness is highest around the open and lowest around the close in a sample of stocks in 2018. This is consistent with traders who act on short-lived information based on overnight news. It is not clear, however, that we should observe a change in price discovery at the open over our sample period. The model of Admati and Pfleiderer (1988) predicts lower volatility at the open since informed traders migrate to the close. The model of Foster and Viswanathan (1990) does not predict such a change since informed traders' short-lived information precludes them from moving to the close. Panel (c) of Figure 8 plots two measures of price discovery at the open. The five-minute return autocorrelation measured between 9:30am and 10:00am shows no clear trend, but the weighted price contribution of the first 15 minutes of trading increases by about three to four percentage points over the sample period. This represents an increase in the open price contribution of roughly $20 \%$ relative to the first year of the sample. Figure IA. 2 in the Internet Appendix plots realized volatility at the open. Without controls, there is no clear pattern in open volatility. However, controlling for intraday volatility, realized volatility at the open tends to increase over the sample period by about $5 \%$, which is statistically significant. Overall, the evidence supports the view that, as uninformed volume migrates from the open to the close, adverse selection and volatility increase at the open.

Our interpretation of changes in intraday volume relies on trends over several years. Since investors likely adjust their trading patterns slowly over time, a decrease in open volume is difficult to causally link to an increase in auction volume. Other factors can also contribute to the shift in
volume towards the close. For example, a report by Norges Bank (2020) conjectures that, as top asset managers increase their market share, they look for liquidity focal points such as the auction. But the increase in passive investing is likely a key contributor to the increased concentration among asset managers. Changes in market structure, such as increased fragmentation, could also contribute to what we observe around the open. This section simply highlights a potential side effect of the increase in passive investing: As investors cluster their trades at the close, liquidity decreases during the rest of the day. Such changes raise broad questions about optimal market design. Budish, Cramton, and Shim (2015) show theoretically that frequent batch auctions can reduce the risk of being picked off by high-frequency traders relative to continuous trading. This could be one reason why some investors migrate to the closing auction. Such important policy considerations call for further research.

## 4 Application: put-call parity violations

In this section, we provide an application of how price deviations at the close can make a difference. Specifically, closing price deviations from the pre-close midquote help explain the put-call parity violations. Stock prices implied from options by the put-call parity often deviate from actual stock prices, presenting apparent arbitrage opportunities. An extensive literature started by Stoll (1969) studies these violations, which are puzzling because modern option market-makers instantly observe stock price changes and can adjust option prices within milliseconds. A related puzzle is that the put-call violations predict next-day stock returns (Cremers and Weinbaum (2010)); i.e., the future stock return is lower if the option-implied stock price is below the actual stock price. This result is often interpreted as evidence that option prices contain superior private information.

We show that price deviations at the closing auction partially resolve these two puzzles. In particular, the equity options market closes at $4: 00 \mathrm{pm}$, the same time as the equity market. But the closing auction for the stock price occurs a few seconds later. Thus, option prices are based on the 4 pm stock midquote, and a stock price deviation at the close can cause a parity violation. Moreover, put-call parity violations predict next-day returns because violations and returns depend on current-day closing price that temporarily deviates from the closing midquote.

We compute the put-call parity violations in a standard way. We use daily option prices from

OptionMetrics from 2010 to 2017. We apply mild filters and keep options with (i) the bid price greater than ten cents, (ii) well-defined option delta and implied volatility, (iii) option maturity between 15 and 90 days. To avoid early exercise issues, we focus on at-the-money options with call delta between 0.4 and 0.6. We compute the implied stock price using the standard put-call parity following equation (11.10) in Hull (2022):

$$
\begin{equation*}
I S_{i}=C_{i}-P_{i}+K_{i} \exp \left(-r T_{i}\right)+D i v, \tag{6}
\end{equation*}
$$

Implied stock price $\left(I S_{i}\right)$ is computed for a given put-call pair $\left(C_{i}, P_{i}\right)$ with the same strike ( $K_{i}$ ) and annualized time-to-expiration $\left(T_{i}\right)$. The risk-free rate (r) equals the maturity-matched LIBOR rate. Dividends (Div) are from CRSP. Implied bid (ask) price is computed using this equation with call bid and put ask (call ask and put bid). For every stock and day, we compute a median over all implied bid and ask prices across all option contracts.

True violations must be transitory, which we focus on. Yet some violations persist for many days because it is difficult to perfectly account for American exercise (Kamara and Miller (1995)), shorting costs (Ofek, Richardson, and Whitelaw (2004) and Muravyev, Pearson, and Pollet (2018)), dividends, and the risk-free rate. There is no standard way to account for all of these factors at once. We propose the following approach to account for persistent violations: we adjust the implied prices using an average violation between implied midquote and actual closing price in the last ten trading days. If the moving average cannot be computed (in $1.7 \%$ of stock days) because the options with required maturity and moneyness are missing, this adjustment is set to zero. That is, we subtract the average violation in the last ten days from the current violation: $\left(I S_{i, t}-S_{i, t}\right)-M A_{t-1: t-10}\left(I S_{i, t}-S_{i, t}\right)$. To account for large option bid-ask spreads, we raise a parity violation only if the stock price is outside the implied bid and ask price range and compute this violation indicator separately using the closing auction price and midquote:

$$
\begin{equation*}
\text { IViolat }=\left[I S^{b i d}>S\right] O R\left[I S^{a s k}<S\right] . \tag{7}
\end{equation*}
$$

The results are presented in Table 8, which shows the frequency of parity violations based on closing stock price versus mid-quote. Out of $2,500,777$ stock-days, $4.69 \%$ or 117,245 violate
the parity relative to the closing price. If parity violations are computed with relative to closing midquote instead of closing price, the number of violations drops from 117,245 to 107,041 , or 10,204 fever violations. Thus, even though the auction is only few seconds after the close, and the closing price is usually close to midquote, this mis-synchronization explains at least $9 \%$ of all violations, which is statistically and economically significant. To highlight the auction's role, we explore the subsample where auction price deviates by more than 10 bps from the midquote, $10.5 \%$ of the total sample. Closing price triggers 8,489 violations, while midquote triggers 6,499 , or $23 \%$ fewer violations. Violations are likely caused by multiple reasons. We study just one explanation: mis-synchronization between option and stock prices due to the closing auction.

While mis-synchronization explains a large number of violations, it is even more important for explaining why put-call violations predict stock returns. The predictability is concentrated on the day following the violation and is typically attributed to informed option trading. ${ }^{20}$ We argue that violations predict next-day stock return because option prices reflect the closing midquote, while the closing price temporarily deviates from the closing midquote. To test this hypothesis, we decompose the next-day stock return into the overnight part from closing auction to 9:35 am next morning $\operatorname{Ret}_{\text {open }(t+1)}^{\operatorname{auc}(t)}$, and from next morning till closing auction $R e t_{\text {auc }(t+1)}^{\text {open }(t+1)}$, as auction mispricing is corrected right after market open. The last panel of Table 8 shows that parity violations based on closing price strongly predict overnight returns with a $t$-statistic of 9.0 , but the predictability disappears after the open. Parity violations based on midquote fail to predict overnight or intraday returns. The results are robust to controlling for intraday returns during the current day or adding permanent parity violations to the sample (besides the temporary violations that we focus on).

Overall, as the auction price sometimes deviates from the closing midquote, these deviations can be sufficiently large to trigger put-call parity violations even accounting for large option bid-ask spreads. Since the closing price reverts to the midquote the next morning, parity violations based on closing prices predict overnight returns but violations based on closing midquotes do not.

[^13]
## 5 Conclusion

The closing auction is a central element of current equity market structure. The auction handles large volumes that grow significantly over 2010 to 2018. ETF ownership and passive mutual fund ownership, but not active fund ownership, are strongly associated with closing auction volume. Closing auction volume permanently increases (decreases) relative to intraday volume after a stock is added (dropped) from the S\&P 500.

Despite the large auction volume, deviations between auction price and closing quote midpoint are small on average. Hence, closing auctions appear to accommodate large volume cheaply on an absolute basis or relative to trading costs during continuous trading. Even on S\&P index rebalancing days, we find little evidence of abnormal price deviations at the auction relative to the volume traded. The bid-ask spread and tick size bind in most auctions. While this friction is small on a per trade basis, we estimate that it increases the aggregate costs at the close by up to $\$ 3$ billion in 2018 since closing prices contain almost no incremental information compared to closing quote midpoints. Price deviations at the close mostly reverse overnight, and about half of the reversal occurs right after the auction.

Our evidence suggest that non-passive investors shift their trading to the closing auction. Our results are consistent with the growth of indexing improving liquidity at the close. However, liquidity deteriorates and price discovery increases at the open over our sample period. How much of this trend can be explained by the increase in passive investing is an important question since an orderly opening of the market is critical.

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Figure 1. Tesla's (TSLA) stock price and volume on the day of its inclusion to the S\&P 500 $(12 / 18 / 2020)$. The stock price is the midpoint of the best bid and ask at the end of each oneminute interval. Volume is the cumulative volume in a five-minute interval. The vertical dashed line indicates the closing auction.


Figure 2. Fraction of aggregate daily dollar volume executed intraday and around the close. Daily dollar volume is summed across stocks over a given period (9:30am-3:30pm, $3: 55 \mathrm{pm}-4: 00 \mathrm{pm}$, or auction) and then divided by the total daily dollar volume across stocks over the day. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.


Last five minutes (3:55pm-4:00pm)


Auction


Figure 3. Histogram of auction absolute dollar deviation divided by half-spread. The auction absolute dollar deviation is the difference between the auction price and the midquote at 4:00pm. The x -axis is truncated at a value of 10 . Tick size is binding for most of the auctions with halfspread equal to the auction deviation. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.


Figure 4. Cross-sectional daily median absolute auction deviation among small stock and large stock capitalization quintiles. Absolute deviation $\left(=\left|\log \left(p_{\text {auc }} / p_{4: 00}\right)\right|\right)$ is expressed in basis points. Stocks are allocated into quintiles of market capitalization at the beginning of each year. The vertical dashed line indicates the start of the Tick Size Pilot program. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.


Figure 5. Weighted price contributions at the end of the day. Weighted price contribution (WPC) is computed each day across stocks in the bottom and top market capitalization quintiles (formed at the beginning of each year) for five-minute intraday periods from $3: 30 \mathrm{pm}$ to 4 pm , the period between 4 pm and auction, and the overnight period. More precisely, the WPC in interval $k$ is given by $\mathrm{WPC}_{k}=\sum_{i=1}^{N}\left(\frac{\left|r_{i, 3: 30-9: 45}\right|}{\sum_{j=1}^{N}\left|r_{j, 3: 30-9: 45 \mid}\right|}\right)\left(\frac{r_{i, k}}{r_{i, 3: 30-9: 45}}\right)$, where $r_{i, 3: 30-9: 45}$ is the return of stock $i$ from 3:30pm until 9:45am on the following day. Panel (a) reports the average WPC. In Panel (b), WPC is computed for each day-interval separately for NYSE and Nasdaq stocks in a given market capitalization quintile. The following difference-in-difference specification is then estimate: $\mathrm{WPC}_{t, k, e}=\alpha+\alpha_{\mathrm{NYSE}} 1_{\mathrm{NYSE}, \mathrm{e}}+\sum_{k} \alpha_{k} 1_{k}+\sum_{k} \alpha_{\mathrm{NYSE} * k} 1_{k} 1_{\mathrm{NYSE}}+\epsilon$, where $\mathrm{WPC}_{t, k, e}$ is the WPC on day $t$ in interval $k$ across stocks in exchange $e$ (either Nasdaq or NYSE), $1_{k}$ is an indicator for interval $k$, and $1_{\text {NYSE,e }}$ is an indicator for the NYSE WPC. Panel (b) reports the interaction coefficients between NYSE and end-of-day intervals. These coefficients are the difference in WPC between NYSE and Nasdaq stocks in interval $k$ minus the difference in WPC between NYSE and Nasdaq stocks between $3: 30 \mathrm{pm}$ and $3: 35 \mathrm{pm}$. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.


