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

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#### Abstract

We document the growing importance of the closing auction in the U.S. equity market and study its implications. The auction accounts for a striking $7.5 \%$ of daily volume in 2018, up from 3.1\% in 2010. Our difference-in-difference analyses suggest that this growth is fueled by the growth of indexing and ETFs. Despite massive volumes, closing prices match the pre-close bid or ask prices in $68 \%$ of cases. Price deviations can occasionally be large but mostly revert overnight. Overall, the auction matches large volumes cheaply, but the increase in auction volume coincides with a decrease in liquidity at the open.


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## 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 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. ${ }^{1}$

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 during that period. Recently, however, the auction has received a lot of attention from the financial press: Numerous stories suggest that trading volume is shifting towards the end of day and raise concerns about this trend. These concerns are fueled by occasional abnormalities at the close. ${ }^{2}$ For example, Figure 1 shows the price and volume of Tesla's stock on the day of its addition to the S\&P 500 . The price fluctuates wildly in the last half hour of trading, which culminates with a $3 \%$ surge in the closing price from the pre-close quote midpoint with $\$ 150.8$ billion traded in the auction. This price spike at the close fully reverts overnight. Regulators are also concerned. The Autorité des Marchés Financiers (AMF) identified the "concentration of transactions in the closing auction on Euronext" as a new market risk. Furthermore, the European Securities and Markets Authority (ESMA) raised the question of whether it should "take actions to influence this market trend."

Did closing volume indeed drastically increase? The growth of indexing and ETFs is another recent trend that raises some concerns. Are the trends in closing volume and ETF ownership related? Can the close shed light on how indexing affects the market? Does the high auction volume distort closing prices (as in the Tesla example)? Does the shift in trading towards the close affect intraday liquidity and price discovery?

To our knowledge, we are the first to comprehensively examine the properties of end-of-day trading and especially the closing auction under the "new regime" of record volume at the close.

[^1]We first show that the closing auction has become a major trading mechanism that is increasingly important. In 2018, $\$ 15.2$ billion are traded in the closing auction across U.S. stocks on a typical day, which hypothetically makes it the fifth largest equity market in the world by trading volume. ${ }^{3}$ Aggregate auction volume accounts for $7.48 \%$ of aggregate daily dollar volume in 2018, up from $3.11 \%$ in 2010. In contrast, Smith (2006) estimates that auction volume is only $0.49 \%$ of daily total after Nasdaq's introduction of a closing auction in 2004. Volume during 3:30-to-3:55pm as a share of total volume declined between 2010 and 2018. Thus, trading volume migrates not just to the end of the trading day but to the last five minutes and especially the auction.

Who trades at the close? Passive institutional investors are benchmarked against closing prices for indices they track and thus seek to trade at the auction price to minimize tracking error. Indeed, according to a survey by Greenwich Associates (2017), investors trade in the auction for two main reasons: execution at the official auction price and efficient price discovery. Using a diff-in-diff approach, we show that ETF and passive ownership are major determinants of auction volume. ETF and passive mutual fund ownership, but not active mutual fund ownership, are strongly associated with auction volume, while the associations with volume right before the auction are much weaker. Consistent with indexing and institutional rebalancing effects, auction volume spikes on index rebalancing days and end-of-month days. Hedges are also rebalanced at the close. Auction volume spikes on option expiration days because option market makers drop their stock delta-hedges at the close after options expire. In contrast, auction volume is lower on and around earnings announcements, major recurrent informational events, whereas pre-close volume is higher. ${ }^{4}$

While index funds and ETFs affect closing volume directly by rebalancing (especially leveraged ETFs) and through the creation and redemption process, their direct trading is unlikely to fully explain the closing volume. Indexing and ETFs also indirectly affect closing volume. Other investors can be attracted by the higher volume (and presumably higher liquidity) at the close. A diff-in-diff analysis shows that closing volume increases by $20 \%$ (decreases by $15 \%$ ) relative to intraday volume after a stock is added to (deleted from) the S\&P 500 index.

Does the massive closing volume distort prices? The closing price deviates from the closing

[^2]quote midpoint measured at the 4 pm market close in $98.2 \%$ of cases. But these price deviations are small. The average (absolute) deviation is 8.1 basis points (bps), only slightly higher than the average half bid-ask spread of 7.6 bps . The closing price matches the pre-close best bid or ask price in $68.5 \%$ of all auctions. The tick size is binding in $41.8 \%$ of all auctions. Furthermore, closing price deviations increase sharply for small stocks after the 2016 Tick Size Pilot program increased tick size for small stocks. Auction price deviations exceed the half spread in only $23.4 \%$ of cases and tend to increase with auction volume. Deviations are occasionally large and exceed 63 bps in $1 \%$ of cases. Closing price deviations are highly correlated across stocks, but the aggregate price deviation is too small to materially affect diversified portfolios. Overall, auction price deviations are on average small and would have been even smaller if not for the binding tick size.

Auction volume can move prices beyond the spread, but does it make them more or less efficient? Concentrated trading at specific times of the day can lower costs and make prices more efficient (Admati and Pfleiderer (1988)). Prices can also deviate from fair values when risk-averse liquidity providers absorb large order imbalances (Grossman and Miller (1988); Hendershott and Menkveld (2014)). Hence, more trading at the close could lead to uninformative prices. Consistent with uninformed price pressure, closing price deviations reverse almost fully overnight, even adjusted for the half spread. Variance ratio and weighted price contribution tests further confirm that little price discovery occurs at the auction. Price discovery linked to auction volume can occur when auction imbalance information is disseminated before the auction. We exploit the timing difference in the dissemination of imbalance information between the NYSE and Nasdaq. Imbalance information contributes to price discovery, but the magnitude is not large enough to explain the low informativeness of the closing price deviation.

For stocks with sufficient after-hours liquidity, one-third to one-half of the reversal occurs within the first 30 minutes after the close. Quick reversal is consistent with imperfect liquidity provision in the auction. Exchanges have an effective monopoly over closing auctions for their listed securities and charge higher fees to both sides of auction trades. High fees and execution uncertainty increase auction participation costs for external liquidity providers. The rest of the reversal can compensate liquidity providers for bearing overnight risk. Differences in auction design between the NYSE and Nasdaq also matter but do not change our overall conclusions. NYSE floor brokers, and thus their clients, have an exclusive right to submit so-called D-quote orders. These widely-used orders
bypass most restrictions of standard market- and limit-on-close orders. Consistent with imperfect competition, price deviations are 1.2 bps larger for NYSE auctions than for Nasdaq auctions but are similar pre-auction. ${ }^{5}$ This difference is large relative to the average auction deviation but is small in absolute terms. Our main findings are robust across these two designs for the closing process.

