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

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Abstract

We document the growing importance of the closing auction in the U.S. equity market and study its causes and implications. The closing auction accounts for a striking 7.5% of daily volume in 2018, up from 3.1% in 2010. The growth of indexing and ETFs shifts trading towards the close and distorts closing prices: they often deviate from closing quote midpoints, but the deviations revert by half shortly after the close and fully overnight. As volume migrates towards the close, liquidity at the open deteriorates. Finally, we introduce a novel measure of investor disagreement, the ratio of auction-to-total volume, and show that higher disagreement positively predicts future stock returns.

Keywords: Closing auction, passive investing, price pressure, liquidity, investor disagreement

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1 Introduction

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

While the introduction of closing auctions in the late 1990s and early 2000s has been studied (for example, Pagano and Schwartz (2003)), little trading occurred at the auction during that period. Recently, however, the auction has received a lot of attention from the financial press: numerous stories suggest that trading volume is shifting towards the end of day and raise concerns about this trend.[2] Did closing volume indeed drastically increase? The growth of indexing and ETFs is another recent trend. Are the trends in closing volume and ETF ownership related? Does the high auction volume distort closing prices? Does the shift in trading towards the close worsen intraday liquidity? What are the broader implications of trading at the close? To our knowledge, we are the first to comprehensively examine the properties of end-of-day trading and especially the closing auction under the "new regime" of enormous volume at the close.

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

Who trades at the close? Passive institutional investors are benchmarked against closing prices

[1]We describe the NYSE and Nasdaq auctions in Appendix A. Appendix B lists quotes from corporate executives, market participants, and members of the U.S. congress on how important a proper closing price is. Closing prices in CRSP and other databases are generally determined in these closing auctions.

[2]For example, "The 30 minutes that have an outsized role in US stock trading. An increasing concentration of volumes from 3.30pm to 4pm is causing concern." *Financial Times*, April 24, 2018; "NYSE Arca Suffers Glitch During Closing Auction." *Wall Street Journal*, March 20, 2017.

[3]The 2018 World Federation of Exchanges report shows that average daily volume is $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, and $8B at Euronext.

for indices they track and thus seek to transact at the auction price to minimize tracking error. Indeed, a survey by Greenwich Associates (2017) shows that investors trade in the closing auction for two main reasons: execution at the official auction price and efficient price discovery. Using a difference-in-difference approach, we show that ETF and passive ownership are major determinants of auction volume. ETF and passive mutual fund ownership, but not active mutual ownership, are strongly associated with auction volume. But ETF, active, and passive ownership have similar and much weaker relation to volume right before the auction. Auction volume spikes on index rebalancing days and end-of-month days, confirming that indexing and institutional rebalancing contribute to trading at the close. Hedges are also rebalanced at the close. Auction volume spikes on option expiration days because option market makers drop their stock delta-hedges at the close after options expire. In contrast, auction volume is lower on and around earnings announcements, major recurrent informational events, whereas pre-close volume is higher. Overall, passive and other uninformed investors seem to be the primary users of the closing auction.[4]

We find that the closing price often substantially deviates from the closing quote midpoint measured at the 4pm market close (and other pre-close benchmarks). Although the median time between the end of regular trading and the 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 for 1% of stock-days the closing price deviates by more than 0.63%. An average deviation corresponds to 6 million dollars in market capitalization and accounts for 5% of intraday volatility. Higher auction volume, which likely corresponds to a larger order imbalance, leads to larger auction deviations. Closing price deviations are highly correlated across stocks and thus affect diversified portfolios.

Auction volume moves prices, but does it make them more or less efficient? Models such as that of Admati and Pfleiderer (1988) predict that concentrated trading at specific times of the day should lower costs and make prices more efficient. Prices can also deviate from fair values if risk-averse liquidity providers absorb large order imbalances (Grossman and Miller (1988)). Hence, more trading at the close may lead to uninformative prices. Price impact remains permanent after

[4]Investors can also trade at the close to avoid holding positions overnight, to avoid the complexity of executing large orders intraday, and to synchronize multi-leg trades. Although 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.

informed order flow, 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. Even when adjusted for the half-spread, auction deviations still entirely reverse. For comparison, the overnight reversal is five times smaller for the last five minutes of trading despite similar price deviations. Variance ratio and weighted price contribution tests further confirm that little price discovery occurs at the auction.[5]

Why are price distortions so large? First, for stocks with sufficient after-hours liquidity, we find that one-third to one-half of the reversal occurs within the first half hour after the close. Quick reversal is consistent with imperfect liquidity provision in the auction. Exchanges have an effective monopoly over the closing auctions for their listed securities and charge high fees to *both* sides of auction trades. High fees and execution uncertainty make it more costly for external liquidity providers to participate in the auction. The rest of the reversal can compensate liquidity providers for bearing overnight risk. Second, differences in auction design further shed light on how imperfect competition can distort prices at the auction. NYSE floor brokers, and thus their clients, have an exclusive right to submit so-called D-quote orders. These widely-used orders can bypass most restrictions of standard market- and limit-on-close orders. Consistent with imperfect competition, price deviations are consistently larger for NYSE than for Nasdaq auctions but are similar pre-auction. Also, auction price deviations increase for firms that switch from the Nasdaq to the NYSE.

We find that closing volume is growing and mostly uninformed. Does this shift of uninformed volume to the close worsen liquidity during the rest of the day? Theory predicts that intraday liquidity may deteriorate because traders optimally cluster their trades at times of higher liquidity; i.e., "liquidity begets liquidity" (for example, Foster and Viswanathan (1990)). Our results are consistent with this prediction. Turnover in the first 15 minutes of trading decreases by 22% for S&P 500 stocks over our sample period. Liquidity worsens: effective spread increases by 10 basis points, and depth at the best quotes declines by 63%. These large changes highlight a potential side effect of the rise in passive investing. As investors cluster at the end of the day, liquidity may

[5]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.

dry up during the rest of the day. This trend is concerning as the opening period is crucial for pricing in overnight news. Indeed, traders voice concerns about the lack of intraday liquidity.[6]

We next show how auction volume can help measure investor disagreement. Investors trade for two broad reasons: they rebalance portfolios, and they disagree with each other (Harris and Raviv (1993)). Although trading volume is regarded as the most direct manifestation of investor disagreement, the rebalancing and disagreement components are difficult to separate. We introduce a novel measure of disagreement – (minus) the ratio of closing auction volume to total daily volume. As we show, auction volume is driven primarily by institutional rebalancing and indexing rather than disagreement, while intraday volume is driven by both rebalancing and disagreement. Thus, disagreement is high when intraday volume is high relative to auction volume. The disagreement ratio is positively correlated with analyst and social media disagreements, but our measure is available for all public stocks daily and relies on public data. Consistent with predictions of disagreement theories, disagreement is persistent, is positively related to volatility and volume, and is higher around earnings announcements. Finally, we study how disagreement affects asset prices. Consistent with Banerjee and Kremer (2010), increased disagreement is associated with higher expected returns next week and month with little subsequent reversal. Decile portfolio sorts yield a 4.2% annualized alpha, while most other return predictors are not significant in our sample. The predictability is robust to excluding hard-to-borrow, attention-grabbing, volatile, or illiquid stocks.

Our tests imply that the last midquote, which is available in CRSP, is more informationally efficient than the official closing price. Replacing the CRSP price with the midquote matters for two applications that we consider.[7] First, using detailed daily data on the SPDR S&P 500 ETF (SPY) and its constituents, we find that the average ETF mispricing decreases by 59% once we use the closing midquotes for the ETF and its constituents. Thus, ETF mispricing in daily data may largely be due to closing price deviations. Second, many violations of the put-call parity disappear if the parity is computed with stock midquotes instead of closing prices because daily option prices are as of 4pm, but the closing stock price is from the auction shortly after 4pm.

[6] "Stock-Market Traders Pile In at the Close", *Wall Street Journal*, May 27, 2015. Also, The unusual market volatility at the open on August 24, 2015 illustrates the potential fragility of the opening period (SEC (2015)).

[7] Blume and Stambaugh (1983); Asparouhova, Bessembinder, and Kalcheva (2010, 2013) show that noise in closing prices can affect asset pricing tests. Hendershott and Menkveld (2014) highlight how shocks to the inventory of liquidity providers cause temporary price deviations. We highlight a specific channel: how the large auction volume introduces noise into closing prices.

This price mis-synchronization and the fact that closing price deviations fully revert overnight also explain why parity violations predict next-day stock return.[8] The two put-call parity puzzles are often interpreted as evidence that option prices contain superior information (Cremers and Weinbaum (2010)); we suggest an alternative explanation.

This paper contributes to several literatures. Prior literature on equity auctions mostly focuses on the introduction of closing auctions. Bacidore and Lipson (2001) find that closing auctions provide little benefits for firms that switch listing from the NYSE to the Nasdaq. In contrast, Pagano and Schwartz (2003), Comerton-Forde, Lau, and McInish (2007), Chelley-Steeley (2008), Kandel, Rindi, and Bosetti (2012), and Pagano, Peng, and Schwartz (2013) find that market quality mostly improved when a closing auction is introduced on the Nasdaq and international exchanges in late 1990s early 2000s. Barclay, Hendershott, and Jones (2008) find that the consolidation of order flow in the opening auction improves price discovery. Recently, Hu and Murphy (2020) show that auction order imbalances disseminated by the NYSE ahead of the auction are less accurate than for the Nasdaq, which can make the NYSE auctions less efficient. They highlight that floor brokers' market power may come not only from exclusive access to D-quote orders but also through their access to better order imbalance information. Wu and Jegadeesh (2020) argue that reversal strategies based on market-on-close order imbalances are profitable.[9] We contribute to this literature by comprehensively examining the closing auction – the economic mechanisms for closing volume, price deviations, and their implications – in the new regime with high volume at the close.

Our results do not imply that the closing auction is problematic. It might be the best trading mechanism to produce reliable closing prices and accommodate closing volume. In fact, Nasdaq introduced the closing cross following demand for more robust closing prices (Pagano et al. (2013)).

We also contribute to the literature that studies how the growth of passive investing, especially ETFs, affects financial markets.[10] We show that this growth contributes to the migration of trading volume towards the close, which distorts closing prices and worsens liquidity at the beginning of

[8] Battalio and Schultz (2006) emphasize the importance of synchronizing stock and option prices. We show that the closing auction leads to mis-synchronized prices (a new mechanism) and relate it to future returns.

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

[10] Cushing and Madhavan (2000) find that stock volatility is disproportionately higher in the last five minutes of trading and partially attribute it to institutional trading. Ben-David, Franzoni, and Moussawi (2018) find that ETF ownership is associated with increased volatility and reversal for the underlying constituents. Baltussen, van Bekkum, and Da (2019) associate a decline in index return autocorrelation across countries with increased passive investing.

the day. Our results provide a starting point to estimate aggregate costs of trading around the close and infer indexing costs.

We contribute to the literature on investor disagreement by introducing a novel disagreement measure that relies on auction volume to separate disagreement and portfolio rebalancing components of volume. Existing studies mostly rely on measures of disagreement such as the dispersion in analysts' forecasts (Diether, Malloy, and Scherbina (2002)) or differences in opinions expressed on social media (Cookson and Niessner (2020)) that are available for a limited sample. In contrast, our measure is easy to compute for all publicly traded stocks at a daily frequency. We also contribute to the active debate about the effect of disagreement on asset prices.

The paper is organized as follows. Section 2 describes the data. Section 3 explores auction volume and price deviations at the close and their reversal. Section 4 studies the implications of our findings for intraday liquidity and investor disagreement. Section 5 concludes. The appendix shows that closing price distortions matter for ETF mispricing and put-call parity violations.

2 Data

We study common stocks listed on the NYSE and Nasdaq with a price greater than \$5 and a market capitalization greater than \$100 million at the beginning of a month. Observations with a missing CRSP return are excluded. We obtain auction price and volume data from the Trade and Quote dataset (TAQ) over January 2010 to December 2018. Auction trades are reported with a special condition by the NYSE and Nasdaq. The procedure to identify auction trades and the relevant filters are detailed in Appendix C. 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 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 the CRSP midquote because it is easy to substitute for the closing price for researchers who already have access to CRSP. The noisier 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 and compute active and passive mutual fund ownership. A mutual fund is classified as passive if the R^2 of a regression of the fund's holdings-implied returns on the Fama-French three factors is greater than 95%.[11] ETF ownership is obtained from the CRSP mutual fund database for 2010 and 2011, and from ETF Global from 2012 to 2018. Option and ETF data used in two applications are described further in the corresponding sections.

