Should We Use Closing Prices?
Institutional Price Pressure at the Close*

Vincent Bogousslavsky
Carroll School of Management
Boston College
vincent.bogousslavsky@bc.edu

Dmitriy Muravyev
Eli Broad College of Business
Michigan State University
muravyev@msu.edu

May 29, 2020

Abstract

The closing stock price is determined in a special call auction. This single trade accounts for 7.3% of daily volume in 2018 and is strongly associated with ETF ownership and institutional rebalancing. Strikingly, this huge volume contributes little to price discovery. Closing prices frequently and significantly deviate from closing quote midpoints, but these deviations on average fully revert overnight. Half of the reversal occurs shortly after the close. These price deviations matter for ETF mispricing and put-call parity violations and their ability to predict next-day stock returns. Finally, closing-to-total daily volume negatively predicts future stock returns.

*We greatly appreciate comments from Hank Bessembinder, Terry Hendershott, Slava Fos, Marc Lipson, Charles Martineau, Michael Pagano, Neil Pearson, Jeff Pontiff, Chris Reilly, Andriy Shkilko, and Haoxiang Zhu and seminar participants at Boston College and the Microstructure Exchange. All errors remain our responsibility.

1 Introduction

The closing price is the most important stock price of the day. It is used to price mutual fund shares, report performance by institutional investors to their clients, compute stock indices such as the S&P 500, Dow Jones, and MSCI, price derivatives, compute asset value for exchange-traded funds (ETFs), make margin and settlement calculations, among other applications. Passive institutional investors are typically benchmarked against closing prices for indices they track.[1] Academic research relies on closing prices to compute stock returns and other essential variables.

Equity closing prices are determined in a special call auction. The auction is conducted at the exchange that lists a stock shortly after the end of regular trading hours. While details differ, exchanges implement the auction similarly. Investors can direct their trading orders into the auction, which clears them at once to maximize executed volume in a single large trade. Closing prices in CRSP and other databases are generally determined in these closing auctions. We study closing auctions for NYSE- and Nasdaq-listed stocks over the 2010-2018 sample period.[2]

The closing auction is a major trading mechanism that is becoming even more important recently. We find that 15.2 billion dollars are traded in the closing auction across US stocks on a typical day in 2018, which hypothetically makes it the fifth equity market in the world by trading volume.[3] Aggregate auction dollar volume accounts for 7.48% of aggregate daily volume in 2018, up from 3.11% in 2010. The large and growing volume executed in the closing auction raises several concerns about its stability. What if a large non-fundamental order imbalance or a glitch materially affects auction prices and destabilizes the market?[4] How efficient is the closing price? How important are institutional features such as exchange monopoly power in determining closing prices? An inaccurate closing price could result in erroneous margin calls, forced margin selling, and other price inefficiencies. In spite of the auction's importance, few papers study its properties. Previous literature mostly relies on data from the pre-algorithmic trading era and focuses on the introduction of closing auctions.[5] In contrast, this paper focuses on understanding trading at the

[1]Appendix C lists quotes from heads of public corporations, financial market participants, and members of the U.S. congress that emphasize the importance of determining a proper closing price.

[2]We describe the inner workings of the NYSE and Nasdaq auctions in Appendix A.

[3]According to the 2018 World Federation of Exchanges report, average daily dollar volume is $130B in the U.S., $62B in China, $23B in Japan, $19B in India, $13B in Korea, $10B in U.K., $9B in Hong Kong, $8B at Euronext, and $7B in Germany.

[4]For example, "NYSE Arca Suffers Glitch During Closing Auction." *Wall Street Journal*, March 20, 2017.

[5]Bacidore and Lipson (2001) find little evidence that closing auctions are beneficial for firms that switch listing

close and its implications for prices under the "new regime" of enormous volume at the close.

Who trades at the close? According to a survey by Greenwich Associates (2017), investors trade in the closing auction for two main reasons: execution at the official auction price and efficient price discovery. Passive equity fund managers seek to transact at the auction price to minimize tracking error. The auction also allows arbitrageurs to exit their positions before the overnight period and to synchronize the timing of multi-leg trades. For example, option market makers unload their delta-hedges in the underlying at the close on option expiration days. Our results support these hypotheses. ETF ownership, but not institutional ownership, is strongly associated with auction volume. Also, auction volume spikes on index rebalancing days, end-of-month days, and option expiration days. Consistent with auction volume not being driven by information events, it is slightly lower on and around earnings announcements, whereas volume in the last five minutes of trading is higher (controlling for intraday volume). Overall, passive and other uninformed investors seem to be the primary users of the closing auction.[6]

Does high auction volume make auction prices deviate from closing quote midpoints? We find that the closing price frequently deviates from the closing quote midpoint (measured at the 4pm market close). Although, the median time between the close and auction is only seven seconds, closing price deviations are much larger than typical seven-second price changes. The average (absolute) deviation is 8.1 basis points, and in 5% (1%) of cases the closing price deviates by more than 26.8 (63.1) basis points. An average deviation corresponds to $6M in market capitalization and accounts for 5% of intraday volatility. Auction deviations are particularly large for small and high-volatility stocks and increase with auction volume. Intuitively, a high volume is more likely to reflect a high order imbalance.

Closing price deviations are correlated across stocks. Thus, even a diversified portfolio can exhibit price swings at the close, which can lead to erroneous margin calls. The average value-weighted price deviation is economically significant and is strongly correlated with the VIX index.

---

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) mostly find positive effects on market quality when a closing auction is introduced on the Nasdaq, London, Paris, and Milan stock exchanges, respectively. Barclay, Hendershott, and Jones (2008) find that the consolidation of order flow during the opening auction improves price discovery. Theoretically, Madhavan (1992) shows that a periodic auction offers greater price efficiency than a continuous system.

[6] Although we cannot rule out that some of the trading at the close aims to manipulate the closing price, it is unlikely to account for a significant fraction of total auction volume.

Perhaps, institutional investors often have to acquire or sell large multi-stock portfolios. Indeed, we find that the value-weighted deviation spikes on days associated with institutional rebalancing such as the first and last days of the month and Russell reconstitution days.

Auction volume moves prices, but does more volume mean more efficient or noisier closing prices? Models such as that of Admati and Pfleiderer (1988) predict that concentration of trading at specific times of the day should lead to lower transaction costs and more efficient prices. Prices can also deviate from fair values if order imbalances are large and liquidity providers are risk-averse (Grossman and Miller (1988)). Hence, a large volume of trading in the auction may lead to uninformative prices. Informed order flow has a permanent price impact, whereas prices fully revert after (uninformed) price pressure. Consistent with price pressure being mostly uninformed, the closing price deviation mostly reverses overnight for small stocks. The reversal is complete for large stocks. To benchmark the closing price reversal, the midquote price change between 3:55 and 4:00pm shows a five times smaller reversal despite similar price deviations. Variance ratio and weighted price contribution tests further confirm that little price discovery occurs at the auction.[7] Even when adjusted for the half-spread, the auction price deviation still entirely reverses.

Price reversal is consistent with liquidity provision ahead of the overnight period. Risk-averse liquidity providers are compensated to hold inventories overnight because of low liquidity and overnight price jump risk. Reversal can also be due to increased "segmentation" at the auction. Exchanges have an effective monopoly over the closing auctions for their listed securities. To distinguish between these two explanations, we examine after-hours trades.[8] The segmentation hypothesis predicts some reversal right after the auction, whereas overnight risk predicts that the reversal should occur mostly overnight. Focusing on large stocks with sufficient liquidity, we find that between one-third and one-half of the reversal occurs in the first half hour after the market closes. Thus, market segmentation appears to be an important cause of auction price deviations beyond overnight risk.

Differences in auction mechanisms further shed light on how imperfect competition can affect

[7] Price discovery linked to auction volume can occur when auction imbalance information starts being disseminated shortly before the auction. We estimate a difference-in-difference regression that exploits the timing difference in the dissemination of auction imbalance information between the NYSE and Nasdaq. We find evidence consistent with auction imbalance information contributing to price discovery for small stocks but only weak evidence for large stocks.

[8] Barclay and Hendershott (2003) find that there is little price discovery in the post-close (4:00-6:30pm) compared to the pre-open (8:00-9:30am). They examine trading after market hours for a sample of Nasdaq stocks in 2000, before the implementation of a closing auction.

auction deviations. In the minutes preceding the auction, Nasdaq's rules constrain investors to reduce closing order imbalances by posting offsetting orders. In contrast, the NYSE offers to floor brokers and their clients special orders (so-called D-quote orders) that can be posted regardless of order imbalance and are widely used. From this perspective, the NYSE auction is arguably less transparent and competitive. Strikingly, auction price deviations are consistently larger for NYSE than for Nasdaq auctions after controlling for stock characteristics. But this is not the case for price deviations before the auction. This result is consistent with costly liquidity provision.[9]

Motivated by the finding that auction volume is primarily uninformed, auction volume can serve as a benchmark to identify unusual trading patterns during the rest of the day. In particular, if trading volume by informed investors is high during regular trading hours, then the ratio of auction-to-total trading volume will be low. We find that auction-to-total volume negatively predicts weekly and monthly stock returns after controlling for the high-volume indicator of Gervais, Kaniel, and Mingelgrin (2001) and standard return predictors. That is, unusually high volume during regular trading predicts returns positively. When we decompose the ratio into its monthly average and surprise (the difference between current value and monthly average), only the surprise predicts returns. Thus, the predictability is driven by time-series shocks in auction-to-total volume rather than persistent differences across stocks. Sorting stocks into deciles based on the auction surprise produces a four-factor Fama-French alpha of 0.26% per month. In contrast, the ratio of pre-close to total trading volume fails to predict returns despite pre-close period is adjucent to the auction and has similar volume. Perhaps, pre-close and daily volumes have similar information content that cancels by taking the ratio. These predictability results are consistent with theories that associate higher informed trading with higher future returns.

We argue that closing prices deviate due to large order imbalances that reflect liquidity or other non-informational motives. The substantial volume traded in the auction does not result in higher price efficiency. Our tests imply that the last midquote is more informationally efficient than the official closing price, which contains noise from auction price pressure. Thus, the midquote should

[9] Stoll and Whaley (1990) argue that the market power of the specialist can increase the volatility of the NYSE opening auction. In contrast, Madhavan and Panchapagesan (2000) find that specialists do not appear to adjust opening prices to manage their inventory. Comerton-Forde and Rydge (2006) find evidence supporting the importance of auction design and in particular pre-trade transparency for auction price efficiency. Also, Chakraborty, Pagano, and Schwartz (2012) show that for a call auction to be most efficient, the order book should be "open" rather than "closed" for all market participants.

be preferred for many applications that require stock returns. The end-of-day midquote is easy to obtain from CRSP data. This point relates to papers showing that temporary price deviations can affect asset pricing tests.[10] We complement Blume and Stambaugh (1983) and Asparouhova et al. (2010, 2013) by highlighting a specific channel: how the large volume at the auction introduces noise into closing prices. We also suggest how to correct for this price noise.

Does using the midquote instead of the CRSP price make a difference? It does for two applications that we explore: ETF arbitrage, and put-call parity violations. The proliferation of ETFs is a key (and contentious) recent development in financial markets. ETF prices can deviate from their net asset values (NAVs). These deviations present apparent arbitrage opportunities and are often linked to arbitrageur's capital and funding liquidity. We investigate whether closing price deviations can explain ETF mispricing. First, the ETF closing price can deviate from the midquote. Second, NAVs are in general computed with closing prices for stock constituents, which can also deviate from midquotes. Using detailed daily data on the SPDR S&P 500 ETF (SPY) and its constituents, we find that the average ETF mispricing decreases from 2.50 bps to 1.59 bps once we account for the first effect, and to only 1.03 bps once we account for the second effect, a 59% drop. Apparent ETF mispricing at the close is not tradable since closing price deviations cannot be fully predicted and are subject to execution risk. Our evidence suggests that ETF mispricing measured from daily data may largely be due to closing price deviations.

Finally, we consider put-call parity violations, an apparent arbitrage where prices of a call and a put with the same strike and expiration deviate from the underlying stock price. Although option prices are quoted by sophisticated market makers, put-call parity violations are surprisingly frequent. We help resolve this puzzle by showing that many violations disappear if put-call parity is computed with stock midquotes instead of closing prices. That is, daily option and stock prices commonly used to compute put-call parity are not synchronized. The equity options market closes promptly at 4pm, which coincides with the timing of the closing stock midquote but is ahead of the closing auction. A related puzzle is that the put-call violations predict next-day stock return (Cremers and Weinbaum (2010)). That is, future stock return is lower if the option-implied stock price is below the actual price. Parity violations computed with closing price strongly predict

[10] E.g., Blume and Stambaugh (1983); Lamoureux and Wansley (1989); Asparouhova, Bessembinder, and Kalcheva (2010, 2013).

overnight returns in our sample, but not post-open returns. However, parity violations computed with midquote fail to predict either overnight or intraday returns. The closing price reverts to the midquote overnight, and this is why parity violations computed with closing price only predict overnight returns. The two put-call parity puzzles are often interpreted as evidence that option prices have superior informational content. We argue that option prices simply reflect the current stock price, but the closing option and stock prices are recorded at different time due to the closing auction. Battalio and Schultz (2006) use intraday data for a few stocks to show that stock and option closing prices are often mis-synchronized leading to put-call parity violations. We suggest a simple correction by using the quote midpoint from CRSP.

This paper focuses on the efficiency of closing prices and highlights their distortions. Our results do not imply that the closing auction itself is problematic. It might be the best trading mechanism in light of the institutional incentives discussed above (see the references in footnote 5). Our results provide a starting point to estimate aggregate costs of trading around the close and infer indexing costs. We also highlight the role of institutional constraints such as benchmarking on asset prices. Trading volume at the close is strongly associated with (passive) institutional variables, such as ETF ownership, and a high volume at the close is associated with larger price deviations. The ratio of closing volume can be used as a measure of institutional rebalancing. The paper therefore contributes to the literature on institutions and asset pricing.[11] The paper also contributes to the literature on price pressure (e.g., Hendershott and Menkveld (2014)). Our price pressure results raise a concern about potential manipulation of closing prices, the incentives are certainly there.[12]

The paper is organized as follows. Section 2 describes the data. Section 3 studies price deviations at the close and the informational efficiency of closing prices. This section also explores trends in trading volume. Section 4 examines several apparent arbitrages under the light of closing price deviations. Section 5 concludes.