How does trade clustering at the close affect trading during the rest of the day? ETF and passive mutual fund ownerships are associated with volume around the close but do not account for all of the increase in volume. An increase in closing volume due to passive investors can attract discretionary traders who optimally move their trades to the close. This "liquidity begets liquidity" effect can explain why auction volume increases, but the average price deviation does not change over our sample period. As investors cluster at the end of the day, this explanation predicts that liquidity could decrease during the rest of the day (Admati and Pfleiderer (1988); Foster and Viswanathan (1990)) -a side effect of the rise in passive investing. Indeed, turnover in the first 15 minutes of trading decreases by $22 \%$ for S\&P 500 stocks over our sample period. Liquidity worsens substantially: Effective spread increases by 10 basis points on average, and depth at the best quotes declines by $63 \%$. This trend is concerning as overnight news is priced at the open. Indeed, traders voice concerns about the lack of intraday liquidity. ${ }^{6}$ Open volatility increases over the sample period when controlling for volatility during the rest of the day. The price contribution of the open to the intraday return also increases. Hence, prices are more resilient at the close, but liquidity deteriorates and adverse selection increases around the open.

Prior literature on equity auctions mostly focuses on the introduction of closing auctions. Bacidore and Lipson (2001) find that closing auctions provide little benefits for firms that switch listing from the NYSE to the Nasdaq. In contrast, Pagano and Schwartz (2003), Comerton-Forde, Lau, and McInish (2007), Chelley-Steeley (2008), Kandel, Rindi, and Bosetti (2012), and Pagano, Peng, and Schwartz (2013) find that market quality mostly improved when a closing auction is introduced on the Nasdaq and international exchanges in late 1990s and early 2000s. In fact, Nasdaq introduced the closing cross following demand for more robust closing prices (Pagano et al. (2013)). Barclay, Hendershott, and Jones (2008) find that the consolidation of order flow in the opening

[^3]auction improves price discovery. Recently, Hu and Murphy (2020) show that auction order imbalances disseminated by the NYSE ahead of the auction are less accurate than for the Nasdaq, which can make NYSE auctions less efficient. They conclude that floor brokers' market power may come not only from exclusive access to D-quote orders but also through their access to better order imbalance information. Wu and Jegadeesh (2020) argue that reversal strategies based on market-on-close order imbalances are profitable. ${ }^{7}$ Budish, Cramton, and Shim (2015) argue that frequent batch auctions can be preferred to continuous trading. The concentration of trading at the close is potentially consistent with their theory. We contribute to this literature by comprehensively examining the closing auction-the economic mechanisms for closing volume, price deviations, and their implications - in the new regime with record volume at the close. We conclude that the auction matches large volumes cheaply.

A growing literature studies how the growth of passive investing, especially ETFs, affects financial markets. For example, Cushing and Madhavan (2000) find that volatility is higher in the last five minutes of trading and partially attribute it to institutional trading. Ben-David, Franzoni, and Moussawi (2018) find that ETF ownership is associated with increased volatility and reversal for the underlying constituents. Baltussen, van Bekkum, and Da (2019) associate a decline in index return autocorrelation across countries with increased passive investing. We contribute to this literature by showing that passive investing directly affects the market in the last five minutes of trading and especially the auction. Indexing is associated with improved liquidity at the close but can occasionally result in large price deviations that quickly and almost fully revert. However, our results suggest that indexing can indirectly affect trading during the rest of the day through the actions of other investors. Specifically, as closing volume increases over our sample period, liquidity worsens and adverse selection increases at the open. Finally, while passive investors are relatively easy to identify, their daily trading is hard to observe. We suggest that closing volume relative to intraday volume can proxy for passive trading intensity for a given stock and day.

The paper is organized as follows. Section 2 describes the data. Section 3 explores auction volume and price deviations at the close and their reversal. Section 4 studies the effect of S\&P 500 additions/deletions. Section 5 studies intraday liquidity and price discovery. Section 6 concludes.

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## 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. 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. End-of-day quote midpoint and spread are obtained from CRSP. The results are similar if we use the end-of-day quote midpoint from TAQ. We exclude observations with a crossed quote. Intraday returns and trading volumes are obtained from TAQ.

We compare the auction price to both the CRSP daily 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.

In our empirical tests, we use the CRSP closing price to compute the price deviation at the close. We use the CRSP closing price instead of the TAQ auction price because CRSP is much more widely used. The two prices match in $98.95 \%$ of observations. 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 (i.e., 2015 to 2018).

We use the end-of-day midquote reported by CRSP, which matches with the 4 pm midquote from TAQ for $95.80 \%$ stock-days. Again, 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.

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 $95 \% .{ }^{8}$ ETF ownership is obtained from the CRSP mutual fund database for 2010 and 2011, and from ETF Global from 2012 to 2018.

## 3 Volume and price deviations at the close

We first study the properties of closing auction volume and price. Auction volume is strongly associated with proxies for uninformed trading. Price deviations in the auction are small on average and reverse quickly and almost entirely.

### 3.1 Auction volume

Figure 2 plots the trends in the fraction of aggregate daily dollar volume (sum of dollar volume across stocks) 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 executed in the last five minutes of trading increases from slightly below $5 \%$ to about $6 \%$ and varies in a narrow range (middle plot). In contrast, the fraction of aggregate daily volume executed in the auction increases from $4 \%$ in 2010 to $11 \%$ in 2018 (bottom plot). Auction volume regularly spikes from the baseline level to about $20 \%$ of daily volume. Hence, the fraction of aggregate volume executed in closing auctions has increased significantly from 2010 to 2018.

Table 1 confirms that the aggregate volume results in Figure 2 hold for an average stock and describes end-of-day volume for the entire sample and size quintiles. Auction volume is $5.69 \%$ of total daily volume for an average stock-day. Auction volume is large as a share or total daily volume, and its share has been growing steadily. The last five minutes (3:55pm to $4: 00 \mathrm{pm}$ ) and the preceding 25 minutes (3:30pm 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 no clear pattern. Overall, auction volume is large, has increased greatly relative to total volume, and behaves differently from intraday volume. ${ }^{9}$

[^5]What determines auction and pre-close turnovers? We estimate a panel regression where auction turnover is regressed on proxies for potential reasons to trade at the close and on trading environment controls. We contrast the auction turnover results using 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 also include the lag of the dependent variable.

Table 2 reports the results. 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. Linear and quadratic 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. They can achieve this goal by trading in the auction since closing auction prices often set benchmarks. We proxy for indexing by using 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) provide further insights on 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.

We find that investors extensively use the closing auction for stocks with high ETF ownership. ETF ownership is highly significant for auction turnover but its effect on pre-close turnover is only half as large in Table 2. Similarly, passive mutual fund ownership is strongly associated with auction turnover but only marginally so with pre-close turnover: a coefficient of 0.037 versus 0.006 .