3 Volume and price deviations at the close

We first study the properties of closing auction volume and closing price. Our results suggest that auction volume is significantly less informative than pre-close and intraday volumes. Auction volume is strongly associated with proxies for uninformed trading. Price deviations in the auction reverse quickly and almost entirely.

[11] We thank Jiacui Li for sharing data on fund activeness.

3.1 Auction volume

Figure 1 plots the fraction of aggregate daily dollar volume (sum of volume across stocks) executed intraday and around the close. The top plot shows that the fraction of daily volume executed intraday (9:30am-3:30pm) has been decreasing over our sample period. The middle plot shows that the fraction of volume executed in the last five minutes of trading increased from slightly below 5% to just above this level and varies in a narrow range that never exceeds 10% of daily volume. In contrast, the bottom plot shows that the fraction of aggregate daily volume executed in the auction increased substantially from 4% in 2010 to 11% in 2018. Auction volume regularly spikes from the baseline level to about 20% of daily volume. Table 1 confirms that the aggregate volume results in Figure 1 hold for an average stock and describes end-of-day volume for the entire sample and size quintiles. Auction volume is 5.69% of total daily volume for an average stock-day.[12] Not only is auction volume large as a share or total daily volume, its share has been steadily growing. The last five minutes (3:55pm to 4:00pm) account for 6.96% of total daily volume, more than double the volume in the preceding 25 minutes (3:30pm to 3:55pm), which is 10.90%. The auction volume share changes little across size quintiles: 5.67% for large firms versus 6.06% for small firms. Similarly, no clear pattern is observed for the pre-close volume. Overall, auction volume is large, has increased greatly relative to total volume, and behaves differently from intraday volume.

Which factors determine auction and pre-close turnovers? We estimate a panel regression of auction turnover on proxies for potential reasons to trade at the close and on trading environment controls. We contrast the results for the auction turnover with with similar regressions but with intraday (9:30am-3:30pm) or pre-close turnovers (3:30-3:55pm) as dependent variables. As for the trading environment, we control for same-day changes in turnover that may not be specific to the auction by including intraday turnover, defined as volume on the same day divided by total number of shares outstanding on the previous day. Table 2 reports the results. As expected, a higher intraday turnover is associated with higher auction and pre-close turnovers. A 1% increase in

[12] In our sample, 0.22% of stock-days have zero trading volume (or about five stocks a day), and 2.48% of stock-days have zero auction volume. Table 1 shows that the effect is mostly driven by small stocks, 0.72% of which have zero daily volume and 9.56% have zero auction volume. Only 0.21% of stock-days in the top size quintile do not have an auction. Madhavan (1992) predicts that auctions are more important for thinly-traded stocks since the pooling of trades reduces adverse selection. Consistent with this intuition, the auction volume share is similar across size groups despite smaller stocks having more days without an auction. Nevertheless, our results suggest that a minimum amount of trading activity is needed to make an auction viable.

intraday turnover is associated with a 0.33% increase in auction turnover. We control for volatility (the average absolute return over the past five days including the current day), lagged return, market capitalization, and month-of-the-year and day-of-the-week seasonalities. Linear and quadratic trend variables are measured in years and imply that auction turnover has been increasing by about 11.6% per year, pre-close volume turnover has a trend of 6.4% per year, and intraday turnover stays unchanged. Stock fixed effects control for time-invariant stock-specific factors. To facilitate interpretation, we use the logarithm of each variable except for the lagged return, trend variables, and indicator variables. We also estimated these regressions including the lag of the dependent variable with similar results.

Why do investors trade at the close? Passive investors strive to minimize tracking error by trading at the auction because closing auction prices often set their benchmarks. We proxy for indexing by ETF and passive mutual fund ownership and contrast them with active mutual fund ownership. We control for market capitalization to distinguish the effect of institutional ownership from size. Russell index rebalancing days (Friday in late June) provide further insights on how passive investors trade as approximately $9 trillion in assets under management are benchmarked to the Russell U.S. Indices. Other variables that proxy for institutional rebalancing include indicators for beginning- and end- of-the-month, last day of the quarter, option expiration (typically third Friday of each month). We contrast them with indicators for the day before, the day of, and the day after an earnings announcement that proxy for periods with high informed trading.

We find that investors extensively use the closing auction for stocks with high ETF ownership. ETF ownership is highly significant for auction turnover, but its effect on pre-close turnover is only half as large (see Table 2). Similarly, passive mutual fund ownership is strongly associated with auction turnover but only marginally so with pre-close and intraday turnover: a coefficient of 0.037 versus 0.006 and 0.010. In contrast, active mutual fund ownership is positively associated with intraday and pre-close turnover even after controlling for size, but it does not affect auction turnover, if anything the point estimate is negative. These results are consistent with auction volume being primarily uninformed.

To further contrast the effect of passive and active ownership, Figure 2 plots the elasticity of turnover to ETF, passive, and active mutual fund ownership for each five-minute interval between 3:30pm and the auction. The ETF ownership elasticity of turnover gradually increases through the end of trading and spikes at the close. It is five times greater for auction turnover than for turnover between 3:30pm and 3:35pm. The pattern for passive ownership is even more remarkable: the volume elasticity remains roughly flat and close to zero before spiking in the auction. In contrast, active mutual fund ownership elasticity increases gradually but drops at the auction. These results have a difference-in-difference interpretation; the first difference compares the auction with the pre-close; the second difference compares ETF and passive ownership with active ownership.

More formally, we estimate a two-step difference-in-difference specification. In the first step, turnover elasticity relative to active mutual fund, passive mutual fund, and ETF ownership is estimated for each stock over the sample period. The elasticity is estimated separately for auction turnover and turnover in every five-minute interval from 3:30pm until 4pm with the same set of control variables as in Table 2. In the second step, the elasticities are regressed on indicators for time-of-day, ownership type, and interactions between time-of-day and ownership type. Table 3 reports the results. In the first column, the coefficient Auction*ETF measures the difference between the turnover elasticities of ETF ownership and active mutual fund ownership in the auction relative to their difference in the five-minute intervals from 3:30pm to 4pm. Consistent with Figure 2, we find that ETF and passive mutual fund elasticities are significantly larger than active mutual fund ownership in the auction relative to the intervals before. This holds true when we only compare 3:55-4:00pm with the auction, or when we focus separately on small and large stocks. This difference-in-difference analysis helps alleviate some of the endogeneity concerns and alternative explanations of the impact of passive ownership on closing volume.[13]

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

[13] We also estimate an extension of the panel regression in Table 2 in which we regress auction and pre-auction turnover on interval-stock fixed effects, and control variables and their interactions with auction/pre-auction indicators. This specification maps directly to the coefficients in Figure 2 except that we can formally test for the difference-in-difference. The results are similar.

closing auction to complete arbitrage trades that were initiated earlier during the day.

Russell index rebalancing days provide a quasi-exogenous shock to indexing that let us confirm its effect on closing turnover. Auction and pre-close (3:55-4:00) turnovers are 230% and 78% higher, whereas intraday (3:30-3:55) turnover is only 7.8% higher on index rebalancing days. Index funds rebalance in the last five minutes of trading and especially at the auction, because they want to minimize the tracking error. Other calendar effects confirm that institutional rebalancing contributes to closing volume. Auction and pre-close turnovers are 87% and 33% higher on the last day of the month, while intraday turnover is unchanged. Institutional investors report their portfolio and are benchmarked with month-end prices, which encourages them to trade at the close to minimize tracking error. Etula et al. (2020) show that many institutional investors accommodate inflows in the first days of the month. Indeed, turnover tends to be higher in all periods on the first day of the month but especially so at the auction. Auction turnover is 60% higher on option expiration days, while pre-close and intraday turnovers increase mildly (12% and 16%). Option market-makers and other option investors, who hedge their positions in the underlying, unwind the delta-hedge right after options expire at the close. Auction turnover is between 5% and 10% higher in months marking a quarter-end, but there is no significant increase in auction turnover on the last day of the quarter beyond the last day of the month increase. These results can further alleviate endogeneity concerns as these calendar indicators are largely exogenous to the trading process.

Auction volume appears uninformed and liquidity-driven around earnings announcements. It is well-known that informed trading is more likely around these announcements. Indeed, intraday turnover is 22% higher on pre-announcement day, the last day before the market learns about the news. Controlling for intraday turnover, pre-close turnover is 23% higher. In contrast, auction turnover is virtually unchanged, a mere 1.6% increase beyond what would be predicted by higher intraday turnover. Similarly, intraday turnover is 96% and 49% higher on the announcement and post-announcement days, while auction turnover is about 2% lower.

Overall, auction volume appears special relative to volume at other times of the day. Auction volume is strongly associated with proxies of uninformed and liquidity-driven trading unlike pre-close and intraday volumes. Passive investors (index rebalancing days), other institutional investors (month-ends), option market-makers (expiration days) extensively use the closing auction, while informed investors (earnings announcements) do not appear to, or at least not in a substantial way. Supporting this view, auction turnover depends differently on active and passive mutual fund ownership. 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 the close could be large enough to dwarf informed trading. Second, trading at the close is risky because of price and execution uncertainty on top of higher exchange fees, which we discuss further below. Ultimately, more informed trading should lead to improved price discovery, which we investigate next.

3.2 Price deviations at the close

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

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

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

Table 4 Panel (a) reports the distribution of closing price deviations for the entire sample and across size quintiles. Auction price deviations are 8.12 bps on average and range from 20.6 bps for small stocks to 2.66 bps for large stocks. To put these numbers into perspective, 8.12 bps corresponds to 5% of daily volatility and 6 million dollars in market capitalization for an average stock. The distribution has positive skewness: the closing price is usually close to the midquote but occasionally deviates by a sizable amount. In 5%, 1%, and 0.1% of stock-days closing prices deviate by more than 0.26%, 0.63%, and 1.95%, respectively. That is, prices for about 30 stocks deviate by more than 0.63% on a typical day.[14] In dollar terms, the numbers in Table 4 are economically large given the large volume traded in the auction.

Auction price deviations contribute to daily volatility. To estimate the auction's contribution, we consider the volatility ratio, 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 4 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

[14] Price deviations are also large for alternative benchmarks such as VWAP between 3:55 and 4:00pm instead of 4pm midquote. 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 D.2).

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 stocks to 3% for large stocks. We will examine two explanations for these results below. 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.[15]

Auction trades are rarely executed at the quote midpoint. Hence, we decompose the (absolute) deviation into spread and price impact components: $|\text{deviation}| = \text{half-spread\%} + \text{price impact\%}$. 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. Table IA.1 in the Internet Appendix reports the distribution of the half-spread and price impact components. 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. Indeed, the average half spread is 7.56 bps, while price impact is 0.55 bps. Thus, the price deviation equals the half spread for most auctions similar to the bid-ask bounce. For large stocks, the half-spread and price impact are about equal: 1.47 and 1.19 bps. Nevertheless, price impact can be much larger than the half spread, for example, when closing volume is large.

We use panel regressions to study the determinants of closing price deviations and report the results in Table 5.[16] Higher auction turnover leads to larger price deviations: 0.88 bps higher deviation for a 1% increase in turnover, and the impact is larger for smaller stocks. Intraday turnover is negatively related to auction deviations perhaps because auction volume has a larger impact on low volume days due to low liquidity. As expected, when the spread or volatility are high, price deviations are larger. Auction volume proxies for order imbalance by liquidity seekers, which is not directly observable in TAQ. The coefficients are quantitatively close whether we examine

[15] Also, for stocks of above-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.

[16] We include 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. The main specification in Panel (a) includes stock fixed effects to focus on time-series variation. Deviation and spread variables are winsorized at 0.05%.

the absolute price deviation or price impact as reported in the Internet Appendix. Finally, NYSE auctions have much larger deviations than Nasdaq auctions. We discuss this point in detail below. Table 5 Panel (b) focuses on cross-stock variation by including date fixed effects instead of stock fixed effects.