[11] Greenwood and Thesmar (2011), Lou (2012), Vayanos and Woolley (2013), Ben-David, Franzoni, and Moussawi (2018). Cushing and Madhavan (2000) find that the last five minutes of trading explain a disproportionate fraction of daily volatility. They conjecture that institutional trading may explain in part this result but do not test it formally. Furthermore, their analysis is limited to twelve months of stock return data starting in July 1997 and does not use auction prices. In concurrent work, Wu (2019) shows that market-on-close orders submitted to the closing auction is an important trading channel through which passive investing affects underlying stocks.

[12] Different markets use different mechanisms to determine settlement prices. For instance, futures markets typically settle based on a volume-weighted average price. Relatedly, a recent literature examines the role of benchmarks in OTC markets (e.g., Duffie, Dworczak, and Zhu (2017)).

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 over the sample period 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 in 2010-2013 and 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 the of the sample (2015-2018).

We use the end-of-day midquote reported by CRSP, which matches with the 4pm 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 using the CRSP midquote because it is easy to use as a substitute for the closing price for researchers who already have access to CRSP. The more noisy the CRSP midquote is, the more it pushes us against finding an improvement when using it instead of the closing price.

We retrieve institutional ownership data from the 13F filings reported in the Thomson Reuters database. ETF ownership is obtained from the CRSP mutual fund database for 2010 and 2011, and from ETF Global from 2012 to 2018. In our applications, we make use of option and ETF data, which are described further in the corresponding sections.

3 Volume and price deviations at the close

In this section, we first study the properties of closing auction volume and argue that it is mostly uninformed. We then show that this uninformed volume generates temporary price deviations at the close that quickly reverse.

3.1 Auction volume

Table 1 describes end-of-day volume for the entire sample and size quintiles. Auction volume is 5.69% of total daily volume on average across all stock-day observations. Not only is auction volume large as a share or total daily volume, it has been trending up over time. We are interested in understanding what drives auction volume and, in particular, whether it is mostly uninformed. Figure 1 shows how the pre-close volume (in the last five minutes) and the auction volume have been steadily increasing over the sample period. In this figure, aggregate volumes are obtained by dividing total dollar auction volume or total dollar volume in the last five minutes of trading (excluding the auction) across all stocks by total daily dollar volume. The pre-close aggregate volume shows a small but positive trend. It increases from slightly below 5% to just above this level and varies in a relatively narrow range that never exceeds 10% of daily volume. Aggregate auction volume increased from 4% in 2010 to 11% in 2018. Auction volume spikes with apparent calendar regularity from the baseline level to about 20% of daily volume. The last 30 minutes including the auction accounts for almost a quarter of total daily volume. These results suggest that auction volume is large and that some of its drivers differ from volume in the regular session.[13]

[13] Although the U.S. equity market is extremely active, 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. These numbers are mostly driven by small stocks, 0.72% of which have zero daily volume and 9.56% have zero auction volume. In contrast, only 0.21% of stocks in the top size quintile do not have an auction on a given day. The information asymmetry channel in Madhavan (1992) predicts that auctions are more important for thinly-traded securities since the pooling of trades attenuates the adverse selection problem. The numbers in Table 1 suggest that an auction is not viable without a minimum amount of trading activity, in spite of the potential gain from lower adverse selection.

When is auction volume high? What variables drive auction and pre-close turnovers? Our list of explanatory variables includes intraday turnover, defined as volume on the same day between 9:30am and 3:30pm divided by total number of shares outstanding on the previous day. This variable controls for same-day changes in turnover that may not be specific to the auction.[14] We control for stock specific variables such as volatility (the average absolute return over the past five trading days including the current day), lagged return, market capitalization, and ETF and institutional ownerships. Market capitalization helps distinguish the effect of ETF and institutional ownerships from size. Stock fixed effects control for time-invariant stock-specific factors. We include a set of calendar indicator variables for beginning- and end- of-the-month, last day of the quarter, option expiration (typically third Friday of each month), month-of-the-year and day-of-the-week. Russell index rebalancing date indicators (Friday in late June) let us study trading by passive investors as approximately $9 trillion in assets under management are benchmarked to the Russell US Indexes. We include indicators for the day before, the day of, and the day after an earnings announcement. Finally, linear and quadratic trend variables are measured in years and formally test whether closing volume increases over time. To facilitate interpretation, we use the logarithm of each variable except for the lagged return, trend variables, and indicator variables. The regression for intraday turnover (9:30am-3:30pm) serves as a benchmark for auction turnover. We also estimated the same regressions but including the lag of the dependent variable with similar results.

Table 2 reports the results. As expected, a higher intraday turnover (between 9:30am and 3:30pm) is associated with higher auction and pre-close turnovers. A 1% increase in intraday turnover is associated with a 0.33% increase in auction turnover. Based on trend estimates, auction turnover has been increasing by about 11.6% per year in relative terms, while pre-close volume turnover has a trend of 6.4% per year, and intraday turnover stayed unchanged. Volatility is positively related to turnover for all subperiods. This is expected given volatility persistence and the strong relation between volatility and volume.

ETF investors extensively use the closing auction for their trades. ETF ownership is highly significant for auction turnover, but its effect on pre-close turnover is only half as large. In contrast, institutional ownership, excluding ETF ownership, has a positive effect on intraday and pre-close

[14] An alternative approach would be to work directly with the ratio of closing volume to daily volume. This approach makes it more difficult to interpret what drives closing volume since fluctuations in the denominator could be responsible for most of the ratio's variance.

turnover even after controlling for size, but its effect on the auction turnover is insignificant. To further disentangle the effects of ETF and institutional ownerships, Figure 2 plots the elasticity of turnover to ETF and institutional ownerships for each five-minute interval between 3:30pm and the auction. The ETF ownership elasticity of turnover strongly increases as we approach the end of day. It is five times greater for auction turnover than for turnover between 3:30pm and 3:35pm. On the other hand, the institutional ownership elasticity remains unchanged throughout the last half hour.[15] Several strategies contribute to the strong association between ETF ownership and auction turnover. ETFs are often traded to hedge market risk intraday, and these hedges are closed at the end of the day. The arbitrage activity of market participants translates to higher volume in the underlying stocks. Also, leveraged ETFs must rebalance at the close on a daily basis (Cheng and Madhavan (2009)).

Strong calendar effects are also consistent with institutional rebalancing playing a major role for auction volume. Auction and pre-close turnovers spike on Russell rebalancing days, while intraday turnover remains unchanged. Auction turnover is 230% higher, while pre-close volume is 80% higher. This striking result highlights how passive investors concentrate their trading around the close. The most likely explanation is that these investors trade to minimize tracking error. Indeed, auction and pre-close turnovers are 87% and 33% higher on the last month day. In contrast, 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, Rinne, Suominen, and Vaittinen (2020) show that many institutional investors rebalance their portfolios to accommodate inflows in the first days of the month. Consistent with their results, turnover tends to be higher in all periods on the first day of the month but especially so at the auction.

Auction turnover is 60% higher on option expiration days, while pre-close and intraday turnovers increase mildly (12% and 16%). Option market-makers and other option investors hedge their positions in the underlying. They unwind the hedge at the same moment as options expire, which is right after market close on expiration day. Thus, they prefer to unwind delta-hedges during the

[15]ETF ownership is measured at the beginning of each month, while institutional ownership is measured on a quarterly basis. This difference in measuring frequency cannot explain the pattern in Figure 2. It may, however, lead us to underestimate the importance of institutional ownership. If we measure ETF ownership on a quarterly basis instead, institutional ownership becomes a significant predictor of auction turnover, but the magnitude remains small compared to that of ETF ownership.

closing auction.

We observe mild day-of-week and month-of-year effects. Auction turnover is highest on Tuesdays and Fridays even after excluding option expiration Fridays. In contrast, intraday volume is lower on Fridays, and pre-close turnover has no apparent day-of-week seasonality. The high auction volume on Fridays is consistent with investors who want to exit their positions before the weekend, which represents an extended non-trading period. Auction turnover is between 5% and 10% higher in months marking a quarter-end (March, June, September, December), but there is not significant increase in auction turnover on the last day of the quarter beyond the last day of the month increase.

Numerous studies rely on earnings announcement to study informed trading. Consistent with this argument, intraday turnover is 22% higher on pre-announcement day.[16] Controlling for intraday turnover, pre-close turnover is 23% higher. Auction turnover is, however, virtually unchanged, a mere 1.6% increase, beyond what would be predicted by the increase in intraday turnover. Thus, the majority of auction volume appears uninformed and liquidity-driven. Intraday turnover is 96% and 49% higher on the announcement and post-announcement days. In contrast, auction turnover is about 2% lower.

Overall, these results suggest that closing volume is mostly uninformed. Passive investors (index rebalancing days), other institutional investors (month-ends), option market-makers (expiration days) extensively use the closing auction, while informed investors (earnings announcements) do not appear to, or at least not in a substantive way. A natural question is why informed investors do not migrate to the auction if it is mostly composed of uninformed volume, as predicted by models such as Admati and Pfleiderer (1988) and Collin-Dufresne and Fos (2016). First, the amount of uninformed trading at that time could be large enough to dwarf any informed trading. Second, there are specific risks associated with trading in the auction such as uncertainty about the price and about the execution, in addition to special fees levied on auction orders by the exchanges. Also, the informational advantage of some informed traders may be short-lived and low at the end of day. Ultimately, an increase in informed trading should be associated with improved price discovery, which we formally investigate next.

[16]When an announcement is made after trading hours, the day of the announcement is set to the following trading day.

3.2 Price deviations at the close

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

$$\text{deviation\%} = |\log(p_{\text{auc}}/p_{4:00})|, \tag{1}$$

where p_{auc} is the auction price and $p_{4:00}$ is the quote midpoint at 4pm.

Table 3 Panel (a) reports the distribution of closing price deviations for the entire sample and across size quintiles. It includes average, standard deviation, and percentiles. Auction price deviation is 8.12 bps on average and ranges from 20.6 bps for small stocks to 2.66 bps for large stocks. To put the numbers into perspective, a 8.12 bps corresponds to 5% of daily volatility and 6 million dollars in market capitalization for an average stock. The distribution have positive skewness: the closing price is usually close to midquote but occasionally deviates by a lot. In 5%, 1%, and 0.1% of cases closing prices deviate by more than 26.8, 63.13, and 195.22 bps, respectively. That is, prices for about 30 stocks deviate by more than 0.63% on a typical day.[17] In dollar terms, the numbers in Table 3 are economically large given the large volume traded at the auction.[18]

Auction price deviations contribute substantially to daily volatility. The auction represents a single trade, which makes it harder to compare it to other intervals. We consider a simple benchmark: the volatility ratio is defined as the 20-day average of absolute deviation at the auction divided by the 20-day average of absolute midquote return between 9:45am and 3:45pm. Table 3 Panel (b) reports the distribution for this ratio. The jump from midquote to auction price that occurs in a few seconds (the median time between close and auction is seven seconds) accounts for 5% of daily price variation and for more than 23% for the top 1% of the sample. Even for large stocks, average and first percentile are 3% and 12% of daily volatility. The volatility ratio decreases monotonically with size from 9% for small to 3% for large stocks. We will examine two potentially complementary explanations for these results. First, the auction may improve price discovery more for less actively-traded stocks (Madhavan (1992)). Second, transitory liquidity shocks may have a larger impact for smaller stocks due to limited market making capacity. Also, for stocks of above-

[17] We also study price deviations for large ETFs (SPY, QQQ, and S&P sectors) and find that they behave similar to large stocks with average deviation of 3.63 bps, and 99$^{\text{th}}$ percentile of 16.32 bps (see Section 4.2).

[18] Descriptive statistics for auction deviations computed with TAQ end-of-day midquote instead of CRSP midquotes are reported in the appendix.

median size, the closing price is above the midquote more often than below. For instance, for the top-size quintile, 650,633 (597,586) deviations are above (below) the midpoint with a mean of 2.88 (2.70) basis points. Thus, positive imbalances are more frequent than negative imbalances.

Auction trades are rarely executed at the quote midpoint. Hence, we decompose the (absolute) deviation into spread and price impact components:

$$|\text{deviation}\%| = \text{half-spread}\% + \text{price impact}\%. \tag{2}$$

The (realized) half-spread is defined as $\log(p_{\text{ask}}/p_{4:00})$ if $p_{\text{auc}} \geq p_{4:00}$ and $\log(p_{4:00}/p_{\text{bid}})$ otherwise. Similarly, price impact% is $\log(p_{\text{auc}}/p_{\text{ask}})$ if $p_{\text{auc}} \geq p_{4:00}$ and $\log(p_{\text{bid}}/p_{\text{auc}})$ otherwise. Price impact can be negative if the auction price is less than half the spread away from the closing midpoint.

The distribution of the half-spread and price impact components of the closing deviation is reported in Table C2 in the appendix. 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. Consistent with this interpretation, the average half spread is 7.56 bps and exceeds 70.18 bps for the top percentile, while price impact is 0.55 bps on average and exceeds 19.7 bps for the top percentile. That is, the price deviation equals the half spread for the majority of auctions. In this regard, the closing auction is like a typical trade that can occur at the bid or ask, and thus the mechanism for deviations is similar to the bid-ask bounce. Nevertheless, price impact can be large and substantially larger than the half spread. As we show below, when closing volume is large, stocks experience large price impact. For small stocks, the half-spread exceeds the price deviation on average as the average price impact is negative (-1.6 bps). Thus, the auction price is often within the 4pm spread, even though it rarely equals the 4pm quote midpoint. For large stocks, the half-spread and price impact components are equally important: 1.47 and 1.19 bps, respectively.

We formally study the determinants of closing price deviations in Table 4 using panel regressions. The list of variables includes auction turnover (volume normalized by shares outstanding), intraday volume excluding auction, realized volatility during the last hour and the rest of the day (computed from five-minute midquote returns), bid-ask spread, stock price, (all the variables listed so far are in logs) linear and quadratic trends, and NYSE-listing indicator. Our main specification of interest is in Panel (a) and includes stock fixed effects to focus on time-series variation. Deviation and spread variables are winsorized at 0.05%. Higher auction turnover leads to larger price deviations: 0.88 bps deviation for a 1% increase in turnover. Auction turnover has a larger impact for smaller stocks. However, intraday turnover has a negative effect perhaps because auction volume has a larger impact on low volume days due to low liquidity. When the spread is high, price deviations are larger, as these two are obviously related. Higher volatility leads to larger price deviations. Auction volume and the other variables serve as proxies for order imbalance by liquidity seekers that is not directly observable in TAQ. The coefficients are quantitatively close whether we examine the absolute price deviation or price impact (of course, except for the spread coefficient). These results are reported in the appendix.