In contrast, active mutual fund ownership is positively associated with pre-close turnover even after controlling for size and intraday turnover. But active mutual fund ownership does not affect auction turnover. If anything, the point estimate is negative.

To further contrast the effects of passive and active ownership, Figure 3 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 turnover between $3: 30 \mathrm{pm}$ and $3: 35 \mathrm{pm}$. 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 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 interval from 3:30pm until 4 pm with the same set of control variables as in Table 2. 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. Table 3 reports the results. 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 . Consistent with Figure 3, 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 $3: 55-4: 00 \mathrm{pm}$ with the auction, or when we focus separately on small and large stocks. This difference-in-difference analysis helps alleviate some of the endogeneity concerns and alternative explanations of the passive ownership's impact on closing volume. ${ }^{10}$

Since ETFs do not trade once a day at their NAVs, the benchmarking motive is not as obvious

[^6]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, as discussed in Section 5.

Russell index rebalancing days provide a quasi-exogenous shock to indexing that confirms its effect on closing turnover. Auction and pre-close turnovers are $904 \%\left(e^{2.307}-1\right)$ and $119 \%\left(e^{0.784}-1\right)$ higher for an average stock on index rebalancing days. 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 2. Intraday turnover is not significantly higher on index rebalancing days (right column). In sum, index funds rebalance in the last five minutes of trading and especially at the auction to minimize tracking error.

Section 4 further explores the effect of indexing on the auction by studying a short window around S\&P 500 additions and deletions. First, auction volume is about $3,000 \%$ higher on the rebalancing stock-days. Second, a difference-in-difference analysis shows that the closing volume increases by $20 \%$ (decreases by $15 \%$ ) relative to intraday volume after a stock is added (deleted) from the S\&P 500 index. Thus, indexing affects the auction beyond index rebalancing days.

Other calendar effects confirm that institutional rebalancing contributes to closing volume. Auction and pre-close turnovers are $138 \%\left(e^{0.869}-1\right)$ and $38 \%\left(e^{0.322}-1\right)$ higher on the last day of the month, while 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 $89 \%\left(e^{0.639}-1\right)$ 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 there is no significant increase in auction turnover on the last day of the quarter beyond the last day of the month increase. These results further alleviate endogeneity concerns as these calendar indicators are largely exogenous to the trading environment.

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 2. Pre-close turnover increases substantially beyond what would be predicted by higher intraday turnover. In contrast, auction turnover is virtually unchanged (controlling for intraday turnover).

Overall, auction volume is strongly associated with proxies of uninformed and liquidity-driven trading, unlike pre-close and intraday volumes. Passive investors (index rebalancing days), other institutional investors (month-ends), option market-makers (expiration days) appear to use the closing auction extensively, while informed investors (earnings announcements) do not appear to use it much. Supporting this view, auction turnover depends differently on active and passive mutual fund ownership. Importantly, while we show that index funds and ETFs affect closing volume directly by rebalancing (especially for leveraged ETFs), their direct trading is unlikely to fully explain the closing volume. As we discuss in Section 5, other investors can be attracted by the higher uninformed volume at the close. Though some of these investors could provide liquidity at the close, informed investors could also migrate to the auction, as predicted by models such as Admati and Pfleiderer (1988) and Collin-Dufresne and Fos (2016). Ultimately, more informed trading should lead to improved price discovery, which we investigate next.

### 3.2 Price deviations at the close

To study how prices deviate at the close, we define the absolute percentage 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 .
Table 4 reports the distribution of closing price deviations for the entire sample and across size quintiles. 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. ${ }^{11}$ Thus, while deviations can be large occasionally, they are small most of the time.

To study the relation between price deviations and the spread, we decompose the (absolute) deviation into spread and price impact components:

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

where the (realized) 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, price impact 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. Price impact can be negative if the auction price is less than half the spread away from the closing midpoint. Table 5 reports the distribution of the half-spread and price impact. If the auction is like a regular small trade, then the price deviation from the midquote will only reflect half the bid-ask spread. Larger trades will walk the limit order book, creating price impact. The average half spread is 7.56 bps , while price impact is only 0.55 bps . Thus, the price deviation equals the half spread for most auctions, and the average (absolute) deviation of 8.1 bps is only slightly higher than the average half spread. For large stocks, the half-spread and price impact are about equal: 1.47 and 1.19 bps .

To gain more intuition, Figure 4 plots a histogram of auction absolute dollar deviation divided by the half spread at $4: 00 \mathrm{pm}$. First, only $1.8 \%$ of auctions execute at the midpoint. Second, the majority of auctions ( $68.5 \%$ ) execute at the best bid or ask (i.e, deviation equal to half spread). The tick size is binding for $42 \%$ of all auctions, which mostly explains why so many auctions execute at the half spread. Auction price deviations are larger than the half spread in only $23.4 \%$ of cases.

To establish a casual link between the tick size and the closing price deviations, we use the 2016 Tick Size Pilot program as an exogenous shock to the tick size. This Pilot program increased the tick size for selected small stocks, which lets us use large stocks for comparison. Figure 5 plots 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. In untabulated results, we confirm that this increase is highly statistically significant. The discontinuity in price deviations at the start of the Pilot supports a causal interpretation. In contrast, price deviations

[^7]declines over the sample period among large stocks despite the large increase in auction volume, which we further study in Section 5 .

What drives auction price deviations? We use panel regressions to study the determinants of price impact at the close and report the results in Table 6. 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. ${ }^{12}$ Higher auction turnover leads to larger price deviations: 0.81 bps higher deviation per $1 \%$ increase in turnover, and the impact 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 price impact. When volatility is high, liquidity providers require a higher compensation to hold inventory positions. The trend coefficients confirm the pattern in Figure 4.

For robustness, we also estimate the price impact regression separately for NYSE stocks and Nasdaq stocks and find similar results. The volume elasticity of auction deviation is slightly larger for NYSE stocks ( 1.00 bps ) than for Nasdaq stocks ( 0.71 bps ). Perhaps, the NYSE auction volume is a better proxy for the auction imbalance than the Nasdaq auction volume. In Table 6, price deviations are larger for NYSE auctions than for Nasdaq auctions, which we explore further below.

Do 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 in the Appendix 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

[^8]confirms that auction volume drives aggregate closing deviation as they both spike on the same days, such as institutional rebalancing days.

Overall, auction prices almost away deviate from the closing midquote. However, the closing price matches the pre-close best bid or ask price in $68.5 \%$ of all auctions. Deviations equal the half-spread most of the time due to binding tick size and are small on average. Hence, the closing auction appears to accommodate large volumes at a low cost.