Figure 6. Elasticity of turnover to ETF, passive mutual fund, and active mutual fund ownerships. For each five-minute interval between 3:30 and $4: 00 \mathrm{pm}$ and the auction, log turnover is regressed on the logarithm of ETF and mutual fund ownerships, as well as control variables described in the caption of Table 6. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month. The $95 \%$ confidence intervals are based on standard errors that are double-clustered by date and stock.


Figure 7. Auction volume relative to intraday volume around S\&P 500 additions and deletions. This figure reports the daily average log auction volume over intraday volume (9:30am-3:30pm) for stocks added to the S\&P 500 (top plot) and stocks deleted from the S\&P 500 (bottom plot). The plots also report values for control stocks matched on average log auction volume over intraday volume 60 days prior to the addition/deletion. The plots exclude the event day and the four days prior and post event. The sample includes 113 additions and 66 deletions over 2010 to 2018.


Figure 8. Volume, liquidity, and price discovery at the open relative to 2010. This figure reports year indicator estimates from the stock-day panel regression: $V_{i, t}=\alpha_{i}+\alpha_{y}+$ controls $+\epsilon_{i, t}$. The baseline level is set to zero for 2010. In Panel (a), $V_{i, t}$ is $\log$ turnover in the first 15 minutes of trading or in the closing auction. In Panel (b), $V_{i, t}$ is the $\log$ dollar-weighted percentage effective spread or log time-weighted depth at the NBBO over the first 15 minutes of trading. In Panel (c), $V_{i, t}$ is the five-minute midpoint return autocorrelation computed over the first 30 minutes of trading or the weighted price contribution (WPC) at the open, where $\mathrm{WPC}_{\text {open }}=\sum_{i=1}^{N}\left(\frac{\left|r_{i, 9: 30-4: 00 \mid}\right|}{\sum_{j=1}^{N}\left|r_{j, 9: 30-4: 00 \mid}\right|}\right)\left(\frac{r_{i, 9: 30-9: 45}}{r_{i, 9: 30-4: 00}}\right)$, where $r_{i, 9: 30-4: 00}\left(r_{i, 9: 30-9: 45}\right)$ is the midpoint return of stock $i$ from 9:30am until 4:00pm (9:45am). Control variables are day-of-week and month-of-year indicators, $\log$ price, log market capitalization, log average absolute return over the past five trading days, and log intraday turnover (not included in Panel (a)). In Panels (a) and (b), coefficients are converted to percentage change using the delta method. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018 that are in the top market capitalization quintile and traded over the full sample period. The $95 \%$ confidence intervals are based on standard errors that are double-clustered by date and stock.
(a) Volume

(b) Liquidity at the open (first 15 minutes of trading)

(c) Price discovery at the open



Table 1. Descriptive statistics. The table reports mean, median, and standard deviation for volume-related variables: share of daily volume at the closing auction, in the last five minutes, and between $3: 30$ and $3: 55 \mathrm{pm}$, as well as end-of-day relative bid-ask spread, stock price, market capitalization, share of days with zero volume during the entire day, from 9:30am to 3:30pm, and at the closing auction. In Panel (a), $\sigma_{w}$ indicates the within standard deviation of observations for which the time-mean has been subtracted (i.e., $x_{i t}-\bar{x}_{i}$ ). In Panel (b), $\sigma_{w}$ indicates the within standard deviation of observations for which the firm-mean has been subtracted (i.e., $x_{i t}-\bar{x}_{t}$ ). Stocks are allocated into quintiles of market capitalization at the beginning of each year. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.
(a) Summary statistics: time series

|  | Full sample |  |  | 2010 |  |  | 2018 |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mu$ | Median | $\sigma_{w}$ | $\mu$ | Median | $\sigma_{w}$ | $\mu$ | Median | $\sigma_{w}$ |
| Auction vol. share (\%) | 5.69 | 4.38 | 4.48 | 4.13 | 2.79 | 3.75 | 7.27 | 6.18 | 4.53 |
| 3:55-4:00 vol. share (\%) | 6.96 | 6.06 | 4.46 | 5.79 | 4.88 | 4.15 | 7.28 | 6.50 | 4.12 |
| 3:30-3:55 vol. share (\%) | 10.90 | 10.21 | 5.76 | 11.60 | 10.86 | 5.87 | 10.04 | 9.42 | 5.35 |
| Bid-ask spread (bps) | 19.19 | 6.81 | 119.78 | 17.18 | 8.91 | 48.51 | 24.05 | 6.45 | 71.41 |
| Price (\$) | 40.20 | 26.58 | 29.75 | 28.09 | 20.79 | 14.80 | 54.95 | 33.26 | 12.75 |
| Market cap. (\$b) | 7.50 | 1.27 | 9.73 | 4.99 | 0.94 | 1.59 | 10.23 | 1.60 | 3.80 |
| No volume (\%) | 0.22 | 0.00 | 3.89 | 0.10 | 0.00 | 2.79 | 0.30 | 0.00 | 4.42 |
| No 9:30-3:30 vol. (\%) | 0.37 | 0.00 | 4.99 | 0.26 | 0.00 | 4.15 | 0.41 | 0.00 | 5.20 |
| No auction (\%) | 2.48 | 0.00 | 11.85 | 3.02 | 0.00 | 12.43 | 2.69 | 0.00 | 9.82 |
| Num. obs. |  | 5,720,876 |  |  | 629,014 |  |  | 635,401 |  |

(b) Summary statistics: cross-section

|  | Size quintile |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Low |  |  | Mid |  |  | High |  |  |
|  | $\mu$ | Median | $\sigma_{w}$ | $\mu$ | Median | $\sigma_{w}$ | $\mu$ | Median | $\sigma_{w}$ |
| Auction vol. share (\%) | 6.06 | 4.22 | 5.87 | 5.69 | 4.53 | 3.80 | 5.67 | 4.56 | 3.40 |
| 3:55-4:00 vol. share (\%) | 7.23 | 5.65 | 6.85 | 7.35 | 6.63 | 3.75 | 5.83 | 5.40 | 2.37 |
| 3:30-3:55 vol. share (\%) | 9.84 | 8.12 | 8.71 | 11.42 | 10.72 | 4.84 | 10.70 | 10.23 | 3.37 |
| Bid-ask spread (bps) | 59.59 | 26.70 | 256.94 | 9.13 | 6.68 | 36.52 | 2.98 | 2.24 | 5.66 |
| Price (\$) | 15.59 | 12.05 | 13.74 | 33.15 | 27.80 | 26.25 | 78.95 | 57.34 | 97.59 |
| Market cap. (\$b) | 0.22 | 0.21 | 0.07 | 1.32 | 1.26 | 0.33 | 31.54 | 13.74 | 55.41 |
| No volume (\%) | 0.72 | 0.00 | 8.45 | 0.03 | 0.00 | 1.67 | 0.00 | 0.00 | 0.19 |
| No 9:30-3:30 vol. (\%) | 1.25 | 0.00 | 11.06 | 0.06 | 0.00 | 2.37 | 0.02 | 0.00 | 1.51 |
| No auction (\%) | 9.56 | 0.00 | 29.08 | 0.61 | 0.00 | 7.74 | 0.21 | 0.00 | 4.62 |
| Num. obs. |  | 1,157,020 |  |  | 1,135,338 |  |  | 1,162,620 |  |

Table 2. Auction price deviations. Panel (a) reports descriptive statistics across size quintiles for the absolute deviation between the log closing auction price and the log midquote at 4:00pm $\left(=\left|\log \left(p_{\text {auc }} / p_{4: 00}\right)\right|\right)$ expressed in basis points. Panel (b) reports Descriptive statistics for absolute return to share volume ratios around the end of the day. $r_{4: 00-A u c}$ indicates the log return from the $4: 00 \mathrm{pm}$ midquote to the auction price. $r_{4: 00-A u c}^{A}$ uses the closing auction price adjusted for the bid-ask spread by adding (subtracting) half the spread for trades made below (above) the 4 pm midpoint. $V_{A u c}$ indicates the auction share volume. $r_{3: 30-3: 45}\left(V_{3: 30-3: 45}\right)$ indicates the midquote return (share volume) from 3:30pm to $3: 45 \mathrm{pm}$. $r_{3: 45-4: 00}\left(V_{3: 45-4: 00}\right)$ indicates the midquote return (share volume) from $3: 45 \mathrm{pm}$ to $4: 00 \mathrm{pm}$. The ratios are winsorized at $0.05 \%$. Statistics are reported for the full sample and across market capitalization quintiles, which are formed at the beginning of each year. The $x^{\text {th }}$ percentile is denoted as p0.x. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.
(a) $\left|\log \left(p_{\text {auc }} / p_{4: 00}\right)\right|$ (basis points)

|  |  | Size quintile |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | All | Low | 2 | 3 | 4 | High |
| Mean | 8.12 | 20.60 | 8.99 | 5.49 | 3.97 | 2.66 |
| StdDev | 15.91 | 30.28 | 11.44 | 6.20 | 4.65 | 3.56 |
| p0.05 | 0.66 | 2.79 | 1.63 | 1.03 | 0.69 | 0.45 |
| p0.5 | 4.21 | 12.35 | 6.32 | 3.97 | 2.73 | 1.73 |
| p0.9 | 17.37 | 42.11 | 17.81 | 11.03 | 8.27 | 5.69 |
| p0.99 | 63.13 | 141.18 | 45.98 | 25.41 | 19.95 | 13.37 |
| p0.999 | 195.22 | 356.52 | 124.84 | 56.70 | 43.79 | 31.42 |
| Obs. | $5,578,901$ | $1,046,362$ | $1,104,289$ | $1,128,456$ | $1,139,671$ | $1,160,123$ |

(b) Absolute return to share volume

|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ | $(5)$ |
| :--- | :---: | :---: | :---: | :---: | :---: |
|  | $\frac{\left\|r_{4: 00-\text { Auc }}\right\|}{V_{\text {Auc }}} \times 10^{6}$ | $\frac{\left\|r_{3: 30-3: 45}\right\|}{V_{3_{3: 30}-3: 45}} \times 10^{6}$ | $\frac{\left\|r_{3: 45-4: 00}\right\|}{V_{3: 45-4: 00}} * 10^{6}$ | $\frac{\left\|r_{4: 00-A u c}^{A}\right\|}{V_{\text {Auc }}} \times 10^{6}$ | $\frac{\mid r_{3: 45}}{V_{3: 45-A u c} \mid} \times 10^{6}$ |
| Mean | 0.421 | 0.886 | 0.263 | 0.124 | 0.179 |
| StDev | 2.670 | 6.887 | 1.213 | 1.255 | 0.716 |
| p0.05 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 |
| p0.5 | 0.022 | 0.061 | 0.029 | 0.000 | 0.023 |
| p0.9 | 0.501 | 1.200 | 0.483 | 0.067 | 0.350 |
| p0.99 | 7.835 | 13.034 | 4.024 | 2.128 | 2.726 |
| p0.999 | 44.817 | 96.824 | 19.159 | 21.826 | 10.925 |
| Obs. | $5,297,895$ | $5,297,895$ | $5,297,895$ | $5,297,895$ | $5,297,895$ |