Panel (b) focuses on cross-stock variation by including date fixed effects instead of stock fixed effects. For large stocks, auction turnover is positively associated with auction deviation. Interestingly, this relation flips among small stocks. While we do not explore this issue in detail, it may be linked to the puzzling observation in Table 1 that small stocks have an abnormally high number of days without an auction, even though theory predicts that the benefits of consolidating order flow in an auction should be largest for these stocks. It appears that unless a critical amount of trading volume is achieved, an auction is unstable and subject to large price deviations. NYSE auctions have significantly larger deviations than Nasdaq auction. We discuss this point in detail below when we discuss the role of segmentation for auction price deviations.

Do price deviations affect diversified portfolios and thus carry systematic risk? Yes, they do as price deviations are correlated across stocks. The mechanism is intuitive: investors often simultaneously buy or sell multiple stocks at the auction. This simultaneous buying leads to correlation in order imbalances and price deviations across stocks. To compute the aggregate price deviation, we first aggregate *signed* price deviations across individual stocks for each day in proportion to their capitalization and then take the absolute value. That is, if half of the stocks have a positive deviation and the other half a negative deviation, the aggregate deviation will be close to zero. Aggregate price deviation is 0.93 bps on average, or about three billion dollars per day if adjusted for total market capitalization. The aggregate deviation is about one third of average individual deviation for large stocks (2.66 bps in Table 3). Thus, deviations are highly correlated across stocks. Therefore, closing price noise can lead to spurious margin calls and affect even broadly diversified portfolios. The largest value of aggregate deviation was 12 bps on August 11, 2011, when the market rebounded after S&P downgraded U.S. sovereign debt for the fist time in history. Thus, extreme market returns amplify the effect of aggregate price deviation on portfolio value.

Figure 3 compares the aggregate price deviation (its ten-day moving average) with the VIX index during sample period. The two variables are highly correlated; prices are more likely to deviate at the close when aggregate risk is high. These results are robust to using only the price impact component of the aggregate price deviation and therefore not driven by a commonality in spreads. Table C4 in the appendix confirms that the aggregate closing deviation is driven by auction volume as it spikes on the same days; i.e., days associated with institutional rebalancing. In the time series regression of aggregate deviation on calendar indicator variables, the deviation is 27% higher on the first day of a month and on option expiration days, 60% higher on month-end, and 159% higher on Russell rebalancing days.

These results show that price deviations matter not only for individual stocks but also at the aggregate level as price deviations are highly correlated across stocks.

3.3 Do price deviations reflect information or noise?

Auction prices deviate frequently and sometimes substantially from the 4pm midquote. Do auction prices deviate because information is incorporated through trading or do they deviate because of price pressure? The information hypothesis predicts that the deviation should be permanent while deviations caused by price pressure should be reversed shortly. We test this prediction with a simple model that studies how log overnight return depends on log auction deviation:

$$\log(p_{9:45,t+1}/p_{\text{auc},t}) = a + b\log(p_{\text{auc},t}/p_{4:00,t}) + e_t, \tag{3}$$

where $p_{9:45,t+1}$ is the midquote price on the following day at 9:45am, $p_{\text{auc},t}$ is the auction price, and and $p_{4:00,t}$ is the midquote price at 4:00pm. The next-day price is adjusted for share splits and dividends. Since quotes can be noisy and unreliable over the first couple minutes of trading, we use the midquote 15 minutes after the open. We also control for the last five-minute return (from 3:55pm to 4pm) in some specifications.

The coefficient for price reversal b should be close to zero if auction price deviations are fully efficient and close to -1 if the deviation is entirely due to price pressure. Table 5 shows that the coefficient is -0.85, or 85% of the auction deviation is reversed by the next morning. For large and small stocks, 110% and 85% of the price closing deviation is reversed, respectively. The coefficient is not statistically different from -100% for large stocks. The reversal coefficient approaches -1 (complete reversal) if we control for the 3:55-4:00 price change. These results confirm that price deviations are primarily 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 4pm midquote change is mostly efficient.[19]

As pointed out above, the auction price incorporates half the spread. Hence, we also check how much of the reversal is driven by a mechanical bounce effect. To do so, we adjust the reported auction price by adding (subtracting) half the spread for trades made below (above) the 4pm midpoint. We then estimate (3) using this spread-adjusted auction price. The reversal coefficient becomes closer to -1 after this adjustment, -0.97 and -0.98 for large and small stocks. Overall, most of the auction deviation reverses overnight and is uncorrelated with the bid-ask bounce.

To provide another perspective, we compute a popular price discovery measure: the weighted price contribution (e.g., Barclay and Hendershott (2003)). We divide the 3:30pm-9:45am 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, the weighted price contribution (WPC) for interval k is defined as

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

where $r_{i,3:30-9:45}$ is the (log) return of stock i from 3:30pm to 9:45am on the next day, $r_{i,k}$ is the return over interval k (for instance, between 3:50 and 3:55pm), and N the number of stocks in the sample on that day. A stock is included on a given day, if it has an auction price and a valid midquote at 9:45am on the next day. All returns are winsorized at 0.005%.

The auction represents only one trade, but matches a large volume. As 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

[19] As mentioned in Section 2, the results in this section are similar if we use the last available TAQ midpoint instead of the CRSP midpoint.

auction should have a similar price contribution as other intervals. Table 6 reports WPC estimates for size quintiles and full sample. The closing auction contributes little to price discovery as its price contribution is 0.003 or about ten times lower than what other periods with similar volume contribute (e.g., 0.029 for the last five minutes). The results are similar for all size categories with the auction having slightly higher WPC for smaller stocks. Interestingly, if we use the auction price adjusted for the spread (aũc), the auction's contribution of the WPC drops to zero in the last two columns of Table 6. Thus, auction only conveys information on whether it takes place at the ask or at the bid. Overall, this alternative price discovery measure confirms that auction price deviations contribute little to price discovery.

An uninformative auction deviation does not imply that auction volume is fully uninformative since exchanges release information about order imbalance ahead of the auction (see, for instance, Mayhew, McCormick, and Spatt (2009)). The NYSE (Nasdaq) starts releasing imbalance information at 3:45pm (3:50pm) over most of our sample period. If the imbalance indicator is informative, weighted price contributions would increase at 3:45pm (3:50pm) for NYSE (Nasdaq) stocks. To test it formally, we perform a simple difference-in-difference regression. WPCs between 3:40-45 and 3:45-55 are averaged each day separately for NYSE and Nasdaq stocks in a given market capitalization quintile. These WPCs are regressed on an intercept, a NYSE and 3:45-50 interval indicators and their interaction. This interaction term reflects that NYSE disseminates closing order imbalances during 3:45-50 while Nasdaq does not. Table C5 in the appendix reports the results for each market capitalization quintile. Among large stocks, the difference in price contribution between 3:40-45 and 3:45-50 is weakly statistically different for NYSE stocks compared to Nasdaq stocks. Among other size quintiles, the difference is significant: WPC increases by about 25% compared to the control sample.[20] Hence, our tests suggest that auction volume contributes to price discovery, but that this contribution is not substantial relative to the associated trading volume and is quite limited for large stocks.

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 C6 in the appendix reports descriptive statistics for the variance

[20] 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 NYSE and Nasdaq WPC suggests that this channel, if it exists, is economically small.

ratios of daily returns. The average ratio of 1.014 means that the closing price adds 1.4% of non-informative variance. The average ratio for large small stocks is 4.5%. These numbers are statistically significantly different from one at the 1% level. Interestingly, equal-weighted and value-weighted portfolios have high variance ratios. The variance ratio of a value-weighted portfolio of large stocks is 1.010, which is significantly larger than the mean variance ratio across large stocks of 1.003. This result supports our previous findings of a common component in deviations.

These results indicate that the 4pm midquote is more informative than the closing price, which mostly adds noise. Price reversal is consistent with liquidity provision ahead of the overnight period. Risk-averse liquidity providers likely require compensation to hold inventories overnight due to its low liquidity and high price jump risk. A larger reversal is also consistent with increased market power (segmentation) at the auction. Exchanges have an effective monopoly over the closing auctions for their listed securities.

To disentangle among these two explanations, we examine after-hours trades. Market power hypothesis predicts that some reversal should start right after the auction, whereas overnight risk predicts that the reversal should occur mostly overnight. To compute after-hour returns, we compute VWAP between 4:10-4:20pm, 4:20-4:30pm, ..., 4:50-5:00pm.[21] We start at 4:10pm to avoid guaranteed close orders and to make sure that the auction has already taken place and estimate

$$r_{\text{auc-}\tau} = a + br_{4:00-\text{auc}} + e, \tag{5}$$

where τ is 4:20pm, 4:30pm, etc. (with stock fixed effects). 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 twenty-minute window. The price mostly reverses right after the close, which supports the market power/segmentation hypothesis. Table 7 shows that the price reverts half-way to the pre-close midquote in just twenty minutes after the close. Consistent with the full sample results, their prices fully revert to pre-close miqquote the next morning as a -1.08 coefficient on the closing price deviation indicates. 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. The bottom panel of the table confirms that the results are not affected by the bid-ask spread bounce. Overall, prices revert

[21] We keep only regular trades with indicators: @ TI, @ T, @FTI, @FT for Nasdaq and T, TI, FTI, FT for NYSE.

quickly half-way supporting reversal stemming from both market power and overnight risk.

A comparison of NYSE and Nasdaq auction price deviations provides additional suggestive evidence on the role of transparency. Although the two auctions have a similar design as explained in the appendix, they differ in one important way. NYSE offers a unique order type, so-called "D-Quote." Unlike regular MOC/LOC auction order types, which must be submitted prior to 3:45pm 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 therefore lead to larger price deviations. D-Quotes are fully electronic orders and effectively allow traders to circumvent the standard auction rules. Although officially they are accessible only to NYSE floor brokers, today nearly all brokers have relationships with floor brokers in order to access D-Quotes.

Table 4 shows that absolute auction deviations are 1.2 to 1.4 bps higher on the NYSE than on the Nasdaq, everything else being equal and independently of the specification (cross-section or time series). The difference represents about 18% of the average price deviation (8.12 bps). Larger price deviations for NYSE are consistent with the argument of Stoll and Whaley (1990) that the market power of the specialist can increase the volatility of the NYSE opening auction.

To benchmark the NYSE closing auction deviation, we estimate the cross-sectional regression in Table 4 for end-of-day absolute five-minute log returns. We focus on large stocks to avoid issues related to thin trading. Figure 4 plots the coefficient and confidence interval for the NYSE indicator variable. For the 3:30-35pm, 3:35-40pm, 3:40-45pm intervals, NYSE and Nasdaq deviations are not statistically different. At 3:45pm, the NYSE coefficient becomes positive and statistically significant. This coincides with the dissemination of auction order imbalance information on the NYSE. The opposite takes place at 3:50pm, which corresponds to the dissemination of Nasdaq order imbalance information. The magnitude is, however, much larger than for the NYSE. At 3:55pm, there is no significant difference despite the diffusion of D-Quotes order imbalance on the NYSE (see Appendix A). At the auction, the NYSE indicator is strongly positive and statistically significant.[22] The muted response of price deviations for NYSE large stocks (relative to Nasdaq large stocks) to order imbalance information, combined with a surge at the auction, supports the

[22]The auction coefficient corresponds to the value for large stocks in Panel (b) of Table 4. The coefficient differs slightly since we do not control for realized volatility between 3:00pm and 3:55pm due to the overlap with end-of-day returns in the other regressions.

view that lower transparency leads to increased deviations. As pointed out before, these deviations do not contribute to price discovery.

To conclude this section, we briefly discuss how trading costs compare between the auction and pre-close. Price deviations at the close can be interpreted as costs of institutional trading and indexing. These costs can be quite large, but the costs of trading during the pre-close are also non-trivial. For institutional investors, VWAP is more relevant than the bid-ask spread. We pick the last five minutes before the close as a benchmark because its trading volume is comparable to the auction volume. Thus, we compare the closing price deviation with the VWAP price deviation in the last five minutes. The two price deviations are computed similarly except that the VWAP deviation compares VWAP price in the last five minutes with the midquote at 3:55. We find that the VWAP deviation is larger (13.0 versus 8.1 bps) as Table C8 in the appendix shows. This result does not account for the fact that more information arrives in the last five minutes than in the auction. To account for this, we also compare price impacts measured as price deviation divided by dollar trading volume. These VWAP and closing price impacts are comparable (Table C9 in the appendix). A deeper analysis would require account-level data, as we do not account for the opportunity costs of taking versus providing liquidity. Also, the auction price deviation reversal effectively makes auction participants that trade in the direction of the imbalance pay a cost to get an execution at the closing price. This cost comes in addition to fees charged by the exchanges on orders participating in the auction.

3.4 Closing volume and return predictability

In this section, we discuss what the above results about the information content of closing auction volume imply about future stock returns. As closing volume is mostly uninformed, it can help detect unusual trading activity, such as informed trading, during the rest of the day. Consider a ratio of auction volume to total daily volume. A low auction-to-total volume ratio, i.e., when intraday volume is high relative to auction volume, can indicate more informed trading during regular trading hours. The assumptions that closing volume is mostly uninformed and is indicative about uninformed trading during regular trading follow from our prior results. We compare auction-to-total volume's ability to predict returns with pre-close-to-total volume computed between 3:50pm and 4:00pm. Our earnings announcement results suggest that more informed trading occur pre-close than at the auction, even though the two volumes are comparable and adjacent in time. To distinguish between persistent differences across stocks and dynamic time-series effects, we decompose auction-to-total volume into monthly average and surprise: the difference between current value and monthly average.

We estimate a panel regression of next-week and next-month stock returns on volume predictors, day fixed effects, and control variables. We skip a day between predictors and weekly or monthly returns to avoid confounding effects as closing price today is an input to next-day return (however, we do report next-day return results for completeness). The control variables include returns during each of three previous days, idiosyncratic volatility (from abnormal daily returns from the Fama-French four-factor model estimated over the previous month), momentum (stock returns from six months to one month prior to the date), monthly reversal (previous month return), logarithm of market capitalization, beta, Amihud (2002) illiquidity measure, and a high-volume indicator, which Gervais et al. (2001) set to one (-1) if current volume is greater (lower) than 90% (10%) over the previous 49 days. All right-hand-side variables, except for indicators and fixed effects, are standardized to have a zero mean and unit variance. Stock returns are computed from daily returns in CRSP and are adjusted for stock delistings as in Shumway (1997). Standard errors are clustered by stock and day to account for overlapping returns.

We first study the raw volume ratios and then decompose them into monthly average and surprise. Table 8 shows the results. Both auction and pre-close volume ratios predict next-day returns but with negative and positive signs, respectively. A high auction volume ratio corresponds to low returns next day. We mainly focus on weekly and monthly returns that are computed skipping the next-day and are consistent with next-day return results. Auction-to-total volume continues to predict returns negatively with t-statistics of -3.3 and -1.8 for weekly and monthly returns. The coefficient for pre-close volume is positive but not statistically significant. We report the coefficients for control variables in Table C7 in the Appendix. Idiosyncratic volatility, and short-term stock reversal (monthly and daily return lags), and the high-volume premium indicator are the strongest return predictors.