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

Auction prices can deviate substantially from the 4 pm midquote. Do auction prices deviate because information is incorporated through trading or do they deviate because of price pressure? Deviations caused by new information should be permanent whereas deviations caused by price pressure should reverse. We test this prediction with a simple model that studies how log overnight return depends on log auction deviation:

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

where $p_{9: 45, t+1}$ is the midquote price on the next day at $9: 45 \mathrm{am}, p_{\text {auc }, t}$ 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 (2020)). Some specifications control for the last five-minute return ( $3: 55 \mathrm{pm}$ to 4 pm ).

The coefficient for price reversal, $b$, should be close to zero if auction price deviations are fully efficient and close to -1 if they are entirely due to price pressure. Table 7 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. 2 in the Internet Appendix). The reversal is complete if we control for the 3:55-4:00 price change. 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. In Section 3.1, we show that auction volume differs from pre-close volume. This difference translates into prices: The auction price stands out relative to the pre-close price.

Since the auction price reflects half the spread, we check how much of the reversal is driven by a mechanical bounce effect. 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 spreadadjusted 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 (Table IA.2). The last column of Table 7 restricts the sample to the top $1 \%$ of auctions with largest price impact (i.e., price impact greater than 19.70 bps as shown in Panel (b) of Table 5). In this sample, about $66 \%$ of the price impact reverses overnight: 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 the two exchanges. 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 deviation reverses overnight, whether adjusted for the bid-ask bounce or not and whether we consider NYSE or Nasdaq auctions.

Variance ratios are another approach to evaluate price efficiency. 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. 3 in the 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 about $1.4 \%$ of non-informative variance.

The weighted price contribution (WPC) is another well-known price discovery measure (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 contributes to the total return over 3:30pm-9:45am. For each day, WPC for interval $k$ is defined as

$$
\begin{equation*}
\mathrm{WPC}_{k}=\sum_{i=1}^{N}\left(\frac{\left|r_{i, 3: 30-9: 45}\right|}{\sum_{j=1}^{N}\left|r_{j, 3: 30-9: 45}\right|}\right)\left(\frac{r_{i, k}}{r_{i, 3: 30-9: 45}}\right), \tag{4}
\end{equation*}
$$

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. ${ }^{13}$ The auction represents only one trade, but matches a large volume. As

[^9]shown in Table 1, the median auction turnover is comparable to the 3:55-4:00 turnover and exceeds turnover in other five-minute intervals. Thus, in volume time (i.e., the contribution per volume traded), the auction should have a similar price contribution as other intervals, and this is why we picked a five-minute time step.

Panel (a) of Figure 6 plots WPC estimates computed across stocks in the bottom and top size quintiles. The closing auction return contributes little to price discovery as its price contribution is about ten times lower than what other periods with similar volume contribute. The results are similar for all size categories with the auction having slightly higher WPC for smaller stocks. (Table IA. 4 in the Appendix reports WPC estimates for all size quintiles and the full sample.) If we use the auction price adjusted for the spread, the auction's contribution of the WPC drops to zero (Table IA.4). Thus, the auction price only conveys information to the extent that it takes place at the ask or at the bid.

An uninformative auction deviation does not imply that auction volume is completely uninformative since exchanges release information about order imbalance ahead of the auction (Mayhew et al. (2009)). 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, weighted price contributions should increase at 3:45pm (3:50pm) for NYSE (Nasdaq) stocks to reflect the increased information flow.

To study how auction imbalance dissemination affects price discovery, we estimate a diff-indiff 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 market capitalization 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 change in WPC of Nasdaq stocks between the same intervals.

Panel (b) of Figure 6 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. 5 in the Appendix. The economic magnitudes appear small, however. First, Panel (a) of Figure 6 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 6 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 $3: 35 \mathrm{pm} .{ }^{14}$ Overall, auction volume contributes to price discovery but is less informative than volume over other intervals, especially for large stocks.

### 3.4 Why do closing prices reverse?

Price reversal is consistent with increased market segmentation at the auction. Exchanges have an effective monopoly over the closing auctions for their listed securities. A closing auction for CocaCola's stock organized on the Nasdaq does not set the official daily closing price for Coca-Cola because it is listed on the NYSE. Price reversal is also 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.

To disentangle among the two explanations, we examine after-hours trades. Market segmentation predicts that reversal happens right after the auction, whereas overnight risk predicts that reversal occurs mostly 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 $4: 30-4: 40 \mathrm{pm} .{ }^{15}$ We start at $4: 10 \mathrm{pm}$ to avoid guaranteed close orders and to make sure that the auction has already taken place. We estimate the following regression:

$$
\begin{equation*}
r_{\mathrm{auc}-\tau}=a+b * r_{4: 00-\mathrm{auc}}+e \tag{5}
\end{equation*}
$$

where $\tau$ is $4: 20 \mathrm{pm}, 4: 30 \mathrm{pm}$, and $4: 40 \mathrm{pm}$. 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

[^10]twenty-minute window. Table 8 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 trade in this window, and the reversal coefficient is still close to one-half. We confirm that the results are not affected by the bid-ask bounce. This fast reversal supports the segmentation hypothesis. 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.

Segmentation at the auction can arise for several reasons. First, 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. 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, which makes them less willing to absorb imbalances in the closing auction. A failed execution in the auction likely entails carrying a suboptimal inventory overnight. Thus, the reward for providing liquidity should be higher during the auction than during regular trading.

We compare auction price deviations for the NYSE with the Nasdaq to further examine market segmentation. Although the two auctions are designed similarly as explained in Appendix A, they differ in one important way: NYSE offers a unique order type, so-called "D-Quote." Unlike regular market- or limit-on-close (MOC/LOC) order types, which must be submitted prior to $3: 45 \mathrm{pm}$ unless offsetting a regulatory imbalance, D-Quotes can be submitted or modified until 3:59:50pm, regardless of the current imbalance. Thus, they can exacerbate auction order imbalance and lead to larger price deviations. D-Quotes are fully electronic orders and effectively allow traders to circumvent the standard auction rules. D-Quotes orders are officially accessible only to NYSE floor brokers (and thus their clients) and are only included in the NYSE order imbalance dissemination feed at $3: 55$ pm. Hence, the NYSE closing auction arguably subjects external liquidity providers to significantly more uncertainty than the Nasdaq closing auction.