Do price deviations affect diversified portfolios? Passive investors trade baskets of securities. This simultaneous buying or selling translates into correlated order imbalances across stocks, which may produce correlated price deviations at the auction. To compute the aggregate price deviation, we first aggregate *signed* price deviations across individual stocks for each day proportional to their capitalization and then take the absolute value. That is, the aggregate deviation will be close to zero if half of the stocks have a positive deviation and the other half a negative one. Aggregate price deviation is 0.93 bps on average, or about three billion dollars per day in aggregate. The aggregate deviation is about one third of average individual deviations for large stocks (2.66 bps in Table 4). Figure 3 shows that the time series of aggregate price deviation and the VIX index are highly correlated. Prices are more likely to deviate at the close when aggregate risk is high. For instance, the largest 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. These results are robust to using only the price impact component of the aggregate price deviation and thus are not driven by a commonality in spreads. Table IA.3 in the appendix confirms that auction volume drives aggregate closing deviation as they both spikes on the same days, such as institutional rebalancing days. 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. Thus, as price deviations are highly correlated across stocks, they matter not only for individual stocks but also at the aggregate level.

3.3 Do closing 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:

$$\log(p_{9:45,t+1}/p_{\text{auc},t}) = a + b\log(p_{\text{auc},t}/p_{4:00,t}) + e_t, \tag{2}$$

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 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 they are entirely due to price pressure. Table 6 shows that the coefficient is -0.85, or 85% of the deviation is reversed by the next morning. For large and small stocks, 110% and 85% of the price deviation is reversed. The reversal coefficient approaches -1 (complete reversal) if we control for the 3:55-4:00 price change. Thus, price deviations are mainly due to price pressure and not new information. In contrast, only 19% of the last five-minute return is reversed the next morning, i.e., the 4pm midquote change is mostly efficient. Similarly, the return between the 3:55pm midquote and the volume-weighted average price (VWAP) in the last five minutes shows only weak reversal. In Section 3.1, we show that auction volume differs from pre-close volume. This difference translates into prices: auction price stands out relative to pre-close price.

As the auction price reflects half the spread, we check how much of the reversal is driven by a mechanical bounce effect. We adjust the reported auction price by adding (subtracting) half the spread for trades made below (above) the 4pm midpoint and then estimate (2) 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.

Variance ratios are another approach to evaluate price efficiency. For each stock we compute the ratio between daily return variance from auction prices and compare it with the variance from quote midpoints. Table IA.4 in the appendix reports descriptive statistics for the variance ratios of daily returns. The average ratio of 1.014 is statistically significantly different from one at the 1% level and means that the closing price adds 1.4% of non-informative variance. The average ratio for large small stocks is even larger: 4.5%.

We also compute another well-known 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

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

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, if it has an auction price on a given day and a valid midquote at 9:45am on the next day. All returns are winsorized at 0.005%. 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 auction should have a similar price contribution as other intervals, and this is why we picked a five-minute time step.

Panel (a) of Figure 4 plots WPC estimates computed across stocks in the bottom and top size quintiles. The closing auction contributes little to price discovery as its price contribution is about ten times lower than what other periods with similar volume contribute. The results are similar for all size categories with the auction having slightly higher WPC for smaller stocks. (Table IA.5 in the Appendix reports WPC estimates for all size quintiles and the full sample.) If we use the auction price adjusted for the spread, the auction's contribution of the WPC drops to zero (reported in Table IA.5). Thus, the auction price only conveys information to the extent that it takes place at the ask or at the bid. These alternative price discovery measures confirm that auction price deviations contribute little to price discovery.

An uninformative auction deviation does not imply that auction volume is uninformative since exchanges release information about order imbalance ahead of the auction (Mayhew et al. (2009)). As the market learns about these imbalances, prices move to reflect this information. The NYSE (Nasdaq) starts releasing imbalance information at 3:45pm (3:50pm) over most of our sample period.[17] If the imbalance is informative, weighted price contributions should increase at 3:45pm (3:50pm) for NYSE (Nasdaq) stocks to reflect the increased information flow.

We perform a simple difference-in-difference regression. WPCs for every five-minute interval between 3:30pm and 4:00pm and the auction price deviation 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 indicator, indicators for each interval after 3:35pm, and NYSE-interval interaction indicators. These last indicators allow us to test for changes in WPC while controlling for fixed differences in WPC between different five-minute intervals at the end of the day and for fixed differences in WPC between NYSE and Nasdaq stocks. For instance, the NYSE and 3:45pm-3:50pm interaction coefficient allows us to test whether NYSE stocks experience a change between their 3:45-50pm WPC and their 3:30-35pm WPC in excess of the change in WPC of Nasdaq stocks between the same intervals.

Panel (b) of Figure 4 shows that auction volume indeed contains some information. WPC increases for NYSE stocks when the NYSE starts to disseminate imbalance information at 3:45pm, and this increase is not explained by a concurrent increase in the WPC of Nasdaq stocks. The opposite holds true at 3:50pm when the Nasdaq starts to disseminate imbalance information. (The full results are reported in Table IA.6 in the Appendix.) Though auction volume is informative, the economic magnitudes are small. First, Panel (a) of Figure 4 shows that WPCs are stable over 3:30-4:00pm for large stocks, which is inconsistent with order dissemination playing a major role for price informativeness. Second, Panel (b) of Figure 4 suggests that a rough estimate of auction volume price contribution is 1% (0.5%) for small (large) stocks.[18] Even taking this effect into account, auction price contribution remains less than half of the price contribution between 3:30pm and 3:35pm. We conclude that auction volume contributes to price discovery but is less informative than volume over other intervals, and that this contribution is quite limited for large stocks.

[17] For this test, we stop our sample at the end of September 2018 since Nasdaq switched its dissemination time to 3:55pm in October 2018.

[18] One potential concern is spillover effects if market participants learn about imbalances for Nasdaq from observed imbalances for NYSE stocks. We cannot rule out this concern, but a comparison of raw NYSE and Nasdaq WPC suggests that this channel, if it exists, is economically small.

3.4 Why do closing prices reverse?

Price reversal is consistent with increased market segmentation at the auction. Exchanges have an effective monopoly over the closing auctions for their listed securities. A closing auction for Coca Cola's stock organized on the Nasdaq does not set the official daily closing price for Coca Cola since it is listed on the NYSE. Price reversal is also consistent with liquidity provision ahead of the overnight period. Risk-averse liquidity providers likely require compensation to hold inventories in the overnight period due to its low liquidity and high price jump risk.

To disentangle among the two explanations, we examine after-hours trades. Market segmentation predicts that 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 volume-weighted average prices between 4:10-4:20pm, 4:20-4:30pm, and 4:30-4:40pm.[19] We start at 4:10pm to avoid guaranteed close orders and to make sure that the auction has already taken place and estimate

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

where τ is 4:20pm, 4:30pm, and 4:40pm (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 first twenty-minute window. Table 7 shows that the price reverts half-way to the pre-close midquote in just twenty minutes after the close. If the after-close window is expanded to forty minutes, half of large stocks trade in this window, and the reversal coefficient is still close to one-half. We confirm that the results are not affected by the bid-ask bounce. This fast reversal supports the segmentation hypothesis.

Segmentation at the auction can arise for several reasons. First, exchange fees are charged on both sides of an auction trade, whereas a rebate is issued to a trader who places a liquidity-providing order during regular trading. Second, trading in the auction is subject to more uncertainty than during regular hours. For example, Kim and Trepanier (2019) argue that liquidity providers face queuing uncertainty, which makes them less willing to absorb imbalances in the closing auction. A failed execution in the auction likely entails carrying a suboptimal inventory overnight. Thus, the

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

reward for providing liquidity should be higher during the auction than during regular trading.

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

The segmentation hypothesis predicts that price deviations should be higher on the NYSE than on the Nasdaq. To benchmark the NYSE closing auction deviation, we estimate a panel regression for end-of-day absolute five-minute log returns and the auction absolute price deviation. The regression includes a NYSE indicator and control for date fixed effects, volume, volatility, spread, and price. We focus on large stocks to avoid issues related to thin trading but find similar results for other size groups. Figure 5 plots the coefficient and confidence interval for the NYSE indicator. For the 3:30-35pm, 3:35-40pm, 3:40-45pm intervals, NYSE and Nasdaq deviations are not statistically different. Thus, our specification controls well for differences across stocks. At 3:45pm, the NYSE coefficient becomes positive and significant, as the NYSE starts to disseminate auction order imbalance. The opposite takes place at 3:50pm, when the Nasdaq starts to release the information. At 3:55pm, there is no significant difference despite the diffusion of D-Quotes order imbalance on the NYSE. At the auction, the NYSE indicator is strongly positive and statistically significant. Importantly, this excess deviation does not translate to a higher price discovery for NYSE stocks since Panel (b) of Figure 4 shows no difference in price discovery between NYSE and Nasdaq stocks at the auction for large stocks. We find similar evidence from panel regression with stock fixed effects, where identification come from stocks switching exchanges. For large stocks, the excess NYSE price deviation represents more than a third of the average price deviation in

Table 4.[20]

Hu and Murphy (2020) comprehensively study the quality of auction order imbalance information. They argue that order imbalance information is less precise on the NYSE than on the Nasdaq because the NYSE does not include accumulated D-Quotes to compute order imbalance until 3:55pm. They find that auction quality is substantially worse for NYSE stocks than Nasdaq stocks, in line with our above findings.

4 Implications

In this section, we develop several implications from our findings. First, the shift of uninformed trading towards the end of the day that we document affects liquidity at the open. Second, auction volume stands out relative to intraday volume since our results suggest it is primarily associated to liquidity trading. We use this property to introduce a novel measure of investor disagreement, validate it, and study how it affects stock prices. Finally, we show how closing price distortions matter for ETF mispricing and put-call parity violations.

4.1 Intraday liquidity

The results so far imply that liquidity is likely to worsen during the rest of the day. We show in Section 3.1 that closing volume is associated with proxies for passive investment strategies. As more capital flows into these strategies, uninformed trading increases at the close. A "liquidity begets liquidity" effect pushes other traders to also shift their trades to the close.

In models such as Admati and Pfleiderer (1988) and Foster and Viswanathan (1990), discretionary liquidity traders optimally cluster their trades in the same period to lower adverse selection. Consider an economy with two periods – open and close – and the same amount of liquidity trading in both periods. In Admati and Pfleiderer (1988), an increase in liquidity trading at the close causes an increase in volume and liquidity at the close, whereas liquidity and volume decrease at the open. In Foster and Viswanathan (1990), an increase in adverse selection at the open pushes discretionary liquidity traders to delay their trades to the close, resulting in the same prediction. The first model

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

predicts higher volatility at the close since informed traders also migrate to the close. The second model does not predict such a change since informed traders' short-lived information precludes them from moving to the close.

Intraday liquidity should deteriorate as more uninformed volume migrates to the close. To test this prediction, we focus on another key intraday period – the open – and examine volume, liquidity, and volatility in the first 15 and 30 minutes of trading. We restrict the sample to large stocks that are traded over the full sample to make the stocks comparable. The sample includes 333 stocks, with 92% of the observations belonging to S&P 500 stocks. We estimate panel regression of (log) turnover, dollar-weighted percentage effective spread, and (log) time-weighted depth on stock fixed effects, day and month indicators, calendar year indicators, and control variables such as stock price and market capitalization. We focus on calendar year indicators that capture the trend in the dependent variable: turnover, spread, and depth.

Panel (a) of Figure 6 reports the change in (log) turnover at the open and at the auction over the sample period. Auction turnover increases, but turnover at the open decreases. Unlike Figure 1, the plots show raw turnover, not turnover as a fraction of daily volume. The effect is large: turnover at the open declined by around 21% ($\approx e^{-0.24} - 1$) over the sample period. This evidence is consistent with the "liquidity begets liquidity" effect. A decrease in *raw* turnover is hard to explain with alternative theories.

Also consistent with our hypothesis, liquidity deteriorates at the open over the sample period, as shown in Panel (b). Effective spread increases and (log) depth decreases significantly, an unambiguous decline in liquidity at the NBBO. Effective spread increases by around 10 bps, which is large for S&P 500 stocks in our sample. Depth at the best quotes declines by around 63% ($\approx e^{-1} - 1$).