Table 3. Half spread and spread deviation. Absolute auction deviation is decomposed as follows $\mid$ deviation $\mid=$ half spread + spread deviation. Quoted half spread is defined as $\log \left(p_{\text {ask }} / p_{4: 00}\right)$ if $p_{\text {auc }} \geq p_{4: 00}$ and $\log \left(p_{4: 00} / p_{\text {bid }}\right)$ otherwise. Similarly, spread deviation is $\log \left(p_{\text {auc }} / p_{\text {ask }}\right)$ if $p_{\text {auc }} \geq$ $p_{4: 00}$ and $\log \left(p_{\text {bid }} / p_{\text {auc }}\right)$ otherwise. The table reports statistics for half spread and spread deviation. Statistics are reported for the full sample and across market capitalization quintiles, which are formed at the beginning of each year. The $x^{\text {th }}$ percentile is denoted as $\mathrm{p} 0 . x$. Zero pct indicates the last percentile at which the spread deviation is zero. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.
(a) Half spread (basis points)

|  |  | Size quintile |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | All | Low | 2 | 3 | 4 | High |
| Mean | 7.56 | 22.19 | 8.29 | 4.43 | 2.73 | 1.47 |
| StdDev | 17.93 | 35.28 | 11.57 | 4.60 | 3.13 | 1.49 |
| p0.05 | 0.65 | 3.51 | 1.89 | 1.11 | 0.69 | 0.40 |
| p0.5 | 3.30 | 11.97 | 5.68 | 3.33 | 2.00 | 1.12 |
| p0.9 | 15.73 | 45.98 | 15.60 | 8.27 | 5.16 | 2.77 |
| p0.99 | 70.18 | 166.95 | 47.36 | 20.06 | 13.47 | 6.63 |
| p0.999 | 225.87 | 407.14 | 138.26 | 45.24 | 31.45 | 12.94 |
| Count | $5,578,901$ | $1,046,362$ | $1,104,289$ | $1,128,456$ | $1,139,671$ | $1,160,123$ |

(b) Spread deviation (basis points)

|  |  | Size quintile |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | All | Low | 2 | 3 | 4 | High |
| Mean | 0.55 | -1.60 | 0.69 | 1.06 | 1.25 | 1.19 |
| StdDev | 10.94 | 22.30 | 8.59 | 5.14 | 3.94 | 3.28 |
| p0.05 | -4.29 | -20.30 | -5.38 | -2.14 | -0.00 | 0.00 |
| p0.5 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| p0.9 | 4.90 | 7.38 | 6.00 | 5.05 | 4.76 | 3.84 |
| p0.99 | 19.70 | 41.47 | 20.81 | 15.94 | 13.81 | 10.69 |
| p0.999 | 74.35 | 161.47 | 62.82 | 40.85 | 33.79 | 27.56 |
| Zero pct | 0.76 | 0.86 | 0.83 | 0.79 | 0.70 | 0.62 |
| Count | $5,578,901$ | $1,046,362$ | $1,104,289$ | $1,128,456$ | $1,139,671$ | $1,160,123$ |

Table 4. End-of-day volume and volatility on S\&P 500 additions and deletions days. This table examines a sample of 207 S\&P 500 additions and deletions (events) over 2010 to 2018. For additions, the event day is the day before the official inclusion in the S\&P 500. For each event, observations spanning the previous two months are included to control for baseline values. We focus on the last 30 minutes of trading and the auction. We divide the last 30 minutes into five-minute of intervals over which we measure log turnover and absolute return (volatility). The variable of interest (turnover or volatility) is regressed on event fixed effects, an indicator for each five-minute interval and the auction (interval fixed effects, excluding the $3: 30-35 \mathrm{pm}$ interval), an indicator for the event day ( SP (join/exit)), and interactions between five-minute/auction indicators and event day indicator. $t$-statistics based on heteroskedasticity-adjusted standard errors are reported in brackets. *, **, and $* * *$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level.

|  | Turnover (log) | Volatility (bps) | Volatility (bps) |
| :--- | :---: | :---: | :---: |
| SP(join/exit) | $1.419^{* * *}$ | $6.196^{* * *}$ | 0.265 |
|  | $[27.383]$ | $[5.359]$ | $[0.221]$ |
| $3: 35-40^{*}$ SP(join/exit) | 0.051 | -1.988 | -2.203 |
|  | $[0.704]$ | $[-1.283]$ | $[-1.470]$ |
| $3: 40-45^{*}$ SP(join/exit) | $0.194^{* * *}$ | 1.428 | 0.619 |
| $3: 45-50^{*}$ SP(join/exit) | $[2.704]$ | $[0.845]$ | $[0.373]$ |
|  | $0.312^{* * *}$ | $6.667^{* * *}$ | $5.361^{* * *}$ |
| $3: 50-55^{*}$ SP(join/exit) | $0.436^{* * *}$ | $[3.690]$ | $[3.019]$ |
|  | $[6.267]$ | $\left[4.9184^{* * *}\right.$ | $8.503^{* * *}$ |
| $3: 55-4: 00^{*}$ SP(join/exit) | $0.830^{* * *}$ | $17.401^{* * *}$ | $[4.144]$ |
|  | $[11.551]$ | $[6.814]$ | $[5.551]$ |
| Auc*SP(join/exit) | $3.504^{* * *}$ | $14.961^{* * *}$ | 0.316 |
|  | $[43.079]$ | $[5.484]$ | $[0.112]$ |
| Turnover |  |  | $4.179^{* * *}$ |
|  |  |  | $[16.299]$ |
| Event FE | Yes | Yes | Yes |
| Interval FE | Yes | Yes | Yes |
| Adj. $R^{2}$ | $46.74 \%$ | $6.54 \%$ | $10.81 \%$ |
| Num. obs. | 60,200 | 60,200 | 60,200 |

Table 5. Reversals. In Panel (a), overnight returns are regressed on auction price deviations and last five-minute returns. Ret auc 945 denotes the return from the closing auction to 9:45am the next morning, Ret $t_{400}^{a u c}$ denotes the return from the 4 pm midquote to the closing price, Ret $t_{355}^{400}$ denotes the return in the last five minutes of regular trading. Ret Adjauc uses the closing auction price adjusted for the bid-ask spread by adding (subtracting) half the spread for trades made below (above) the 4 pm midpoint. The column "top $1 \%$ " indicates that the sample is restricted to the $1 \%$ of auctions with largest price impact (above 19.70 bps ). In Panel (b), after-hour returns are regressed on auction price deviations and last five-minute returns. Ret $t_{\text {auc }}^{420}$ denotes the return in the twenty minutes after market close. Missing returns are not filled, which explains the change in the number of observations. Returns are winsorized at $0.05 \%$. Standard errors are double-clustered by date and stock and reported in parentheses. ${ }^{*}$, ${ }^{* *}$, and ${ }^{* * *}$ denote significance at the $10 \%$, $5 \%$, and $1 \%$ level. All regressions include stock fixed effects. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month. In Panel (b), the sample is restricted to stocks in the top market capitalization quintile at the beginning of each year.
(a) Reversals

|  | Ret ${ }_{\text {auc }}^{945}$ | Ret $A d j j_{a u c}^{945}$ | Ret $_{400}^{945}$ | Ret ${ }_{\text {auc }}^{945}$ | $\operatorname{Ret} A d j_{a u c}^{945}$ | RetAdjauc ( ${ }_{\text {a }} 9$ (op 1\%) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\operatorname{Ret}_{400}^{a u c}$ | $\begin{gathered} \hline-0.845^{* * *} \\ (0.028) \end{gathered}$ |  |  | $\begin{gathered} \hline-0.872^{* * *} \\ (0.028) \end{gathered}$ |  |  |
| Ret Adj ${ }_{400}$ |  | $\begin{gathered} -0.910^{* * *} \\ (0.036) \end{gathered}$ |  |  | $\begin{gathered} -0.949 * * * \\ (0.037) \end{gathered}$ | $\begin{gathered} -0.6604^{* * *} \\ (0.0483) \end{gathered}$ |
| Ret ${ }_{355}^{400}$ |  |  | $\begin{gathered} -0.186^{* * *} \\ (0.038) \end{gathered}$ | $\begin{gathered} -0.176^{* * *} \\ (0.038) \end{gathered}$ | $\begin{gathered} -0.185^{* * *} \\ (0.038) \end{gathered}$ | $\begin{gathered} -0.2574^{* * *} \\ (0.0439) \end{gathered}$ |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^{2}$ | 0.61\% | 0.19\% | 0.11\% | 0.20\% | 0.30\% | 1.52\% |
| Obs. | 5,363,155 | 5,363,155 | 5,363,155 | 5,363,155 | 5,363,155 | 46,658 |

(b) Reversals after hours (large stocks)

|  | Ret $_{\text {auc }}^{945}$ | Ret $_{\text {auc }}^{420}$ | Ret $_{\text {auc }}^{430}$ | Ret $_{\text {auc }}^{440}$ |
| :--- | :---: | :---: | :---: | :---: |
| Ret $_{400}^{\text {auc }}$ | $-1.088^{* * *}$ | $-0.510^{* * *}$ | $-0.465^{* * *}$ | $-0.434^{* * *}$ |
| Ret $_{355}^{400}$ | $(0.094)$ | $(0.062)$ | $(0.050)$ | $(0.048)$ |
|  | $\left(0.175^{*}\right.$ | $-0.065^{* * *}$ | $-0.068^{* * *}$ | $-0.067^{* * *}$ |
| Stock FE | Yes | $(0.015)$ | $(0.015)$ | $(0.014)$ |
| Adj. $R^{2}$ | $0.20 \%$ | Yes | Yes | Yes |
| Num. obs. | $1,147,683$ | 346,667 | $0.17 \%$ | $0.14 \%$ |

Table 6. Determinants of trading volume in the time series. The log daily closing auction turnover, log turnover in the last five minutes of trading, and log intraday turnover (9:30am-3:30pm) are regressed on explanatory variables and stock fixed effects. The independent variables include the logarithm of ETF ownership as of the beginning of the month; the logarithm of active and passive mutual fund (MFund) ownerships; an indicator for Russell index rebalancing dates; an indicator for the third Friday of each month (3rd Friday), which is typically an option expiration day; a beginning-of-month and end-of-month indicators; and an indicator for the last day of the quarter. EAD-1, EAD, and EAD+1 are indicators for the day before, of, and after an earnings announcement. $\operatorname{Avg}|\operatorname{Ret}|$ is the absolute return averaged over the past five trading days, $\operatorname{Ret}_{t-1}$ is the lagged daily return, and Market cap. is the market capitalization at the end of the previous month. We also estimate but do not report month-of-the-year and day-of-the-week indicators. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month. Standard errors are double-clustered by date and stock and reported in parentheses. ${ }^{*}$, **, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level.