The segmentation hypothesis predicts that price deviations should be higher on the NYSE than on the Nasdaq. To benchmark the NYSE auction deviation, we estimate a panel regression for end-of-day absolute five-minute log returns and the auction absolute price deviation. The regression includes a NYSE indicator and controls for date fixed effects, volume, volatility, spread, and price. We focus on large stocks to avoid issues related to thin trading but find similar results for other size groups. Figure IA. 2 in the Internet Appendix plots the coefficient and confidence
interval for the NYSE indicator. For the $3: 30-35 \mathrm{pm}, 3: 35-40 \mathrm{pm}, 3: 40-45 \mathrm{pm}$ intervals, NYSE and Nasdaq deviations are similar. Thus, our specification controls well for differences across stocks. At 3:45pm, the NYSE coefficient becomes positive and significant, as the NYSE starts to disseminate auction order imbalance. The opposite takes place at $3: 50 \mathrm{pm}$, when the Nasdaq starts to release the information. At $3: 55 \mathrm{pm}$, there is no significant difference despite the diffusion of D-Quotes order imbalance on the NYSE. At the auction, the NYSE indicator is strongly positive and statistically significant. This excess deviation does not translate to a higher price discovery for NYSE stocks since Panel (b) of Figure 6 shows no difference in price discovery between NYSE and Nasdaq stocks at the auction for large stocks. A panel regression with stock fixed effects, where identification come from stocks switching exchanges, produces similar results. For large stocks, the excess NYSE price deviation represents more than a third of the average price deviation in Table $4 .{ }^{16} \mathrm{Hu}$ and Murphy (2020) comprehensively study the quality of auction order imbalance information. They argue that order imbalance information is less precise on the NYSE than on the Nasdaq because the NYSE does not include accumulated D-Quotes to compute order imbalance until 3:55pm. They find that auction quality is substantially worse for NYSE stocks than Nasdaq stocks, in line with our above findings.

## 4 S\&P 500 index rebalancing and the auction

In this section, we provide further causal evidence on the effect of indexing on the closing auction using S\&P 500 index rebalancing. S\&P additions and deletions are often used as a quasi-exogenous stock-level shock to index ownership since the S\&P 500 is the most widely tracked stock index. We study intraday variation in price deviations on rebalancing days and shifts in closing volume after additions/deletions.

### 4.1 Auction price deviations

We show that closing auctions work well on average. However, the Tesla example in Figure 1 shows how the auction price can substantially deviate from the pre-close midquote. How far do

[^11]closing prices deviate when closing volume is extremely large and one-sided? S\&P 500 additions and deletions days help test closing auctions under extreme conditions: Index funds and ETFs must buy stocks that are added to the index and sell stocks that are deleted in one day at the closing price to minimize tracking error.

Our sample period includes 207 S\&P 500 rebalancing events ( 122 additions and 85 deletions). ${ }^{17}$ Since the results are similar for additions and deletions, we focus on the joint sample. For each event, 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 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) tells us by 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 3:30-35pm. This intraday relative variation should mostly rule out identification concerns associated with changes in visibility from S\&P 500 membership.

Table 9 reports the results. To save space, only the SP (join/exit) coefficient and its interactions are reported. Auction volume increases by more than $3,000 \%$ on addition/deletion days relative to $3: 30-35 \mathrm{pm}$ volume. End-of-day volatility also increases on event days: 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. Indeed, the auction price deviation becomes insignificant once the regression controls for turnover. That is, 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.

Overall, the auction is able to handle the massive auction volume on S\&P 500 index addition/deletion stock-days efficiently on average. Our results help alleviate some of the concerns

[^12]about auction robustness under extreme conditions. ${ }^{18}$

### 4.2 Shift in closing volume

How much does the auction volume change after a stock is added or deleted from the S\&P 500? What is the permanent effect beyond the event day? Table 2 shows that higher passive mutual fund ownership and ETF ownership are associated with permanently larger closing volume relative to intraday volume, all else equal. But the standard assumption is that indexers do not to trade much beyond the event day. S\&P 500 rebalancing is one of the largest quasi-exogenous shocks to passive ownership and thus helps us better identify its causal effect on auction volume.

We focus on the closing volume ratio, defined 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. The control stocks are matched based on the listing exchange and the 60-day average closing volume ratio computed 60 days prior to the event. ${ }^{19}$

Figure 7 plots the average closing volume ratio for additions (top plot) and deletions (bottom plot) from 60 days prior to to 120 days after the event. Five days before and after the event are excluded to give investors time to adjust. Added/delisted stocks and control stocks are similar pre event. However, the closing volume ratio increases (decreases) substantially for added (deleted) stocks relative to control stocks. As reported in Table IA. 6 in the Internet Appendix, 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. Figure 7 shows that the volume shift is immediate and remains apparent 120 days after the event.

A plausibly exogenous increase (decrease) to passive ownership leads to a large and permanent increase (decrease) in closing volume relative to intraday volume. This section's results support takeaways from Section 3.1. Passive ownership is a key driver of closing auction volume, even though it does not solely account for the auction volume trend. Passive investors affect auction

[^13]volume directly and indirectly through the ecosystem that they create. E.g., discretionary traders can pool their trades at the close to benefit of increased liquidity at the close, which we examine next.

## 5 Intraday liquidity

How does trade clustering at the close affect trading during the rest of the day? Trends in auction volume and price deviation help answer this question. Auction volume increases strongly over our sample period and auction price impact increases with auction volume (Table 6). But Figure 5 shows no trend in the average price deviation over our sample period for both small and large stocks. If anything, large stocks' price deviations trend down.

A"liquidity begets liquidity" effect can reconcile these findings. Tables 2 and 3 indicate that the increase in passive investing leads to an increase in uninformed trading around the close. 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 2 shows that the trend coefficients are strongly positive and significant for auction volume despite the inclusion of passive mutual fund ownership and ETF ownership in the regression. Also, a report by BlackRock (2020) estimates that only $5 \%$ of trading in individual U.S. stocks is attributable to ETF flows. 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 5. Nonetheless, on any given day, an unexpected increase in auction imbalance moves the auction price away from the $4: 00 \mathrm{pm}$ midquote, as shown in Table 6 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 (log) 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 change in (log) turnover at the open and at the auction over the sample period. Auction turnover increases, but turnover at the open decreases. The plots show raw turnover rather than turnover as a fraction of daily volume as in Figure 2. The effect is large: Turnover at the open declines by around $21 \%\left(\approx e^{-0.24}-1\right)$ over the sample period, which supports the liquidity begets liquidity effect.

Liquidity deteriorates substantially at the open. As shown in Panel (b) of Figure 8, the effective spread increases and (log) depth decreases significantly over the sample period, an unambiguous decline in liquidity at the NBBO. The magnitudes are economically large. Effective spread increases by around 10 bps , which is substantial for S\&P 500 stocks. Depth at the best quotes declines by around $63 \%\left(\approx e^{-1}-1\right)$. Relatedly, 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 and Yao (2020) associate this change with trends in passive investing. These papers 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.

