Intraday Arbitrage Between ETFs and Their Underlying Portfolios

ABSTRACT

Current research suggests that arbitrage activity in exchange traded funds (ETFs) impacts the market quality of their constituent securities. We examine this proposition directly by identifying intraday arbitrage opportunities between 423 domestic equity ETFs and their underlying portfolios. Ultimately, we find little evidence that mispricing events alter the direction of constituent order flow. Furthermore, we observe that arbitrage opportunities are usually preceded by a price shock and order imbalance in the underlying portfolio. Even though prices for the ETF and constituent securities converge quickly, parity is restored through adjustments in the best bid and offer quotes, not arbitrage trading. Moreover, the direction of order flow following a mispricing event is more consistent with liquidity provider hedging, whereby aggressive price quotes for the ETF might serve to offset liquidity provision in the underlying securities.

JEL classification: G12, G14

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The rapid rise of exchange-traded fund (ETF) assets and trading volume has led to apprehension from regulators worldwide.[1] Central to these concerns is the potential impact that ETF ownership might have on the securities held in their portfolios. As

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[1] In recent years, the International Organization of Securities Commissions and regulators in Hong Kong, Germany, Ireland, France and other countries have revisited ETF regulation out of concerns regarding liquidity and potential systemic risk issues. "Parting of the ways? Evolving Asset Management Regulation Report", Chapter 2 – "Systemic risk – the big divide", June 2018, Tom Brown, Julie Patterson, KPMG International.

basket securities, ETFs derive their value from an underlying portfolio of assets. When a discrepancy arises between an ETF market price and the net asset value (NAV) of its underlying portfolio, arbitrage traders can take offsetting positions in the fund and its constituent securities, then later unwind each position after prices converge. While several early studies suggest that ETF trading improves price discovery for the underlying securities,[2] a growing stream of research cautions that ETF liquidity might also attract short-term traders that introduce noise into constituent security prices through the arbitrage mechanism.[3]

While much of this previous research focuses on daily and intraday correlations between the prices of ETFs and their constituent securities, this paper revisits the question by conditioning on intraday ETF mispricing. Using a sample of 423 passively managed U.S. equity ETFs from 2006 to 2015, we examine how trading in both the ETF and the underlying securities resolves price discrepancies.[4] In contrast to the existing

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[2] See Hasbrouck (2003), Yu (2005), Chen and Strother (2008), Fang and Sanger (2012), and Ivanov, Jones and Zaima (2013).

[3] See, e.g., Broman and Shum (2018), Charupat and Mui (2011), Israeli, Lee and Sridharan (2017), and Malamud (2016). ETF ownership is associated with higher trading costs and less informative prices (Israeli, Lee and Sridharan (2017)), excess comovement (Da and Shive (2018)) and excess volatility (Ben-David, Franzoni and Moussawi (2018)) in the underlying portfolio.

[4] Several potential limitations of the ETF arbitrage process are described in previous studies. For instance, market frictions allow some mispricings to persist longer than a potential arbitrageurs' planned trading horizon (Ben-David, Franzoni and Moussawi (2018)). Furthermore, investors may not enforce efficient pricing due to execution risks (Malamud (2016)), transaction costs (Broman and Shum (2018)),

literature, we find that mispricing of the ETF relative to the underlying is typically preceded by a permanent price shock in the constituent portfolio, and is then corrected through quote adjustments, not through arbitrage trading.[5] The direction of order flow following a mispricing event is consistent with liquidity provider hedging, whereby aggressive price quotes for the ETF might serve to offset liquidity provision in the underlying securities. Additionally, we find that the liquidity of the underlying, as measured by the bid-ask spread, remains available during and after arbitrage opportunities.[6] Rather than transmitting non-fundamental shocks to the underlying securities, our results suggest that ETFs may shield the portfolio from demand shocks by offsetting liquidity provision in the underlying securities.

To examine the impact of ETF trading on the underlying securities, we ask empirically whether or not an arbitrageur could profitably buy and sell the ETF and its underlying portfolio at the best bid and ask prices quoted in the market. At the end of each minute, we classify an ETF into one of five relative pricing categories: overvalued

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difficulty borrowing shares, as well as varying arbitrage speeds or difficulties in observing intrinsic values, especially during times of market stress (Madhavan and Sobczyk (2016)).

[5] Ben-David, Franzoni and Moussawi (2018) contend that shocks to ETF prices create arbitrage opportunities, and that subsequent arbitrage trading degrades the liquidity of the ETF's underlying securities. Broman (2016) also suggests that mispricing stems primarily from the ETF, not the underlying portfolio, whereas Staer (2017) finds that ETF fund flows have a large impact on underlying stock returns.

[6] Marshall, Nguyen and Visaltanachoti (2013) find that spreads increase immediately before arbitrage opportunities. Dannhauser (2017) shows that the liquidity of constituent securities falls as ETF ownership and activity rises. In contrast, Hegde and McDermott (2004) find that liquidity improves for Dow Jones Industrial Average and NASDAQ 100 component stocks after trading begins in two ETFs that follow these indices.

(ETF bid is greater than its underlying's ask), partially overvalued (ETF midquote is greater than its underlying's ask), partially undervalued (ETF midquote is less than its underlying's bid), undervalued (ETF ask is less than its underlying's bid), and no arbitrage (ETF midquote is between its underlying's bid and ask).

After analyzing arbitrage opportunities around these five categories, our results reveal a strong relation between the prices quoted for the ETFs and the prices quoted for the constituent securities. For minutes where the ETF becomes overvalued (undervalued), we find that selling (buying) pressure in the underlying securities pushes the portfolio price downward (upward). In both cases, arbitrage opportunities are preceded by shocks to underlying security prices, impounded by directional trading in the portfolio. ETF order flow and returns, on the other hand, remain centered at zero as portfolio prices are pushed away from parity. Arbitrage opportunities are unlikely to be the result of short-term price pressure in the ETF's shares. Additionally, our results indicate that constituent price shocks are not reversed during the 30-minute period following a mispricing event. Disruptions that lead to arbitrage opportunities occur in the underlying portfolio and do not appear to be transitory in nature.

During the minutes following a mispricing event, we observe a swift convergence between the bid and ask prices of the ETF and its underlying portfolio. However, our analysis also suggests that order flow continues to move in the same direction as the mispricing. After the ETF becomes overvalued (undervalued), we see additional buying (selling) pressure in the ETF and net selling (buying) pressure in the portfolio. Price discrepancies between the ETF and the underlying securities are being corrected in the limit order book, but the convergence is not being driven by directional trading. Furthermore, marketable orders appear to be moving prices for the constituent securities and the ETF farther away from parity. If arbitrage activity were the primary motivation for directional trading, we should expect to see order flow that pushes prices closer together.

A sequence of mispricing events may lead to an imbalance in a market maker's inventory of fund and constituent shares. ETFs have a second source of liquidity, however, that mitigates much of the risk associated with market maker inventory accumulation. Specially designated market makers, known as Authorized Participants (AP), can exchange the underlying portfolio for shares of the ETF directly through the fund sponsor.[7] Because ETF shares can be created and redeemed at the fund's closing net asset value (NAV), APs do not have to worry about whether mispricings will eventually converge. Should their inventories ever become large enough, liquidity providers could simply sell their accrual of constituent securities or fund shares in the

[7] Malamud (2016) argues that reductions in primary market trading costs may strengthen the shock propagation channel that allows ETFs to affect stock returns. Petajisto (2017) suggests that primary market activity may not always provide an affordable way to correct price deviations between a fund and its NAV.