|  | Auction turnover |  | Last 5min turnover |  | Intraday turnover |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| log ETF own. | $0.074^{* * *}$ | (0.004) | 0.037*** | (0.002) | $0.037^{* * *}$ | (0.003) |
| $\log$ MFund own. (active) | -0.005 | (0.004) | 0.019*** | (0.002) | 0.020*** | (0.004) |
| log MFund own. (passive) | 0.037*** | (0.005) | $0.006^{* *}$ | (0.003) | 0.010* | (0.006) |
| Russell rebal. day | $2.307^{* * *}$ | (0.096) | $0.784^{* * *}$ | (0.062) | 0.078 | (0.054) |
| 3rd Friday | 0.639*** | (0.078) | 0.125*** | (0.020) | 0.210*** | (0.021) |
| First of month | 0.195*** | (0.030) | 0.079*** | (0.015) | $0.133^{* * *}$ | (0.012) |
| Last of month | 0.869*** | (0.049) | 0.322*** | (0.020) | 0.008 | (0.015) |
| End of quarter | -0.024 | (0.065) | 0.055* | (0.030) | $-0.092^{* * *}$ | (0.027) |
| EAD-1 | 0.016* | (0.009) | 0.227*** | (0.005) | 0.224*** | (0.005) |
| EAD | -0.016* | (0.009) | $0.083^{* * *}$ | (0.005) | $0.966^{* * *}$ | (0.009) |
| EAD+1 | $-0.025^{* * *}$ | (0.009) | 0.019*** | (0.004) | 0.494*** | (0.006) |
| $\log$ Avg $\mid$ Ret $\mid$ | $0.087^{* * *}$ | (0.006) | 0.075*** | (0.003) | $0.244^{* * *}$ | (0.005) |
| Ret $_{t-1}$ | -0.400** | (0.174) | $-0.364^{* * *}$ | (0.092) | $-0.318^{* * *}$ | (0.103) |
| log Market cap. | $0.037^{* * *}$ | (0.009) | 0.020*** | (0.006) | $0.158^{* * *}$ | (0.013) |
| Trend | $0.054^{* * *}$ | (0.013) | 0.061*** | (0.006) | $-0.063^{* * *}$ | (0.007) |
| Trend ${ }^{2}$ | $0.005^{* * *}$ | (0.001) | -0.000 | (0.001) | $0.006^{* * *}$ | (0.001) |
| log Turnover(9:30-3:30) | $0.323^{* * *}$ | (0.005) | 0.562*** | (0.004) |  |  |
| Calendar month FE | Yes |  | Yes |  | Yes |  |
| Day of week FE | Yes |  | Yes |  | Yes |  |
| Stock FE | Yes |  | Yes |  | Yes |  |
| $R^{2}(\%)$ | 30.70\% |  | $36.35 \%$ |  | 8.97\% |  |
| Num. obs. | 5,399,673 |  | 5,447,479 |  | 5,501,841 |  |

Table 7. Auction volume relative to intraday volume around S\&P 500 additions and deletions. This table examines the logarithm of closing auction share volume divided by intraday (9:30am$3: 30 \mathrm{pm}$ ) share volume (closing volume ratio) for stocks added to/deleted from the S\&P 500 and control stocks in a regression setting. The dependent variable is the closing volume ratio. Treated is an indicator variables that takes the value one for added/deleted stocks and zero for control stocks. Post addition (deletion) is an indicator variable that takes the value one after an addition (deletion). The regression includes event fixed effects. Three stocks are matched to each addition and deletion. The matching is based on the listing exchange and the 60 -day average closing volume ratio computed 60 days prior to the event. The average closing volume ratio of the three stocks is computed each day as the control value for each addition and deletion. Each added/deleted stocks is required to have at least 30 valid observations after the event. The sample includes 60 days pre event and 120 days post event, and excludes the event day and the four days prior and post event. The sample consists of 113 additions and 66 deletions over 2010 to 2018. $t$-statistics based on standard errors clustered by event are reported in parentheses. ${ }^{*},{ }^{* *}$, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level.

| Dep. variable: | Closing volume ratio |
| :--- | :---: |
| Treated | $-0.062^{* * *}$ |
|  | $(-3.008)$ |
| Post addition | $0.089^{* * *}$ |
|  | $(4.186)$ |
| Post deletion | $0.101^{* * *}$ |
|  | $(4.525)$ |
| Post addition*Treated | $0.201^{* * *}$ |
|  | $(6.858)$ |
| Post deletion*Treated | $-0.153^{* * *}$ |
|  | $(-4.499)$ |
| Event FE | Yes |
| $R^{2}$ | 0.0228 |
| Obs. | 59,770 |

Table 8. Put-call parity violations. The table reports the frequency of put-call parity violations if the parity is computed with the closing stock price ("Yes" row for violations and "No" for nonviolations) versus with the last midquote (columns). The last column reports the total number and the share of violations that disappear after switching from the closing price to midquote. The reduction in the number of violations is statistically and economically significant. The last panel shows how put-call parity violations (computed with closing stock price and with the last midquote) predict next-day stock returns from the close to 9:45am the next day ( $\operatorname{Ret}_{\mathrm{auc}_{t}}^{\mathrm{open}_{t+1}}$ ) and from 9:45am the next day to the next-day close ( $\operatorname{Ret}_{\mathrm{open}_{t+1}}^{\mathrm{auc}_{t+1}}$ ). Controls include the last five-minute and intraday returns ( $\left.\operatorname{Ret}_{3: 55 t}^{4: 00 t}, \operatorname{Ret}_{9: 35 t}^{3: 55 t}\right)$. Date fixed effects are included. Standard errors are double-clustered by date and stock and reported in parentheses. *, ${ }^{* *}$, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level.
(a) Full sample

|  | Violation midquote |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
|  |  | No | Yes | Total | Reduction in \# of violations <br> if midquote used |
| Violation | No | $2,370,414$ | 13,118 | $2,383,532$ |  |
| Closing price | Yes | 23,322 | 93,923 | 117,245 | 10,204 |
|  | Total | $2,393,736$ | 107,041 | $2,500,777$ | $9 \%$ |

(b) Subsample of large deviations between closing price and pre-close midquote

|  | Violation midquote |  |  |  | Reduction in \# of violations |
| :--- | :---: | :---: | :---: | :---: | :---: |
|  |  | No | Yes | Total | if midquote used |
| Violation | No | 254,515 | 1,660 | 256,175 |  |
| Closing price | Yes | 3,650 | 4,839 | 8,489 | 1,990 |
|  | Total | 258,165 | 6,499 | 264,664 | $23 \%$ |

(c) Return predictability

|  | $\operatorname{Ret}_{\text {auc }_{t}}^{\text {open }_{t+1}}$ |  |  |  | $\operatorname{Ret}_{\text {open }}^{\text {apat }}$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $I S_{t}-S_{\text {auc }_{t}}$ | $\begin{gathered} 0.1240^{* * *} \\ {[9.0]} \end{gathered}$ |  | $\begin{gathered} 0.0845 * * * \\ {[5.2]} \end{gathered}$ |  | $\begin{gathered} 0.0098 \\ {[0.9]} \end{gathered}$ |  |
| $I S_{t}-S_{\text {mid }_{t}}$ |  | $\begin{gathered} 0.0284^{*} \\ {[1.8]} \end{gathered}$ |  | $\begin{gathered} 0.0156 \\ {[1.5]} \end{gathered}$ |  | $\begin{aligned} & 0.0061 \\ & {[1.5]} \end{aligned}$ |
| Intercept | $\begin{gathered} 0.1052^{* * *} \\ {[84.2]} \end{gathered}$ | $\begin{gathered} 0.1052^{* * *} \\ {[84.1]} \end{gathered}$ | $\begin{gathered} 0.1054^{* * *} \\ {[84.7]} \end{gathered}$ | $\begin{gathered} 0.1054^{* * *} \\ {[84.8]} \end{gathered}$ | $\begin{gathered} -0.0053^{* * *} \\ {[-5.6]} \end{gathered}$ | $\begin{gathered} -0.0054^{* * *} \\ {[-5.6]} \end{gathered}$ |
| Controls | No | No | Yes | Yes | No | No |

## A Appendix: institutional details of closing auctions

In this section, we describe the inner workings of the closing auctions conducted by the NYSE and Nasdaq. The Nasdaq closing call auction was introduced in 2004. The NYSE also adopted a closing auction process in 2004. A matching procedure of market-on-close orders had been in effect on the NYSE since 1990 at a price set by the prevailing ask or bid, or last trade price in case of no imbalance (Hasbrouck, Sofianos, and Sosebee (1993)).

Both exchanges feature opening and closing auctions in addition to continuous trading. These are single price auctions where buy and sell orders are matched at a price that maximizes executed volume. During most of the continuous trading session, market-on-close and limit-on-close orders can be submitted to be executed in the auction. After a cutoff time, such orders cannot be submitted and existing orders cannot be canceled. It is possible, however, to submit orders after the cutoff time if they are on the opposite side of an order imbalance - meaning, if there are more sell orders than buy orders in a particular name, then it is possible to submit a buy order after the cutoff time to help balance the book. Orders standing in the limit order book at the end of the day also participate in the auction but with a lower priority. At the cutoff time, the exchange starts disseminating information about the auction, including the current order imbalance and the indicative price. Figure A. 1 illustrates the main features of the auction process.

Figure A.1. Conceptual trading timeline.


## A. 1 Nasdaq closing auction

The Nasdaq auction is simpler, so we describe it first. The Nasdaq closing cross is a call auction that cross orders at a single price. It was launched on March 29, 2004 and changed little since then, except when the closing cross cutoff was extended from 3:50pm to 3:55pm in October 2018.

Nasdaq starts accepting market-on-close (MOC), limit-on-close (LOC) and imbalance-only (IO) orders at 4am. A MOC order has size and direction but is entered without a price. A LOC order is executed only if its limit price is equal or worse than the auction price. IO orders are limit orders that provide liquidity to offset on-close orders during the cross. An IO order to buy (or sell) is essentially converted into a limit order at the 4 pm Nasdaq best bid (ask). That is, it is re-priced to the best bid/ask on the Nasdaq book prior to the execution of the closing cross.

Orders can be easily canceled or modified prior to $3: 50 \mathrm{pm}$ (3:55pm since October 2018). At this time, Nasdaq stops accepting entry, cancellation, or modification of MOC orders. LOC orders received after 3:50pm are accepted only if there is a First Reference Price. Since October 2018, LOC orders may be entered until $3: 58$ pm but may not be canceled or modified. IO orders may be entered but not updated or canceled until 4:00pm. Dissemination of closing information begins at 3:50pm (changed to $3: 55 \mathrm{pm}$ in October 2018). The closing process begins at 4:00pm.

From 3:50pm to $4: 00 \mathrm{pm}$ ( $3: 55 \mathrm{pm}$ to $4: 00 \mathrm{pm}$ since October 2018), Nasdaq disseminates information about current auction order imbalance and an indicative closing price every five seconds via Nasdaq TotalView ITCH and the Nasdaq Workstation (changed to every second since October 2018). Thus, investors have to subscribe to a special exchange data feed to observe the auction. The following information is included: current reference price within the Nasdaq Inside at which paired shares are maximized, the imbalance is minimized, and the distance from the bid-ask midpoint is minimized, in that order; near indicative clearing price that will maximize the number of shares matched based on on-close orders (MOC, LOC, IO) and continuous market orders (effectively, this is the price at which the closing cross would occur at that moment in time); "far indicative clearing price," which is defined as the price that will maximize the number of shares matched based on closing interest only (MOC, LOC, IO), this calculation excludes continuous market orders; the number of paired shares that can be paired off at the current reference price; imbalance quantity seeking additional liquidity at the current reference price; and imbalance side.

The closing cross occurs at 4:00pm. Nasdaq calculates the price that will maximize the number of shares matched based on on-close orders (MOC, LOC, IO) and continuous market orders and execute the cross at a single price called the Nasdaq Official Close Price (NOCP). Only interest on the Nasdaq book is eligible to participate in the cross. Closing cross execution priority is as follows. MOC orders in time priority. IO orders and displayed interest of limit orders/quotes in
price/time priority. Reserve size for the above executes last at each price level before moving on to the next price level. LOC orders in price/time priority. Priority for IO orders will be applied after the limit prices of IO orders have been adjusted to reflect the Nasdaq inside quote at the time of the closing cross. The price is then disseminated and executions are sent to the consolidated tape. Short selling is permitted subject to applicable short sale rules.

## A. 2 NYSE closing auction

The NYSE auction has the same features as the Nasdaq auction (time cutoffs and order times), but floor brokers are given privileges adding complexity to the auction. MOC/LOC orders can be entered starting at 6:30am. Imbalance information is published to Floor Broker at 2pm. The cutoff for MOC and LOC order entry, modification, and cancellation (except for legitimate error) is $3: 45 \mathrm{pm}$ over our sample period and was changed to $3: 50 \mathrm{pm}$ in January 2019. Thereafter, only offsetting MOC/LOC and closing offset (CO) orders allowed. The cutoff for canceling a MOC/LOC for legitimate error is at $3: 58 \mathrm{pm}$. Cutoff for Closing D Order entry, modification, and cancellation is at $3: 59: 25 \mathrm{pm}$. The auction is initiated at 4 pm .