What happens to volatility and price discovery at the open? Panel (a) of Figure 9 plots realized volatility at the open. Without controls (left plot), 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. Panel (b) of Figure 9 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 (left plot). However, 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. This increase in adverse selection at the open is consistent with informed traders who act on short-lived information based on overnight news. These traders cannot delay their trades because of competition with other informed trades and the risk that public news reveal their information. As uninformed volume migrates from the open to the close, adverse selection and volatility increase at the open.

The liquidity begets liquidity effect rationalizes several stylized facts that appear puzzling at first. However, we acknowledge that our interpretation of changes in intraday volume relies on trends over several years. Since investors likely adjust their trading patterns slowly over time, an increase in auction volume is difficult to causally link to a decrease in open volume. Other factors can also contribute to the shift in volume towards the close. 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 of the increased concentration among asset managers.

Overall, this section 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. Indeed, traders seem concerned about the lack of intraday liquidity (see Footnote 6). These changes raise broad questions about optimal market design. What is the "optimal" duration of the continuous trading period? The last time trading hours were changed the U.S. stock market was in September 1985, a lifetime ago for markets. Budish et al. (2015) show theoretically that frequent batch auctions can reduce the risk of being picked off by high-frequency traders relative to continuous trading. Perhaps, this is why some investors migrate to the closing auction. We believe that these important policy questions call for further research.

## 6 Conclusion

Closing auctions handle huge volumes that have grown significantly over 2010 to 2018. We show that ETF ownership and passive mutual fund ownership, but not active fund ownership, are strongly associated with closing auction volume. The auction volume permanently increases (decreases) relative to intraday volume after a stock is added (dropped) from the S\&P 500. Despite the
large volume executed at the auction, deviations between the auction price and the closing quote midpoint are small on average. $68 \%$ of the deviations occur at the best bid or ask before the close. Furthermore, the tick size is binding for $42 \%$ of all auctions. Hence, closing auctions accommodate large volume cheaply, though price deviations can be large occasionally. Price deviations beyond the spread occur in $24 \%$ of executions. But closing prices contain almost no incremental information compared to closing quote midpoints. Price deviations at the close mostly reverse by the next morning. About half of the reversal occurs right after the auction.

As volume migrates to the close, discretionary traders optimally shift their trades to the close liquidity begets liquidity. Consistent with this effect, turnover around the open decreases over our sample period. Moreover, liquidity deteriorates substantially and adverse selection increases at the open. Hence, the growth of indexing could affect market liquidity unevenly over the day.

Overall, the closing auction works well. Our results alleviate some of the concerns related to the growth of closing volume and the growth of passive investing, but the concentration of volume at a single point during the day raises questions about optimal market design.

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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 interval 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.

Intraday (9:30am-3:30pm)


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


Auction


Figure 3. 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 2. 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 4. 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 5. 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 6. 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 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. Liquidity and volume 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. 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 dollar-weighted percentage effective spread (in basis points) or log time-weighted depth at the NBBO over the first 15 minutes of trading. Control variables are day-of-week and month-of-year indicators, log price, log market capitalization, volatility (log average absolute return over the past five trading days), and log intraday turnover (only in Panel (b)). Turnovers and depth are in logs. For instance, a change in log depth of -1 over the sample period corresponds to a change of $\exp (-1)-1 \approx-63 \%$ in depth. 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


Figure 9. Volatility and price discovery 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. In Panel (a), $V_{i, t}$ is log realized volatility in the first 15 minutes of trading (left). 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). In the left figure of Panel (b), $V_{i, t}$ is the five-minute midpoint return autocorrelation computed over the first 30 minutes of trading. In the right figure of Panel (b), the weighted price contribution at the open is regressed on year indicators. The weighted price contribution at the open on each day is given by $\mathrm{WPC}_{\text {open }}=$ $\sum_{i=1}^{N}\left(\frac{\left|r_{i, 9: 30-4: 00}\right|}{\sum_{j=1}^{N}\left|r_{j, 9: 30-4: 00 \mid}\right|}\right)\left(\frac{r_{i, 9: 30-9: 45}}{r_{i, 9}: 30-4: 00}\right)$, 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). 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 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 (bp) | 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. 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 \|Ret| | $0.087^{* * *}$ | (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 3. 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 2. 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: $\epsilon_{i, k, o}=\alpha+1_{\text {Auction }} \alpha_{\text {Auction }}+1_{\text {ETF }} \alpha_{\mathrm{ETF}}+1_{\text {Passive }} \alpha_{\text {Passive }}+1_{\text {Auction }} 1_{\mathrm{ETF}} \alpha_{\text {Auction*ETF }}+$ $1_{\text {Auction }} 1_{\text {Passive }} \alpha_{\text {Auction*Passive }}+u$, 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 4. Auction price deviations. This table reports descriptive statistics 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. 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 | 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 |  |
| Count | $5,578,901$ | $1,046,362$ | $1,104,289$ | $1,128,456$ | $1,139,671$ | $1,160,123$ |  |

Table 5. Half spread and price impact. The absolute auction deviation is decomposed as follows $\mid$ deviation $\% \mid=$ half-spread $\%+$ price impact\%. The (realized) 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, price impact\% 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 the half spread and price impact. 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 price impact 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) Price impact (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 6. Price impact determinants. Price impact is expressed in basis points. Explanatory variables include logs of auction turnover (volume divided by shares outstanding), half bid-ask 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 7. Reversals. Overnight returns are regressed on auction price deviations and last fiveminute returns. Ret ${ }_{a u c}^{945}$ 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. RetAdjauc 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 ). 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.

|  | Ret ${ }_{\text {auc }}^{945}$ | $\operatorname{RetAdj}{ }_{\text {auc }}^{945}$ | $\operatorname{Ret}_{400}^{945}$ | Ret ${ }_{\text {auc }}^{945}$ | RetAdjauc ${ }_{\text {a }} 945$ | RetAdjauc ${ }_{\text {a }}^{945}(\operatorname{top} 1 \%)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Ret ${ }_{400}^{a u c}$ | $\begin{gathered} \hline-0.845^{* * *} \\ (0.028) \end{gathered}$ |  |  | $\begin{gathered} -0.872^{* * *} \\ (0.028) \end{gathered}$ |  |  |
| Ret Adja ${ }_{400}^{\text {auc }}$ |  | $\begin{gathered} -0.910^{* * *} \\ (0.036) \end{gathered}$ |  |  | $\begin{gathered} -0.949^{* * *} \\ (0.037) \end{gathered}$ | $\begin{gathered} -0.6604^{* * *} \\ (0.0483) \end{gathered}$ |
| $\operatorname{Ret}_{355}^{400}$ |  |  | $\begin{gathered} -0.186^{* * *} \\ (0.038) \end{gathered}$ | $\begin{gathered} -0.176^{* * *} \\ (0.038) \end{gathered}$ | $\begin{gathered} -0.185^{* * *} \\ (0.038) \end{gathered}$ | $\begin{gathered} -0.2574^{* * *} \\ (0.0439) \end{gathered}$ |
| 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 |