ETF's primary market, then use the creation or redemption to offset any accumulated short position.[8]

While our analysis focuses on intraday trading, APs have six days from the original arbitrage event to unwind their arbitrage or liquidity provision position.[9] As a result, the time horizon over which APs could accumulate the ETF or underlying shares as part of a position could extend past our observation window. To address this issue, we examine the ETF share creation/redemption process over a six-day time horizon conditioned on the frequency of intraday arbitrage opportunities. Consistent with Evans, Moussawi, Pagano and Sedunov (2018), our intraday mispricing measure is positively related to ETF share creation over the following six days, and we find no relation between arbitrage opportunities and future daily returns or directional volume of the constituents. Our results indicate that, in their dual roles of arbitrage trader and often as a market maker in both the ETF and the underlying, Authorized Participants'

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[8] Another form of potential ETF arbitrage involves a pairs trading strategy, whereby investors exploit price discrepancies between correlated equivalent assets. Box, Davis and Fuller (2018) document competition between ETFs that hold nearly identical portfolios. Marshall, Nguyen and Visaltanachoti (2013) study price discrepancies between two ETFs that track the S&P 500 and, ultimately, find evidence of intraday arbitrage. Likewise, Broman (2016) reports that unexpected shocks to ETF trading activity are correlated across funds with similar holdings.

[9] Evans, Moussawi, Pagano and Sedunov (2018) document that APs have this option to delay creation of ETF shares that have already been sold and show that they often exercise this option.

market making activities are responsible for eliminating price discrepancies between the fund and its underlying portfolio, not their arbitrage trading.[10]

In addition to reporting how prices and order flow respond to arbitrage opportunities, we document two important empirical artifacts about ETFs that are sometimes misrepresented in the academic literature. First, across all of our 94 million fund-minutes, the quoted spread of the underlying portfolio only exceeds that of the ETF in roughly 45% of our observations. In general, ETFs do not offer superior liquidity relative to their underlying securities. Second, while we observe a strong correlation between returns and order flow in the constituents, the correlation between returns and order flow in the ETF shares is effectively zero. ETF prices do not move up and down because market participants are buying and selling. If trading in the ETF does not affect the price of the fund itself, it should not be surprising that underlying security prices are also unaffected by ETF order flow.

Overall, while our findings preserve the possibility that non-fundamental shocks in the ETF may extend to the constituent securities, they suggest that arbitrage trading is not the primary channel through which these pricing pressures are transferred.

[10] Pan and Zeng (2017) highlight the dual roles of arbitrage trader and liquidity provider (i.e. bond dealer in their setting) of authorized participants and the potentially conflicting motivations of these two roles.

I. Data and Methodology

From the CRSP Survivor-Bias-Free US Mutual Fund Database, we collect available monthly holdings for 423 passively managed U.S. equity funds between 2006 and 2015. Together, these ETFs account for nearly $2.1 trillion of the $2.5 trillion total net assets invested in U.S. registered funds during 2015. Due to the prevalence of errors in self-reported holdings, we verify the accuracy of each Mutual Fund Database position by corroborating the value of each holding using the CRSP Daily Stock File. The details of this verification process are provided in Appendix A.

Based on bid and ask quotes collected from TAQ, we are able to calculate 94,605,900 fund-minute observations of quote prices for ETFs (ETF_f^{Bid} and ETF_f^{Ask}) and their underlying portfolios (Und_f^{Bid} and Und_f^{Ask}).[11] While previous studies document relative mispricing between ETFs and their holdings, an observable premium or discount does not imply that an arbitrage trader could profitably exchange the fund for its underlying portfolio. A novelty of our approach is that we consider whether an arbitrageur could profitably buy and sell the ETF and its underlying portfolio at the best bid and ask prices quoted in the market.

[11] Please see Appendices B, C, and D for details on constructing the bid and ask prices of the ETF and its underlying portfolio.

Figure 1 describes four mispricing associations between an ETF and its underlying portfolio. In all four cases, the ETF is trading at a premium or discount as measured by the percentage difference in midquote prices. However, only Panel A and Panel D describe a tradeable arbitrage opportunity. In Panel A, for instance, the ETF bid price is above the ask price of the underlying portfolio. Therefore, the simultaneous purchase of the underlying portfolio, and sale of the ETF, would result in realized profits if prices later converged. In Panel B, the midqoute price of the ETF is still much higher than that of its underlying portfolio, but this discrepancy cannot be arbitraged away by submitting marketable orders.

For our subsequent analysis, we compare ETF and underlying bid and ask prices at the end of every minute. All fund-minute observations are designated as $Arb_t^{EB>UA}$, $Arb_t^{UA>EB>UM}$, $Arb_t^{UM>EA>UB}$ or $Arb_t^{UB>EA}$, in accordance with Figure 1, or classified as $NoArb_t$ when none of these conditions is satisfied. Table I reports the percentage of fund-minute observations which are mispriced across our entire sample. Out of 94,605,900 total fund-minute observations, 813,815 and 749,441 are classified as overvalued and undervalued, respectively. Thus, tradeable arbitrage opportunities exist between an ETF and its underlying portfolio approximately 1.66% of the time. The classifications $Arb_t^{UA>EB>UM}$ and $Arb_t^{UM>EA>UB}$ account for 3.69% and 3.63% of our observations, respectively, leaving 91.02% of fund-minutes designated as $NoArb_t$.

As the relation between an ETF and its underlying portfolio may be conditional on the size of both the ETF and the underlying stocks, we report averages across four distinct subsets: *Small Underlying and Small ETF*, *Small Underlying and Large ETF*, *Large Underlying and Small ETF*, and *Large Underlying and Large ETF*. ETFs are considered large when their mean daily market capitalization falls in the top tercile of our sample during a particular month. The size of the underlying is measured as the dollar-weighted average market capitalization of all stocks held by the ETF each month, based on their CRSP price and shares outstanding reported at the end of the previous year. Once again, the underlying is considered large when average market capitalization of the holdings falls in the top tercile of ETFs for a given month.[12]

While smaller ETFs are likely to have less liquidity, and ETFs that hold smaller securities are probably more difficult to value, Table I indicates that the proportion of overvalued and undervalued fund-minutes is roughly equal across all size subsamples. To understand why, quoted spreads for the ETF and underlying portfolio are also reported in the in the far-right columns of the table. As expected, the *Large ETF* and *Large Underlying* classifications have lower spreads. However, these narrower spreads mean that relatively minor discrepancies between the ETF and its portfolio can lead to arbitrage opportunities. Thus, the margin for error shrinks with fund and security size. Furthermore, contrary to popular assumptions that improved ETF liquidity attracts short-term traders that introduce noise into constituent prices (Broman and Shum

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[12] The top tercile of ETFs (underlying portfolios) ranked by market capitalization accounts for 95.6% (78.6%) of aggregate ETF market capitalization on average.

(2018), Charupat and Mui (2011), Israeli, Lee and Sridharan (2017), and Malamud (2016)), quoted spreads for U.S. equity ETFs are usually wider than those of their underlying holdings. Only when ETFs are large relative to the size of their portfolios do transaction costs favor the fund.

Panel A of Figure 2 demonstrates that the frequency of arbitrage opportunities has remained somewhat stable throughout our sample period. With regards to the magnitude of arbitrage opportunities, however, Panel B indicates that there has been considerable variation across time. Specifically, we observe a surge in magnitudes during the financial crisis as well as the 2013 "Taper Tantrum." More recently, market disruptions on August 24th, 2015 led to wide discrepancies between the prices of ETFs and their underlying portfolios.[13] Figure 3 presents the frequency and magnitude of arbitrage opportunities by time of day. According to the figure, mispricing is most common, and most severe, during the opening minutes of the trading day.

II. Graphical Analysis

A. Minute-by-minute analysis immediately surrounding mispricing

Our analysis begins with an examination of market conditions during the minutes surrounding each of our five relative pricing classifications, $Arb_t^{EB>UA}$, $Arb_t^{UA>EB>UM}$,

[13] "Equity Market Volatility on August 24, 2015" prepared by the staff of the SEC available at https://www.sec.gov/marketstructure/research/equity_market_volatility.pdf.