The NYSE disseminates the following information: beginning at 3:45pm (changed to $3: 50 \mathrm{pm}$ in January 2019), NYSE disseminates closing auction order imbalance information; at 3:55pm, the NYSE includes Closing D Orders at their discretionary price range in the closing auction order imbalance information. This provides the market with information about the level of buyers and sellers in a particular security, and aims to give investors the opportunity to decide whether to participate in the last trade of the day. The information is published every five seconds until 4:00pm. Key data points include: imbalance side, reference price used to calculate continuous book clearing price (generally last sale), paired quantity matched at the continuous book clearing price, and continuous book clearing price where all better-priced orders on the side of the imbalance could be traded.

The most important distinction between the NYSE and Nasdaq auctions is the D-Quotes order type unique to the NYSE. D-Quotes (or Discretionary E-quotes) are available only to floor brokers. They differ from standard on-close orders in that they can be: a) transmitted until 3:59:25pm (nearly 15 minutes later than MOC/LOC orders); b) entered on either side of the market regardless of the published imbalance; c) modified and/or canceled at any time up to 3:59:25pm. D-Quote
orders are hidden from the imbalance feed until 3:55pm. D-Quotes effectively allow the trader to circumvent the standard auction rules. Although they are accessible only to NYSE floor brokers, they are fully electronic orders. Today nearly all brokers have relationships with floor brokers in order to access D-Quotes, and trading algorithms are able to route orders directly via FIX.

## B Appendix: data description

## B. 1 Closing auction data

This appendix describes how we obtain the closing auction data.
Over the period 2010 to 2013 (included), we use the Monthly TAQ database. Nasdaq closing cross trades are reported with a specific condition number (COND $=@ 6$ ). Similarly, NYSE auction trades are indicated by COND $=6$ (market center closing trade). We focus on the closing auction trade executed on the listing exchange. In general, this trade has a much larger volume than other closing trades (if any).

Over the period 2014 to 2018 (included), we use the Daily TAQ database. Nasdaq closing cross trades are reported with a specific condition number (TR_SCOND $=@ 6$ X). Entries are often duplicated with the condition @ M. We focus on the former because it is the closing cross according to Nasdaq documentation. ${ }^{21}$ Similarly, NYSE auction trades are indicated by TR_SCOND $=6$. We focus on the closing auction trade executed on the listing exchange. In general, this trade has a much larger volume than other closing trades (if any).

## B. 2 Volume data

This appendix describes how we obtain the volume data from TAQ.
Over the period 2010 to 2013 (included), we use the Monthly TAQ database. We exclude trades for which CORR is not equal to 0 and trades with a negative price. In addition, we remove duplicated opening auction trades $(\mathrm{COND}=\mathrm{Q})$ and duplicated closing auction trades $(\mathrm{COND}=$ M) for Nasdaq-listed stocks.

Over the period 2014 to 2018 (included), we use the Daily TAQ database. We exclude trades

[^14]for which TR_COND is not equal to 00 and trades with a negative price. In addition, we remove duplicated opening auction trades (TR_SCOND = Q or @ Q) and duplicated closing auction trades (TR_SCOND $=\mathrm{M}$ or TR_SCOND $=@ \mathrm{M}$ ) for Nasdaq-listed stocks.

## Internet Appendix to "Who Trades at the Close? Implications for Price Discovery and Liquidity"

This Internet Appendix reports additional analyses, figures, and tables to supplement the main text.

## IA.A Commonality in auction price deviations

Do auction price deviations affect diversified portfolios? Passive investors trade baskets of securities. This simultaneous buying or selling translates into correlated order imbalances across stocks, which could produce correlated price deviations at the auction. To compute the aggregate price deviation, we first aggregate signed price deviations across individual stocks for each day proportional to their capitalization and then take the absolute value. That is, the aggregate deviation will be close to zero if half of the stocks have a positive deviation and the other half a negative deviation. Aggregate price deviation is 0.93 bps on average. Hence, while there is a common component to price deviations, it is too small to materially affect a diversified portfolio. Figure IA. 1 shows that the time series of aggregate price deviation and the VIX index are highly correlated. Prices are more likely to deviate at the close when aggregate risk is high. Table IA. 1 confirms that auction volume drives aggregate closing deviation as they both spike on the same days, such as institutional rebalancing days.

## IA.B Which factors drive auction spread deviation?

We use panel regressions to study the determinants of spread deviation at the close and report the results in Table IA.2. We include auction turnover, realized volatility (computed from five-minute midquote returns), half spread at the close, stock price (all the variables listed so far are in logs), linear and quadratic trends, and NYSE listing indicator. The regression includes stock fixed effects to focus on time-series variation. Higher auction turnover leads to larger spread deviations: 0.81 bps higher deviation per $1 \%$ increase in turnover, and the deviation is higher for small stocks than for large stocks. Auction volume proxies for order imbalance by liquidity seekers, which is not available in TAQ. As expected from market microstructure theories, a larger imbalances pushes the auction price further away from the last midpoint. Also consistent with theory, volatility is positively related to spread deviation. When volatility is high, liquidity providers require a higher compensation to hold inventory positions. The trend coefficients confirm the pattern in Figure 3. Since we control for the spread, we do not add an indicator for the Tick Size Pilot as suggested from Figure 4.

For robustness, we also estimate the regression separately for NYSE stocks and Nasdaq stocks and find similar results. The volume elasticity of spread deviation is slightly larger for NYSE stocks
( 1.00 bps ) than for Nasdaq stocks ( 0.71 bps ). The NYSE auction volume is possibly a better proxy for the auction imbalance than the Nasdaq auction volume. In Table IA.2, spread deviations are larger for NYSE auctions than for Nasdaq auctions by 1.1 bps , or about $14 \%$ relative to the average deviation. The difference in price deviation between NYSE and Nasdaq stocks is mostly unchanged when we control for the time elapsed until the auction, which we discuss in Section IA.C.

## IA.C Auction duration

Table IA. 4 reports descriptive statistics for the time between the end of continuous trading and the auction ("time until auction"). The median time until auction is seven seconds. The median duration between 4 pm and the auction is higher on the NYSE than on the Nasdaq ( 122.3 seconds vs 0.2 seconds). This large difference comes from the fact that the Nasdaq closing cross is fully automated whereas the NYSE auction relies on floor brokers. It is important to keep in mind, however, that this analysis conditions on the existence of an auction.

In our sample, 699 auctions have a time until auction greater than 15 minutes ( $0.013 \%$ of observations). More than half of these occur on October 11, 2010, when the NYSE had a delayed close. This issue appears unrelated to market conditions as volume was low on that day and the market closed flat. Specific market events can be associated with delayed auctions. For example, on the day of the Knight Capital trading glitch (e.g., Bogousslavsky et al. (2021)), 28 stocks had a time until auction greater than 15 minutes. In terms of operational risk, the sample does not include days on which the closing auction was canceled. This has happened. For example, on November 12, 2012, the NYSE did not hold a closing auction for more than 200 stocks due to a glitch. ${ }^{1}$

Table IA. 5 reports regressions where time until auction is regressed on explanatory variables and stock or date fixed effects, separately for NYSE auctions and Nasdaq closing crosses. Turnover is generally negatively associated with time until auction. Volatility is positively associated with time until auction. This pattern is stronger on a given day across NYSE stocks. In contrast, turnover and volatility have no explanatory power for Nasdaq's time until auction when controlling for day fixed effects. NYSE auctions tend to take longer on Russell rebalancing days, but there is no evidence that auctions take longer to execute when a stock is added to or removed from the S\&P 500.

## Additional Figure and Tables

[^15]Figure IA.1. VIX index (left scale, dashed grey line) and absolute value-weighted auction deviation in basis points (right scale, solid black line). To compute the auction deviation, we first compute signed price deviation at the close, then value-weight it across stocks on a given day, and finally take an absolute value. The signed auction deviation is the difference between the log auction price and the log midquote at 4pm. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.


Figure IA.2. Volatility at the open. This figure reports year indicators from the following panel regression: $V_{i, t}=\alpha_{i}+\alpha_{y}+$ controls $+\epsilon_{i, t}$, where $V_{i, t}$ is the variable under consideration, where $V_{i, t}$ is $\log$ realized volatility in the first 15 minutes of trading. Control variables are day-of-week and month-of-year indicators, $\log$ price, $\log$ market capitalization, and $\log$ intraday realized volatility excluding the open (right plot only). Coefficients are converted to percentage change using the delta method. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018 that are in the top market capitalization quintile and traded over the full sample period. The $95 \%$ confidence intervals are based on standard errors that are double-clustered by date and stock (or robust for the weighted-price contribution).


Table IA.1. Determinants of commonality in absolute value-weighted auction deviation. The absolute value-weighted auction deviation ( $\left|r_{4: 00 \mathrm{pm} \text {-auction }}^{\mathrm{vw}}\right|$ ) is regressed on calendar indicators and intraday volatility. Intraday volatility ( $\left|r_{9: 30-3: 30}^{\mathrm{vw}}\right|$ ) is the absolute value-weighted return between $9: 45 \mathrm{am}$ and $3: 30 \mathrm{pm}$ on the same day; First of month is a beginning-of-month indicator; Last of month is an end-of-month indicator; 3rd Friday is an indicator for the third Friday of each month, usually an option expiration day; and Russell rebal is an indicator for Russell index rebalancing dates. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month. Standard errors are heteroskedasticity-adjusted and reported in parentheses. ${ }^{*},{ }^{* *}$, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level.

| Dep. variable: | $\left\|r_{4: 00 \mathrm{pm} \text {-auction }}^{\mathrm{vw}}\right\|$ |  |
| :--- | :---: | :---: |
| Intercept | $0.931^{* * *}(0.021)$ | $0.657^{* * *}(0.041)$ |
| Russell rebal. |  | $1.4845^{*}(0.770)$ |
| First of month |  | $0.2536^{* * *}(0.082)$ |
| Last of month | $0.5604^{* * *}(0.134)$ |  |
| 3rd Friday | $0.2509^{* * *}(0.090)$ |  |
| $\left\|r_{9: 30-3: 30}^{\mathrm{vw}}\right\|$ |  | $0.005^{* * *}(0.001)$ |
| Adj. $R^{2}$ | - | $9.30 \%$ |
| Num. obs. | 2,243 | 2,243 |

Table IA.2. Spread deviation determinants. Spread deviation is expressed in basis points. Explanatory variables include logs of auction turnover (volume divided by shares outstanding), bid-ask half spread at the close, realized volatility over 9:30am-3:00pm (computed from five-minute midquote returns), linear and quadratic trends, NYSE-listing indicator, and stock fixed effects. Stocks are allocated into quintiles of market capitalization at the beginning of each year. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month. Standard errors are double-clustered by date and stock and reported in parentheses. ${ }^{*},{ }^{* *}$, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level.