Table 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

|  | Ret $_{\text {auc }}^{945}$ | Ret $_{\text {auc }}^{4: 20}$ | $\operatorname{Ret}_{\text {auc }}^{4: 30}$ | Ret $_{\text {auc }}^{4: 40}$ |
| :--- | :---: | :---: | :---: | :---: |
| Ret $_{400}^{a u c}$ | $-0.985^{* * *}$ | $-0.458^{* * *}$ | $-0.378^{* * *}$ | $-0.346^{* * *}$ |
|  | $(0.110)$ | $(0.079)$ | $(0.068)$ | $(0.067)$ |
| $R e t_{355}^{400}$ | $-0.175^{*}$ | $-0.061^{* * *}$ | $-0.063^{* * *}$ | $-0.063^{* * *}$ |
|  | $(0.104)$ | $(0.015)$ | $(0.015)$ | $(0.014)$ |
| Stock FE | Yes | Yes | Yes | Yes |
| Adj. $R^{2}$ | $0.12 \%$ | $0.11 \%$ | $0.08 \%$ | $0.07 \%$ |
| Num. obs. | $1,147,683$ | 346,667 | 500,768 | 583,987 |

Table 9. 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) | $0.830^{* * *}$ | $17.401^{* * *}$ | $13.144]$ |
|  | $[11.551]$ | $[6.814]$ | $(5.551]$ |
| 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 |

## 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 $3: 58 \mathrm{pm}$ 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 $3: 50 \mathrm{pm}$ (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 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 $4: 00 \mathrm{pm}$. 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. ${ }^{20}$ 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.

[^14]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 (COND $=$ M) for Nasdaq-listed stocks.

Over the period 2014 to 2018 (included), we use the Daily TAQ database. We exclude trades for which TR_COND is not equal to 00 and trades with a negative price. In addition, we remove duplicated opening auction trades $\left(T R \_S C O N D=Q\right.$ or @ Q) and duplicated closing auction trades $\left(T R \_S C O N D=M\right.$ or TR_SCOND $\left.=@ M\right)$ for Nasdaq-listed stocks.

## B. 3 ETF data

We obtain ETF auction and intraday volume data as described in the two above appendices. Most ETFs are listed on the NYSE Arca exchange, for which auction identifiers are similar to that of the NYSE. An added caveat is that before July 4, 2014, auction trades do not appear to be aggregated on NYSE Arca. That is, multiple small trades are reported with closing identifiers for an ETF on the same day at the same price. We sum these trades to obtain the auction volume. We verify that the aggregated series' magnitude and volatility are comparable to that of the auction volume series starting from July 4.

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

This Internet Appendix reports citations about the importance of the closing auction as well as additional figures and tables to supplement the main text.

## Citations about the closing auction

"While there have been many debates about U.S. equity market structure and whether there are ways to improve it, centralizing auction functions with a primary listing exchange has not been brought into question. Rather, the current auction processes of the primary listing exchanges represent the best aspect of U.S. equity market structure." Elizabeth K. King, NYSE. ${ }^{1}$
"While there have been many debates about U.S. equity market structure and whether there are ways to improve it, centralizing auction functions with a primary listing exchange has not been brought into question. Rather, the current auction processes of the primary listing exchanges represent the best aspect of U.S. equity market structure."
"The Nasdaq Closing Cross is one of these key functions in which Nasdaq has invested significantly to ensure that the close of the market is effective, robust, and resilient. The close of the market is a unique moment in the trading day that is of paramount importance. The Nasdaq Closing Cross generates a value used throughout the world as a reference price for indices, funds, investment decisions, measures of economic well-being and much more." Edward S. Knight, Nasdaq. ${ }^{2}$
"One aspect of the market we believe to be particularly healthy and robust is the closing auction. We have confidence in the ability of our Designated Market Maker to properly assess supply and demand and ensure a fair, transparent, and stable price discovery process." Mickey Foster, Fedex. ${ }^{3}$
"We believe that the integrity of NASDAQ's closing process is integral to the role it serves for listed companies like PayPal, and that NASDAQ's market maker model helps to ensure that investors have a deep and liquid market to purchase stock at the most reliable price." Gabrielle Rabinovitch, PayPal. ${ }^{4}$

A number of public companies "are concerned it will disrupt what these companies view as a critical aspect of listing on a particular listing exchange, namely that one has access to a centralized closing process that the company knows and understands." Sean P. Duffy and Gregory W. Meeks, Members of Congress. ${ }^{5}$

[^15]"The closing auctions are one of the critical features of listing on an exchange. Issuers want a centralized closing process for their shares because of the integrity of the closing price derived by the centralized auctions. If we take away this most basic and fundamental feature of our equity market structure, issuers will have yet one more reason to forgo going public and listing on an exchange. This would be disastrous for the U.S. capital markets and for its investors." Ari M. Rubenstein, Co-Founder \& CEO, GTS. ${ }^{6}$
"The primary market close has gained in parallel importance with the growth of passive investment. These auctions, which attract and aggregate the overwhelming proportion of share volume, function as the central liquidity pool and price discovery mechanism for listed securities. Equity fund managers- both active and passive in nature - seek to transact at prices at or as close as possible to the auction marks to ensure that their funds are accurately measured against appropriate benchmarks. ... In short, the close is a critical daily price point." Alexander J. Matturri, CEO, S\&P Dow Jones Indices. ${ }^{7}$
"If the primary listing exchange, whether it be the NYSE or Nasdaq, can't run the closing auction, all hell breaks loose." Greg Tusar, former global head of electronic trading at Goldman Sachs Group. ${ }^{8}$
"The amount of total volume in closing auctions is not increasing, but the percentage of total volume has increased dramatically. "This shift has been driven by passive exchange traded funds (ETFs) and index tracking volumes aiming to benchmark at the close. These funds just need to achieve the closing price for valuation purposes with creations and redemptions. It is not unusual for stocks to spike in the closing auction then reopen the next day at the previous level last seen in continuous trading. This isn't healthy, as it isn't a reflection of where valuations have been throughout the trading day." Daniel Nicholls, Hermes Investment Management. ${ }^{9}$

## Additional Figures and Tables

[^16]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. Absolute price deviation for NYSE large stocks relative to Nasdaq large stocks. NYSE (Nasdaq) starts disseminating imbalance information at $3: 45 \mathrm{pm}$ (3:50pm). For each fiveminute interval between $3: 30 \mathrm{pm}$ and $4: 00 \mathrm{pm}$ and the auction, a panel regression is estimated where log absolute price deviation (in basis points) is regressed on an indicator for NYSE-listed stocks, date fixed effects, and a set of control variables. The control variable include log turnover in the same interval, log turnover between 9:30am and $3: 30 \mathrm{pm}$, log bid-ask spread, log of five-minute realized volatility between 9:30am and $3: 30 \mathrm{pm}$, and log price. The sample consists of NYSE and Nasdaq common stocks from January 2010 to September 2018 that are in the top market capitalization quintile at the beginning of each year. To be included in a given month, a stock must have a price greater than $\$ 5$ at the beginning of the month. The $95 \%$ confidence intervals are based on standard errors that are double-clustered by date and stock.