$NoArb_t$, $Arb_t^{UM>EA>UB}$ and $Arb_t^{UB>EA}$. Specifically, we consider the sample average midpoint return and directional volume of the ETF and underlying portfolio for the minute preceding, the minute during and the minute following each pricing designation. Here, we are most concerned with the timing of market responses to changes in relative valuation.

1. Midpoint returns

In Panel A of Figure 4, we report midpoint returns during the minute $t-2$ to $t-1$ before the realization of each pricing classification. Regardless of the relative valuation between an ETF and its underlying portfolio, we find no discernable pattern in midpoint returns across any of the size subsets. However, we observe large disparities in midpoint returns during minutes $t-1$ to t. According to Panel B, the underlying portfolio typically experiences a negative return during the minute t when the ETF becomes overvalued. Likewise, the underlying portfolio rises in price as the ETF becomes undervalued. When the ETF is large relative to the underlying securities, the fund's price adjusts in a way that somewhat aggravates the mispricing. Otherwise, the price discrepancy originates entirely in the underlying portfolio, not the ETF.

Panel C of Figure 4 describes average midpoint returns during minute t to $t+1$. In the aftermath of mispricing events, we observe a more balanced reaction between the ETF and the underlying portfolio. Here, the share prices of overvalued (undervalued) funds fall (rise) as the price shock to the portfolio is partially reversed. Nevertheless, the three panels of Figure 4 imply that arbitrage opportunities are preceded by changes in the value of the underlying securities, with subsequent adjustments in the ETF helping to alleviate some of the discrepancy. Across all four size categories, the portfolio appears to drive the mispricing and the partial correction for all four mispricing classifications.

2. Directional volume

The midpoint prices of equity securities fluctuate whenever competitive limit orders are added or removed from the book. In some cases, quotes are updated when a marketable order is filled by an existing limit order. For instance, a marketable buy order would remove the most competitive limit sell order from the book, causing the best ask price to rise and the midpoint return to be positive. Other times, midpoint prices might adjust simply because an offer to provide liquidity was authorized or rescinded. Here, we could observe a positive midpoint return simply because a trader chose to cancel the most competitive limit sell order or submit a limit buy order that improved the quoted spread. In Figure 5, we analyze the direction of order flow around mispricing events to determine whether midpoint returns reported in Figure 4 are more consistent with directional trading or adjustments to the price of available liquidity.

For each time t, we calculate the average directional volume, $VolDiff_t$, of the ETF and its underlying portfolio as follows:

$$VolDiff_t = \frac{BuyVol_t - SellVol_t}{\frac{1}{T} \times \sum_{t=1}^{T}(BuyVol_t + SellVol_t)}, \tag{1}$$

where $BuyVol_t$ is the dollar value of all trades occurring at prices above the prevailing midpoint during minute t, and $SellVol_t$ represents the dollar value of trades occurring below the quoted midpoint. $VolDiff_t$ is then Winsorized at the 1st and 99th percentiles. To generate a number that is comparable across securities, our measure of directional volume is scaled by total volume averaged across all minutes in the trading day. When calculating directional volume for the underlying portfolio, the dollar value of buy and sell orders is based on the portfolio-weighted directional order flow of the underlying constituents. For any minute during the trading day, the magnitude of the order flow imbalance is usually larger for the ETF than for the underlying securities. This is because directional volumes for the individual constituents often have opposing signs that draw the portfolio's weighted-average imbalance towards zero.

In Panel A of Figure 5, we report average directional volume for the ETF and constituents during the minute $t-2$ to $t-1$ before observing each mispricing classification. Similar to the average midpoint returns in Figure 4, we observe no clear pattern in ETF or constituent directional volume during this window. As we move closer to the mispricing event, however, we begin to see order flow in the portfolio pushing constituent prices away from parity. In Panel B of Figure 5, selling (buying) pressure accumulates in the underlying securities just as the ETF becomes overvalued (undervalued) relative to its portfolio. The magnitude of constituent directional volume is also strongest when the underlying securities are large relative to the ETF. Conversely, we find no discernable pattern in ETF order imbalance during the minute of the mispricing event.

Generally, the average directional volumes reported in Panels A and B of Figure 5 align with the midpoint returns described in the previous figure. Prices rise as traders' demand for shares increases and fall as order imbalances become negative.

During the minute following a pricing event, Figure 4 also describes a partial reversal whereby the midpoint returns of the ETF and constituents help to mitigate some of the mispricing. In Figure 5, however, we find that this minor reversal is not led by directional trading. On the contrary, Panel C indicates that marketable orders typically flow in the same direction as the mispricing. When the ETF is overvalued, we see additional buying pressure in the ETF and net selling pressure in the underlying. Similarly, when the underlying is overvalued, we observe buying pressure in the underlying and selling pressure in the ETF. Even though price discrepancies between the ETF and the underlying securities are being corrected in the limit order book, the reversal in midpoint returns is not being driven directional trading. According to Figure 5, marketable orders are moving the prices for constituent securities and the ETF away from each other. If arbitrage trading were the primary motivation for directional trading, we should expect to see trading that pushes prices closer together. The behavior reported in Panel C is more consistent with hedging on the part of liquidity providers, whereby aggressive pricing for ETF shares offsets liquidity provision in the underlying securities.

B. 45-minute cumulative price and order flow

From Figure 4 and Figure 5, we learn that directional trading pushes the underlying portfolio price away from parity with the ETF during the minute that immediately precedes a mispricing event. During the subsequent minute, however, we find no evidence that directional trading, from potential arbitrageurs, encourages convergence between the ETF and its constituent securities. Perhaps the three-minute window around mispricing events is too narrow for us to capture arbitrage behavior. We therefore also examine the path of midpoint returns and directional trading volume during 45-minute windows around arbitrage opportunities. To maximize the likelihood of observing arbitrage behavior, we limit our focus only to clear arbitrage scenarios, where either $Arb_t^{EB>UA}$ or $Arb_t^{UB>EA}$. After identifying all of the arbitrage opportunities in our sample, we remove any observations that proceed another event by fifteen minutes or less. Results are presented separately for each of the four size categories discussed in the previous section.

1. Cumulative midpoint returns

For each of the eligible arbitrage opportunities, we cumulate the ETF and underlying portfolio midpoint return after each minute beginning at $t-15$ and extending through $t+30$. Next, we calculate the average cumulative midpoint return for each event-window-minute across all observations within a particular size category.[14] When these minute-by-minute averages are depicted in Figure 6, several empirical artifacts become clear. Most notably, the figure demonstrates that arbitrage opportunities often center around the arrival of information relevant to the value of constituent securities, whose cumulative returns are represented by the dotted blue line. With the exception of the *Small Underlying* and *Large ETF* case, the value of the underlying portfolio experiences a persistent decline during 45-minute event windows where the ETF becomes overvalued, and a persistent increase during events where the ETF becomes undervalued. Following a price shock to the constituent during the first fifteen minutes, the portfolio stays at this new level for the remaining thirty minutes of the event window. Therefore, price adjustments to the underlying portfolio are not, on average, transient deviations from fundamental values.

Conversely, when the ETF is large relative to the value of constituents, fluctuations in the price of the portfolio do not persist through the end of the event window. For these cases, which represent 17.75% of the sample's observations, arbitrage opportunities are less likely to be associated with material information about the underlying holdings. According to Table I, this is the only size classification where transaction costs are lower in the ETF than in the underlying securities. Therefore, as suggested by Broman and Shum (2018), Charupat and Mui (2011), Israeli, Lee and Sridharan (2017), and

[14] After cumulative returns are calculated, they are Winsorized each minute at the 1st and 99th percentiles.

Malamud (2016), the superior liquidity of these ETFs might attract short-term traders that could introduce noise into the prices for constituent securities.