Does volatility change at the open? Controlling for intraday realized volatility, realized volatility at the open tends to increase over the sample period (see Figure IA.1 in the Internet Appendix). This result is consistent with informed traders who act on short-lived information based on overnight news. The release of public information over the day or competition with other informed traders prevent these traders from delaying their trades to later during the day. Overall, as uninformed volume migrates from the open to the close, adverse selection and volatility increase at the open.

The trading decisions of investors connect liquidity at different times of the day, and thus variations in liquidity over the day ought to be examined jointly. The above results support this idea and highlight a potential side effect of the increase in passive investing: as investors cluster at the end of the day, liquidity may dry up during the rest of the day. Indeed, stock market traders are concerned about the lack of intraday liquidity (see Footnote 6). The decrease in liquidity at the open may also increase market fragility at that time. This could exacerbate events such as the August 24, 2015, flash crash at the open, where abnormal volatility led to delayed openings for many securities (SEC (2015)). Upson and Van Ness (2017) report that spreads do not follow a U-Shape over the trading day anymore, with a lower spread at the close. Jiang and Yao (2020) associate this change with trends in passive investing. These papers do not examine variations in liquidity at the open, though their results support the "liquidity begets liquidity" effect. We believe more work is needed in this direction given the importance of establishing a proper price after the overnight period.

4.2 Closing volume and investor disagreement

In this section, we introduce and validate a novel measure of investor disagreement and study how it affects asset prices. Cochrane (2011) demands that "we must answer why people trade so much." Harris and Raviv (1993) argue that investors are heterogeneous and trade for two broad reasons: portfolio rebalancing and disagreement. They further clarify that "disagreements can arise either because speculators have different private information or because they simply interpret commonly known data differently." Thus, informed trading can be viewed as a special type of investor disagreement even though the two concepts are usually modeled differently. Investors can also rebalance their portfolios in response to private liquidity shocks or changes in investment opportunities among other reasons. Investors of course do not report why they trade; and according to Wang (1994), a "challenge is how to identify empirically the nature of heterogeneity across investors." We take up this challenge.

How can we separate portfolio rebalancing and disagreement? As we show, closing volume is mainly driven by indexing and institutional rebalancing and behaves differently from intraday volume. We rely on these results to introduce a novel measure of disagreement – (minus) a ratio of closing auction volume to total daily volume.[21]

$$\text{Disagreement}_{i,t} = -\frac{\text{Auction volume}_{i,t}}{\text{Total volume}_{i,t}}. \tag{5}$$

The disagreement ratio is high when the daily volume is high relative to the closing volume. Assuming the closing volume is indicative about daily rebalancing while the intraday volume contains significant disagreement-driven trading, the ratio of the two volumes is informative about investor disagreement. For example, if disagreement and rebalancing are split 70/30 intraday and 30/70 at the close, then the ratio of auction to intraday volume is related to the ratio of rebalancing to disagreement (assuming intraday and auction rebalancing are correlated).

We compute a weekly average of daily disagreement ratios to facilitate the comparison with other disagreement measures that are observed at lower frequency. Thus, the unit of observation is stock-by-week, while the paper's other results are at the stock-by-day level.

We first validate the disagreement ratio. Theories of disagreement such as Harris and Raviv (1993) and Kandel and Pearson (1995) predict that it should positively relate to trading volume and price volatility. Investors agree on how to interpret information most of the time, and periods of high disagreement are often associated with high volume and volatility. Consistent with the theoretical prediction, the disagreement ratio has a correlation of 28% with idiosyncratic volatility and 24% with log daily volume in Table 8. Also, the ratio predicts volatility next month (t-stat = 3.0) controlling for last-month volatility in a panel regression with stock and week fixed effects. Similarly, the ratio strongly predicts total daily volume for several months in the future; a t-statistic of 30.0 for the next-week log volume that slowly decays over time. Standard errors in all the panel regressions in this section are clustered by stock and by week unless noted otherwise.

Most theories predict that disagreement should be persistent: if investors disagree this week, they will likely continue to disagree next week. Consistent with this prediction, the disagreement ratio is persistent. In a panel regression with stock and week fixed effects, the current-week ratio predicts next-week ratio with a coefficient of 0.41, which declines to 0.31 for predicting the ratio in four weeks. The persistence is highly statistically significant and is robust to including controls.

[21] The minus sign is required because prior studies focus on investor disagreement rather than agreement. We explore two alternative definitions – a ratio of total to auction volume and a log difference between total and auction volume – with similar results.

Kandel and Pearson (1995) make another prediction: disagreement should be higher around earnings announcements. The disagreement ratio is indeed consistently higher during earnings weeks in Table 8 (Panel (b)) even after controlling for idiosyncratic volatility, market capitalization, and week (or stock) fixed effects.

The disagreement ratio is positively correlated with popular disagreement measures including the analyst dispersion by Diether et al. (2002) and the social media sentiment by Cookson and Niessner (2020).[22] Panel (b) of Table 8 goes beyond raw correlations and shows that the disagreement ratio positively and significantly depends on concurrent analyst and social media disagreements and idiosyncratic volatility after controlling for log market capitalization, stock price, and weekly fixed effects in a joint panel regression (with standard errors clustered by stock and week). Thus, we find a robust relation between the disagreement measures. The social media and analyst disagreements are only available for half of the sample, and the sample size drops four-fold if both are included, but the results remain robust for these four samples. In contrast, the disagreement ratio is available for any listed stock at a daily frequency, including securities without analyst coverage such as ETFs.

After validating the disagreement ratio, we study how differences of opinion affect stock prices. We estimate a panel regression of next-week and next-month stock returns on the change in disagreement, week fixed effects (to account for the commonality of stock returns), and standard return predictors as control variables. Stock returns are computed from daily returns in CRSP and adjusted for stock delistings as in Shumway (1997). We skip a day between predictors and returns to avoid confounding effects as today's closing price is an input to tomorrow's return. The change in disagreement is computed as the difference between its value this week and last month. Other predictors include idiosyncratic volatility (computed from abnormal daily returns from the Fama-FrenchCarhart four-factor model over the prior month), momentum (stock returns from six months to one month prior to the date), monthly reversal (previous month return), log market capitalization, CAPM beta, Amihud (2002) illiquidity measure, and a visibility indicator, which Gervais, Kaniel, and Mingelgrin (2001) set to one (-1) if current volume is greater (lower) than 90% (10%) over the prior 49 days. Predictors are winsorized at a 0.05% level to avoid outliers. The

[22]We thank Tony Cookson for providing the social media disagreement measure on his website. It is based on messages posted on https://stocktwits.com/ between 2010 and 2018. Following Diether et al. (2002), analyst forecast dispersion in prior month is scaled by absolute mean forecast. Analyst forecasts are from the I/B/E/S database.

standard stock price and market capitalization filters are already applied to the auction sample. (Table IA.7 in the Internet Appendix reports summary statistics for the main variables.) Standard errors are clustered by stock and week to account for overlapping returns and cross-stock dependencies. The main results remain robust if a Fama-MacBeth regression is estimated instead of a panel regression or if alternative specifications are used (for example, if current-week variables such as return and turnover are included).

The model of Banerjee and Kremer (2010) implies that increased disagreement should be associated with higher expected returns. Disagreement shocks are persistent (similar to ARCH effects for volatility). Higher anticipated disagreement in the future leads to more uncertainty in payoffs today, and this increase in risk leads investors to require a higher expected return. Consistent with this theoretical prediction, we find that increased disagreement is associated with higher expected returns next week and month. Table 9 reports that the change in disagreement has t-statistics of 3.1 and 4.7 for predicting weekly and monthly returns. In contrast, idiosyncratic volatility is the only other robust predictor of monthly returns; it is well-known that many anomalies became much weaker post-2009 which coincides with our sample period. Few variables consistently predict returns, we identify a new return predictor. Consistent with a risk premium explanation, we observe no significant return reversal if we predict second month returns with the disagreement change. We find strong return predictability for the change in disagreement but not for its level.

We supplement panel regressions with portfolio analysis. Table 10 reports returns and alphas from the Fama-FrenchCarhart six-factor model for equally-weighted portfolios sorted on the disagreement change. The return difference between the top and bottom decile portfolios is 12 bps for weekly returns and 34 bps for monthly returns, or 4.2% annualized, with the corresponding t-statistics of 3.3 and 4.9. The portfolio returns increase roughly monotonically across portfolios, and the long leg produces most of the abnormal return, thus short-sale constraints are less likely to affect this predictability. Alphas and average returns match for the top-minus-bottom portfolio, and factor loadings for Fama-French risk adjustment are not significantly different across top and bottom decile portfolios. Models with fewer than six factors produce similar results.

We study increased disagreement around earnings announcements (e.g., Kandel and Pearson (1995)) with our measure to confirm its robustness and to identify the underlying mechanism. Banerjee and Kremer (2010) suggest that earnings announcements are likely associated with large jumps in disagreement that are followed by more positive returns. Consistent with this prediction, the disagreement ratio predicts returns more strongly around earnings announcements. We set an earnings indicator to one if an announcement is within ten days of the current date (before or after) and then interact this indicator with the disagreement ratio change. As reported in Table 9, the return predictability increases two-fold around earnings announcements: a coefficient for the disagreement ratio of 0.055 (t-stat = 5.0) versus 0.023 (t-stat = 2.7) during non-earnings period, and this difference between the two periods is statistically significant. This application also highlights the advantage of having a high-frequency measure of disagreement, which contrasts with analyst forecasts that are updated less frequently.

The predictability remains unaffected when we explore important subsamples as reported in Table IA.8 in the Internet Appendix. The results are unchanged if we exclude stocks with a non-zero visibility indicator. Gervais et al. (2001) argue that a positive volume shock can attract new investors, who push the stock price higher (and the reverse for negative volume shocks). Our results are robust to excluding such stocks with visibility shocks. In untabulated results, we also confirm that the disagreement surprise remains significant after we control for the surprise in log daily volume (the disagreement coefficient decreases slightly from 0.033 to 0.028). Thus, benchmarking daily volume to the auction volume (as compared to its historical average) in the disagreement ratio makes a difference. Excluding the decile of most illiquid stocks for each week has the biggest effect on predictability; the coefficient for disagreement decreases from 0.033 to 0.025 but remains significant with a t-statistic of 3.4. The results are robust to excluding hard-to-borrow stocks, i.e., 10% of stocks each week with the highest utilization or borrowing fee. The remaining 90% of stocks are easy to borrow and have a borrowing fee of less than 1% per year. Many stock anomalies are concentrated in illiquid or hard-to-borrow stocks, but the disagreement ratio continues to predict returns even if such stocks are excluded. Thus, this result favors the risk premium explanation rather than market inefficiency. The predictability decreases only slightly if we exclude the decile of most volatile stocks. The return predictability is the same in the first and second parts of our sample (pre and post 2014). Finally, the predictability is stronger for smaller firms: the coefficient for disagreement is 0.038 for the quintile of smallest firms versus 0.023 for the quintile of largest firms, both are significant. This is consistent with higher disagreement for small stocks.

The auction volume helps us separate disagreement from rebalancing and thus identify investor disagreement. But the pre-close volume, especially outside the last five minutes of trading, is only weakly associated with ETF ownership and institutional rebalancing. Thus, the disagreement ratio computed from pre-close volume should be a weaker proxy for disagreement and thus a weaker return predictor. Indeed, if the auction volume in the disagreement ratio is replaced with the 3:55-4:00pm or 3:30-3:55pm volumes, the disagreement change loses most of its predictive power for future returns, even though these two periods are adjacent to the auction and have comparable volume. The last two columns in Table 9 show that for monthly returns, the auction-based disagreement remains unaffected by adding the pre-close "disagreements:" the 3:55-4:00pm disagreement is barely significant, and the 3:30-3:55pm disagreement does not predict returns. The 3:55-4:00 pm or 3:30-3:55pm disagreement ratios do not predict weekly returns. Thus, consistent with the earlier ETF sensitivity results, the closing volume is indeed special relative to the pre-close volume and can proxy for the rebalancing component of volume.