To explore the auction volume ratio, we decompose it into monthly average and surprise. The auction-to-total surprise negatively predicts returns (t-statistics of -4.2 and -4.6 for weekly and monthly returns) while its monthly average does not (t-statistics of -0.6 and 0.0). Thus, the predictability is driven by time-series shocks rather than persistent differences across stocks. In untabulated results, portfolio sorts confirm the negative relation between auction-to-total surprise and future returns. The bottom decile portfolio outperforms the top decile by 26 bps and 10 bps for monthly and weekly alphas from Fama-French four-factor model. Figure C1 in the appendix shows a monotonic linear relation between auction volume percentile and weekly returns, while for monthly returns, alphas are concentrated in below-median part that corresponds to high daily volume relative to auction volume. In contrast, pre-close volume surprise fails to predict returns, and pre-close volume average is positively associated with monthly returns (t-statistics of 2.5) but is insignificant for weekly returns. Overall, the ratio of auction-to-total volume and especially its surprise negatively predict returns while pre-close volume does not.

Few variables consistently predict returns, we identify a new return predictor, auction-to-total volume ratio and its surprise. This predictor is motivated by our results about the information content of auction volume and price deviations. Of course, this ratio may predict returns for many reasons. One possibility is that shocks to auction-to-total volume reflect a change in the informational content of the order flow. More informed trading, as reflected by higher daily volume relative to auction, may lead to higher future returns if informed investors are more likely to trade on positive information and the information diffuses slowly. Indeed, Kraus and Stoll (1972), Chan and Lakonishok (1993), Campbell, Ramadorai, and Schwartz (2009), and others show that institutional purchases are more informed than sales. Several other results support this information hypothesis. The returns predicted by auction-to-total volume are permanent. In contrast, the pre-close volume ratio fails to predict returns perhaps because the pre-close informational content is similar to that of the rest of the day and thus cancels when their ratio is taken. The return predictability results are also consistent with the hypothesis by Gervais et al. (2001) that shocks in the trading activity of a stock affect its visibility, and in turn the subsequent demand and price for that stock. Passive investors, who have little discretion about which stocks to hold, are major auction participants. Thus, auction clientele is likely quite stable. In contrast, a volume spike during regular trading may indicate that new investors are attracted to the stock. To partially account for this channel, the return regressions in our analysis control for the high-volume indicator introduced by Gervais et al. (2001).

4 Do closing price deviations matter?

We next focus on the implications of price pressure around the close. In particular, since the midquote at 4:00pm is more efficient than the closing price, we argue that the former should replace the later in many applications. This recommendation is easy to implement as both prices are available in CRSP. Closing prices frequently deviate from closing midquotes, and these deviations are fully reversed, but does using the midquote instead of the CRSP price make a difference? It does in two applications that we explore: put-call parity violations and ETF mispricing.

4.1 Put-call parity violations

Closing price deviations from pre-close midquote help explain put-call parity violations. Stock prices implied from option prices by put-call parity often significantly deviate from actual stock prices, presenting apparent arbitrage opportunities. An extensive literature started by Stoll (1969) and Klemkosky and Resnick (1979) studies these violations, mostly with daily data. Parity violations are particularly puzzling because in modern markets, option market-makers, who quote almost all option bid and ask prices, are fully automated, instantly observe changes in the underlying price, and can respond by adjusting option prices within milliseconds. A related puzzle is that the put-call violations predict next-day stock return (Cremers and Weinbaum (2010)). That is, the future stock return is lower if the option-implied stock price is lower than the actual stock price. This result is often interpreted as evidence of option prices containing superior private information.

We show that the price deviations at the closing auction partially resolve these two puzzles. In particular, even if the two markets are perfectly synchronized, put-call parity violations can occur because the option market closes before the closing auction in the underlying. Indeed, the equity option market closes at 4pm EST, which coincides with the end of the regular trading session in the underlying. However, the closing auction that determines underlying closing price takes place a few seconds later. Thus, if the closing price deviates from the 4pm midquote reflected in option prices, this price deviation can cause a parity violation. According to this explanation, put-call parity violations predict returns not because of informed option trading but because they reflect the closing midquote and the closing price temporarily deviates from the midquote.

We first explain how put-call parity violations are computed and then discuss the results. Daily option prices are from OptionMetrics. The data currently end in 2017, and thus our sample period is from 2010 to 2017. Dividends are from CRSP. We apply mild filters and keep options with (i) bid price greater than ten cents, (ii) well-defined option delta and implied volatility, (iii) option maturity between 15 and 90 days. To avoid early exercise issues, we focus on at-the-money options with call delta between 0.4 and 0.6. We compute implied stock price using the standard put-call parity:

$$IS_i = C_i - P_i + K_i\, exp(-rT_i) + PV(D), \tag{6}$$

Implied stock price (IS_i) is computed for a given put-call pair (C_i,P_i) with the same strike (K_i) and annualized time-to-expiration (T_i). The risk-free rate (r) equals the maturity-matched LIBOR rate. Implied bid (ask) price is computed using equation (1) with call bid and put ask (call ask and put bid). For every stock and day, we compute a median (to avoid outliers) over all implied bid and ask prices across all available option contracts. True violations must be transitory, yet some violations persist for many days because it is difficult to properly account for American exercise features (Kamara and Miller (1995)), shorting costs (Ofek, Richardson, and Whitelaw (2004) and Muravyev, Pearson, and Pollet (2018)), dividends, and risk-free rate. To account for persistent violations, we adjust the implied prices using an average violation between implied midquote and actual closing price in the last ten trading days. If the moving average cannot be computed, this adjustment is set to zero. That is, we subtract the average violation in the last ten days from the current violation: $(IS_{i,t} - S_{i,t}) - MA_{t-1:t-10}(IS_{i,t} - S_{i,t})$.

Phillips and Smith Jr (1980) and others argue that accounting for large option bid-ask spreads is crucial, which we do by counting a deviation as a violation only if the stock price is outside the implied bid and ask price range:

$$IViolat = [IS^{bid} > S]\, OR\, [IS^{ask} < S]. \tag{7}$$

We compute this violation indicator separately using the closing auction price and the closing midquote. Table 9 presents the frequency of parity violations relative to these two prices. Out of 2,500,777 stock-days, 4.69% or 117,245 violate the parity relative to the closing price. Violations are surprisingly frequent and are likely caused by multiple reasons. For example, the implied price can be wrong due to noise in option prices or due to limitations of put-call parity discussed above. We study one particular explanation, mis-synchronization between option and stock prices due to the closing auction. If parity violations are computed with respect to closing quote midpoint instead of closing price, the number of violations drops from 117,245 to 107,041, or 10,204 fever violations. Thus, even though the auction is conducted only few seconds after the close, and the closing price is usually close to the closing midquote. This mis-synchronization explains at least 9% of all violations, which is statistically and economically significant.

The closing price is usually close to the closing midquote, and thus the difference between implied and actual prices is almost identical in those cases. To highlight the role of the closing auction, we focus on the subsample where auction price deviates significantly (by more than 10 bps) from the closing midquote or 10.5% of the total sample. Closing price triggers 8,489 violations, while midquote triggers 6,499, or 23% fewer violations. In untabulated results, we show that the midquote at 15:55, five minutes before close, produces about the same number of parity violations as the closing price. That is, auction price is as "bad" as price, which is stale by several minutes.

Noise in closing prices not only triggers put-call parity violations but also systematically biases implied volatility, which is a function of the closing price. For example, implied volatility for puts is systematically higher than for calls when auction stock price deviates above the closing midquote. Numerous studies rely on the implied volatility surface that OptionMetrics computes with closing stock prices. The results in some of these studies could be sensitive to the implied volatility bias induced by closing auctions.

While mis-synchronization explains a large number of violations, it is even more important for explaining why parity violations predict stock returns. The predictability is concentrated on the day following the violation. Currently, this next-day predictability is attributed to informed option trading and by institutional price pressure. Cremers and Weinbaum (2010) argue that informed investors push option prices creating parity violations because the equity market is slow to react to their trading. E.g., investors with negative information about the stock buy put options making puts expensive relative to calls. Alternatively, Goncalves-Pinto et al. (2019) argue that the option implied price is more efficient than the stock price because uninformed price pressure is higher in the underlying than in options, making the implied price closer to "fundamental value." Thus, both theories argue that option prices are more efficient than the underlying price, and that violations are short-lived.[23] All of these papers use stock returns computed from closing auction prices, despite Battalio and Schultz (2006), who showed that synchronized intraday data should be preferred to closing prices when computing put-call parity relations.

We argue that violations predict next-day stock return because option prices reflect the closing midquote, while the closing price temporarily deviates from the midquote. To test this hypothesis, we decompose next-day stock return into the overnight part from closing auction to 9:35am next morning $Ret_{auc(t)}^{open(t+1)}$, and from next morning till closing auction $Ret_{open(t+1)}^{open(t+1)}$, as auction mispricing is corrected right after market open. The last panel of table 9 shows that parity violations based on closing price strongly predict overnight returns with a t-statistic of 9.0, but the predictability disappears immediately after open. However, parity violations based on midquote fail to predict overnight or intraday returns. The results remain unchanged if we control for intraday returns during the current day (9:35 to 15:55 and 15:55 to 16:00 returns). Also, we obtain similar results if permanent violations are included in the analysis (i.e., if ten-day average is not subtracted from the current violation to focus on temporary violations).

What do these results mean? We previously showed that the auction price sometimes deviates from the closing midquote, which triggers a put-call parity violation. Since the closing price reverts to the midquote the next morning, closing price parity violations predict overnight returns. There is no return predictability in all other cases, including when parity violations are properly computed using synchronized option and stock prices at 4pm. That is, our results are consistent with option prices perfectly reflecting the concurrent underlying price except that the options market is closed as during the closing auction. This mis-synchronization leads to put-call parity violations and stock return predictability. This explanation complements the existing literature that argues option prices are more informationally efficient than the underlying stock price. Overall, price deviations at the closing auction explain a significant share of put-call parity violations and fully explain the next-day stock return predictability.

[23] Also, Muravyev et al. (2018) argue that persistent put-call parity violations are proxy for shorting fees that are known to predict stock returns. We complement their results by focusing on only short-term violations as the persistent lending fee is eliminated in our measure since we measure violations relative to its ten-day moving average.

4.2 ETF mispricing

An Exchange-Traded Fund (ETF) derives its value from a basket of underlying securities. ETF prices may, however, deviate substantially from their net asset values (NAVs) despite the existence of authorized participants. In particular, many papers examine ETF mispricing using daily ETF prices and NAVs (e.g., Broman (2016); Ben-David et al. (2018)). Similar to stocks, the daily reported ETF price is in general the one derived from the closing auction. Furthermore, for most ETFs the NAV is computed using the underlying securities' closing prices. As a result, price pressure at the close can generate mispricing that does not effectively reflect an arbitrage opportunity.

To shed light on this question, we first examine price deviations around the close for a range of well-known ETFs. We focus on our analysis on the SPY ETF (which tracks the S&P 500 index), QQQ ETF (which tracks the Nasdaq-100 index), and the sector SPDR ETFs: XLB, XLV, XLP, XLY, XLE, XLF, XLI, XLK, and XLU. The data collection process is described in Appendix B. Panel (a) of Table 10 describes the absolute price deviation at the close and decomposes it into half spread and price impact. Both QQQ and SPY can experience significant price deviation at the close. The mean absolute price deviation is 1.68 (1.83) basis points for QQQ (SPY), which compares to a mean absolute price deviation of 2.66 basis points across the quintile of large stocks (Table 3). When further compared to large stocks, these two ETFs experience relatively small half spreads but sizable price impact on average. The average price impact of the SPY is 1.54 basis points, which is greater than that of large stocks.[24]

Can trading around the close explain ETF mispricing? Two effects may be at play. First, as highlighted in Table 10, the ETF price can substantially deviate from the midquote at the end of the day, which could generate mispricing. This issue is not new in the ETF literature. For instance, Broman (2016) and Petajisto (2017) use the bid-ask midpoint to compute mispricing. However, the motivation for doing so in these papers is to mitigate concerns about the illiquidity of smaller ETFs. In contrast, here we argue that even for large ETFs such as SPY or QQQ the use of closing prices may result in spurious mispricing. The second potential effect of trading around the close on ETF mispricing is related to the NAV. Typically, NAVs are computed using closing prices of the

[24] In untabulated results, we find that the auction deviation sensitivity to turnover is large and significant for both QQQ and SPY. Interestingly, for SPY only the realized volatility in the last half hour of trading significantly predicts the auction deviation. The coefficient on the intraday realized volatility is close to zero and statistically insignificant.

underlying constituents. Hence, auction price deviations may distort the NAV itself.

To assess the above two effects. We consider three components of mispricing: $|\log(\text{price}/\text{NAV})|$, $|\log(\text{midpoint}/\text{NAV})|$, and $|\log(\text{midpoint}/\text{NAV}_{\text{mid}})|$. The first one is the standard measure of mispricing and the second one accounts for ETF closing price deviation. The third one accounts for both the ETF closing price deviation and the closing price deviation of the underlying constituents. More precisely, NAV_{mid} is the NAV compute using closing midquotes instead of closing prices. The computation of this quantity requires to know precisely the weight of each constituent in the ETF. We describe the data and procedure in the appendix. Due to the time-intensive nature of computing this quantity in an accurate way, we focus our analysis on the SPY in the last year of the sample (2018). Panel (b) of Table 10 reports the results. In 2018, the mean absolute deviation is 2.50 basis points for the SPY. The mean deviation drops to 1.59 basis points when the SPY closing midpoint is used. The mean deviation drops by an additional 0.56 basis points once the NAV is computed using closing midquotes. The bottom part of the panel shows that these differences are highly statistically significant. In total, the average mispricing is reduced by 1-1.03/2.50=58.8% when taking into account the distortions in closing prices.

Overall, this section shows that the use of closing prices can inflate ETFs mispricing. This distortion is induced by trading volume and can therefore affect large and actively-traded ETFs such as SPY. Furthermore, it is likely not to represent an actual arbitrage opportunity since trading in the auction exposes an arbitrageur to both price uncertainty and execution uncertainty.