To test this proposition, Figure 6 allows us to compare the timing of price adjustments between an ETF and its constituent securities. First, we see that the 45-minute event window provides enough time to observe total convergence between the fund's price, represented by the solid red line, and that of its portfolio. In three of the four size classifications, we also observe that the value of the underlying securities begins moving several minutes before the arbitrage opportunity materializes. Meanwhile, the ETF price does not begin adjusting to new information about the constituent securities until $t + 1$. As before, we observe different behavior when the ETF is large relative to the underling portfolio. Here, the fund's price shifts several minutes before the arbitrage event. Furthermore, the prices of constituent securities appear to follow those of the ETF, at least temporarily, before the fund and portfolio shift back towards their $t - 15$ values. Thus, for the *Small Underlying* and *Large ETF* case, Figure 6 provides some evidence that short-term fluctuations in ETF prices could introduce noise into their underlying portfolios. Yet, for all other size classifications, we observe persistent shocks to the constituent securities with ETF price adjustments lagging by several minutes.

One remaining empirical detail visible in each of the cases described by Figure 6 is the peculiar short-term reversal in ETF midpoint returns between minutes $t - 1$ and $t + 1$. To better understand this artifact, we provide the cumulative bid and ask returns around arbitrage opportunities in Figure 7. The top and bottom of each vertical line represent the average path of the best offer and bid price, respectively, and the horizontal dash in the center represents the average path of the midpoint.

For the underlying securities, the bid and ask prices adjust smoothly and symmetrically to the arrival of new information during the minutes preceding an arbitrage opportunity. Conversely, the adjustment process is less balanced for the ETF's quotes. In Panel A, negative information lowers the prices of constituent securities, and, at $t + 1$, the ETF's best offer price begins to fall as expected. For bid prices, however, we observe a sharp increase during minute t that temporarily pushes up midpoint prices. Here, the market appears to temporarily offer liquidity to ETF sellers at favorable prices before adjusting quotes downward to reflect new information about the constituent securities. We observe a similar pattern in Panel B, except that ETF bid prices adjust smoothly while offer prices fluctuate. In either case, these asymmetrical shifts in quoted prices could arise from conditioning our graphical analysis on arbitrage opportunities. Had the quotes adjusted smoothly and symmetrically instead, the arbitrage opportunity might not materialize. Nevertheless, the overall behavior in Figure 7 is still consistent with hedging on the part of liquidity providers, whereby aggressive price quotes for the ETF might serve to offset liquidity provision in the underlying securities.

2. On-balance volume

Next, we examine the flow of marketable orders for the ETF and its underlying securities during the same 45-minute event windows depicted in Figure 6. To calculate on-balance volume, we cumulate $VolDiff_t$ after each minute from $t - 15$ through $t + 30$. Then, we take the average event-window-minute on-balance volume across all observations within a particular size category.[15] Once again, we observe a consistent pattern for all three size classifications where the size of the ETF is not large relative to its constituents. In these cases, we find persistent buying or selling pressure in the underlying portfolio during the minutes immediately surrounding the arbitrage event, followed by relatively balanced trading during the remainder of the event window. Therefore, the price shocks highlighted in Figure 6 appear to be impounded by informed directional trading in the underlying securities. Conversely, on-balance volume for the ETF flows in the opposite direction as midpoint prices throughout the event window. Here, marketable ETF buy orders arrive more frequently as midpoint prices fall, whereas the intensity of ETF sell orders increases with rising prices.

For the *Small Underlying* and *Large ETF* case, we observe less informed trading in the underlying portfolio and almost no evidence of liquidity provider hedging in the ETF. Here, transient shocks to the price of the ETF coincide, rather weakly, with fluctuations

[15] After cumulative $VolDiff_t$ is calculated, it is Winsorized each minute at the 1st and 99th percentiles.

in ETF order flow. Yet, on-balance ETF volume returns to zero by the end of the window. Thus, it is difficult to determine why ETF prices adjust to create arbitrage opportunities in these situations. Furthermore, cumulative directional volume for the constituents is negative when $Arb_t^{EB>UA}$, but roughly zero when $Arb_t^{UB>EA}$. Therefore, it is difficult to draw conclusions about whether trading in portfolios of small securities is influenced by short-term price fluctuations in larger ETFs.

3. Discussion of graphical results

Table II provides a summary of the cumulative return and volume results from the previous three figures. During event windows where the underlying portfolio experiences a persistent price shock, marketable order flow can be classified as informed or uninformed depending on whether the direction of trading is consistent with the ETF or portfolio's cumulative return. In Panel A, negative price shocks are accompanied by informed marketable sell orders for the constituents that are executed below the midpoint. As a result, negative price shocks lead to a buildup of liquidity provider inventory in the underlying securities. When exposure to the portfolio rises, liquidity providers might choose to offset their position by selling shares of the ETF. From Figure 7 and Figure 8, we observe that lowering the offer price for ETF shares encourages uniformed marketable orders and reduces the number of fund shares in the liquidity providers' inventory. From Panel B, positive underlying price shocks lead to a decline in liquidity provider constituent inventory and an increase in ETF bid prices that encourage marketable sell orders.

A sequence of mispricing events associated with negative price shocks would lead to an accumulation of constituent securities held by liquidity providers. Similarly, repeated positive shocks would lead to a buildup in ETF shares. Should their inventories become large enough, liquidity providers could sell their accrual of constituent securities or fund shares in the ETF's primary market, then use the creation or redemption to offset their accumulated short position.

III. Multivariate Analysis

Besides the mispricing events at the center of our graphical analysis, a myriad of additional factors could influence the returns and order flow of ETFs and their constituent securities. Therefore, we proceed with an examination of these market dynamics in a multivariate panel setting that accounts for cross-sectional and time series variation security trading activity.

A. Intraday Regressions

We begin our multivariate analysis with an examination of Ret_t^{Und}, Ret_t^{ETF}, $VolDiff_t^{Und}$ and $VolDiff_t^{ETF}$ calculated over 1-, 15- and 30-minute spans within each trading day. Table III provides summary statistics for each of the dependent variables. Regardless of the frequency with which these measures are calculated, midpoint returns and directional volume for the constituents typically have average values that are centered near zero and demonstrate little evidence of skewness. For the ETFs, however, Table III reports that the average of $VolDiff_t^{ETF}$ is positive for each of the 1-, 15- and 30-

minute spans. Thus, the funds in our sample experience persistent buying pressure, whereby trades are executed above the midpoint between bid and offer prices most of the time. While a little unusual, positive average directional volume is generally consistent with the dramatic increase in total ETF net asset value observed during our sample period.

Table III also provides correlations between each of our intraday midpoint return and directional volume variables in Panels A, B and C. As should be expected, the correlation between fund and portfolio returns is positive and large in magnitude. Next, we see that these variables become even more strongly correlated as the measurement frequency falls. Also, the correlations between Ret_t^{Und} and $VolDiff_t^{Und}$ are positive, implying that order flow in the underlying portfolio typically trends in the same direction as price changes. For the ETF, however, we find almost no evidence that directional trading has any relation to midpoint returns. Furthermore, at the 1-minute frequency, the correlation between Ret_t^{ETF} and $VolDiff_t^{ETF}$ is even slightly negative. Thus, according to Table III, ETF order flow appears to be nearly devoid of information, regardless of measurement frequency. This finding is consistent with much of the graphical analysis described in the previous section, whereby directional trading trended in the opposite direction of fund returns throughout most mispricing events.