We contribute to the debate on the relation between disagreement and future stock returns. We find that the disagreement *level* is not significantly related to future returns, while the *change* in disagreement positively predicts returns. Diether et al. (2002) show that the *level* of analyst disagreement is negatively related to future returns. They explain the predictability by arguing that prices reflect a more optimistic valuation if pessimistic investors are kept out of the market by high short-sale costs (Miller (1977)). Cen, Wei, and Yang (2017) argue that the analyst forecast dispersion measure captures not only disagreement but also other return-predictive information contained in the normalization scalars of the measure. Indeed, we find that analyst disagreement negatively predict returns in our sample even for the subsample of easy-to-borrow stocks. Banerjee and Kremer (2010) measure *changes* in disagreement with abnormal daily turnover and find that an increase in disagreement is followed by positive returns in the next ten days on average. They assume that volume shocks are entirely due to disagreement, while we show that rebalancing volume varies over time and helps separate the two components. Overall, our results are consistent with a positive risk premium for changes in disagreement.

4.3 Do closing price deviations matter?

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? We show that it does for two applications: put-call parity violations and their ability to predict next-day stock returns, and ETF mispricing. The put-call parity is typically computed with the closing stock price and 4:00pm option bid and ask prices. This mis-synchronization between stock and option prices explains many put-call parity violations. It also explains why put-call parity violations predict next-day stock returns because as we show closing price deviations completely reverse by next morning. We discuss the put-call parity results in Appendix D.1.

ETF closing auction prices are also subject to price deviations. Most ETFs' net asset values (NAVs) are computed using the underlying securities' closing prices. Hence, a standard measure of ETF mispricing based on the absolute difference between the daily ETF price and the NAV does not effectively reflect an arbitrage opportunity. In Appendix D.2, we examine how this bias affects the mispricing of the SPY ETF, "The King of Liquidity." An easy fix is to account for the closing deviation in both the ETF price and its NAV by using the midquote at 4pm. This reduces SPY mispricing by almost 60% in 2018.

5 Conclusion

Closing auctions handle a huge volume that has grown significantly over 2010 to 2018. We show that ETF ownership and passive mutual fund ownership, but not active fund ownership, are strongly associated with closing auction volume. Our methodology helps alleviate endogeneity concerns and rule out alternative explanations. Consistent with auction volume being mostly uninformed, closing prices contain almost no incremental information compared to closing quote midpoints. Price deviations at the close are reversed by the next morning. About half of the reversal occurs right after the auction, which is consistent with imperfect liquidity provision at the auction. In line with this intuition, NYSE auctions produce consistently larger price deviations than Nasdaq auctions. The two auctions differ in that NYSE floor brokers have access to special orders that may increase auction imbalance.

We develop several implications for our findings that closing auction volume is growing and mostly uninformed. First, theory predicts that liquidity may worsen at other times during the day as volume migrates towards the close. Indeed, turnover at the start of the day decreases over our sample period, while effective spread increases and depth decreases. Therefore, a potential negative externality of the rise of passive investing is that liquidity may dry up during the day. Second, we introduce a novel measure of investor disagreement, which correlates with other disagreement measures, but is available for all public stocks daily. Future stock returns are higher after disagreement increases. Finally, replacing the closing price with the 4pm quote midpoint, which is available in CRSP, greatly reduces apparent ETF mispricing and the number of put-call parity violations.

Our results highlight several policy relevant issues. Auction participants pay high exchange fees and can incur indirect costs of subsequent price reversal. Since auction deviations are highly 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 trading in the auction. Still, a closing call auction may be the best trading mechanism in light of existing institutional incentives. The ongoing shift towards passive investing may lead to a further concentration of trading volume around the close and make our analysis even more relevant. We leave for future research to investigate how alternative auction designs interact with institutional benchmarks.

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*.

Baltussen, G., S. van Bekkum, and Z. Da (2019). Indexing and stock market serial dependence around the world. *Journal of Financial Economics 132*(1), 26–48.

Banerjee, S. and I. Kremer (2010). Disagreement and learning: Dynamic patterns of trade. *Journal of Finance 65*(4), 1269–1302.

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.

Cen, L., K. J. Wei, and L. Yang (2017). Disagreement, underreaction, and stock returns. *Management Science 63*(4), 1214–1231.

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

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.

Cochrane, J. H. (2011). Presidential address: Discount rates. *Journal of Finance 66*(4), 1047–1108.

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.

Cookson, J. A. and M. Niessner (2020). Why don't we agree? evidence from a social network of investors. *Journal of Finance 75*(1), 173–228.

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.

Diether, K. B., C. J. Malloy, and A. Scherbina (2002). Differences of opinion and the cross section of stock returns. *Journal of Finance 57*(5), 2113–2141.

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

Foster, F. D. and S. Viswanathan (1990). A Theory of the Interday Variations in Volume, Variance, and Trading Costs in Securities Markets. *Review of Financial Studies 3*(4), 593–624.

Gervais, S., R. Kaniel, and D. H. Mingelgrin (2001). The high-volume return premium. *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.

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

Harris, M. and A. Raviv (1993). Differences of opinion make a horse race. *Review of Financial Studies 6*(3), 473–506.

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.

Hu, E. and D. Murphy (2020). Vestigial tails: Floor brokers at the close in modern electronic markets. working paper.

Jiang, W. and C. Yao (2020). U disappeared: Indexing and the shift of diurnal patterns. working paper.

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. and N. D. Pearson (1995). Differential interpretation of public signals and trade in speculative markets. *Journal of Political Economy 103*(4), 831–872.

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.

Kim, S. and D. Trepanier (2019). Violations of price-time priority and implications for market quality. working paper.

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

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

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.

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *Journal of Finance 32*(4), 1151–1168.

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.

SEC (2015). Research Note: Equity Market Volatility on August 24, 2015. Staff of the U.S. Securities and Exchange Commission.

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

Smith, J. W. (2006). Nasdaq's electronic closing cross: An empirical analysis. *Journal of Trading 1*(3), 47–64.

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.

Upson, J. and R. A. Van Ness (2017). Multiple markets, algorithmic trading, and market liquidity. *Journal of Financial Markets 32*, 49–68.

Wang, J. (1994). A model of competitive stock trading volume. *Journal of political Economy 102*(1), 127–168.

Wu, Y. and N. Jegadeesh (2020). Closing auctions: Information content and timeliness of price reaction. Working paper Emory University.

Figure 1. Fraction of aggregate daily dollar volume executed intraday and around the close. Daily dollar volume is summed across stocks over a given interval and then divided by the total daily dollar volume across stocks over the day. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $5 and a market capitalization larger than 100 million at the beginning of the month.

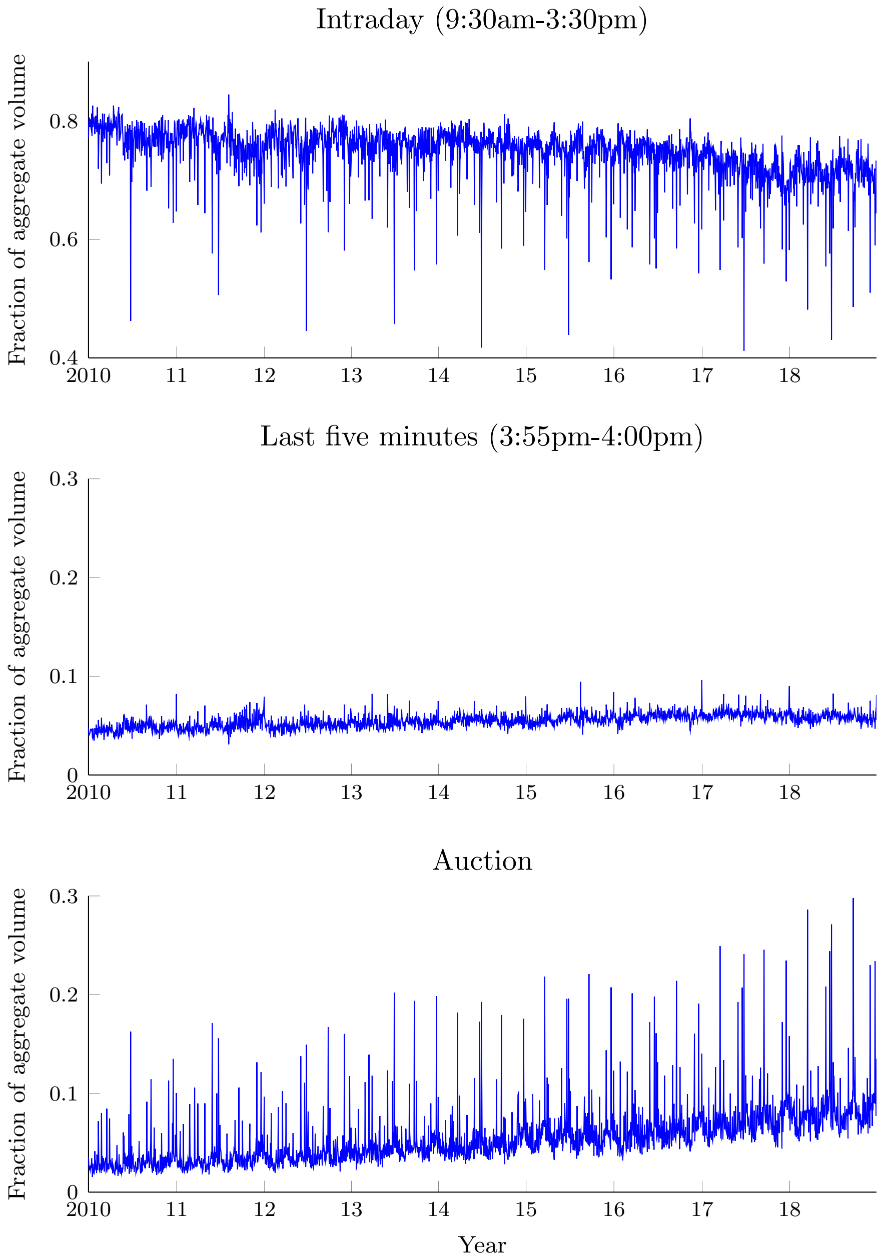


Figure 2. Elasticity of turnover to ETF, passive mutual fund, and active mutual fund ownerships. For each five-minute interval between 3:30 and 4:00 pm and the auction, log turnover is regressed on the logarithm of ETF and mutual fund ownerships, as well as control variables described in the caption of Table 2. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than \$5 and a market capitalization larger than 100 million at the beginning of the month. The 95% confidence intervals are based on standard errors that are double-clustered by date and stock.

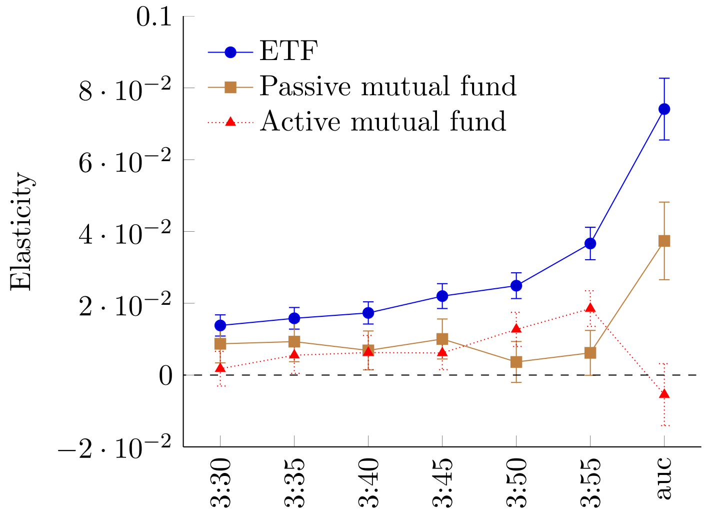


Figure 3. VIX index (left scale, dashed grey line) and absolute value-weighted auction deviation in basis points (right scale, solid black line). To compute the auction deviation, we first compute signed price deviation at the close, then value-weight it across stocks on a given day, and finally take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