5 Conclusion

Closing auctions handle huge volume, which will only increase as passive investing continues to expand. However, we find that closing prices contain almost no incremental information compared to closing quote midpoints. Price deviations at the close are mostly reversed the next morning for small stocks and completely reversed for large stocks. Price deviations are highly correlated across stocks and therefore introduce a non-diversifiable risk. Thus, the closing midquote is a better benchmark and should replace the closing price in computing price-related variables such as stock returns. Replacing the closing price with the midquote is easy as both are readily available in CRSP.

NYSE auctions produce consistently larger price deviations than Nasdaq auctions. Unlike NYSE, Nasdaq auction's rules force investors to mitigate closing order imbalances. We leave for future research to explore how closing auction design can be modified to produce more efficient prices. An investigation of alternative market designs and their interactions with institutional benchmarks is a fruitful area for future research, especially since the shift towards passive investing may lead to a further concentration of trading volume around the close.

Price reversal makes auction participants that trade in the direction of the imbalance pay a cost to get an execution at the closing price on top of exchange fees. Since auction deviations are correlated across stocks, this suggests that institutions trading in the same direction (e.g., for benchmarking reasons) are likely to bear this "cost of indexing." For these traders, our analysis highlights the cost associated with trading in the auction. However, a closing call auction may be the best trading mechanism in light of existing institutional incentives. Also, independently of the magnitude of the cost relative to a similar volume traded during the day, there is the question of whether it is a good thing to use distorted prices as benchmarks for research and in practice.

We show two applications for which replacing closing price with the midquote makes a difference. ETF mispricing decreases by 59%. The number of put-call parity violations decreases, and the parity violations stop predicting next-day stock returns. Other potential applications include the effect of closing deviations on price reversal, correlations and volatility.

References

Admati, A. R. and P. Pfleiderer (1988). A Theory of Intraday Patterns: Volume and Price Variability. *Review of Financial Studies 1*(1), 3–40.

Amihud, Y. (2002). Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets 5*(1), 31–56.

Asparouhova, E., H. Bessembinder, and I. Kalcheva (2010). Liquidity biases in asset pricing tests. *Journal of Financial Economics 96*(2), 215–237.

Asparouhova, E., H. Bessembinder, and I. Kalcheva (2013). Noisy Prices and Inference Regarding Returns. *Journal of Finance 68*(2), 665–714.

Bacidore, J. M. and M. L. Lipson (2001). The effects of opening and closing procedures on the nyse and nasdaq. In *AFA 2001 New Orleans Meetings*.

Barclay, M. J. and T. Hendershott (2003). Price discovery and trading after hours. *Review of Financial Studies 16*(4), 1041–1073.

Barclay, M. J., T. Hendershott, and C. M. Jones (2008). Order consolidation, price efficiency, and extreme liquidity shocks. *Journal of Financial and Quantitative Analysis 43*(1), 93–121.

Battalio, R. and P. Schultz (2006). Options and the bubble. *Journal of Finance 61*(5), 2071–2102.

Ben-David, I., F. Franzoni, and R. Moussawi (2018). Do ETFs increase volatility? *Journal of Finance 73*(6), 2471–2535.

Blume, L. and R. F. Stambaugh (1983). Biases in Computed Returns. *Journal of Financial Economics 12*(3), 387–404.

Broman, M. S. (2016). Liquidity, style investing and excess comovement of exchange-traded fund returns. *Journal of Financial Markets 30*, 27–53.

Campbell, J. Y., T. Ramadorai, and A. Schwartz (2009). Caught on tape: Institutional trading, stock returns, and earnings announcements. *Journal of Financial Economics 92*(1), 66–91.

Chakraborty, A., M. S. Pagano, and R. A. Schwartz (2012). Order revelation at market openings. *Journal of Financial Markets 15*(2), 127–150.

Chan, L. K. and J. Lakonishok (1993). Institutional trades and intraday stock price behavior. *Journal of Financial Economics 33*(2), 173–199.

Chelley-Steeley, P. L. (2008). Market quality changes in the london stock market. *Journal of Banking & Finance 32*(10), 2248 – 2253.

Cheng, M. and A. Madhavan (2009). The dynamics of leveraged and inverse exchange-traded funds. *Journal of Investment Management 16*(4), 43.

Collin-Dufresne, P. and V. Fos (2016). Insider Trading, Stochastic Liquidity and Equilibrium Prices. *Econometrica 84*(4), 1441–1475.

Comerton-Forde, C., S. T. Lau, and T. McInish (2007). Opening and closing behavior following the introduction of call auctions in singapore. *Pacific-Basin Finance Journal 15*(1), 18 – 35.

Comerton-Forde, C. and J. Rydge (2006). The influence of call auction algorithm rules on market efficiency. *Journal of Financial Markets 9*(2), 199–222.

Cremers, M. and D. Weinbaum (2010). Deviations from put-call parity and stock return predictability. *Journal of Financial and Quantitative Analysis 45*(2), 335–367.

Cushing, D. and A. Madhavan (2000). Stock returns and trading at the close. *Journal of Financial Markets 3*(1), 45–67.

Duffie, D., P. Dworczak, and H. Zhu (2017). Benchmarks in search markets. *Journal of Finance 72*(5), 1983–2044.

Etula, E., K. Rinne, M. Suominen, and L. Vaittinen (2020). Dash for cash: Monthly market impact of institutional liquidity needs. *The Review of Financial Studies 33*(1), 75–111.

Gervais, S., R. Kaniel, and D. H. Mingelgrin (2001). The high-volume return premium. *The Journal of Finance 56*(3), 877–919.

Goncalves-Pinto, L., B. D. Grundy, A. Hameed, T. van der Heijden, and Y. Zhu (2019). Why do option prices predict stock returns? the role of price pressure in the stock market. FIRN Research Paper 2695145.

Greenwood, R. and D. Thesmar (2011). Stock price fragility. *Journal of Financial Economics 102*(3), 471–490.

Grossman, S. J. and M. H. Miller (1988). Liquidity and Market Structure. *Journal of Finance 43*(3), 617–633.

Hasbrouck, J., G. Sofianos, and D. Sosebee (1993). New york stock exchange systems and trading procedures. NYSE Working Paper 93-01.

Hendershott, T. and A. J. Menkveld (2014). Price pressures. *Journal of Financial Economics 114*(3), 405–423.

Kamara, A. and T. W. Miller (1995). Daily and intradaily tests of european put-call parity. *Journal of Financial and Quantitative Analysis 30*(4), 519–539.

Kandel, E., B. Rindi, and L. Bosetti (2012). The effect of a closing call auction on market quality and trading strategies. *Journal of Financial Intermediation 21*(1), 23–49.

Klemkosky, R. C. and B. G. Resnick (1979). Put-call parity and market efficiency. *Journal of Finance 34*(5), 1141–1155.

Kraus, A. and H. R. Stoll (1972). Price impacts of block trading on the new york stock exchange. *The Journal of Finance 27*(3), 569–588.

Lamoureux, C. G. and J. W. Wansley (1989). The pricing of when-issued securities. *Financial Review 24*(2), 183–198.

Lou, D. (2012). A flow-based explanation for return predictability. *Review of Financial Studies 25*(12), 3457–3489.

Madhavan, A. (1992). Trading Mechanisms in Securities Markets. *Journal of Finance 47*(2), 607–641.

Madhavan, A. and V. Panchapagesan (2000). Price discovery in auction markets: A look inside the black box. *Review of Financial Studies 13*(3), 627–658.

Mayhew, S., T. McCormick, and C. Spatt (2009). The information content of market-on-close imbalances, the specialist and nyse equity prices. Work. Pap. 1364178.

Muravyev, D., N. D. Pearson, and J. M. Pollet (2018). Understanding returns to short selling using option-implied stock borrowing fees. *Available at SSRN 2851560*.

Ofek, E., M. Richardson, and R. F. Whitelaw (2004). Limited arbitrage and short sales restrictions: Evidence from the options markets. *Journal of Financial Economics 74*(2), 305–342.

Pagano, M. S., L. Peng, and R. A. Schwartz (2013). A call auction's impact on price formation and order routing: Evidence from the nasdaq stock market. *Journal of Financial Markets 16*(2), 331–361.

Pagano, M. S. and R. A. Schwartz (2003). A closing call's impact on market quality at euronext paris. *Journal of Financial Economics 68*(3), 439–484.

Petajisto, A. (2017). Inefficiencies in the pricing of exchange-traded funds. *Financial Analysts Journal 73*(1), 24–54.

Phillips, S. M. and C. W. Smith Jr (1980). Trading costs for listed options: The implications for market efficiency. *Journal of Financial Economics 8*(2), 179–201.

Shumway, T. (1997). The delisting bias in crsp data. *The Journal of Finance 52*(1), 327–340.

Stoll, H. R. (1969). The relationship between put and call option prices. *Journal of Finance 24*(5), 801–824.

Stoll, H. R. and R. E. Whaley (1990). Stock Market Structure and Volatility. *Review of Financial Studies 3*(1), 37–71.

Vayanos, D. and P. Woolley (2013). An institutional theory of momentum and reversal. *Review of Financial Studies 26*(5), 1087–1145.

Wu, Y. (2019). Closing auction, passive investing, and stock prices. Working paper Emory University.

Figure 1. Fraction of aggregate daily dollar volume executed around the close. Daily dollar volume is summed across stocks for the last five minutes of trading and for the auction and then divided by the total daily dollar volume across stocks. Left plot: percentage of daily dollar volume executed in the last five minutes of trading (3:55 pm to 4:00 pm). Right panel: percentage of daily dollar volume executed in the closing auction. 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.

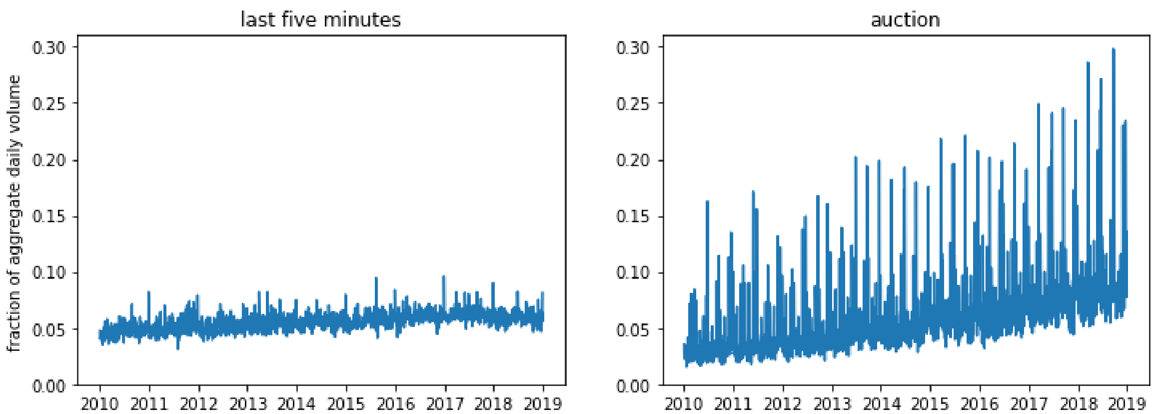


Figure 2. Elasticity of turnover to ETF and institutional ownerships. For each five-minute interval between 3:30 and 4:00 pm and the auction, log turnover is regressed on the logarithm of ETF and institutional ownerships, as well as other control variables described in the main text. The sample consists 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.

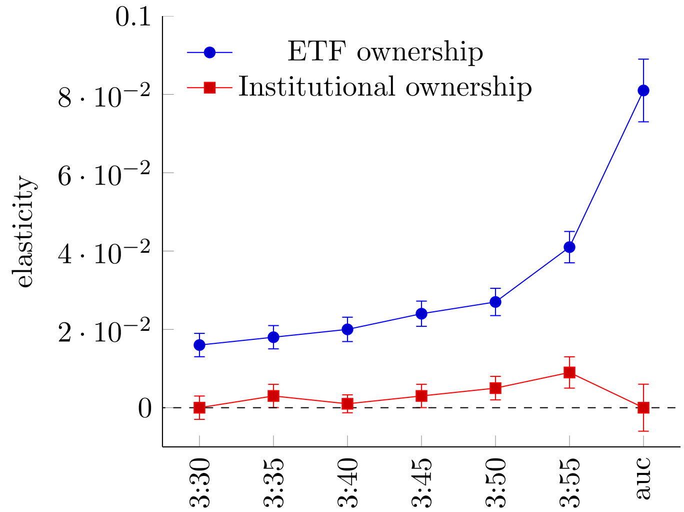


Figure 3. VIX index (left scale, dashed grey line) and absolute value-weighted auction deviation in basis points (right scale, solid black line). To compute the auction deviation, we first compute signed price deviation at the close, then value weight it across stocks on a given day, and finally take 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.

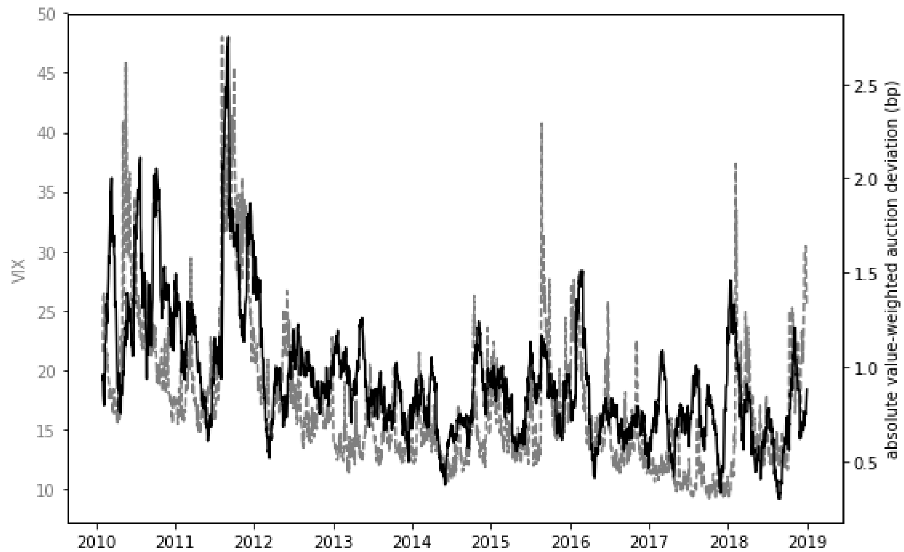


Figure 4. Absolute price deviation for NYSE large stocks relative to Nasdaq large stocks. For each five-minute interval between 3:30pm and 4:00pm and the auction, a panel regression is estimated where log absolute price deviation (in basis points) is regressed on an indicator for NYSE-listed stocks, 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 3:30pm, log bid-ask spread, log of five-minute realized volatility between 9:30am and 3:30pm, and log price. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 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.