1. Midpoint returns

Our multivariate analysis of underlying intraday midpoint returns is based on the following specification:

$$
\begin{aligned}
Ret_{t+1}^{Und} = \sum_{k=0}^{K} \phi_k Ret_{t-k}^{Und} + \beta_0 + \beta_1 Ret_t^{ETF} + \beta_2 VolDiff_t^{Und} \\
+ \beta_3 VolDiff_t^{ETF} + \sum_{k=4}^{11} \beta_k Control_{kt} + \beta_{12} Arb_t^{EB>UA} \\
+ \beta_{13} Arb_t^{UA>EB>UM} + \beta_{14} Arb_t^{UM>EA>UB} + \beta_{15} Arb_t^{UB>EA} \\
+ \alpha_d + \varepsilon_{t+1},
\end{aligned}
\tag{2}
$$

where the dependent variable is either 1-, 15-, or 30-minute midpoint returns, calculated at time $t+1$, and α_d is a fixed effect for each fund-day. The contemporaneous control variables, $Control_{kt}$, account for the depth and accuracy of prevailing bid and offer quotes at the end of minute t. Specifically, we include the logged market-weighted dollar value of underlying shares available at the best ask, $DolAsk_t^{Und}$, and bid, $DolBid_t^{Und}$, prices. Similarly, $DolAsk_t^{ETF}$ and $DolBid_t^{ETF}$ measure existing depth for the ETF's quotes. We also include the proportion of missing or inferred bid, $MisBid_t^{Und}$, and ask, $MisAsk_t^{Und}$, quotes as regressors, along with the binary variables $MisBid_t^{ETF}$ and $MisAsk_t^{ETF}$, that are discussed in Appendix B.

Our variables of interest are the four mispricing indicators, $Arb_t^{EB>UA}$, $Arb_t^{UA>EB>UM}$, $Arb_t^{UM>EA>UB}$ and $Arb_t^{UB>EA}$, recorded at the end of minute t. Thus, similar to the 45-minute graphical analysis presented in Section II.B, we can observe the cumulative midpoint returns of the underlying portfolio during the 1-, 15-, and 30-minute windows following certain mispricing events. However, the multivariate panel setting also allows us to properly control for variety of additional fund and market characteristics that can also impact portfolio returns.

Panel A of Table IV provides OLS estimates of the coefficients from Equation (2) with standard errors clustered by fund, date, and time of day. Even when daily fund-specific fixed effects are included in the specifications, the fit statistics imply that there is very little predictability in intraday portfolio returns. Furthermore, there is little evidence that Ret_t^{Und} is autocorrelated at the 1- and 15-minute frequencies.[16] Thus, intraday underlying returns could approximate a random walk.

Coefficients for the included control variables are generally consistent with expectations. For instance, we find that increasing depth at the portfolio and ETF's offer price precedes a decline in constituent value. Likewise, an accumulation of liquidity at the bid anticipates positive portfolio returns. The positive and negative coefficients for $MisAsk_t^{Und}$ and $MisBid_t^{Und}$, respectively, indicate that increases in missing or inferred

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[16] In period $t+1$, Ret_{t+1}^{Und} is determined by a linear function with fund-specific daily fixed effects, α_d, on the right-hand-side. Because Ret_t^{Und} also appears in the function generating Ret_{t+1}^{Und}, the time-independent fixed effects are correlated with the disturbances (Greene (2008)). Fortunately, the bias introduced by this correlation disappears as the length of the time series increases. With 390 (26) 1-minute (15-minute) observations during each trading day, the inclusion of lagged dependent variables in Equation (2) is unlikely to introduce bias into our coefficient estimates. However, the inclusion of lagged dependent variables and fixed effects into specifications with 30-minute frequencies could introduce bias into our estimates.

quotes for one side of the prevailing midpoint signal that prices will trend in that direction. We also find some evidence that ETF returns, Ret_t^{ETF}, predict price changes in the underlying portfolio for the 1-minute specifications, but this relation disappears at lower frequencies.

With regards to our variables of interest, our findings in Panel A of Table IV closely mirror those from our 45-minute window graphical analysis. Following either of the clear arbitrage scenarios, $Arb_t^{EB>UA}$ or $Arb_t^{UB>EA}$, we find no significant trend in underlying midpoint returns at the 1-, 15-, or 30-minute frequencies. Figure 6 demonstrated that constituent cumulative returns were mostly flat following arbitrage opportunities because, in most cases, the mispricing is instigated by a persistent price shock to the underlying portfolio. While we observe significant coefficients for the partially overvalued and undervalued mispricing classifications, $Arb_t^{UA>EB>UM}$ and $Arb_t^{UM>EA>UB}$, at 1-minute frequencies, this relation also becomes insignificant as measurement frequency falls. Panel A provides little evidence that mispricing events subsequently affect the prices of constituent securities.

In Panel B of Table IV, we report coefficient estimates of specifications that are similar to Equation (2) where the ETF midpoint return at time $t+1$ is substituted as the dependent variable. The sign and significance for most controls variables appears to be somewhat similar across Panels A and B. However, we do find more evidence of autocorrelation in ETF prices. Furthermore, Panel A showed that fund returns, do not predict constituent price changes at lower frequencies, whereas Panel B demonstrates that Ret_t^{Und} can predict cumulative ETF returns for at least 15 minutes. Finally, unlike Panel A, we find no evidence that missing or inferred bid and offer quotes have any impact on fund prices.

With regards to our variables of interest, our findings are, once again, consistent in the 45-minute window graphical analysis. For the 1-, 15-, or 30-minute specifications, we observe ETF prices adjusting in a way that would alleviate mispricing between the fund and its underlying portfolio. Taken together, Panels A and B imply that there are no residual shocks to the prices of constituent securities following a mispricing event, and that nearly all of the discrepancy is alleviated by a subsequent change in the ETF's price. Just as in Figure 6, Table IV suggests that persistent shocks to the value of constituent securities trigger mispricing events where ETF price adjustments lag by several minutes.

2. Directional volume

Our analysis of intraday trading activity is based on a specification that is similar to Equation (2), where directional volume at time $t + 1$ is substituted as the dependent variable:

$$
\begin{aligned}
VolDiff_{t+1}^{Und} = \sum_{k=0}^{K} \phi_k VolDiff_{t-k}^{Und} + \beta_0 + \beta_1 VolDiff_t^{ETF} \\
+ \beta_2 AskRet_t^{Und} + \beta_3 BidRet_t^{Und} + \beta_4 AskRet_t^{ETF} \\
+ \beta_5 BidRet_t^{ETF} + \sum_{k=6}^{13} \beta_k Control_{kt} + \beta_{14} Arb_t^{EB>UA} \\
+ \beta_{15} Arb_t^{UA>EB>UM} + \beta_{16} Arb_t^{UM>EA>UB} + \beta_{17} Arb_t^{UB>EA} \\
+ \alpha_d + \varepsilon_{t+1}.
\end{aligned}
\tag{3}
$$

In place of midpoint returns, we include the percentage change in ask price, either $AskRet_t^{Und}$ or $AskRet_t^{ETF}$, and bid price, either $BidRet_t^{Und}$ or $BidRet_t^{ETF}$, for the underlying portfolio and ETF. As demonstrated in Figure 7, midpoint price adjustments are sometimes associated with changes to only one side of the quote. Asymmetric adjustments to bid and ask prices change the relative cost of liquidity between marketable buy and sell orders, and ultimately encourage directional trading in the underlying securities.

Coefficient estimates for (3) are reported in Panel A of Table V. While reported fit statistics are larger than those from our analysis of midpoint returns, most of the variance in underlying directional volume remains unexplained. However, positive and significant coefficients for each of the lagged dependent variables imply that order flow in the constituent securities is at least somewhat persistent. We also find that underlying directional volume at time $t + 1$ is negatively associated with ETF volume during the previous minute, but this relation disappears as measurement frequency falls.

Regardless of whether midpoint price adjustments are instigated by changes to the bid or offer quote, Panel A indicates that constituent order flow trends in the same direction as recent underlying returns. Conversely, there is very little evidence that directional trading in the portfolio is influenced by changes in ETF prices. Just as an accumulation of liquidity above or below the midpoint predicted midpoint returns in Table IV, we also find that increasing depth at the bid or offer anticipates order flow in the portfolio. However, we find no evidence that missing or inferred quotes play a significant role in directional trading.