Table IA.1. Determinants of commonality in absolute value-weighted auction deviation. The absolute value-weighted auction deviation $\left(\left|r_{4: 00 \mathrm{pm} \text {-auction }}^{v \mathrm{w}}\right|\right)$ is regressed on calendar indicators and intraday volatility. Intraday volatility $\left(\left|r_{9: 30-3: 30}^{\mathrm{vw}}\right|\right)$ is the absolute value-weighted return between 9:45am and 3:30pm 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. $R^{2}$ | - |  |
| Num. obs. | 2,243 | $9.30 \%$ |

Table IA.2. 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.3. 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.4. 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.5. 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*3:50 30 | $-0.011^{* * *}$ | $-0.010^{* * *}$ | $-0.007^{* * *}$ | $-0.001)$ | $0.007^{* * *}$ |
|  | $(0.001)$ | $(0.001)$ | $(0.001)$ | $(0.001)$ |  |
| 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.6. 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 |


[^0]:    *We greatly appreciate comments from Snehal Banerjee, Hank Bessembinder, Douglas Cumming (discussant), Terry Hendershott, Edwin Hu (discussant), Slava Fos, 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 7th Annual Conference on Financial Market Regulation, Boston College, Chapman University, Copenhagen Business School, European Finance Association Annual Meeting, FMA Annual Meeting, the Microstructure Exchange, the 3rd Future of Financial Information Conference, the AFA Annual Meeting, University of Alberta, University of Cincinnati, and Cornell University. 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]:    ${ }^{1}$ We describe the NYSE and Nasdaq auctions in Appendix A. The Internet Appendix reports quotes from corporate executives, market participants, and members of the U.S. congress on how important a proper closing price is. Closing prices in CRSP and other databases are generally determined in these closing auctions.
    ${ }^{2}$ 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 3.30pm to 4 pm is causing concern." Financial Times, April 24, 2018; "NYSE Arca Suffers Glitch During Closing Auction." Wall Street Journal, March 20, 2017.

[^2]:    ${ }^{3}$ 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.
    ${ }^{4}$ Investors can also trade at the close to avoid holding positions overnight, to avoid the complexity of executing large orders intraday, and to synchronize multi-leg trades. Although some of the trading at the close may aim to manipulate the closing price, it is unlikely to account for a significant fraction of total auction volume.

[^3]:    ${ }^{5}$ Also, closing price deviations increase for firms that switch listing from the Nasdaq to the NYSE.
    6 "Stock-Market Traders Pile In at the Close," Wall Street Journal, May 27, 2015.

[^4]:    ${ }^{7}$ Stoll and Whaley (1990), Madhavan and Panchapagesan (2000), Comerton-Forde and Rydge (2006), Mayhew, McCormick, and Spatt (2009), and Chakraborty, Pagano, and Schwartz (2012) study the role that specialists and information disclosure plays for opening and closing auctions.

[^5]:    ${ }^{8}$ We thank Jiacui Li for sharing data on fund activeness.
    ${ }^{9}$ 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. 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.

[^6]:    ${ }^{10}$ We also estimate an extension of the panel regression in Table 2 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 3 except that we can formally test for the difference-in-difference. The results are similar.

[^7]:    ${ }^{11}$ We also study price deviations for large ETFs (SPY, QQQ, and S\&P sectors) and find that they behave similarly to large stocks with average deviation of 3.63 bps , and $99^{\text {th }}$ percentile of 16.32 bps .

[^8]:    ${ }^{12}$ Since we control for the spread, we do not add an indicator for the Tick Size Pilot as suggested from Figure 5.

[^9]:    ${ }^{13}$ 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 $0.005 \%$.

[^10]:    ${ }^{14}$ One potential concern is spillover effects if market participants learn about imbalances for Nasdaq from observed imbalances for NYSE stocks. We cannot rule out this concern, but a comparison of raw NYSE and Nasdaq WPC suggests that this channel, if it exists, is economically small.
    ${ }^{15}$ We keep only regular trades with indicators: @ TI, @ T, @FTI, @FT for Nasdaq and T, TI, FTI, FT for NYSE.

[^11]:    ${ }^{16}$ The Nasdaq closing cross is fully automated whereas the NYSE auction relies on floor brokers. As expected, the median duration between 4 pm and the auction is usually higher on the NYSE than on the Nasdaq ( 122 seconds vs 0.2 seconds). This does not explain our results: The difference in price deviation between NYSE and Nasdaq stocks is mostly unchanged when we control for the time elapsed until the auction.

[^12]:    ${ }^{17}$ 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.

[^13]:    ${ }^{18}$ Though not our main focus, our previous results suggest that variations in the closing process between NYSE and Nasdaq can affect closing auction volatility (see also Hu and Murphy (2020)). In untabulated results, a triple difference-in-difference specification shows that NYSE has statistically significant excess volatility of about -16 bps at $3: 50-55 \mathrm{pm}, 12 \mathrm{bps}$ at $3: 55-4: 00 \mathrm{pm}$, and 25 bps at the auction relative to the Nasdaq. These differences are roughly consistent with the pattern in Figure IA.2.
    ${ }^{19}$ 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. The results are robust to the details of the matching procedure.

[^14]:    ${ }^{20}$ https://www.nasdaqtrader.com/content/technicalsupport/specifications/dataproducts/ NQLastSalespec.pdf

[^15]:    ${ }^{1}$ Source: https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-1801145-153699.pdf
    ${ }^{2}$ Source: https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-1797187-153614.pdf
    ${ }^{3}$ Source: https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-1856933-156193.pdf
    ${ }^{4}$ Source: https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-2445187-161064.pdf
    ${ }^{5}$ Source: https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-2218270-160673.pdf

[^16]:    ${ }^{6}$ Source: https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-2227619-160772.pdf
    ${ }^{7}$ Source: https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-2020594-156840.pdf
    ${ }^{8}$ Source: "What's the Biggest Trade on the New York Stock Exchange? The Last One." Wall Street Journal, March 14, 2018 (link).
    ${ }^{9}$ Source: "Passive strategies continue to overwhelm asset managers as market hits $\$ 11$ trillion." The Trade, January 13, 2020 (link).