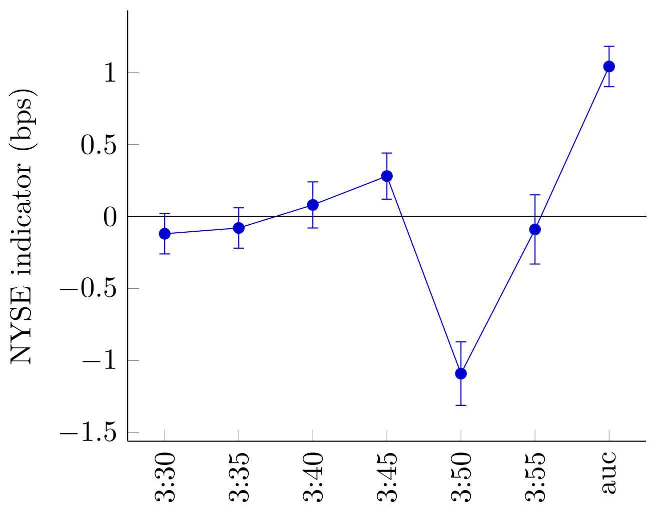


Table 1. Descriptive statistics. The table reports mean, median, and standard deviation for volume-related variables: share of daily volume at the closing auction, in the last five minutes, and between 3:30 and 3:55, as well as end-of-day relative bid-ask spread, stock price, market capitalization, share of days with zero volume during the entire day, from 9:30 to 15:30, and at the closing auction. In Panel (a), σ_w indicates the within standard deviation of observations for which the time-mean has been subtracted (i.e., $x_{it} - \bar{x}_i$). In Panel (b), σ_w indicates the within standard deviation of observations for which the firm-mean has been subtracted (i.e., $x_{it} - \bar{x}_t$). 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		
	μ	Median	σ_w	μ	Median	σ_w	μ	Median	σ_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		
	μ	Median	σ_w	μ	Median	σ_w	μ	Median	σ_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 (bp)	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 institutional ownership as of the beginning of the month (excluding ETF ownership); an indicator for Russell index rebalancing dates; 3rd Friday is an indicator for the third Friday of each month: typically, an option expiration day; a beginning-of-month and end-of-month indicators; an indicator for the last day of the quarter. Also, EAD-1, EAD, and EAD+1 are indicators for the day before, of, and after an earnings announcement. Avg$|Ret|$ is the absolute return averaged over the past five trading days; Ret_{t-1} is the lagged daily return; We also estimate but 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.	0.081***	(0.004)	0.041***	(0.002)	0.042***	(0.003)
log Inst. own.	-0.000	(0.003)	0.009***	(0.002)	0.010***	(0.004)
Russell rebal. day	2.321***	(0.098)	0.788***	(0.063)	0.082	(0.054)
3rd Friday	0.638***	(0.078)	0.125***	(0.020)	0.208***	(0.020)
First of month	0.199***	(0.030)	0.080***	(0.015)	0.133***	(0.012)
Last of month	0.871***	(0.049)	0.322***	(0.019)	0.007	(0.015)
End of quarter	-0.021	(0.065)	0.055*	(0.030)	-0.089***	(0.028)
EAD-1	0.016*	(0.009)	0.228***	(0.005)	0.225***	(0.005)
EAD	-0.020**	(0.009)	0.081***	(0.005)	0.965***	(0.009)
EAD+1	-0.026***	(0.009)	0.019***	(0.004)	0.492***	(0.006)
log Avg$|Ret|$	0.087***	(0.006)	0.076***	(0.003)	0.254***	(0.005)
Ret_{t-1}	-0.404**	(0.172)	-0.367***	(0.090)	-0.450***	(0.102)
log Market cap.	0.021**	(0.009)	0.011*	(0.006)	0.149***	(0.013)
Trend	0.062***	(0.012)	0.064***	(0.005)	-0.060***	(0.007)
Trend^2	0.005***	(0.001)	-0.000	(0.001)	0.006***	(0.001)
log Turnover(9:30-3:30)	0.327***	(0.005)	0.565***	(0.004)	-	-
Calendar month FE	Yes		Yes		Yes	
Day of week FE	Yes		Yes		Yes	
Stock FE	Yes		Yes		Yes	
R^2	30.90%		36.44%		8.88%	
Num. obs.	5,495,085		5,546,448		5,605,664	

Table 3. Auction deviation. Panel (a) reports descriptive statistics for the absolute deviation between the log closing auction price and the log midquote at 4:00pm ($= |\log(p_{\text{auc}}/p_{4:00})|$) expressed in basis points. Panel (b) reports descriptive statistics for the deviation ratio, which is defined as the 20-day rolling average absolute auction deviation divided by the 20-day rolling average absolute intraday (9:45am-3:30pm) deviation. The deviation ratio is reported in percentage points and is 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^{th} percentile is denoted as p0.x. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than \$5 and a market capitalization larger than 100 million at the beginning of the month.

(a) Absolute auction deviation (basis points)

		Size quintile				
	All	Low	2	3	4	High
Mean	8.12	20.60	8.99	5.49	3.97	2.66
StdDev	15.91	30.28	11.44	6.20	4.65	3.56
Skew	13.06	7.69	14.50	20.11	16.97	33.87
p0.01	0.00	0.00	0.00	0.00	0.00	0.00
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
p0.8	10.25	27.69	12.45	7.80	5.74	3.90
p0.9	17.37	42.11	17.81	11.03	8.27	5.69
p0.95	26.80	60.94	24.18	14.78	11.05	7.65
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

(b) Deviation ratio (%)

		Size quintile				
	All	Low	2	3	4	High
Mean	5.01	8.68	6.25	4.75	4.14	3.41
StdDev	4.69	6.60	5.12	4.26	3.93	2.81
Skew	5.27	3.38	5.07	6.76	6.70	7.53
p0.01	0.89	1.80	1.31	0.98	0.81	0.76
p0.05	1.34	2.64	1.95	1.45	1.20	1.12
p0.5	3.80	6.92	5.02	3.79	3.20	2.78
p0.7	5.42	9.57	6.81	5.17	4.46	3.78
p0.9	9.28	15.91	11.02	8.31	7.42	5.95
p0.95	12.34	20.37	14.24	10.68	9.60	7.45
p0.99	22.58	33.24	24.64	19.36	17.82	12.10
p0.999	56.72	75.03	68.74	59.95	52.04	35.44
Count	4,544,253	509,243	875,216	999,243	1,055,056	1,105,495

Table 4. Absolute auction deviation determinants. Absolute deviation ($= |\log(p_{\text{auc}}/p_{4:00})|$) is expressed in basis points. Explanatory variables include logs of auction turnover (volume divided by shares outstanding), intraday turnover (9:30am to 3:30pm), relative bid-ask spread, realized volatility during the last hour and the rest of the day (computed from five-minute midquote returns), linear and quadratic trends, and NYSE-listing indicator. Deviation and spread variables are winsorized at 0.05%. The top panel includes stock-fixed effect, while the bottom panel includes date 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.

(a) Absolute deviation determinants (time series)

	Full sample	Small stocks	Large stocks
log Turnover(auc)	0.88*** (0.05)	1.43*** (0.13)	0.65*** (0.04)
log Turnover(9:30-3:30)	-0.49*** (0.03)	-0.61*** (0.06)	-0.13*** (0.03)
log Bid-ask spread	0.34*** (0.00)	0.34*** (0.00)	0.36*** (0.08)
log $\text{RVol}_{5\text{min}}$(3:00-3:55)	0.57*** (0.03)	0.81*** (0.07)	0.25*** (0.03)
log $\text{RVol}_{5\text{min}}$(9:30-3:00)	0.37*** (0.04)	0.61*** (0.09)	0.19*** (0.04)
log Price	-1.13*** (0.05)	-4.19*** (0.25)	0.08 (0.15)
NYSE	1.20*** (0.15)	1.62** (0.68)	0.94*** (0.16)
Trend	-0.93*** (0.03)	-0.98*** (0.11)	-0.74*** (0.04)
Trend^2	0.07*** (0.00)	0.06*** (0.01)	0.05*** (0.00)
Stock FE	Yes	Yes	Yes
Adj. R^2	48.41 %	50.32%	14.74%
Num. obs.	5,425,109	987,232	1,150,044

(b) Absolute deviation determinants (cross-section)

	Full sample	Small stocks	Large stocks
log Turnover(auc)	0.03 (0.03)	-0.43*** (0.08)	0.36*** (0.04)
log Turnover(9:30-3:30)	-0.62*** (0.03)	-0.63*** (0.06)	-0.25*** (0.04)
log Bid-ask spread	0.35*** (0.00)	0.34*** (0.00)	0.44*** (0.06)
log $\text{RVol}_{5\text{min}}$(3:00-3:55)	0.74*** (0.04)	0.78*** (0.07)	0.35*** (0.05)
log $\text{RVol}_{5\text{min}}$(9:30-3:00)	0.78*** (0.04)	0.98*** (0.09)	0.21*** (0.05)
log Price	-1.01*** (0.04)	-2.26*** (0.13)	0.06 (0.10)
NYSE	1.40*** (0.05)	2.62*** (0.18)	1.04*** (0.06)
Date FE	Yes	Yes	Yes
Adj. R^2	63.86 %	60.11%	15.47%
Num. obs.	5,425,109	987,232	1,150,044

Table 5. Reversals. Overnight returns are regressed on auction price deviations and last five-minute returns. Ret^{945}_{auc} denotes the return from the closing auction to 9:45am the next morning, Ret^{auc}_{400} denotes the return from the 4pm midquote to the closing price, Ret^{400}_{355} denotes the return in the last five minutes of regular trading. $RetA^{945}_{auc}$ uses the closing price adjusted for the bid-ask spread. Results are reported for the full sample and for 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) Full sample (5,363,155 observations)

	Ret^{945}_{auc}	$RetA^{945}_{auc}$	Ret^{945}_{400}	Ret^{945}_{auc}	$RetA^{945}_{auc}$	Ret^{945}_{vwap}
Ret^{auc}_{400}	-0.8455***			-0.8721***		
	(0.0282)			(0.0288)		
$RetA^{auc}_{400}$		-0.9105***			-0.9496***	
		(0.0368)			(0.0372)	
Ret^{400}_{355}			-0.1860***	-0.1763***	-0.1851***	
			(0.0379)	(0.0381)	(0.0380)	
Ret^{vwap}_{355}						-0.1306***
						(0.0417)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.61%	0.19%	0.11%	0.20%	0.30%	0.03%

(b) Large stocks (1,147,683 observations)

	Ret^{945}_{auc}	$RetA^{945}_{auc}$	Ret^{945}_{400}	Ret^{945}_{auc}	$RetA^{945}_{auc}$	Ret^{945}_{vwap}
Ret^{auc}_{400}	-1.0961***			-1.0883***		
	(0.0948)			(0.0943)		
$RetA^{auc}_{400}$		-0.9693***			-0.9856***	
		(0.1104)			(0.1104)	
Ret^{400}_{355}			-0.1758*	-0.1749*	-0.1753*	
			(0.1040)	(0.1040)	(0.1040)	
Ret^{vwap}_{355}						0.0968
						(0.1447)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.15%	0.07%	0.05%	0.20%	0.12%	0.01%

(c) Small stocks (939,506 observations)

	Ret^{945}_{auc}	$RetA^{945}_{auc}$	Ret^{945}_{400}	Ret^{945}_{auc}	$RetA^{945}_{auc}$	Ret^{945}_{vwap}
Ret^{auc}_{400}	-0.8494***			-0.8879***		
	(0.0202)			(0.0203)		
$RetA^{auc}_{400}$		-0.9827***			-1.0201***	
		(0.0268)			(0.0260)	
Ret^{400}_{355}			-0.2851***	-0.2681***	-0.2852***	
			(0.0218)	(0.0221)	(0.0219)	
Ret^{vwap}_{355}						-0.3380***
						(0.0248)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	1.87%	0.63%	0.45%	2.26%	1.08%	0.46%

Table 6. Weighted price contributions. The average weighted price contribution is reported for five-minute intraday subperiods from 3:30pm to 4pm, the period between 4pm and auction, and the overnight period. The last two columns use the adjusted auction price ($\tilde{auc}$) 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-$\tilde{\text{Auc}}$	$\tilde{\text{Auc}}$-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 7. Reversals after hours. After-hour returns are regressed on auction price deviations and last five-minute returns. Ret_{400}^{auc} denotes the return from the 4pm midquote to the closing price, Ret_{auc}^{945} denotes the return from the closing auction to 9:45am the next morning, Ret_{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_{auc}^{945}	$Ret_{auc}^{4:20}$	$Ret_{auc}^{4:30}$	$Ret_{auc}^{4:40}$	$Ret_{auc}^{4:50}$	$Ret_{auc}^{5:00}$
Ret_{400}^{auc}	-1.0883***	-0.5105***	-0.4657***	-0.4341***	-0.4068***	-0.3982***
	(0.0943)	(0.0621)	(0.0506)	(0.0482)	(0.0447)	(0.0451)
Ret_{355}^{400}	-0.1749*	-0.0656***	-0.0680***	-0.0677***	-0.0636***	-0.0677***
	(0.1040)	(0.0154)	(0.0156)	(0.0143)	(0.0137)	(0.0147)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.20%	0.20%	0.17%	0.14%	0.12%	0.12%
Num. obs.	1,147,683	346,667	500,768	583,987	629,648	652,723

(b) Auction price adjusted for bid-ask bounce

	Ret_{auc}^{945}	$Ret_{auc}^{4:20}$	$Ret_{auc}^{4:30}$	$Ret_{auc}^{4:40}$	$Ret_{auc}^{4:50}$	$Ret_{auc}^{5:00}$
Ret_{400}^{auc}	-0.9856***	-0.4586***	-0.3781***	-0.3463***	-0.3166***	-0.3036***
	(0.1104)	(0.0796)	(0.0680)	(0.0674)	(0.0613)	(0.0614)
Ret_{355}^{400}	-0.1753*	-0.0617***	-0.0635***	-0.0633***	-0.0590***	-0.0630***
	(0.1040)	(0.0154)	(0.0155)	(0.0142)	(0.0137)	(0.0147)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.12%	0.11%	0.08%	0.07%	0.06%	0.06%
Num. obs.	1,147,683	346,667	500,768	583,987	629,648	652,723