According to our 45-minute window graphical analysis, price shocks are impounded by informed directional trading in the portfolio before the mispricing with relatively balanced trading in the constituents after the event. Similarly, the indicator variables denoting each of the clear arbitrage scenarios, either $Arb_t^{EB>UA}$ or $Arb_t^{UB>EA}$, are not predictors of subsequent order flow in the constituent securities. Thus, arbitrage opportunities do not seem to encourage directional trading in the underlying portfolio. However, when the ETF is only partially overvalued, $Arb_t^{UA>EB>UM}$, or undervalued, $Arb_t^{UM>EA>UB}$, Panel A implies that subsequent order flow trends in the direction that would correct mispricing. It is unclear why directional trading in the underlying securities follows partial mispricings that cannot be arbitraged with marketable orders.

The results in Panel B of Table V, where we examine ETF signed volume, suggest that the return correction post-mispricing is not driven by trading. Columns 2, 4 and 6 show buying volume in the ETF following ETF overvaluation and selling volume in the

ETF following underlying overvaluation at 1-, 15- and 30-minute increments. Overall and consistent with our univariate analyses in the prior two sections, these results suggest that the return correction following the mispricings shown in Table IV do not appear to be fully corrected by trading volume in the underlying.

Overall, our multivariate analyses in Table IV and Table V support the conclusion drawn from the univariate figures in Sections II.A. and II.B.: midquote prices correct following arbitrage opportunities, and this response appears, primarily, to be a result of updates to the limit order book and not to market orders.

B. Daily Regressions

1. ETF creations and redemptions

As described in the introduction, arbitrage can occur either in the secondary market or in the primary market. While our analysis to this point has focused on the secondary market, we now turn our attention to potential arbitrage in the primary market. When an ETF's price deviates from the price of its underlying portfolio, Authorized Participants (APs) can buy or sell the underlying basket of securities and then exchange the portfolio for shares of the ETF directly through the fund sponsor. In Table VI, we take a closer look at the determinants of creations and redemptions of ETF shares in the primary market.

For most of the individual securities in our analysis, the distribution of intraday midpoint returns is highly leptokurtic. We collect the ETF and underlying midpoint price, Mid_t, at the end of each 1-, 15- and 30-minute period t in our sample. To measure intraday returns, we adjust the midpoint percent change in with the following function:

$$Ret_t = \begin{cases} \ln\left(1 + \dfrac{Mid_t - Mid_{t-1}}{Mid_{t-1}}\right), & if\ Mid_t \geq Mid_{t-1} \\ -\ln\left(1 + \left|\dfrac{Mid_t - Mid_{t-1}}{Mid_{t-1}}\right|\right), & if\ Mid_t < Mid_{t-1} \end{cases} \tag{4}$$

From Bloomberg, we collect the daily total of shares outstanding, $ShrOut_d$, for each fund in our sample. To measure share creation and redemption, we adjust the daily change in $ShrOut_d$ with the following function:

$$\Delta ShrOut_d = \begin{cases} \ln(1 + ShrOut_d - ShrOut_{d-1}), & if ShrOut_d \geq ShrOut_{d-1} \\ -\ln(1 + |ShrOut_d - ShrOut_{d-1}|), & if ShrOut_d < ShrOut_{d-1} \end{cases}. \tag{5}$$

By logging the change in shares outstanding, we mitigate concerns that the creation and redemption events of larger ETFs are driving our results, while still capturing variation in the magnitude of these events across small- and medium-sized funds.

We also capture the severity and direction of arbitrage opportunities within a trading day d, by aggregating the binary arbitrage variables from Figure 1 with the following equation:

$$\begin{aligned} ArbSum_d = \sum_t [&(2 \times Arb_t^{EB>UA}) + (1 \times Arb_t^{UA>EB>UM}) \\ &+ (-1 \times Arb_t^{UM>EA>UB}) + (-2 \times Arb_t^{UB>EA})]. \end{aligned} \tag{6}$$

Larger realizations of $ArbSum_d$ imply that the ETF was frequently priced at premium relative to the underlying portfolio many times during the trading day. To provide a comparison with existing literature, we also calculate daily the discount or premium, $DiscPrem_d$, based on the NAV reported by the fund sponsor and the ETF closing share price from CRSP.

All of the specifications in Table VI include cumulative intraday returns, as well as controls for directional and total volume for the underlying and ETF. When considering the change in shares outstanding reported in Table VI, our results indicate that price changes, directional volume and total volume in underlying portfolios predict increased primary market activity. However, while ETF returns fail to predict changes in shares outstanding, both directional and total volume in the ETF are positive and statistically significant. We also note the persistence in creation and redemption events as the changes in the previous days' shares outstanding predict additional primary activity the following trading day.

From Table VI, the persistence in share creations and redemptions is consistent with the idea that multiple APs accumulate and redeem shares at similar times. The positive and significant coefficients on $ArbSum_d$ and its lags indicate that ETFs frequently trading at large premiums will likely encourage AP activity. Perhaps the most interesting result in Table VI is the lack of statistical significance on $DiscPrem_d$, indicating that discounts and premiums in the ETF do not impact primary market activity. This result is in sharp contrast to previous studies suggesting that creation and redemption events are largely a byproduct of observed ETF premiums and discounts (e.g., Broman and Shum (2018), Ben-David, Franzoni and Moussawi (2018) and Malamud (2016)).

2. The effect of ETFs on the underlying portfolio

Malamud (2016) introduces a theoretical model that demonstrates how the creation and redemption mechanism of ETF shares serves as a shock propagation channel that allows temporary demand shocks to leave an enduring impact on constituent security prices. We explore this hypothesis directly in the last portion of our empirical analysis. In Table VII we consider the effects of primary market activity, the severity and direction of arbitrage opportunities, as well as discounts and premiums on returns and directional volume in both the underlying and ETF. Overall, the results in Table VII provide no evidence that shocks to the ETF are transferred to the underlying securities. Not only do creations and redemptions appear to have no meaningful impact on the underlying constituents, arbitrage activity is also unable to predict directional volume in the underlying. ETF premiums and discounts also provide no ability to predict returns or directional volume in the underlying. We also note a large distinction between these and those in recent studies suggesting that price and trading pressures migrate from the ETF to the underlying basket.

IV. Conclusion

Recent studies suggest that ETFs may attract short-term traders that introduce noise in the underlying securities prices through the arbitrage mechanism (Broman and Shum (2018), Ben-David, Franzoni and Moussawi (2018), Charupat and Miu (2011), Israeli, Lee and Sridharan (2017) and Malamud (2016)). As traders take opposing positions in the ETF and underlying shares, price pressures resulting from ETF demand may extend to the constituent securities. We directly examine this proposition by identifying intraday arbitrage opportunities between ETFs and the constituents and find little evidence that arbitrage opportunities precede trading in the underlying. Instead, arbitrage opportunities are initiated by shocks to the underlying and subsequently corrected through updates in the best bid and offer quotes. Thus, while we observe quote adjustments in response to price discrepancies, we find limited evidence of arbitrage trading. Additionally, our results indicate that bid-ask spreads remain steady during arbitrage opportunities. Not only are we unable to document arbitrage in the face of mispricing, we also find no evidence that the convergence of prices removes liquidity from the market.

After considering the primary market activity of ETFs, we find no evidence that discounts or premiums affect the shares outstanding of an ETF, consistent with a lack of arbitrage activity since such activity would result in a net increase or decrease in ETF shares. Additionally, when considering returns and directional volume around creations and redemptions, we find no evidence that price pressure in ETFs extend to their underlying constituents. Our results stand in sharp contrast to recent studies suggesting that ETF shares serves as a shock propagation channel that allows temporary demand shocks to leave an enduring impact on constituent security prices. In fact, our results suggest that in the presence of an information event in the underlying, ETF trading may help to shield the portfolio from demand shocks by offsetting liquidity provision in the underlying securities.