|  | Full sample | Small stocks | Large stocks |
| :--- | :---: | :---: | :---: |
| Auction turnover (log) | $0.81^{* * *}(0.06)$ | $1.39^{* * *}(0.13)$ | $0.64^{* * *}(0.04)$ |
| Price $(\log )$ | $-1.34^{* * *}(0.06)$ | $-4.73^{* * *}(0.27)$ | $0.10(0.15)$ |
| Bid-ask spread (log) | $-0.32^{* * *}(0.01)$ | $-0.33^{* * *}(0.01)$ | $-0.27^{*}(0.16)$ |
| Volatility (log) | $0.46^{* * *}(0.03)$ | $0.65^{* * *}(0.08)$ | $0.31^{* * *}(0.04)$ |
| NYSE | $1.10^{* * *}(0.16)$ | $1.50^{*}(0.81)$ | $0.94^{* * *}(0.16)$ |
| Trend | $-0.94^{* * *}(0.03)$ | $-0.98^{* * *}(0.12)$ | $-0.75^{* * *}(0.04)$ |
| Trend ${ }^{2}$ | $0.07^{* * *}(0.00)$ | $0.05^{* * *}(0.01)$ | $0.05^{* * *}(0.00)$ |
| Stock FE | Yes | Yes | Yes |
| Adj. $R^{2}$ | $2.60 \%$ | $5.83 \%$ | $5.26 \%$ |
| Num. obs. | $5,473,946$ | $1,017,384$ | $1,150,191$ |

Table IA.3. Half spread and spread deviation across price groups. Absolute auction deviation is decomposed as follows |deviation| = half spread + spread deviation. Quoted half spread is defined as $\log \left(p_{\text {ask }} / p_{4: 00}\right)$ if $p_{\text {auc }} \geq p_{4: 00}$ and $\log \left(p_{4: 00} / p_{\text {bid }}\right)$ otherwise. Similarly, spread deviation is $\log \left(p_{\text {auc }} / p_{\text {ask }}\right)$ if $p_{\text {auc }} \geq p_{4: 00}$ and $\log \left(p_{\text {bid }} / p_{\text {auc }}\right)$ otherwise. The table reports statistics for half spread and spread deviation. Statistics are reported for the full sample and across price quintiles, which are formed at the beginning of each month. The $x^{\text {th }}$ percentile is denoted as $\mathrm{p} 0 . x$. Zero pct indicates the last percentile at which the spread deviation is zero. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.
(a) Half spread (basis points)

|  | Price quintile |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
|  | Low | 2 | 3 | 4 | High |
| Mean | 13.44 | 9.66 | 6.92 | 4.21 | 3.61 |
| StdDev | 21.01 | 20.00 | 16.76 | 12.10 | 16.49 |
| p0.05 | 3.91 | 2.25 | 1.40 | 0.85 | 0.39 |
| p0.5 | 7.57 | 3.89 | 2.52 | 1.55 | 1.04 |
| p0.9 | 26.85 | 18.96 | 13.18 | 7.11 | 5.56 |
| p0.95 | 40.50 | 31.87 | 24.23 | 12.57 | 10.37 |
| p0.99 | 92.79 | 80.75 | 69.26 | 45.88 | 45.69 |
| p0.999 | 253.89 | 256.76 | 211.87 | 158.00 | 228.67 |
| Count | $1,118,324$ | $1,111,330$ | $1,109,931$ | $1,115,999$ | $1,123,317$ |

(b) Spread deviation (basis points)

|  | Price quintile |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: |
|  | Low | 2 | 3 | 4 | High |
| Mean | 0.96 | 0.34 | 0.27 | 0.61 | 0.58 |
| StdDev | 14.43 | 11.78 | 10.07 | 7.41 | 9.75 |
| p0.05 | -9.45 | -6.59 | -4.23 | -2.37 | -1.48 |
| p0.5 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| p0.9 | 9.52 | 6.37 | 4.54 | 3.72 | 3.86 |
| p0.95 | 14.28 | 8.35 | 7.40 | 6.30 | 5.85 |
| p0.99 | 35.21 | 22.15 | 15.93 | 12.53 | 12.35 |
| p0.999 | 134.32 | 79.83 | 51.46 | 36.63 | 37.53 |
| Count | $1,118,324$ | $1,111,330$ | $1,109,931$ | $1,115,999$ | $1,123,317$ |

Table IA.4. Time until auction. This table reports descriptive statistics for the time between the closing of continuous trading and the auction. Statistics are reported for the full sample, NYSE auctions, and Nasdaq closing crosses. The $x^{\text {th }}$ percentile is denoted as $\mathrm{p} 0 . x$. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.

|  | All | NYSE | Nasdaq |
| :--- | ---: | ---: | ---: |
| Mean | 70.30 | 144.05 | 1.13 |
| StDev | 97.40 | 94.58 | 10.38 |
| Min | 0.00 | 0.00 | 0.00 |
| $10 \%$ | 0.00 | 41.41 | 0.00 |
| $25 \%$ | 0.18 | 88.00 | 0.00 |
| $50 \%$ | 7.00 | 122.35 | 0.19 |
| $75 \%$ | 122.14 | 183.00 | 0.37 |
| $90 \%$ | 202.00 | 266.00 | 1.00 |
| $95 \%$ | 263.92 | 322.00 | 5.00 |
| $99 \%$ | 392.00 | 446.88 | 17.00 |
| $99.9 \%$ | 581.00 | 646.50 | 45.00 |
| Max | 3587.00 | 3587.00 | 792.00 |
| Obs. | 5578901 | 2700179 | 2878722 |

Table IA.5. Time until auction determinants. This table reports regressions where time until auction is regressed on explanatory variables and stock or date fixed effects, separately for NYSE auctions and Nasdaq closing crosses. The independent variables include log intraday turnover; log intraday realized volatility; an indicator for Russell rebalancing dates (Russell); and a stock-day indicator for whether a stock was included or deleted from the S\&P 500 (SP). The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month. $t$-statistics based on standard errors clustered by stock and date are reported in parentheses. ${ }^{*},{ }^{* *}$, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level.

| Dep. variable: | NYSE |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Nasdaq | NYSE | Nasdaq |  |
| Turnover $(\log )$ | $-2.13^{* * *}(-3.58)$ | $-0.04(-0.73)$ | $-9.04^{* * *}(-11.24)$ | $0.00(0.58)$ |
| Volatility $(\log )$ | $1.30(1.20)$ | $1.13^{* * *}(7.11)$ | $11.87^{* * *}(8.60)$ | $0.00(1.43)$ |
| Russell | $103.41^{* * *}(5.04)$ | $-0.21(-0.56)$ |  |  |
| SP | $-2.22(-0.16)$ | $-0.79^{* * *}(-3.38)$ | $-31.35^{* *}(-2.27)$ | $-0.09(-0.91)$ |
| Fixed effects | Stock | Stock | Date | Date |
| Adj. $R^{2}$ | $0.6 \%$ | $0.3 \%$ | $0.9 \%$ | $-0.0 \%$ |
| Obs. | $2,698,650$ | $2,778,458$ | $2,698,650$ | $2,778,458$ |

Table IA.6. Reversals (size groups). Overnight returns are regressed on auction price deviations and last five-minute returns. Ret auc denotes the return from the closing auction to 9:45am the next morning, $\operatorname{Ret}_{400}^{a u c}$ denotes the return from the 4 pm midquote to the closing price, $\operatorname{Ret}_{355}^{400}$ denotes the return in the last five minutes of regular trading. Ret $A d j_{a u c}^{945}$ uses the closing auction price adjusted for the bid-ask spread by adding (subtracting) half the spread for trades made below (above) the 4 pm midpoint. The column "top $1 \%$ " indicates that the sample is restricted to the $1 \%$ of auctions with largest price impact. Returns are winsorized at $0.05 \%$. Results are reported for the top and bottom market capitalization quintiles, which are formed at the beginning of each year. Standard errors are double-clustered by date and stock and reported in parentheses. ${ }^{*}$, **, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level. All regressions include stock fixed effects. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.
(a) Large stocks (1,147,683 observations)

|  | Ret ${ }_{\text {auc }}^{945}$ | $\operatorname{Ret} A d j j_{\text {auc }}^{945}$ | $\operatorname{Ret}_{400}^{945}$ | Ret ${ }_{\text {auc }}^{945}$ | $\operatorname{Ret} A d j_{a u c}^{945}$ | $\operatorname{Ret} A d j j_{\text {auc }}^{945}(\operatorname{top} 1 \%)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Ret $_{400}^{a u c}$ | $\begin{gathered} \hline-1.096^{* * *} \\ (0.094) \end{gathered}$ |  |  | $\begin{gathered} -1.088^{* * *} \\ (0.094) \end{gathered}$ |  |  |
| RetAdj ${ }_{400}^{\text {auc }}$ |  | $\begin{gathered} -0.969^{* * *} \\ (0.110) \end{gathered}$ |  |  | $\begin{gathered} -0.985^{* * *} \\ (0.110) \end{gathered}$ | $\begin{gathered} -0.728^{* * *} \\ (0.116) \end{gathered}$ |
| $\operatorname{Ret}_{355}^{400}$ |  |  | $\begin{aligned} & -0.175^{*} \\ & (0.104) \end{aligned}$ | $\begin{aligned} & -0.175^{*} \\ & (0.104) \end{aligned}$ | $\begin{gathered} -0.175^{*} \\ (0.104) \end{gathered}$ | $\begin{gathered} -0.354^{* * *} \\ (0.121) \end{gathered}$ |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^{2}$ | 0.15\% | 0.07\% | 0.05\% | 0.20\% | 0.12\% | 1.24\% |
| (b) Small stocks (939,506 observations) |  |  |  |  |  |  |
|  | Ret ${ }_{\text {auc }}^{945}$ | $\operatorname{Ret} A d j j_{a u c}^{945}$ | Ret $_{400}^{945}$ | Ret ${ }_{\text {auc }}^{945}$ | Ret Adj ${ }_{\text {auc }}^{945}$ | $\operatorname{Ret} A d j_{a u c}^{945}($ top 1\%) |
| Ret $_{400}^{a u c}$ | $\begin{gathered} \hline-0.849 * * * \\ (0.020) \end{gathered}$ |  |  | $\begin{gathered} \hline-0.888^{* * *} \\ (0.020) \end{gathered}$ |  |  |
| $\operatorname{Ret} A d j_{400}^{a u c}$ |  | $\begin{gathered} -0.982^{* * *} \\ (0.026) \end{gathered}$ |  |  | $\begin{gathered} -1.020^{* * *} \\ (0.026) \end{gathered}$ | $\begin{gathered} -0.642^{* * *} \\ (0.060) \end{gathered}$ |
| $\operatorname{Ret}_{355}^{400}$ |  |  | $\begin{gathered} -0.285^{* * *} \\ (0.021) \end{gathered}$ | $\begin{gathered} -0.268^{* * *} \\ (0.022) \end{gathered}$ | $\begin{gathered} -0.285^{* * *} \\ (0.022) \end{gathered}$ | $\begin{gathered} -0.287^{* * *} \\ (0.055) \end{gathered}$ |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj. $R^{2}$ | 1.87\% | 0.63\% | 0.45\% | 2.26\% | 1.08\% | 3.91\% |

Table IA.7. Variance ratios. This table reports descriptive statistics for the variance ratio of daily log return variance computed from auction prices and daily log return variance compute from the 4 pm midquote. Statistics are reported across all stocks and across stocks in a given market capitalization quintile, which are formed at the beginning of each year. To be included in the statistics for a given size quintile, a stock must have at least 500 observations in that quintile. The bottom two rows report variance ratios for equal-weighted (EW) and value-weighted (VW) portfolios across all stocks and across stocks in a given size quintile. Auction and midquote returns are winsorized at $0.05 \%$. Statistics are reported for the full sample and across market capitalization quintiles, which are formed at the beginning of each year. The $x^{\text {th }}$ percentile is denoted as $\mathrm{p} 0 . x$. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.