Table 8. Auction volume and stock returns. The table reports a panel regression of next-day, next-week and next-month stock returns on volume predictors, day fixed effects, and control variables. The control variables include returns during each of three previous days, idiosyncratic volatility, momentum, monthly reversal, logarithm of market capitalization, beta, Amihud illiquidity measure, and highvolume indicator, which Gervais et al. (2001) set to one (-1) if current volume is greater (lower) than 90% (10%) over the previous 49 days. The coefficients for controls can be found in Table C7 in the appendix. All right-hand-side variables, except for indicators and fixed effects, are standardized to have a zero mean and unit variance. Stock returns are computed from daily returns in CRSP and are adjusted for stock delistings as in Shumway (1997). Standard errors are clustered by stock and day to account for overlapping returns and t-statistics are reported in brackets. Importantly, a day is skipped between predictors and weekly or monthly returns to avoid confounding effects as closing price today is an input to next-day return. 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) Raw volume ratios

	Ret_1	$Ret_{2:6}$, 1w	$Ret_{2:20}$, 1m
Auction/Total volume	-0.0001**	-0.0002***	-0.0003*
	[-2.4]	[-3.3]	[-1.8]
Pre-close/Total volume	0.0001***	0	0.0001
	[3.1]	[1.0]	[1.5]
Controls	Yes	Yes	Yes
R^2	21%	20%	18%
Num. obs.	5,461,880	5,461,621	5,461,621

(b) Monthly average and surprise

	Ret_1	$Ret_{2:6}$, 1w	$Ret_{2:20}$, 1m
Auction/Total vol surp	-0.0001***	-0.0002***	-0.0004***
	[-3.1]	[-4.2]	[-4.6]
Auction/Total vol average	0	-0.0001	0
	[-0.9]	[-0.6]	[-0.0]
Pre-close/Total vol surp	0.0001***	0	-0.0001
	[3.2]	[0.7]	[-1.1]
Pre-close/Total vol average	0	0.0001	0.0006**
	[0.9]	[1.1]	[2.5]
Controls	Yes	Yes	Yes
R^2	21%	20 %	18%
Num. Obs.	5,461,880	5,461,621	5,461,621

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

(a) Full sample

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

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

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

(c) Return predictability

	$\text{Ret}_{\text{auc}_t}^{\text{open}_{t+1}}$				$\text{Ret}_{\text{open}_{t+1}}^{\text{auc}_{t+1}}$	
$IS_t - S_{\text{auc}_t}$	0.1240***		0.0845***		0.0098	
	[9.0]		[5.2]		[0.9]	
$IS_t - S_{\text{mid}_t}$		0.0284*		0.0156		0.0061
		[1.8]		[1.5]		[1.5]
Constant	0.1052***	0.1052***	0.1054***	0.1054***	-0.0053***	-0.0054***
	[84.2]	[84.1]	[84.7]	[84.8]	[-5.6]	[-5.6]
Controls	No	No	Yes	Yes	No	No

Table 10. ETF auction price deviations and mispricing. This table examines auction price deviations and daily mispricing of the QQQ ETF, the SPY ETF, and S&P sector ETFs (SPsec) over 2010 to 2018. Panel (a) reports descriptive statistics for the price deviation, half spread, and price impact in basis points (bps). The standard deviation is denoted as sd and the x^{th} percentile as p0.x. Panel (b) examines daily mispricing of the SPY ETF measured in basis points in 2018. The second column uses closing prices for ETF and constituents. The third column switches to the quote midpoint for ETF price. The last column, computes price deviations using midquotes for both ETF and its constituents. The bottom part of the table reports t-statistics for difference in mean tests. Standard errors are heteroskedasticity-adjusted.

(a) Descriptive statistics for ETF auction price deviations

	Abs. deviation (bps)			Half spread (bps)			Price impact (bps)		
	QQQ	SPY	SPsec	QQQ	SPY	SPsec	QQQ	SPY	SPsec
Mean	1.68	1.83	3.63	0.53	0.29	1.29	1.15	1.54	2.34
StdDev	1.82	1.98	4.39	0.31	0.11	0.70	1.84	1.97	4.28
Skew	4.24	5.11	17.63	0.08	0.63	2.99	4.22	5.13	18.76
p0.01	0.00	0.18	0.51	0.00	0.00	0.47	-0.00	-0.00	-0.00
p0.05	0.30	0.24	0.68	0.00	0.18	0.60	-0.00	-0.00	-0.00
p0.5	1.06	1.32	2.67	0.48	0.26	1.13	0.59	1.01	1.47
p0.95	4.62	4.89	9.94	1.06	0.45	2.75	4.27	4.51	8.13
p0.99	8.48	9.24	16.32	1.15	0.52	3.54	8.28	8.87	14.21
p0.999	16.42	20.21	37.06	1.56	0.85	4.44	16.10	19.83	36.09
Count	2,222	2,238	20,152	2,222	2,238	20,152	2,222	2,238	20,152

(b) SPY mispricing

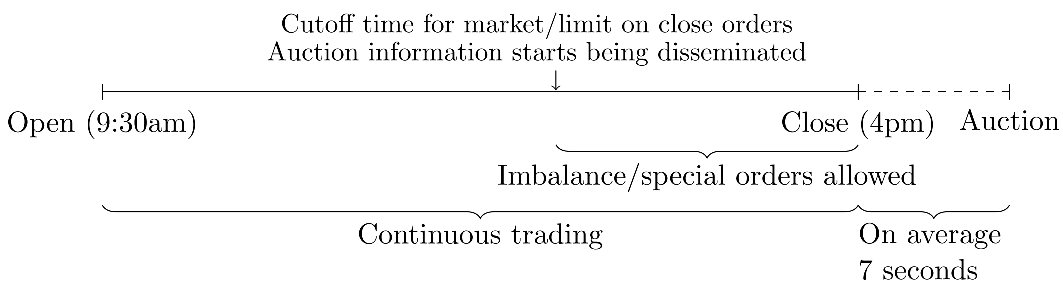
	$\lvert\log(\text{Price/NAV})\rvert$	$\lvert\log(\text{Midpoint/NAV})\rvert$	$\lvert\log(\text{Midpoint/NAV}_{\text{mid}})\rvert$
Mean	2.50	1.59	1.03
StdDev	2.67	1.85	1.32
Skew	3.01	3.60	5.82
p0.01	0.05	0.01	0.02
p0.05	0.17	0.06	0.06
p0.5	1.64	1.11	0.76
p0.95	7.35	4.80	2.75
p0.99	11.15	8.30	5.80
p0.999	19.93	15.07	13.03
Count	250	250	250
$<\lvert\log(\text{Price/NAV})\rvert$?	-	-6.91	-10.76
$<\lvert\log(\text{Midpoint/NAV})\rvert$?	-	-	-8.79

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 5 illustrates the main features of the auction process.

Figure 5. 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 4pm 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 3:50pm (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 3:58pm but may not be canceled or modified. IO orders may be entered but not updated or canceled until 4:00pm. Dissemination of closing information begins at 3:50pm (changed to 3:55pm in October 2018). The closing process begins at 4:00pm.

From 3:50pm to 4:00pm (3:55pm to 4:00pm 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 4:00pm. Nasdaq calculates the price that will maximize the number of shares matched based on on-close orders (MOC, LOC, IO) and continuous market orders and execute the cross at a single price called the Nasdaq Official Close Price (NOCP). Only interest on the Nasdaq book is eligible to participate in the cross. Closing cross execution priority is as follows. MOC orders in time priority. IO orders and displayed interest of limit orders/quotes in price/time priority. Reserve size for the above executes last at each price level before moving on to the next price level. LOC orders in price/time priority. Priority for IO orders will be applied after the limit prices of IO orders have been adjusted to reflect the Nasdaq inside quote at the time of the closing cross. The price is then disseminated and executions are sent to the consolidated tape. Short selling is permitted subject to applicable short sale rules.

A.2 NYSE closing auction

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

The NYSE disseminates the following information: beginning at 3:45pm (changed to 3:50pm 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.[25] Similarly, NYSE auction trades are indicated by TR_SCOND = 6. We focus on the closing auction trade executed on the listing exchange. In general, this trade has a much larger volume than other closing trades (if any).

B.2 Volume data

This appendix describes how we obtain the volume data from TAQ.

Over the period 2010 to 2013 (included), we use the Monthly TAQ database. We exclude trades for which CORR is not equal to 0 and trades with a negative price. In addition, we remove duplicated opening auction trades (COND = 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 (TR_SCOND = Q or @ Q) and duplicated closing auction trades (TR_SCOND = M or TR_SCOND = @ M) 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.

ETF shares outstanding and end-of-day prices and quotes are obtained from CRSP. For the SPY ETF, we obtain shares outstanding and NAVs directly from SPDR's website since they are reported there with additional digits of precision.[26] We obtain daily constituents' shares held by SPY from the ETF Global database. To make sure that the holdings' data are accurate, we verify that the constituents match with those reported in the CRSP mutual fund database. We manually check and correct any mismatch and consider the cash position as a specific security.

The net asset value equals the total value of all assets minus the liabilities of the fund. We back out the value of liabilities on each day by summing the market values of all constituents (reported by ETF Global, but which equal the closing price of the constituent times the number of shares held) and then subtracting the total net asset value of the fund. As a robustness check, we verify that the numbers match the ones reported in the SPY financial statements that are disclosed semi-annually on SPDR's website. Finally, we compute the midquote NAV by multiplying the closing midquote of each constituent by its weight in the SPY ETF and then subtracting the implied liabilities per share outstanding.

C Appendix: 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.[27]

"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.

[25] `https://www.nasdaqtrader.com/content/technicalsupport/specifications/dataproducts/NQLastSalespec.pdf`

[26] `https://us.spdrs.com/en/etf/spdr-sp-500-etf-trust-SPY`

[27] Source: `https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-1801145-153699.pdf`

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.[28]

"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.[29]

"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.[30]

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.[31]

"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.[32]

"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.[33]

"If the primary listing exchange, whether it be the NYSE or Nasdaq, cant run the closing auction, all hell breaks loose." Greg Tusar, former global head of electronic trading at Goldman Sachs Group.[34]

"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.[35]

---

[28]Source: `https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-1797187-153614.pdf`

[29]Source: `https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-1856933-156193.pdf`

[30]Source: `https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-2445187-161064.pdf`

[31]Source: `https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-2218270-160673.pdf`

[32]Source: `https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-2227619-160772.pdf`

[33]Source: `https://www.sec.gov/comments/sr-batsbzx-2017-34/batsbzx201734-2020594-156840.pdf`

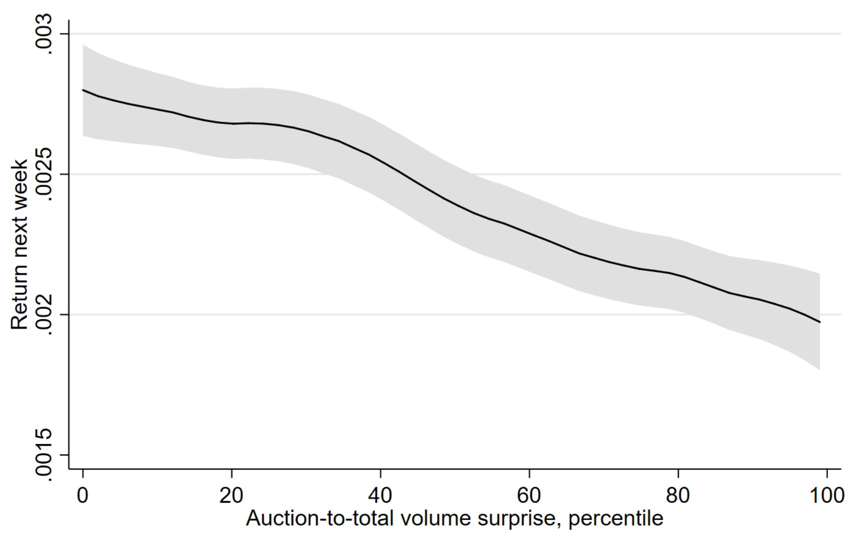
[34]Source: "Whats the Biggest Trade on the New York Stock Exchange? The Last One." *Wall Street Journal*, March 14, 2018 (link).

[35]Source: "Passive strategies continue to overwhelm asset managers as market hits $11 trillion." *The Trade*, January 13, 2020 (link).

D Appendix: additional figures and tables

Figure C1. Returns for auction volume percentiles. The figures show a kernel regression of stock return during next week and month on percentile of auction-to-total ratio surprise. The surprise is the difference between current value and monthly average. Kernel regression relies on Epanechnikov kernel with default bandwidth. Grey area corresponds confidence intervals. This non-parametric regression is analogous to conventional portfolio sorts.

(a) Weekly returns



(b) Monthly returns

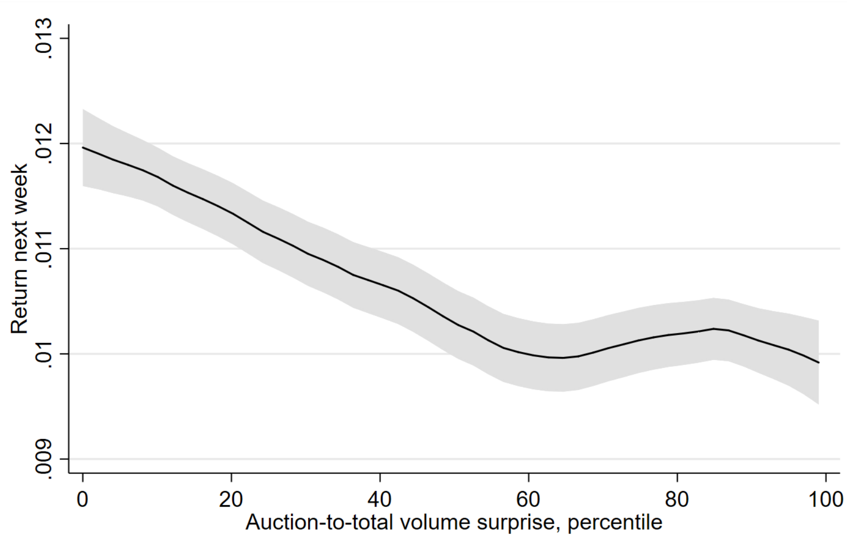


Table C1. Absolute Deviation (basis points) with TAQ end of day midquote. This table reports descriptive statistics for the absolute deviation between the log closing auction price and the log midquote at 4:00pm ($= |\log(p_{\text{auc}}/p_{4:00})|$) expressed in basis points. Statistics are reported for the full sample and across market capitalization quintiles, which are formed at the beginning of each year. The x^{th} percentile is denoted as p0.x. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $5 and a market capitalization larger than 100 million at the beginning of the month.