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Table I

Frequency of mispricing events across size categories

All fund-minute observations are designated as $Arb_t^{EB>UA}$, $Arb_t^{UA>EB>UM}$, $Arb_t^{UM>EA>UB}$ or $Arb_t^{UB>EA}$, in accordance with Figure 1, or classified as $NoArb_t$ when none of these conditions is satisfied. The following table reports the frequency of mispricing events, as well as the average quoted spreads from the end of each minute t, across fund and ETF size categories.

		Frequency					Average Quoted Spread in Basis Points	
	N	$Arb_t^{EB>UA}$	$Arb_t^{UA>EB>UM}$	$NoArb_t$	$Arb_t^{UM>EA>UB}$	$Arb_t^{UB>EA}$	Und	ETF
All Observations	94,305,900	0.86%	3.69%	91.02%	3.63%	0.79%	12.4	19.3
Small ETF	58,886,490	0.85%	1.70%	95.04%	1.65%	0.76%	13.7	26.0
Large ETF	35,419,410	0.88%	7.00%	84.34%	6.93%	0.85%	10.4	8.2
Small Underlying	58,121,310	0.83%	4.24%	89.95%	4.19%	0.78%	16.3	21.4
Large Underlying	36,184,590	0.91%	2.80%	92.75%	2.73%	0.81%	6.2	16.0
Small Und/Small ETF	41,385,630	0.80%	2.09%	94.33%	2.04%	0.74%	16.8	26.5
Small Und/Large ETF	16,735,680	0.91%	9.56%	79.12%	9.53%	0.89%	15.2	8.8
Large Und/Small ETF	17,500,860	0.97%	0.76%	96.72%	0.73%	0.81%	6.4	24.9
Large Und/Large ETF	18,683,730	0.85%	4.71%	89.02%	4.60%	0.82%	6.0	7.6

Table II
Price Shocks and Liquidity Provider Inventory Levels

	Marketable Orders		Liquidity Providers	
	Order Flow	Trading Direction	Order Flow	Inventory Levels
Panel A: Negative Shock to Price of the Underlying Portfolio				
Und	Selling Below Midpoint	Informed	Buying Below Midpoint	Rising
ETF	Buying Above Midpoint	Uninformed	Selling Above Midpoint	Falling
Panel B: Positive Shock to Price of the Underlying Portfolio				
Und	Buying Above Midpoint	Informed	Selling Above Midpoint	Falling
ETF	Selling Below Midpoint	Uninformed	Buying Below Midpoint	Rising

Table III

Summary statistics for midpoint return and directional volume variables

Ret_{t+1}^{Und}, defined in Equation (4), represents the midpoint return of the underlying securities during the future period $t+1$. Likewise, Ret_{t+1}^{ETF}, represents the midpoint return of the ETF. $VolDiff_t^{Und}$ and $VolDiff_t^{ETF}$, defined in Equation (1) measure the difference between buy and sell volume for the underlying securities and ETF shares, respectively.

	Summary Statistics								Correlations		
	Mean	P1	P10	P25	P50	P75	P90	P99	Ret_t^{Und}	Ret_t^{ETF}	$VolDiff_t^{Und}$
Panel A: 1-Minute Window											
Ret_t^{Und}	0.00	-0.17	-0.05	-0.02	0.00	0.02	0.05	0.18			
Ret_t^{ETF}	0.00	-0.18	-0.05	-0.02	0.00	0.02	0.05	0.18	81.6%		
$VolDiff_t^{Und}$	-0.01	-8.66	-7.49	-6.66	0.00	6.66	7.49	8.68	9.5%	8.4%	
$VolDiff_t^{ETF}$	0.24	-11.01	-7.41	0.00	0.00	0.00	8.01	11.28	-1.2%	-2.0%	2.2%
Panel B: 15-Minute Window											
Ret_t^{Und}	0.00	-0.55	-0.20	-0.08	0.00	0.09	0.19	0.55			
Ret_t^{ETF}	0.00	-0.56	-0.20	-0.08	0.00	0.09	0.20	0.56	94.1%		
$VolDiff_t^{Und}$	-0.01	-10.46	-9.33	-8.53	-1.55	8.52	9.35	10.54	24.4%	23.7%	
$VolDiff_t^{ETF}$	1.04	-13.60	-11.24	-8.99	0.00	10.19	11.68	13.74	0.7%	0.9%	2.7%
Panel C: 30-Minute Window											
Ret_t^{Und}	0.00	-0.70	-0.27	-0.11	0.01	0.12	0.26	0.71			
Ret_t^{ETF}	0.00	-0.71	-0.27	-0.11	0.00	0.12	0.26	0.72	95.6%		
$VolDiff_t^{Und}$	-0.01	-10.92	-9.84	-9.05	-2.18	9.04	9.87	11.02	27.1%	26.4%	
$VolDiff_t^{ETF}$	1.34	-14.10	-12.02	-10.17	0.00	11.15	12.44	14.23	1.3%	1.6%	3.5%
Panel D: Daily Window											
Ret_t^{Und}	0.03	-1.60	-0.86	-0.41	0.09	0.48	0.82	1.55			
Ret_t^{ETF}	0.01	-1.63	-0.88	-0.43	0.06	0.47	0.81	1.55	95.5%		
$VolDiff_t^{Und}$	0.00	-0.09	-0.04	-0.02	0.00	0.02	0.04	0.11	30.9%	30.1%	
$VolDiff_t^{ETF}$	0.11	-2.34	-0.37	-0.09	0.04	0.25	0.64	3.04	3.1%	3.1%	4.4%

Table IV

Midpoint return during arbitrage opportunities

The dependent variable in all specifications of Panel A is Ret_{t+1}^{Und}, defined in Equation (4), represents the midpoint return of the underlying securities during the future period $t+1$. Likewise, the dependent variable in all specifications of Panel B is Ret_{t+1}^{ETF}, or the midpoint return of the ETF. The period t denotes either a 1-, 15- and 30-minute window, depending on the specification. $VolDiff_t^{Und}$ and $VolDiff_t^{ETF}$ measure the difference between buy and sell volume for the underlying securities and ETF shares, respectively. $DolAsk_t^{Und}$ and $DolBid_t^{Und}$ represent the market-weighted average dollar-value of the best ask and bid quotes at the end of period t. Similarly, $DolAsk_t^{ETF}$ and $DolBid_t^{ETF}$ are the dollar value of the best quotes available for the ETF. $MisAsk_t^{Und}$ and $MisBid_t^{Und}$ are the percentage of ask and bid prices, for the underlying securities that are classified as missing, according to the approach described in Appendix B, at the end of period t. $MisAsk_t^{ETF}$ and $MisBid_t^{ETF}$ are dummy variable set to one whenever the ETF ask or bid quote is missing. All observations are designated as $Arb_t^{EB>UA}$, $Arb_t^{UA>EB>UM}$, $Arb_t^{UM>EA>UB}$ or $Arb_t^{UB>EA}$, in accordance with Figure 1, or classified as $NoArb_t$ when none of these conditions is satisfied. Coefficients marked *, ** and *** are significant at the 10%, 5% and 1% level, respectively, and t-statistics are reported in parenthesis.