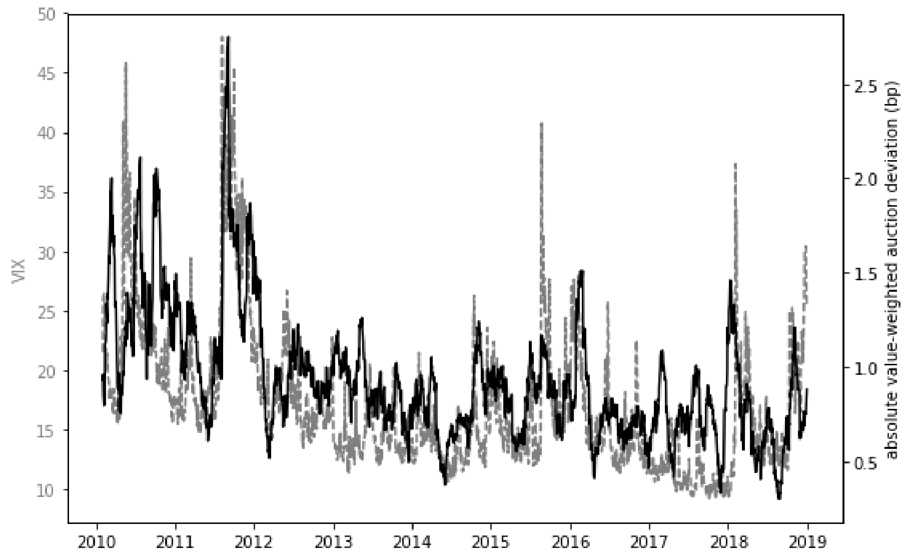


Figure 4. Weighted price contributions at the end of the day. Weighted price contribution (WPC) is computed each day across stocks in the bottom and top market capitalization quintiles (formed at the beginning of each year) for five-minute intraday periods from 3:30pm to 4pm, the period between 4pm and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

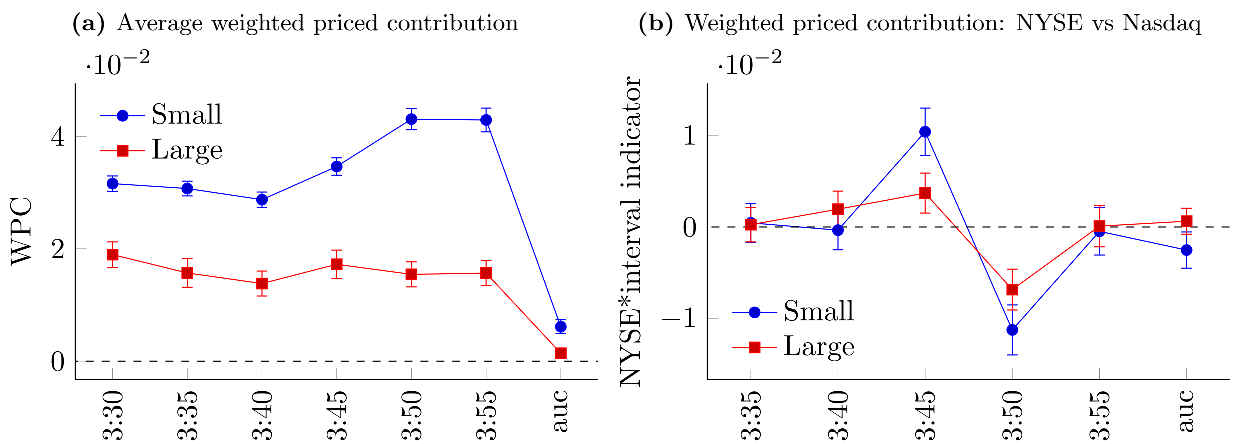


Figure 5. Absolute price deviation for NYSE large stocks relative to Nasdaq large stocks. NYSE (Nasdaq) starts disseminating imbalance information at 3:45pm (3:50pm). For each five-minute interval between 3:30pm and 4:00pm and the auction, a panel regression is estimated where log absolute price deviation (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 September 2018 that are in the top market capitalization quintile at the beginning of each year. To be included in a given month, a stock must have a price greater than $5 at the beginning of the month. The 95% confidence intervals are based on standard errors that are double-clustered by date and stock.

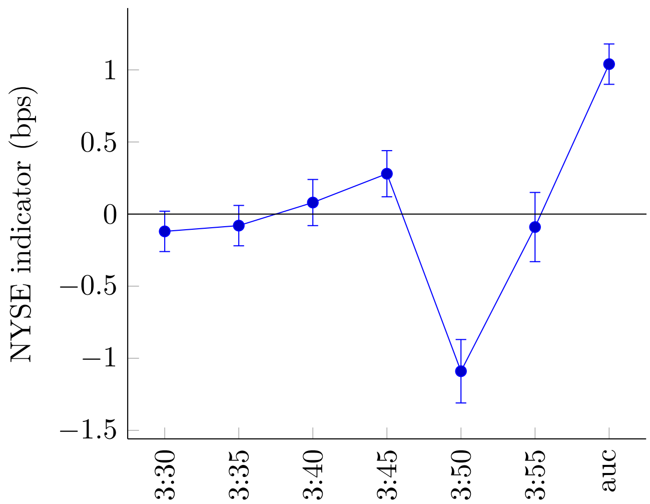
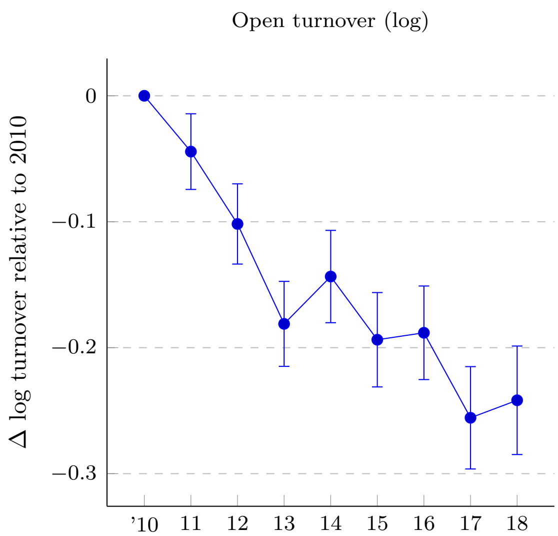
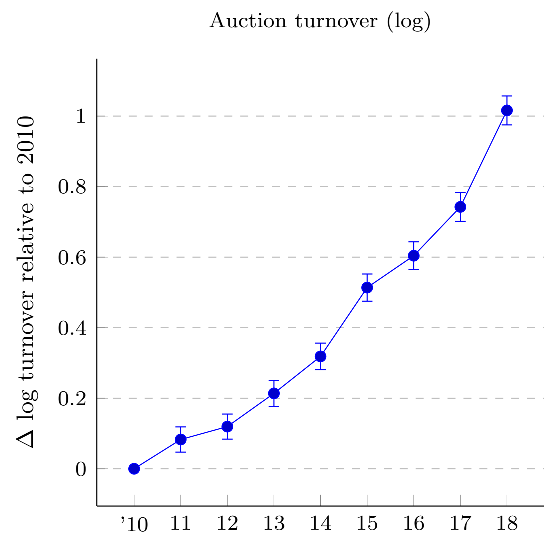


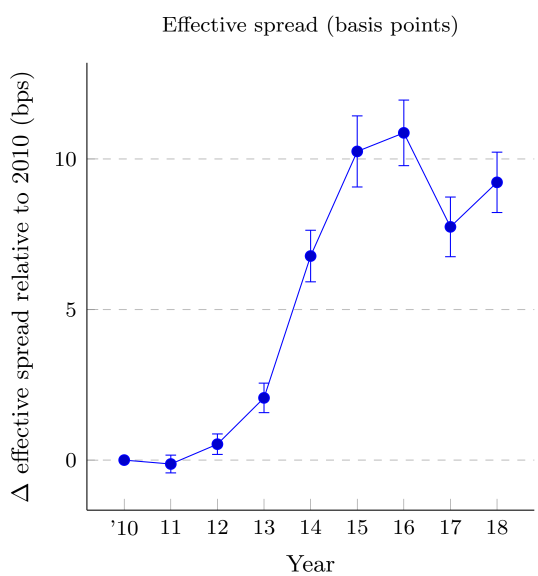
Figure 6. Liquidity and volume at the open. This figure reports year indicators from the following panel regression: $V_{i,t} = \alpha_i + \alpha_y + \text{controls} + \epsilon_{i,t}$, where $V_{i,t}$ is the variable under consideration. In Panel (a), $V_{i,t}$ is log turnover in the first 15 minutes of trading or in the closing auction. In Panel (b), $V_{i,t}$ is the dollar-weighted percentage effective spread (in basis points) or log time-weighted depth at the NBBO over the first 15 minutes of trading. Control variables are day-of-week and month-of-year indicators, log price, log market capitalization, volatility (log average absolute return over the past five trading days), and log intraday turnover (only in Panel (b)). Turnovers and depth are in logs. For instance, a change in log depth of -1 over the sample period corresponds to a change of $\exp(-1) - 1 \approx -63\%$ in depth. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018 that are in the top market capitalization quintile and traded over the full sample period. The 95% confidence intervals are based on standard errors that are double-clustered by date and stock.

(a) Volume





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



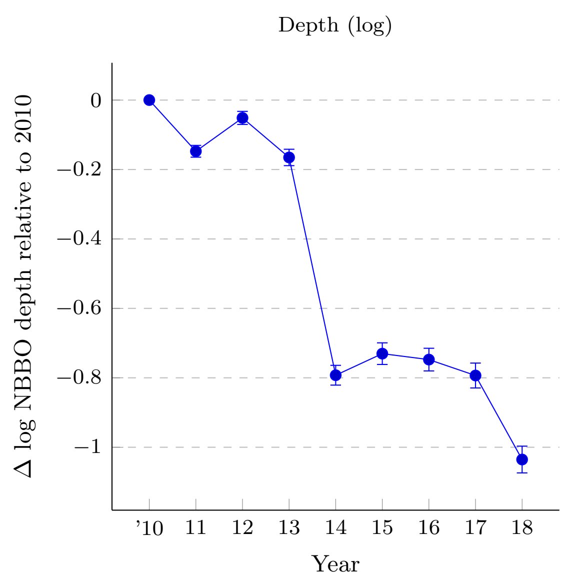


Table 1. Descriptive statistics. The table reports mean, median, and standard deviation for volume-related variables: share of daily volume at the closing auction, in the last five minutes, and between 3:30 and 3:55pm, as well as end-of-day relative bid-ask spread, stock price, market capitalization, share of days with zero volume during the entire day, from 9:30am to 3:30pm, and at the closing auction. In Panel (a), 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 active and passive mutual fund (MFund) ownerships; an indicator for Russell index rebalancing dates; an indicator for the third Friday of each month (3rd Friday), which is typically an option expiration day; a beginning-of-month and end-of-month indicators; and an indicator for the last day of the quarter. EAD-1, EAD, and EAD+1 are indicators for the day before, of, and after an earnings announcement. Avg$|Ret|$ is the absolute return averaged over the past five trading days, Ret_{t-1} is the lagged daily return, and Market cap. is the market capitalization at the end of the previous month. We also estimate but do not report month-of-the-year and day-of-the-week indicators. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $5 and a market capitalization larger than 100 million at the beginning of the month. Standard errors are double-clustered by date and stock and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level.

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

Table 3. Auction volume elasticity: passive and active ownership. This table reports estimates of a two-step difference-in-difference specification. In the first step, turnover elasticity relative to active mutual fund, passive mutual fund, and ETF ownership is estimated for each stock over the sample period. The elasticity is estimated separately for auction turnover and turnover in every five-minute intervals from 3:30pm until 4pm with the same set of control variables as in Table 2. In the second step, the elasticities are regressed on indicators for time-of-day, ownership type, and interactions between time-of-day and ownership type as follows: $\epsilon_{i,k,o} = \alpha + 1_{\text{Auction}}\alpha_{\text{Auction}} + 1_{\text{ETF}}\alpha_{\text{ETF}} + 1_{\text{Passive}}\alpha_{\text{Passive}} + 1_{\text{Auction}}1_{\text{ETF}}\alpha_{\text{Auction*ETF}} + 1_{\text{Auction}}1_{\text{Passive}}\alpha_{\text{Auction*Passive}} + u$, where $\epsilon_{i,k,o}$ is the turnover elasticity of stock i in interval k ($k \in \{$3:35-40, 3:40-45, 3:45-50, 3:50-55, 3:55-4:00, Auction$\}$) relative to ownership type o ($o \in \{$active, passive, ETF$\}$), 1_{Auction} is an indicator that takes the value one if k is the auction, and 1_{ETF} (1_{Passive}) is an indicator that takes the value one if o is ETF (passive) ownership. For instance, in the first column, the coefficient Auction*ETF measures the difference between the turnover elasticities of ETF ownership and active mutual fund ownership in the auction relative to their difference in the five-minute intervals from 3:30pm to 4pm. The second column compares only auction and last five-minute elasticities. The third and fourth columns focus on small and large stocks based on a stock's market capitalization quintile at the time the stock enters the sample. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $5 and a market capitalization larger than 100 million at the beginning of the month. A stock is required to have at least three years of data and have a valid turnover elasticity for every single interval considered. t-statistics based on heteroskedasticity-adjusted standard errors are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% level.