|  |  | Size quintile |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | All | Low | 2 | 3 | 4 | High |
| Mean | 1.014 | 1.045 | 1.017 | 1.008 | 1.005 | 1.003 |
| StdDev | 0.024 | 0.054 | 0.019 | 0.011 | 0.013 | 0.006 |
| Skew | 4.359 | 2.609 | 2.961 | 2.785 | 10.694 | 4.517 |
| p0.01 | 0.996 | 0.992 | 0.992 | 0.994 | 0.993 | 0.994 |
| p0.05 | 0.998 | 0.999 | 0.999 | 0.998 | 0.997 | 0.997 |
| p0.1 | 1.000 | 1.003 | 1.001 | 0.999 | 0.998 | 0.998 |
| p0.2 | 1.002 | 1.009 | 1.003 | 1.001 | 0.999 | 1.000 |
| p0.3 | 1.003 | 1.014 | 1.006 | 1.003 | 1.000 | 1.000 |
| p0.4 | 1.005 | 1.019 | 1.009 | 1.005 | 1.001 | 1.002 |
| p0.5 | 1.007 | 1.026 | 1.012 | 1.006 | 1.002 | 1.002 |
| p0.6 | 1.009 | 1.035 | 1.015 | 1.008 | 1.004 | 1.003 |
| p0.7 | 1.013 | 1.050 | 1.020 | 1.011 | 1.005 | 1.004 |
| p0.8 | 1.018 | 1.072 | 1.026 | 1.015 | 1.007 | 1.006 |
| p0.9 | 1.032 | 1.111 | 1.039 | 1.020 | 1.012 | 1.009 |
| p0.95 | 1.054 | 1.148 | 1.049 | 1.026 | 1.017 | 1.012 |
| p0.99 | 1.130 | 1.241 | 1.089 | 1.042 | 1.034 | 1.021 |
| Count | 2231 | 704 | 840 | 847 | 823 | 647 |
| Portfolios (EW) | 1.037 | 1.095 | 1.044 | 1.025 | 1.011 | 1.008 |
| Portfolios (VW) | 1.012 | 1.089 | 1.042 | 1.024 | 1.010 | 1.010 |

Table IA.8. Reversals after hours. After-hour returns are regressed on auction price deviations and last five-minute returns. Ret $t_{400}^{a u c}$ denotes the return from the 4 pm midquote to the closing price, Ret ${ }_{\text {auc }}^{945}$ denotes the return from the closing auction to 9:45am the next morning, Ret $t_{\text {auc }}^{420}$ denotes the return in the twenty minutes after market close. The sample is restricted to stocks in the top market capitalization quintile at the beginning of each year. Missing returns are not filled, which explains the change in the number of observations. Standard errors are double-clustered by date and stock and reported in parentheses. ${ }^{*},{ }^{* *}$, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level. All regressions include stock fixed effects. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.
(a) Auction price without adjustment

|  | Ret $_{\text {auc }}^{945}$ | Ret $_{\text {auc }}^{420}$ | Ret $_{\text {auc }}^{430}$ | Ret $_{\text {auc }}^{440}$ |
| :--- | :---: | :---: | :---: | :---: |
| Ret $_{400}^{a u c}$ | $-1.088^{* * *}$ | $-0.510^{* * *}$ | $-0.465^{* * *}$ | $-0.434^{* * *}$ |
| Ret $_{355}^{400}$ | $(0.094)$ | $(0.062)$ | $(0.050)$ | $(0.048)$ |
|  | $-0.175^{*}$ | $-0.065^{* * *}$ | $-0.068^{* * *}$ | $-0.067^{* * *}$ |
| Stock FE | $(0.104)$ | $(0.015)$ | $(0.015)$ | $(0.014)$ |
| Adj. $R^{2}$ | Yes | Yes | Yes | Yes |
| Num. obs. | $0.20 \%$ | $0.147,683$ | 346,667 | $0.17 \%$ |

(b) Auction price adjusted for bid-ask bounce

|  | $R e t_{\text {auc }}^{945}$ | $R e t_{\text {auc }}^{4: 20}$ | Ret $_{\text {auc }}^{4: 30}$ | Ret $_{a u c}^{4: 40}$ |
| :--- | :---: | :---: | :---: | :---: |
| Ret $_{400}^{a u c}$ | $-0.985^{* * *}$ | $-0.458^{* * *}$ | $-0.378^{* * *}$ | $-0.346^{* * *}$ |
| Ret $_{355}^{400}$ | $(0.110)$ | $(0.079)$ | $(0.068)$ | $(0.067)$ |
|  | $-0.175^{*}$ | $-0.061^{* * *}$ | $-0.063^{* * *}$ | $-0.063^{* * *}$ |
| Stock FE | $(0.104)$ | $(0.015)$ | $(0.015)$ | $(0.014)$ |
| Adj. $R^{2}$ | Yes | Yes | Yes | Yes |
| Num. obs. | $1,147,683$ | 346,667 | 500,768 | 583,987 |

Table IA.9. Weighted price contributions. The average weighted price contribution is reported for five-minute intraday periods from $3: 30 \mathrm{pm}$ to 4 pm , the period between 4 pm and auction, and the overnight period. The last two columns use the adjusted (for half-the-spread) auction price (AucAdj) instead of the auction price. The average is reported for the full sample ("Full") and across market capitalization quintiles ("Small" to "Large"), which are formed at the beginning of each year. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month.

|  | $30-35$ | $35-40$ | $40-45$ | $45-50$ | $50-55$ | $55-4: 00$ | $4: 00-$ Auc | Auc-9:45 | $4: 00-$ AucAdj | AucAdj-9:45 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Full | 0.026 | 0.024 | 0.022 | 0.027 | 0.030 | 0.029 | 0.003 | 0.840 | -0.000 | 0.844 |
| Small | 0.031 | 0.031 | 0.029 | 0.034 | 0.043 | 0.043 | 0.006 | 0.784 | -0.001 | 0.792 |
| 2 | 0.030 | 0.028 | 0.025 | 0.031 | 0.036 | 0.035 | 0.003 | 0.813 | -0.000 | 0.816 |
| 3 | 0.026 | 0.023 | 0.021 | 0.026 | 0.029 | 0.027 | 0.002 | 0.846 | -0.000 | 0.848 |
| 4 | 0.022 | 0.019 | 0.018 | 0.022 | 0.022 | 0.019 | 0.002 | 0.875 | 0.001 | 0.877 |
| Large | 0.019 | 0.016 | 0.013 | 0.017 | 0.015 | 0.016 | 0.001 | 0.902 | 0.000 | 0.903 |

Table IA.10. Dissemination of closing information and price discovery. Weighted price contributions between $3: 30-35,3: 35-40,3: 40-45,3: 45-50,3: 50-55,3: 55-4: 00$, and $4: 00-$ Auction are averaged each day separately for NYSE and Nasdaq stocks in a given market capitalization quintile. The following regression is then estimated: $\mathrm{WPC}=\alpha+\alpha_{\text {NYSE }} 1_{\text {NYSE }}+$ $\sum_{k \in K} \alpha_{k} 1_{k}+\sum_{k \in K} \alpha_{\mathrm{NYSE} * k} 1_{k} 1_{\mathrm{NYSE}}+\epsilon$, where WPC is the weighted price contribution (averaged across either NYSE stocks or Nasdaq stocks), $1_{\text {NYSE }}$ is an indicator for the NYSEstocks weighted price contribution, and $1_{k}$ is an indicator for interval $k$, which belongs to $K=\{3: 35-40,3: 40-45,3: 45-50,3: 50-55,3: 55-4: 00,4: 00-A u c t i o n\}$. Standard errors are clustered by day and reported in parentheses. ${ }^{*}$, ${ }^{* *}$, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level. Market capitalization quintiles ("Small" to "Large") are formed at the beginning of each year. The sample consists of NYSE and Nasdaq common stocks from January 2010 to September 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than 100 million at the beginning of the month.

|  | Small | 2 | 3 | 4 | Large |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Constant | $0.031^{* * *}$ | $0.031^{* * *}$ | $0.027^{* * *}$ | $0.023^{* * *}$ | $0.019^{* * *}$ |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ |
| NYSE | $0.003^{* * *}$ | $-0.002^{* * *}$ | $-0.002^{* * *}$ | $-0.001^{* *}$ | 0.000 |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ |
| $3: 35$ | -0.001 | $-0.002^{*}$ | $-0.003^{* *}$ | $-0.002^{*}$ | $-0.003^{* *}$ |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.002)$ |
| $3: 40$ | $-0.003^{* * *}$ | $-0.006^{* * *}$ | $-0.007^{* * *}$ | $-0.006^{* * *}$ | $-0.007^{* * *}$ |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.002)$ |
| $3: 45$ | 0.001 | $-0.002^{*}$ | $-0.004^{* *}$ | $-0.004^{* *}$ | $-0.004^{* * *}$ |
|  | $(0.001)$ | $(0.001)$ | $(0.002)$ | $(0.002)$ | $(0.002)$ |
| $3: 50$ | $0.014^{* * *}$ | $0.009^{* * *}$ | $0.006^{* * *}$ | $0.004^{* * *}$ | 0.001 |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.002)$ |
| $3: 55$ | $0.011^{* * *}$ | $0.006^{* * *}$ | 0.002 | -0.002 | $-0.003^{* *}$ |
|  | $(0.001)$ | $(0.001)$ | $(0.002)$ | $(0.001)$ | $(0.002)$ |
| Auc | $-0.025^{* * *}$ | $-0.028^{* * *}$ | $-0.026^{* * *}$ | $-0.021^{* * *}$ | $-0.018^{* * *}$ |
| NYSE*3:35 | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ |
|  | 0.000 | 0.000 | 0.001 | -0.000 | 0.000 |
| NYSE*3:40 | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ |
|  | -0.000 | 0.001 | $0.003^{* * *}$ | $0.002^{* * *}$ | $0.002^{* *}$ |
| NYSE*3:45 | $0.0010^{* * *}$ | $(0.001)$ | $0.009^{* * *}$ | $0.001)$ | $(0.001)$ |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $0.001)$ |  |
| NYSE*3: $3: 50$ | $-0.011^{* * *}$ | $-0.010^{* * *}$ | $-0.007^{* * *}$ | $-0.001)$ | $0.007^{* * *}$ |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ |  |
| NYSE*3:55 | -0.000 | $-0.003^{* *}$ | $-0.002^{* * *}$ | $-0.007^{* * *}$ |  |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ | $0.0001)$ |
| NYSE*Auc | $-0.003^{* *}$ | $0.002^{* * *}$ | $0.003^{* * *}$ | $0.002^{* * *}$ | $(0.001)$ |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001$ |
|  |  |  |  |  |  |
| Adj. $R^{2}$ | $6.5 \%$ | $4.6 \%$ | $3.2 \%$ | $2.1 \%$ | $1.1 \%$ |
| Num. obs. | 30,548 | 30,548 | 30,548 | 30,548 | 30,548 |

Table IA.11. Auction volume elasticity: passive and active ownership. This table reports estimates of a two-step difference-in-difference specification. In the first step, turnover elasticity relative to active mutual fund, passive mutual fund, and ETF ownership is estimated for each stock over the sample period. The elasticity is estimated separately for auction turnover and turnover in every five-minute intervals from $3: 30 \mathrm{pm}$ until 4 pm with the same set of control variables as in Table 6. In the second step, the elasticities are regressed on indicators for time-of-day, ownership type, and interactions between time-of-day and ownership type as follows: $\epsilon_{i, k, o}=\alpha+1_{\text {Auction }} \alpha_{\text {Auction }}+1_{\mathrm{ETF}} \alpha_{\mathrm{ETF}}+1_{\text {Passive }} \alpha_{\text {Passive }}+1_{\text {Auction }} 1_{\mathrm{ETF}} \alpha_{\text {Auction }}{ }^{\mathrm{ETTF}}+$ $1_{\text {Auction }} 1_{\text {Passive }} \alpha_{\text {Auction }}{ }^{*}$ Passive $+u$, where $\epsilon_{i, k, o}$ is the turnover elasticity of stock $i$ in interval $k$ ( $k \in\{3: 35-40,3: 40-45,3: 45-50,3: 50-55,3: 55-4: 00$, Auction\}) relative to ownership type $o(o \in$ \{active, passive, ETF\}), $1_{\text {Auction }}$ is an indicator that takes the value one if $k$ is the auction, and $1_{\text {ETF }}\left(1_{\text {Passive }}\right)$ is an indicator that takes the value one if $o$ is ETF (passive) ownership. For instance, in the first column, the coefficient Auction*ETF measures the difference between the turnover elasticities of ETF ownership and active mutual fund ownership in the auction relative to their difference in the five-minute intervals from $3: 30 \mathrm{pm}$ to 4 pm . The second column compares only auction and last five-minute elasticities. The third and fourth columns focus on small and large stocks based on a stock's market capitalization quintile at the time the stock enters the sample. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $\$ 5$ and a market capitalization larger than $\$ 100$ million at the beginning of the month. A stock is required to have at least three years of data and have a valid turnover elasticity for every single interval considered. $t$-statistics based on heteroskedasticity-adjusted standard errors are reported in brackets. *, **, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level.