		Size quintile				
	All	Low	2	3	4	High
Mean	7.95	20.00	8.92	5.49	3.97	2.67
StdDev	14.91	28.06	10.73	6.14	4.57	4.65
Skew	15.47	9.48	12.37	20.39	12.11	133.39
p0.01	0.00	0.00	0.00	0.00	0.00	0.00
p0.05	0.65	2.75	1.61	1.02	0.68	0.45
p0.5	4.19	12.34	6.34	3.98	2.74	1.73
p0.8	10.20	27.36	12.48	7.84	5.75	3.91
p0.9	17.20	41.17	17.79	11.06	8.27	5.69
p0.95	26.34	58.59	24.01	14.80	11.03	7.64
p0.99	60.15	129.87	44.74	25.16	19.85	13.28
p0.995	85.16	174.15	58.76	31.70	25.16	17.21
p0.999	175.96	315.23	114.57	55.10	43.59	31.11
Count	5,461,112	1,010,812	1,073,680	1,103,920	1,122,769	1,149,931

Table C2. Half spread and price impact. The absolute auction deviation is decomposed as follows |deviation%| = half-spread% + price impact%. The (realized) half-spread is defined as $\log(p_{\text{ask}}/p_{4:00})$ if $p_{\text{auc}} \geq p_{4:00}$ and $\log(p_{4:00}/p_{\text{bid}})$ otherwise. Similarly, price impact% is $\log(p_{\text{auc}}/p_{\text{ask}})$ if $p_{\text{auc}} \geq p_{4:00}$ and $\log(p_{\text{bid}}/p_{\text{auc}})$ otherwise. Panel (a) reports statistics for the half spread. Panel (b) reports statistics for the 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^{th} percentile is denoted as p0.x. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than \$5 and a market capitalization larger than 100 million at the beginning of the month.

(a) 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
Skew	14.51	8.17	15.92	19.49	52.84	42.86
p0.01	0.37	2.20	1.21	0.73	0.44	0.21
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
p0.8	8.62	29.14	10.42	6.06	3.67	1.96
p0.9	15.73	45.98	15.60	8.27	5.16	2.77
p0.95	26.85	68.89	22.59	11.06	6.85	3.72
p0.99	70.18	166.95	47.36	20.06	13.47	6.63
p0.995	104.71	226.18	64.94	26.14	17.84	8.03
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
Skew	-5.77	-3.92	2.38	20.67	3.83	34.55
p0.01	-22.59	-72.20	-17.44	-6.51	-3.63	-1.68
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
p0.8	1.71	0.00	0.00	1.52	2.50	2.27
p0.9	4.90	7.38	6.00	5.05	4.76	3.84
p0.95	8.47	14.42	10.28	7.94	7.12	5.59
p0.99	19.70	41.47	20.81	15.94	13.81	10.69
p0.995	29.24	64.79	28.53	20.60	17.70	13.94
p0.999	74.35	161.47	62.82	40.85	33.79	27.56
Count	5,578,901	1,046,362	1,104,289	1,128,456	1,139,671	1,160,123

Table C3. Price impact determinants. Price impact is expressed in basis points. Explanatory variables include logs of auction turnover (volume divided by shares outstanding), intraday turnover (9:30 to 15:30), relative bid-ask spread, realized volatility during the last hour and the rest of the day (computed from five-minute midquote returns), linear and quadratic trends, and NYSE-listing indicator. The top panel includes stock-fixed effect, while the bottom panel include date 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.

(a) Price impact determinants (time series)

	Full sample	Small stocks	Large stocks
log Turnover(auc)	0.83*** (0.05)	1.34*** (0.10)	0.63*** (0.03)
log Turnover(9:30-3:30)	-0.38*** (0.02)	-0.41*** (0.04)	-0.12*** (0.03)
log Bid ask spread	-0.14*** (0.00)	-0.14*** (0.00)	-0.11*** (0.03)
log $RVol_{5min}$(3:00-3:55)	0.47*** (0.03)	0.61*** (0.05)	0.23*** (0.02)
log $RVol_{5min}$(9:30-3:00)	0.30*** (0.03)	0.41*** (0.07)	0.19*** (0.03)
log Price	-1.02*** (0.05)	-3.69*** (0.20)	0.12 (0.08)
Trend	-0.94*** (0.03)	-1.03*** (0.10)	-0.73*** (0.03)
$Trend^2$	0.07*** (0.00)	0.07*** (0.01)	0.05*** (0.00)
NYSE	1.24*** (0.14)	1.80*** (0.59)	0.94*** (0.15)
Stock FE	Yes	Yes	Yes
Adj. R^2	16.84 %	19.92%	7.10%
Num. obs.	5,425,109	987,232	1,150,044

(b) Price impact determinants (cross-section)

	Full sample	Small stocks	Large stocks
log Turnover(auc)	0.10*** (0.03)	-0.20*** (0.06)	0.35*** (0.03)
log Turnover(9:30-3:30)	-0.49*** (0.02)	-0.40*** (0.04)	-0.23*** (0.04)
log $RVol_{\mathrm{5min}}$(3:00-3:55)	0.65*** (0.03)	0.61*** (0.05)	0.32*** (0.03)
log $RVol_{\mathrm{5min}}$(9:30-3:00)	0.63*** (0.03)	0.64*** (0.06)	0.19*** (0.04)
log Price	-0.95*** (0.04)	-2.28*** (0.11)	0.08 (0.06)
log Bid ask spread	-0.13*** (0.00)	-0.14*** (0.00)	-0.04* (0.03)
NYSE	1.48*** (0.05)	2.83*** (0.16)	1.05*** (0.04)
Date FE	Yes	Yes	Yes
Adj. R^2	22.28 %	25.97%	4.01%
Num. obs.	5,425,109	987,232	1,150,044

Table C4. Determinants of commonality in absolute value-weighted auction deviation. The absolute value-weighted auction deviation ($|r^{\text{vw}}_{\text{4:00pm-auction}}|$) is regressed on calendar indicators and intraday volatility. Intraday volatility ($|r^{\text{vw}}_{\text{9:30-3:30}}|$) 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:	$\lvert r^{\text{vw}}_{\text{4:00pm-auction}}\rvert$	
Constant	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)
$\lvert r^{\text{vw}}_{\text{9:30-3:30}}\rvert$		0.005*** (0.001)
Adj. R^2	-	9.30%
Num. obs.	2,243	2,243

Table C5. Dissemination of closing information and price discovery. Weighted price contributions between 3:40-45, 3:45-50, 3:50-55, and 3:55-4:00 are averaged each day separately for NYSE and Nasdaq stocks in a given market capitalization quintile. The following regression is then estimated: $\text{WPC} = \alpha + \alpha_{\text{NYSE}} 1_{\text{NYSE}} + \alpha_{3:45} 1_{3:45} + \alpha_{3:50} 1_{3:50} + \alpha_{3:55} 1_{3:55} + \alpha_{\text{NYSE}*3:45} 1_{3:45} 1_{\text{NYSE}} + \alpha_{\text{NYSE}*3:50} 1_{3:50} 1_{\text{NYSE}} + \alpha_{\text{NYSE}*3:55} 1_{3:55} 1_{\text{NYSE}} + \epsilon$, where WPC is the weighted price contribution (averaged across either NYSE stocks or Nasdaq stocks), 1_{NYSE} is an indicator for the NYSE-stocks weighted price contribution, and $1_{3:45}/1_{3:50}/1_{3:55}$) is an indicator for the 3:45-50/3:50-55/3:55-4:00 interval. 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	0.028***	0.025***	0.021***	0.017***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE	0.002***	-0.001	0.000	0.001*	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
3:45	0.004***	0.003**	0.003**	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
3:50	0.017***	0.015***	0.013***	0.010***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
3:55	0.014***	0.011***	0.009***	0.004**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
NYSE*3:45	0.010***	0.008***	0.005***	0.004***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE*3:50	-0.011***	-0.011***	-0.010***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE*3:55	0.000	-0.003***	-0.005***	-0.003***	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.017	0.009	0.006	0.003	0.001
Num. obs.	17,456	17,456	17,456	17,456	17,456

Table C6. 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 4pm 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^{th} percentile is denoted as p0.x. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $5 and a market capitalization larger than 100 million at the beginning of the month.

		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 C7. Auction volume and stock returns, coefficients for controls. The table reports a panel regression of next-day, next-week and next-month stock returns on volume predictors, day fixed effects, and control variables. The control variables include returns during each of three previous days, idiosyncratic volatility, momentum, monthly reversal, logarithm of market capitalization, beta, Amihud illiquidity measure, and highvolume indicator, which Gervais et al. (2001) set to one (-1) if current volume is greater (lower) than 90% (10%) over the previous 49 days. All right-hand-side variables, except for indicators and fixed effects, are standardized to have a zero mean and unit variance. Stock returns are computed from daily returns in CRSP and are adjusted for stock delistings as in Shumway (1997). Standard errors are clustered by stock and day to account for overlapping returns and t-statistics are reported in brackets. Importantly, a day is skipped between predictors and weekly or monthly returns to avoid confounding effects as closing price today is an input to next-day return. 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_1	$Ret_{2:6}$, 1 week	$Ret_{2:20}$, 1 month
Auction/Total vol surp	-0.0001***	-0.0002***	-0.0004***
	[-3.1]	[-4.2]	[-4.6]
Auction/Total vol average	0	-0.0001	0
	[-0.9]	[-0.6]	[-0.0]
Pre-close/Total vol surp	0.0001***	0	-0.0001
	[3.2]	[0.7]	[-1.1]
Pre-close/Total vol average	0	0.0001	0.0006**
	[0.9]	[1.1]	[2.5]
Ret_0	0	-0.0001	-0.0005***
	[-0.9]	[-1.3]	[-3.0]
Ret_{-1}	0.0001	-0.0002**	-0.0004***
	[1.3]	[-2.1]	[-2.6]
Ret_{-2}	-0.0001*	-0.0001	-0.0003*
	[-1.7]	[-1.1]	[-1.8]
log Market capitalization	0	-0.0001	-0.0003
	[-0.6]	[-1.0]	[-1.1]
Beta	0	-0.0001	-0.0002
	[-0.6]	[-0.5]	[-0.5]
Monthly reversal	-0.0001***	-0.0005***	-0.0005*
	[-2.8]	[-3.5]	[-1.8]
Momentum	0	0.0001	0.0005
	[0.8]	[1.1]	[1.2]
Idiosyncratic volatility	-0.0001*	-0.0004***	-0.0019***
	[-1.8]	[-3.1]	[-5.5]
Amihud illiquidity	0	-0.0001	-0.0003
	[0.3]	[-1.0]	[-1.3]
High-volume premium indicator	0.0004***	0.0006***	0.0008***
	[8.7]	[5.5]	[3.6]
R^2	0.21	0.20	0.18
Num. obs.	5,461,880	5,461,621	5,461,621

Table C8. Absolute VWAP deviation. This table reports descriptive statistics for the absolute deviation between the log VWAP between 3:55 and 4:00pm and the log midquote at 3:55pm ($= |\log(\mathrm{VWAP}_{3:55-4:00}/p_{3:55})|$) 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^{th} percentile is denoted as p0.x. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $5 and a market capitalization larger than 100 million at the beginning of the month.

		Size quintile				
	All	Low	2	3	4	High
Mean	13.01	24.06	15.49	11.47	8.79	6.89
StdDev	18.76	30.75	18.35	12.58	10.54	10.72
Skew	23.73	6.38	8.11	4.73	40.70	368.19
p0.01	0.12	0.21	0.16	0.12	0.10	0.08
p0.05	0.61	1.23	0.83	0.63	0.49	0.41
p0.5	7.83	15.59	10.56	7.99	6.16	4.87
p0.8	19.06	35.87	23.77	17.70	13.52	10.51
p0.9	29.35	52.93	34.21	25.24	19.21	14.90
p0.95	41.54	73.00	45.49	33.47	25.43	19.70
p0.99	80.81	139.60	79.64	57.19	43.86	34.40
p0.995	105.05	178.96	100.20	69.94	54.04	43.25
p0.999	187.89	316.93	174.52	113.43	84.24	70.06
Count	5,425,697	979,731	1,070,525	1,103,312	1,122,318	1,149,811

Table C9. Impact per dollar. Panel (a) (Panel (b)) reports descriptive statistics for the absolute deviation between the log auction price (the log VWAP between 3:55 and 4:00pm) and the log midquote at 4:00pm (the log midquote at 3:55pm) in basis points per 100,000 dollar traded. The variables are winsorized at 0.05% over the full sample. Statistics are reported for the full sample and across market capitalization quintiles, which are formed at the beginning of each year. The x^{th} percentile is denoted as p0.x. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than \$5 and a market capitalization larger than 100 million at the beginning of the month.

(a) $\frac{|\log(P_{\text{auc}}/P_{4:00})|}{V^{\$}_{\text{auc}}}10^5$

		Size quintile				
	All	Low	2	3	4	High
Mean	46.55	227.33	21.04	4.61	1.75	0.23
StdDev	362.22	807.75	163.67	55.62	31.27	7.63
Skew	17.45	7.67	35.53	88.25	142.96	127.18
p0.01	0.00	0.00	0.00	0.00	0.00	0.00
p0.05	0.01	1.99	0.32	0.08	0.02	0.00
p0.5	0.88	35.02	4.47	0.93	0.26	0.03
p0.8	11.49	154.89	14.82	3.03	0.96	0.12
p0.9	41.43	397.32	29.61	5.91	1.99	0.24
p0.95	115.75	932.89	56.35	11.00	3.76	0.45
p0.99	891.86	4098.33	249.35	48.93	16.79	1.52
p0.995	1821.61	6501.18	475.27	97.53	35.07	2.58
p0.999	6258.35	9428.94	1905.52	421.59	186.30	12.40
Count	5,425,697	979,731	1,070,525	1,103,312	1,122,318	1,149,811

(b) $\frac{|\log(\text{VWAP}_{3:55-4:00}/P_{3:55})|}{V^{\$}_{3:55-4:00}}10^5$

		Size quintile				
	All	Low	2	3	4	High
Mean	38.32	187.19	18.26	3.28	0.99	0.20
StdDev	331.16	749.54	124.94	25.13	13.77	14.18
Skew	21.59	9.47	45.31	184.53	399.64	616.06
p0.01	0.00	0.21	0.05	0.01	0.00	0.00
p0.05	0.02	1.40	0.27	0.08	0.02	0.00
p0.5	0.94	31.43	4.56	1.16	0.34	0.06
p0.8	10.56	133.38	15.71	3.48	0.97	0.18
p0.9	37.69	306.77	30.67	6.19	1.68	0.30
p0.95	100.39	663.46	55.30	10.26	2.71	0.46
p0.99	629.72	3177.72	203.85	30.62	8.24	1.06
p0.995	1279.34	5756.87	362.18	49.30	13.98	1.52
p0.999	5400.38	9972.64	1233.33	152.74	56.21	4.13
Count	5,425,697	979,731	1,070,525	1,103,312	1,122,318	1,149,811