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

Table 4. Auction price deviations. 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 5. Auction price deviations 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 6. Reversals. Overnight returns are regressed on auction price deviations and last five-minute returns. Ret_{auc}^{945} denotes the return from the closing auction to 9:45am the next morning, Ret_{400}^{auc} denotes the return from the 4pm midquote to the closing price, Ret_{355}^{400} denotes the return in the last five minutes of regular trading. $RetAdj_{auc}^{945}$ uses the closing auction price adjusted for the bid-ask spread by adding (subtracting) half the spread for trades made below (above) the 4pm midpoint. 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_{auc}^{945}	$RetAdj_{auc}^{945}$	Ret_{400}^{945}	Ret_{auc}^{945}	$RetAdj_{auc}^{945}$	Ret_{vwap}^{945}
Ret_{400}^{auc}	-0.845***			-0.872***		
	(0.028)			(0.028)		
$RetAdj_{400}^{auc}$		-0.910***			-0.949***	
		(0.036)			(0.037)	
Ret_{355}^{400}			-0.186***	-0.176***	-0.185***	
			(0.038)	(0.038)	(0.038)	
Ret_{355}^{vwap}						-0.130***
						(0.041)
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_{auc}^{945}	$RetAdj_{auc}^{945}$	Ret_{400}^{945}	Ret_{auc}^{945}	$RetAdj_{auc}^{945}$	Ret_{vwap}^{945}
Ret_{400}^{auc}	-1.096***			-1.088***		
	(0.094)			(0.094)		
$RetAdj_{400}^{auc}$		-0.969***			-0.985***	
		(0.110)			(0.110)	
Ret_{355}^{400}			-0.175*	-0.175*	-0.175*	
			(0.104)	(0.104)	(0.104)	
Ret_{355}^{vwap}						0.096
						(0.144)
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_{auc}^{945}	$RetAdj_{auc}^{945}$	Ret_{400}^{945}	Ret_{auc}^{945}	$RetAdj_{auc}^{945}$	Ret_{vwap}^{945}
Ret_{400}^{auc}	-0.849***			-0.888***		
	(0.020)			(0.020)		
$RetAdj_{400}^{auc}$		-0.982***			-1.020***	
		(0.026)			(0.026)	
Ret_{355}^{400}			-0.285***	-0.268***	-0.285***	
			(0.021)	(0.022)	(0.022)	
Ret_{355}^{vwap}						-0.338***
						(0.024)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	1.87%	0.63%	0.45%	2.26%	1.08%	0.46%

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}^{420}	Ret_{auc}^{430}	Ret_{auc}^{440}
Ret_{400}^{auc}	-1.088***	-0.510***	-0.465***	-0.434***
	(0.094)	(0.062)	(0.050)	(0.048)
Ret_{355}^{400}	-0.175*	-0.065***	-0.068***	-0.067***
	(0.104)	(0.015)	(0.015)	(0.014)
Stock FE	Yes	Yes	Yes	Yes
Adj. R^2	0.20%	0.20%	0.17%	0.14%
Num. obs.	1,147,683	346,667	500,768	583,987

(b) Auction price adjusted for bid-ask bounce

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

Table 8. Relation between disagreement ratio and other disagreement measures. Panel (a) reports raw correlations; Panel (b) reports a panel regression of the disagreement ratio on popular disagreement measures, log market capitalization, stock price, and weekly fixed effects. The disagreement ratio equals minus a ratio of closing auction volume to total daily volume. The disagreement ratio is high when the daily volume is high relative to the closing volume. Analyst dispersion is computed as in Diether et al. (2002) and social media disagreement is from Cookson and Niessner (2020). Idiosyncratic volatility is computed from abnormal daily returns from the Fama-French four-factor model over the previous month. 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. We report multiple specifications since popular disagreement measures are not available for all stocks. Standard errors are clustered by stock and week and t-statistics are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% level.

(a) Correlations

	Disagr. ratio	Idio. volatility	Log volume	Analyst disagr.
Idio. volatility	0.276			
Log volume	0.237	0.037		
Analyst disagr.	0.171	0.339	0.085	
Social media disagr.	0.067	0.100	0.285	0.036

(b) Regressions

	Disagreement ratio			
	(1)	(2)	(3)	(4)
Analyst disagr.	0.0194***	0.0198***		
	[9.0]	[9.5]		
Social media disagr.	0.0085***		0.0111***	
	[12.2]		[19.7]	
Idio. volatility	0.8684***	0.9450***	0.8274***	0.8568***
	[25.9]	[19.8]	[30.1]	[25.2]
I(Earnings week)	0.0056***	0.0093***	0.0034***	0.0087***
	[11.8]	[23.5]	[7.6]	[19.0]
Log market cap	0.0004	0.0027***	0.0020***	0.0051***
	[0.9]	[6.3]	[5.3]	[11.6]
Stock price	0	-0.0000**	-0.0000*	-0.0000***
	[-0.6]	[-2.5]	[-2.0]	[-4.4]
Intercept	-0.0925***	-0.1301***	-0.1130***	-0.1616***
	[-13.9]	[-19.6]	[-20.7]	[-25.4]
R^2	12.05%	10.88%	10.34%	9.91%
N	252,657	464,266	530,741	1,106,832

Table 9. Disagreement ratio and future returns. The table reports panel regressions of future weekly and monthly stock returns on disagreement and other predictors. The disagreement ratio surprise (change) is the difference between the current ratio and its average in the prior month. An earnings indicator (EAD) is one if an announcement is within ten days of the current date. In the last two columns, the disagreement ratio surprise is computed not only for the auction but also for pre-auction volume (3:55-4:00 and 3:30-3:55 pm). We skip a day between predictors and returns. We include idiosyncratic volatility (computed from abnormal daily returns from the Fama-French four-factor model over the previous month), momentum (six-to-one month return), monthly reversal, logarithm of market capitalization, beta, Amihud (2002) illiquidity measure, and a visibility indicator, which is set to one (-1) if current volume is greater (lower) than 90% (10%) over the prior 49 days (Gervais et al. (2001)). Predictors are winsorized at a 0.05% level. 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 clustered by stock and week, and t-statistics are reported in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% level. The regression is based on 1,084,222 stock-weeks and 447 weeks.

	Return		Return		Return	
	Weekly	Monthly	Weekly	Monthly	Weekly	Monthly
Disagr. ratio, surprise	0.012***	0.033***			0.012***	0.0312***
	[3.1]	[4.7]			[2.9]	[4.3]
Disagr. surp. × EAD			0.020***	0.055***		
			[3.2]	[5.0]		
Disagr. surp. × non-EAD			0.008*	0.023***		
			[2.0]	[2.7]		
Disagr. surp. for 3:55-4:00					0.011***	0.031***
					[2.9]	[4.3]
Disagr. surp. for 3:30-3:55					-0.0019	0.0002
					[-0.9]	[0.0]
Log market cap.	-0.0001	-0.0002	-0.0001	-0.0002	-0.0001	-0.0002
	[-0.5]	[-0.7]	[-0.5]	[-0.8]	[-0.5]	[-0.8]
Beta	-0.0002	-0.0006	-0.0002	-0.0006	-0.0002	-0.0006
	[-0.2]	[-0.3]	[-0.2]	[-0.3]	[-0.2]	[-0.3]
Reversal	-0.0053**	-0.0083*	-0.0053**	-0.0083*	-0.0053**	-0.0083*
	[-2.1]	[-1.8]	[-2.1]	[-1.8]	[-2.1]	[-1.8]
Momentum	0.0003	0.001	0.0003	0.001	0.0003	0.001
	[0.3]	[0.5]	[0.3]	[0.5]	[0.3]	[0.5]
Idio. volatility	-0.023	-0.137***	-0.023	-0.137***	-0.023	-0.138***
	[-1.2]	[-3.2]	[-1.2]	[-3.2]	[-1.2]	[-3.2]
Illiquidity	-0.0018	-0.0058	-0.0018	-0.0058	-0.0018	-0.0059
	[-1.0]	[-1.3]	[-1.0]	[-1.3]	[-1.0]	[-1.3]
Visibility	0.0006***	0.0002	0.0006***	0.0002	0.0006***	0.0002
	[3.1]	[0.7]	[3.1]	[0.5]	[3.1]	[0.5]
R^2	0.02%	0.05%	0.02%	0.05%	0.02%	0.05%

Table 10. Disagreement ratio: portfolio sorts. This table reports monthly returns and alphas from the Fama-French six-factor model for equally-weighted portfolios sorted on the disagreement ratio change. The FF model includes market, size, value, momentum, profitability, and investment factors. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018. To be included in a given month, a stock must have a price greater than $5 and a market capitalization larger than 100 million at the beginning of the month. t-statistics are reported in brackets and based on Newey-West standard errors with six lags to account for the overlapping observations due to weekly data. *, **, and *** denote significance at the 10%, 5%, and 1% level.

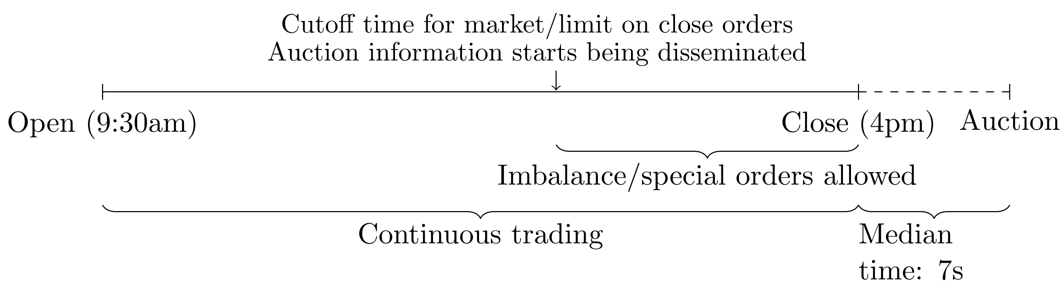
Port.	1	2	3	4	5	6	7	8	9	10	$10-1$
Return, weekly											
Ret.	0.0018*	0.0022*	0.0022*	0.0024**	0.0026**	0.0028**	0.0026**	0.0029***	0.0027**	0.0030***	0.0012***
	[1.7]	[2.0]	[1.9]	[2.0]	[2.2]	[2.4]	[2.3]	[2.6]	[2.4]	[2.9]	[3.3]
α_{FF6}	-0.0003	-0.0001	-0.0003	-0.0001	0.0001	0.0004*	0.0002	0.0005**	0.0003	0.0009***	0.0012***
	[-1.3]	[-0.6]	[-1.5]	[-0.4]	[0.7]	[1.8]	[0.8]	[2.6]	[1.6]	[3.6]	[3.3]
Return, monthly											
Ret.	0.0086**	0.0098**	0.0095**	0.0096**	0.0095**	0.0102**	0.0095**	0.0107***	0.0105***	0.0118***	0.0033***
	[2.3]	[2.5]	[2.4]	[2.4]	[2.4]	[2.5]	[2.4]	[2.8]	[2.8]	[3.3]	[4.9]
α_{FF6}	0.0004	0.0008	0.0006	0.0004	0.0004	0.001	0.0005	0.0018**	0.0015**	0.0038***	0.0034***
	[0.6]	[1.2]	[1.0]	[0.5]	[0.5]	[1.3]	[0.7]	[2.4]	[2.1]	[4.9]	[4.9]

A Appendix: institutional details of closing auctions

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

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

Figure A.1. Conceptual trading timeline.