| Variable | All | Only 3:55 \& Auc | Small | Large |
| :--- | :---: | :---: | :---: | :---: |
|  |  |  |  |  |
| Intercept | $0.03^{* * *}$ | $0.025^{* * *}$ | $0.026^{* * *}$ | $0.024^{* * *}$ |
|  | $[15.35]$ | $[5.39]$ | $[4.55]$ | $[8.86]$ |
| Auction*ETF | $0.055^{* * *}$ | $0.034^{* * *}$ | $0.095^{* * *}$ | $0.06^{* * *}$ |
|  | $[7.38]$ | $[3.79]$ | $[4.06]$ | $[5.86]$ |
| Auction*Passive | $0.068^{* * *}$ | $0.042^{* *}$ | 0.06 | $0.051^{* *}$ |
|  | $[5.15]$ | $[2.37]$ | $[1.53]$ | $[2.33]$ |
| Auction | $-0.044^{* * *}$ | $-0.033^{* * *}$ | -0.014 | $-0.046^{* * *}$ |
|  | $[-6.82]$ | $[-4.27]$ | $[-0.72]$ | $[-4.78]$ |
| ETF | $-0.018^{* * *}$ | 0.005 | -0.002 | $-0.02^{* *}$ |
|  | $[-8.02]$ | $[0.96]$ | $[-0.34]$ | $[-7.02]$ |
| Passive | $0.017^{* * *}$ | $0.047^{* * *}$ | $0.071^{* * *}$ | $-0.02^{* * *}$ |
|  | $[3.93]$ | $[4.14]$ | $[5.08]$ | $[-3.24]$ |
| Num. obs. | 56,385 | 16,962 | 12,660 | 10,353 |

Table IA.12. Institutional ownership and volume dynamics after S\&P 500 additions. This table compares institutional ownership and average auction volume in the calendar month before the month of an S\&P 500 addition to the same quantities in the calendar month four months after the month of the addition. For example, for an April 2010 addition, the table compares institutional ownership and average auction volume in March 2010 to the same quantities in August 2010. After addition is an indicator variable that equals one for post addition observations. $\tau_{A U C} / \tau_{d a y}$ is the auction volume over intraday ( $9: 30 \mathrm{am}-3: 30 \mathrm{pm}$ ) volume averaged over a calendar month. The sample consists of 106 S\&P 500 additions over 2010 to 2018. $t$-statistics based on standard errors clustered by index addition are reported in brackets. ${ }^{*}$, ${ }^{* *}$, and ${ }^{* * *}$ denote significance at the $10 \%, 5 \%$, and $1 \%$ level.

|  | ETF own. | MFund own. (passive) | $\tau_{A U C} / \tau_{\text {day }}$ | $\tau_{A U C} / \tau_{\text {day }}$ |
| :---: | :---: | :---: | :---: | :---: |
| After addition | 0.005* | $0.014^{* * *}$ | $0.018^{* * *}$ | $0.019^{* * *}$ |
|  | (1.863) | (3.461) | (3.956) | (4.006) |
| ETF own. |  |  |  | -0.038 |
|  |  |  |  | (-0.249) |
| MFund own. (passive) |  |  |  | -0.018 |
|  |  |  |  | (-0.250) |
| MFund own. (active) |  |  |  | 0.009 |
|  |  |  |  | (0.061) |
| Addition fixed effects | Yes | Yes | Yes | Yes |
| $R^{2}$ | 0.0320 | 0.1024 | 0.1297 | 0.1303 |
| Obs. | 212 | 212 | 212 | 212 |


[^0]:    *We greatly appreciate comments from Snehal Banerjee, Hank Bessembinder, Douglas Cumming (discussant), Shaun Davies, Terry Hendershott, Edwin Hu (discussant), Slava Fos, Björn Hagströmer (discussant), Marc Lipson, Charles Martineau, Dermot Murphy (discussant), Jayoung Nam (discussant), Michael Pagano (discussant), Neil Pearson, Jeff Pontiff, Chris Reilly, Barbara Rindi (discussant), Gideon Saar, Andriy Shkilko, Paul Whelan, and Haoxiang Zhu and seminar participants at the 3rd Future of Financial Information Conference, 7 th Annual Conference on Financial Market Regulation, AFA Annual Meeting, Boston College, Chapman University, Copenhagen Business School, Cornell University, European Finance Association Annual Meeting, FMA Annual Meeting, Microstructure Exchange, Plato Market Innovator Conference, University of Alberta, and University of Cincinnati. This paper was previously circulated under the title "Should We Use Closing Prices? Institutional Price Pressure at the Close." We are responsible for all errors.

[^1]:    ${ }^{1}$ NYSE and Nasdaq auctions are described in Appendix A.
    ${ }^{2}$ For example, "Hungry Index Funds Cram Tesla Into the S\&P 500 at a Record High." Bloomberg, December 18, 2020. "The 30 minutes that have an outsized role in US stock trading. An increasing concentration of volumes from 3.30 pm to 4 pm is causing concern." Financial Times, April 24, 2018; "NYSE Arca Suffers Glitch During Closing Auction." Wall Street Journal, March 20, 2017.
    ${ }^{3}$ The 2018 World Federation of Exchanges report shows that average daily volume is $\$ 130 \mathrm{~B}$ in the U.S., $\$ 62 \mathrm{~B}$ in China, $\$ 23 \mathrm{~B}$ in Japan, $\$ 19 \mathrm{~B}$ in India, $\$ 13 \mathrm{~B}$ in Korea, $\$ 10 \mathrm{~B}$ in U.K., $\$ 9 \mathrm{~B}$ in Hong Kong, and $\$ 8 \mathrm{~B}$ at Euronext.

[^2]:    ${ }^{4}$ See Bacidore and Lipson (2001); Pagano and Schwartz (2003); Chelley-Steeley (2008), among others. Further work studies the role that information disclosure and market design play for opening and closing auctions (e.g., Chakraborty, Pagano, and Schwartz (2012), Félez-Viñas and Hagströmer (2021)).

[^3]:    ${ }^{5}$ Recent papers show that the tick size matters in current markets; O'Hara, Saar, and Zhong (2019), among others. The recent implementation of the U.S. Tick Size Pilot Program illustrates that regulators and policymakers care about the tick size (e.g., Chung, Lee, and Rösch (2020)).

[^4]:    ${ }^{6}$ We thank Jiacui Li for sharing data on fund activeness.

[^5]:    ${ }^{7}$ Observations with zero auction volume do not have an auction price and thus are excluded from our analyses that require this price. In our sample, $0.22 \%$ of stock-days have zero trading volume (or about five stocks a day), and $2.48 \%$ of stock-days have zero auction volume. Table 1 shows that the effect is mostly driven by small stocks, $0.72 \%$ of which have zero daily volume and $9.56 \%$ have zero auction volume. Only $0.21 \%$ of stock-days in the top size quintile do not have an auction.
    ${ }^{8}$ In Section IA.A in the Internet Appendix, we show that signed auction price deviations are correlated across stocks. This is consistent with auction investors trading baskets of securities, which translates into correlated order

[^6]:    imbalances across stocks.
    ${ }^{9}$ A careful analysis of transaction costs requires account level data because TAQ based measures of trading costs such as the bid-ask spread can be poor proxies for actual institutional trading costs (see, for instance, Bogousslavsky, Collin-Dufresne, and Sağlam, 2021; Eaton, Irvine, and Liu, 2021).
    ${ }^{10}$ In untabulated results, we also consider a benchmark that is stacked against the auction: the ratio of the absolute return from $3: 45 \mathrm{pm}$ to the auction over the auction volume. This benchmark unrealistically assumes that all price moves in the last 15 minutes of trading are associated with auction volume and imbalance information about this volume. This ratio is on average almost the same as the $3: 30 \mathrm{pm}$ to $3: 45 \mathrm{pm}$ ratio: 0.887 vs 0.886 .

[^7]:    ${ }^{11}$ In Table IA. 3 in the Internet Appendix, we reproduce the results in Table 3 using price groups instead of size groups. Auction price deviations increase with the relative tick size.
    ${ }^{12}$ The number of deletions is lower than the number of additions because we require post event data for the delisted company. For example, a deletion due to the merger between two S\&P 500 companies is not included in our sample.

[^8]:    ${ }^{13}$ We reach similar conclusion using variance ratios. For each stock we compute the ratio between daily return variance from auction prices and compare it with the variance from quote midpoints. Table IA. 7 in the Internet Appendix reports descriptive statistics for the variance ratios of daily returns. The average ratio of 1.014 is statistically different from one at the $1 \%$ level and means that the closing price adds only about $1.4 \%$ of non-informative variance.
    ${ }^{14}$ Investors could also enter into a "guaranteed close" contract with an investment bank (see Hu, Liu, and Yu (2022)). However, the bank would need to trade in the auction to hedge its exposure.

[^9]:    ${ }^{15}$ We keep only regular trades with indicators: @TI, @T, @FTI, @FT for Nasdaq and T, TI, FTI, FT for NYSE. We start at $4: 10 \mathrm{pm}$ to avoid guaranteed close orders and to make sure that the auction has already taken place.

[^10]:    ${ }^{16}$ To be included, a stock must have an auction price on a given day and a valid midquote at 9:45am on the next day. All returns are winsorized at $0.005 \%$.

[^11]:    ${ }^{17}$ We also estimate an extension of the panel regression in Table 6 in which we regress auction and pre-auction turnover on interval-stock fixed effects, and control variables and their interactions with auction/pre-auction indicators. This specification maps directly to the coefficients in Figure 6 except that we can formally test for the difference-in-difference. The results are similar.
    ${ }^{18}$ These magnitudes are derived from the coefficient values as $e^{2.307}-1$ and $e^{0.784}-1$.

[^12]:    ${ }^{19}$ Since the regression uses log turnover as dependent variable, calendar year coefficients for percentage changes and associated standard errors are obtained by using the delta method.

[^13]:    ${ }^{20}$ Cremers and Weinbaum (2010) argue that informed investors push option prices creating parity violations. E.g., investors with negative information buy put options making puts expensive relative to calls. Goncalves-Pinto et al. (2019) argue that the option implied price is more efficient than the stock price because uninformed price pressure is higher in the underlying than in options. Thus, both studies argue that option prices are more efficient than stock prices. These papers use closing prices, even though Battalio and Schultz (2006) show that synchronized intraday data should be preferred to closing prices when computing the put-call parity.

[^14]:    ${ }^{21}$ https://www.nasdaqtrader.com/content/technicalsupport/specifications/dataproducts/ NQLastSalespec.pdf

[^15]:    ${ }^{1}$ https://www.reuters.com/article/nyse-trading-glitch-idCNL1E8MCB1820121112