A.1 Nasdaq closing auction

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

Nasdaq starts accepting market-on-close (MOC), limit-on-close (LOC) and imbalance-only (IO) orders at 4am. A MOC order has size and direction but is entered without a price. A LOC order is executed only if its limit price is equal or worse than the auction price. IO orders are limit orders that provide liquidity to offset on-close orders during the cross. An IO order to buy (or sell) is essentially converted into a limit order at the 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: 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.[23]

"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.

[23]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.[24]

"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.[25]

"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.[26]

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.[27]

"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.[28]

"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.[29]

"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.[30]

"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.[31]

C Appendix: data description

C.1 Closing auction data

This appendix describes how we obtain the closing auction data.

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

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

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

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

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

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

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

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

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.[32] 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).

C.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.

C.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.

D Appendix: do closing price deviations matter?

This appendix details two applications for which replacing closing price with the midquote makes a difference: ETF mispricing and put-call parity violations.[33]

D.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.

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

[33] Blume and Stambaugh (1983); Lamoureux and Wansley (1989); Asparouhova et al. (2010, 2013) show that noise in closing prices can affect asset pricing tests. We complement their results by emphasizing a specific source of price noise.

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 IA.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.[34] 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 IA.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.

D.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. ETF shares outstanding and end-of-day prices and quotes are obtained from CRSP. Panel (a) of Table IA.10 describes the absolute price deviation at the close and decomposes it into half spread and price

[34] 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.

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 4). 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. In untabulated results, we find that the auction deviation sensitivity to turnover is large and significant for both QQQ and SPY.

Can trading around the close explain ETF mispricing? Two effects may be at play. First, as highlighted in Table IA.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 underlying constituents. Hence, auction price deviations may distort the NAV itself.

We consider three measures of mispricing based on different prices. The first one, $|\log(\text{price}/\text{NAV})|$, is the standard measure of mispricing. The second one, $|\log(\text{midpoint}/\text{NAV})|$, accounts for ETF closing price deviation. The third one, $|\log(\text{midpoint}/\text{NAV}_{\text{mid}})|$, accounts for both the ETF closing price deviation and the closing price deviation of the underlying constituents. More precisely, NAV_{mid} is the NAV computed using closing midquotes instead of closing prices. The computation of this quantity requires to know precisely the weight of each constituent in the ETF.

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). We obtain SPY shares outstanding and NAVs directly from SPDR's website since they are reported there with additional digits of precision.[35] 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.

Panel (b) of Table IA.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 evidence 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 unlikely to represent an actual arbitrage opportunity since trading in the auction exposes an arbitrageur to both price uncertainty and execution uncertainty.

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

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

This Internet Appendix contains additional figures and tables to supplement the main text.

Figure IA.1. Realized volatility at the open (first 15 minutes of trading). This figure reports year indicators from the following panel regression: $V_{i,t} = \alpha_i + \alpha_y + \text{controls} + \epsilon_{i,t}$, where $V_{i,t}$ is log realized volatility at the open. Control variables are day-of-week and month-of-year indicators, log price, log market capitalization, log intraday realized volatility excluding the open, and log intraday turnover. The sample consists of NYSE and Nasdaq common stocks from January 2010 to December 2018 that are in the top market capitalization quintile and traded over the full sample period. The 95% confidence intervals are based on standard errors that are double-clustered by date and stock.

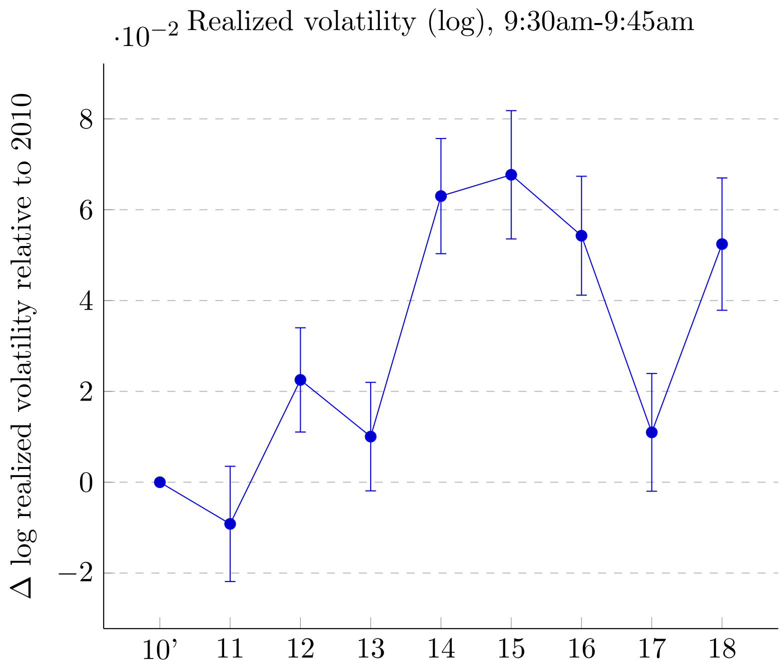


Table IA.1. Half spread and price impact. The absolute auction deviation is decomposed as follows |deviation%| = half-spread% + price impact%. The (realized) half-spread is defined as $\log(p_{\text{ask}}/p_{4:00})$ if $p_{\text{auc}} \geq p_{4:00}$ and $\log(p_{4:00}/p_{\text{bid}})$ otherwise. Similarly, 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 IA.2. 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 IA.3. Determinants of commonality in absolute value-weighted auction deviation. The absolute value-weighted auction deviation ($|r^{\mathrm{vw}}_{\text{4:00pm-auction}}|$) is regressed on calendar indicators and intraday volatility. Intraday volatility ($|r^{\mathrm{vw}}_{\text{9:30-3:30}}|$) 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:	$\lvert r^{\mathrm{vw}}_{\text{4:00pm-auction}}\rvert$	
Intercept	0.931*** (0.021)	0.657*** (0.041)
Russell rebal.		1.4845* (0.770)
First of month		0.2536*** (0.082)
Last of month		0.5604*** (0.134)
3rd Friday		0.2509*** (0.090)
$\lvert r^{\mathrm{vw}}_{\text{9:30-3:30}}\rvert$		0.005*** (0.001)
Adj. R^2	-	9.30%
Num. obs.	2,243	2,243

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

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

Table IA.6. Dissemination of closing information and price discovery. Weighted price contributions between 3:30-35, 3:35-40, 3:40-45, 3:45-50, 3:50-55, 3:55-4:00, and 4:00-Auction are averaged each day separately for NYSE and Nasdaq stocks in a given market capitalization quintile. The following regression is then estimated: $\text{WPC} = \alpha + \alpha_{\text{NYSE}} 1_{\text{NYSE}} + \sum_{k \in K} \alpha_k 1_k + \sum_{k \in K} \alpha_{\text{NYSE}*k} 1_k 1_{\text{NYSE}} + \epsilon$, 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_k is an indicator for interval k, which belongs to $K = \{$3:35-40, 3:40-45, 3:45-50, 3:50-55, 3:55-4:00, 4:00-Auction$\}$. Standard errors are clustered by day and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level. Market capitalization quintiles ("Small" to "Large") are formed at the beginning of each year. The sample consists of NYSE and Nasdaq common stocks from January 2010 to September 2018. To be included in a given month, a stock must have a price greater than $5 and a market capitalization larger than 100 million at the beginning of the month.

	Small	2	3	4	Large
Constant	0.031***	0.031***	0.027***	0.023***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE	0.003***	-0.002***	-0.002***	-0.001**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
3:35	-0.001	-0.002*	-0.003**	-0.002*	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
3:40	-0.003***	-0.006***	-0.007***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
3:45	0.001	-0.002*	-0.004**	-0.004**	-0.004***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
3:50	0.014***	0.009***	0.006***	0.004***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
3:55	0.011***	0.006***	0.002	-0.002	-0.003**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Auc	-0.025***	-0.028***	-0.026***	-0.021***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE*3:35	0.000	0.000	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE*3:40	-0.000	0.001	0.003***	0.002***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE*3:45	0.010***	0.009***	0.008***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE*3:50	-0.011***	-0.010***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE*3:55	-0.000	-0.003**	-0.002***	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NYSE*Auc	-0.003**	0.002***	0.003***	0.002***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	6.5%	4.6%	3.2%	2.1%	1.1%
Num. obs.	30,548	30,548	30,548	30,548	30,548

Table IA.7. Disagreement ratio: descriptive statistics. This table reports pooled descriptive statistics for main variables for our disagreement analysis. The disagreement ratio equals minus a ratio of closing auction volume to total daily volume. The disagreement ratio is high when the daily volume is high relative to the closing volume. Analyst dispersion is computed as in Diether et al. (2002) and social media disagreement is from Cookson and Niessner (2020). Idiosyncratic volatility is computed from abnormal daily returns from the Fama-French four-factor model over the previous month.

Variable	Count	Mean	Std Dev.	1st Pctile	Median	99th Pctile
Disagreement ratio	1,118,125	-0.0655	0.0431	-0.2046	-0.0566	-0.0066
Disagreement ratio, surprise	1,093,259	-0.0007	0.0306	-0.0982	0.0022	0.0694
Log market capitalization	1,118,125	14.276	1.596	11.661	14.100	18.684
Beta	1,106,997	1.004	0.366	0.106	0.989	1.950
Idiosyncratic volatility	1,106,832	0.0184	0.0139	0.0048	0.0149	0.0660
Analyst disagreement	466,494	0.0920	0.1445	0.0022	0.0321	0.5780
Social media disagreement	534,615	0.2153	0.3086	0.0000	0.0000	1.0000

Table IA.8. Disagreement ratio and future returns: subsamples. The table reports panel regressions of future monthly returns on disagreement and other predictors for a few subsamples. The second column of Table 9 reports the full sample benchmark. The subsamples are: include only visibility indicator of zero (1); exclude 10% of most illiquid (Amihud (2002)) stocks on a given week (2); exclude hard-to-borrow stocks identified as either top 10% by utilization (3) or by the stock borrowing fee (4); exclude 10% of most volatile stocks (5); and the second part of the sample (6). The disagreement ratio surprise is the difference between the current ratio and its average in the prior month. Idiosyncratic volatility is computed from abnormal daily returns from the Fama-French four-factor model over the previous month. A visibility indicator (Gervais et al. (2001)) is set to one (-1) if current volume is greater (lower) than 90% (10%) over the prior 49 days. Predictors are winsorized at a 0.05% level. Standard errors are clustered by stock and week.

	Return, monthly					
Subsample:	(1)	(2)	(3)	(4)	(5)	(6)
	Visibility = 0	Illiquidity pcnt. <90%	Utilization pcnt. <90%	Borrowing fee pcnt. <90%	Idio. volatility pcnt. <90%	Year >= 2014
Disagr. ratio, surprise	0.034***	0.025***	0.032***	0.030***	0.030***	0.033***
	[4.4]	[3.4]	[4.6]	[4.3]	[4.1]	[3.9]
Log market cap	-0.0002	0.0002	-0.0004	-0.0004	-0.0004	0.0003
	[-0.7]	[0.5]	[-1.3]	[-1.4]	[-1.4]	[0.6]
Beta	-0.0004	-0.001	-0.0006	-0.001	-0.0012	-0.0034
	[-0.2]	[-0.5]	[-0.3]	[-0.5]	[-0.6]	[-1.4]
Reversal	-0.0072	-0.0058	-0.0097**	-0.0106*	-0.0092*	-0.0098
	[-1.5]	[-1.2]	[-2.1]	[-1.9]	[-1.9]	[-1.6]
Momentum	0.0013	0.001	0.0022	0.0026	0.0019	0.0009
	[0.6]	[0.5]	[1.0]	[1.2]	[0.9]	[0.3]
Idio. volatility	-0.133***	-0.100**	-0.044	-0.149**	-0.033	-0.130**
	[-3.0]	[-2.3]	[-1.1]	[-2.1]	[-0.8]	[-2.3]
Illiquidity	-0.0068	0.0935	-0.0081*	-0.0016	-0.0110*	-0.0025
	[-1.4]	[1.5]	[-1.7]	[-0.3]	[-1.7]	[-0.5]
Visibility		-0.0001	0.0002	0.0002	0.0001	0.0005
		[-0.3]	[0.6]	[0.6]	[0.4]	[1.0]
R^2	0.04%	0.03%	0.03%	0.03%	0.03%	0.07%
N	837,492	987,188	994,346	988,467	994943	616,586

Table IA.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]
Intercept	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 IA.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