Table IV—Continued

Panel A: Future underlying midpoint return, Ret_{t+1}^{Und}, as the dependent variable						
	1-Minute Windows		15-Minute Windows		30-Minute Windows	
Ret_t^{Und}	-0.0894 (-1.221)	-0.0856 (-1.205)	-0.105 (-1.588)	-0.0988 (-1.605)		
Ret_{t-1}^{Und}	-0.0112 (-0.654)	-0.0106 (-0.644)				
Ret_{t-2}^{Und}	-0.00555 (-0.861)	-0.00531 (-0.865)				
Ret_{t-3}^{Und}	-0.0197*** (-6.117)	-0.0195*** (-6.333)				
Ret_{t-4}^{Und}	-0.00141 (-0.361)	-0.00134 (-0.353)				
Ret_t^{ETF}	0.119** (2.011)	0.115** (2.006)	0.0859 (1.388)	0.0799 (1.385)	-0.0325 (-1.190)	-0.0329 (-1.196)
$VolDiff_t^{Und}$	4.70e-05 (1.286)	4.64e-05 (1.293)	-0.000497*** (-5.428)	-0.000497*** (-5.366)	-0.00111*** (-7.502)	-0.00110*** (-7.403)
$VolDiff_t^{ETF}$	1.46e-05** (2.196)	1.66e-05** (2.309)	-6.05e-05** (-2.698)	-6.08e-05** (-2.616)	-0.000120** (-2.689)	-0.000121** (-2.570)
ln ($DolAsk_t^{Und}$)	-0.00629*** (-12.56)	-0.00627*** (-12.52)	-0.0164*** (-6.246)	-0.0164*** (-6.237)	-0.0240*** (-3.682)	-0.0240*** (-3.670)
ln ($DolBid_t^{Und}$)	0.00569*** (11.98)	0.00565*** (11.97)	0.00405* (2.063)	0.00403* (2.055)	-0.00264 (-0.698)	-0.00261 (-0.689)
ln ($DolAsk_t^{ETF}$)	-0.00110*** (-3.946)	-0.00124*** (-3.881)	-0.00130*** (-3.116)	-0.00143*** (-3.028)	-0.000737 (-1.361)	-0.000962 (-1.564)
ln ($DolBid_t^{ETF}$)	0.00107*** (3.533)	0.00121*** (3.499)	0.00106** (2.391)	0.00118** (2.390)	-7.96e-05 (-0.196)	0.000171 (0.397)
$MisAsk_t^{Und}$	0.0265*** (3.572)	0.0223** (2.349)	0.408*** (19.87)	0.407*** (19.20)	0.756** (2.526)	0.749** (2.512)
$MisBid_t^{Und}$	-0.0264*** (-4.064)	-0.0222** (-2.585)	-0.369*** (-12.27)	-0.367*** (-11.99)	-0.700*** (-4.611)	-0.693*** (-4.644)
$MisAsk_t^{ETF}$	-0.00346 (-1.395)	-0.00322 (-1.268)	-0.00647 (-0.181)	-0.00688 (-0.189)	-0.0154 (-0.410)	-0.0150 (-0.398)
$MisBid_t^{ETF}$	0.00370 (1.258)	0.00340 (1.132)	0.00500 (0.151)	0.00534 (0.159)	0.0101 (0.320)	0.00968 (0.316)
$Arb_t^{EB>UA}$		0.0104 (1.395)		0.0254 (1.431)		0.0411 (1.793)
$Arb_t^{UA>EB>UM}$		0.00291*** (6.319)		0.000610 (0.515)		0.00135 (0.641)
$Arb_t^{UM>EA>UB}$		-0.00326*** (-7.754)		-0.00184 (-1.463)		-0.000522 (-0.229)
$Arb_t^{UB>EA}$		-0.00986 (-1.264)		-0.0210 (-1.379)		-0.0370 (-1.401)
Daily ETF Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.010	0.011	0.051	0.051	0.108	0.108
Observations	92,854,109		5,803,395		2,659,894	

Table IV—Continued

Panel B: Future ETF midpoint return, Ret_{t+1}^{ETF}, as the dependent variable						
	1-Minute Windows		15-Minute Windows		30-Minute Windows	
Ret_t^{Und}	0.171*** (3.159)	0.166*** (3.081)	0.174*** (3.763)	0.162*** (3.533)	-0.0326 (-1.295)	-0.0325 (-1.292)
Ret_t^{ETF}	-0.120*** (-2.722)	-0.115*** (-2.612)	-0.184*** (-4.063)	-0.172*** (-3.818)		
Ret_{t-1}^{ETF}	-0.00426 (-1.463)	-0.00373 (-1.280)				
Ret_{t-2}^{ETF}	-0.00306 (-1.306)	-0.00277 (-1.185)				
Ret_{t-3}^{ETF}	-0.0150*** (-6.013)	-0.0148*** (-5.937)				
Ret_{t-4}^{ETF}	-0.000660 (-0.291)	-0.000459 (-0.203)				
$VolDiff_t^{Und}$	4.48e-05*** (4.227)	4.37e-05*** (4.125)	-0.000518*** (-6.740)	-0.000517*** (-6.716)	-0.00108*** (-8.739)	-0.00108*** (-8.144)
$VolDiff_t^{ETF}$	7.11e-05*** (11.38)	6.85e-05*** (11.02)	-3.29e-05 (-1.374)	-2.95e-05 (-1.259)	-0.000112** (-2.653)	-0.000106** (-2.414)
$\ln(DolAsk_t^{Und})$	-0.00516*** (-12.81)	-0.00520*** (-12.86)	-0.0156*** (-6.019)	-0.0158*** (-6.054)	-0.0225*** (-5.241)	-0.0228*** (-5.311)
$\ln(DolBid_t^{Und})$	0.00499*** (12.81)	0.00503*** (12.88)	0.00552** (2.595)	0.00565** (2.654)	0.000692 (0.158)	0.000884 (0.203)
$\ln(DolAsk_t^{ETF})$	-0.00405*** (-16.83)	-0.00387*** (-16.56)	-0.00505*** (-14.17)	-0.00466*** (-13.56)	-0.00647*** (-14.11)	-0.00574*** (-12.53)
$\ln(DolBid_t^{ETF})$	0.00411*** (16.61)	0.00394*** (16.23)	0.00508*** (12.74)	0.00472*** (12.23)	0.00593*** (12.44)	0.00524*** (10.18)
$MisAsk_t^{Und}$	-0.00234 (-0.101)	0.00337 (0.178)	-0.147 (-0.380)	-0.133 (-0.356)	-0.529 (-0.657)	-0.498 (-0.640)
$MisBid_t^{Und}$	0.00357 (0.154)	-0.00217 (-0.113)	0.181 (0.467)	0.166 (0.443)	0.595 (0.754)	0.564 (0.739)
$MisAsk_t^{ETF}$	0.00830 (1.052)	0.00798 (1.012)	0.0296 (0.545)	0.0294 (0.545)	0.124 (0.970)	0.121 (0.956)
$MisBid_t^{ETF}$	-0.00820 (-1.153)	-0.00783 (-1.101)	-0.0318 (-0.524)	-0.0317 (-0.525)	-0.146 (-1.063)	-0.143 (-1.048)
$Arb_t^{EB>UA}$		-0.0118*** (-10.50)		-0.0305*** (-4.858)		-0.0510*** (-5.798)
$Arb_t^{UA>EB>UM}$		-0.00424*** (-8.910)		-0.0139*** (-9.059)		-0.0215*** (-8.680)
$Arb_t^{UM>EA>UB}$		0.00415*** (8.720)		0.0130*** (7.085)		0.0233*** (6.891)
$Arb_t^{UB>EA}$		0.0127*** (6.522)		0.0370*** (3.530)		0.0574*** (4.590)
Daily ETF Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.023	0.024	0.054	0.055	0.106	0.107
Observations	92,853,462		5,803,395		2,659,906	

Table V

Volume differential during arbitrage opportunities

The dependent variable in all specifications of Panel A is $VolDiff_t^{Und}$, defined as the market-weighted average difference between buy and sell volume for the underlying securities during the future period $t+1$. Likewise, the dependent variable in all specifications of Panel B is $VolDiff_t^{ETF}$, or the difference between buy and sell volume for the ETF. The period t denotes either a 1-, 15- and 30-minute window, depending on the specification. $AskRet_{t+1}^{Und}$ and $AskRet_{t+1}^{ETF}$ measure the percentage change of the best ask price for the underlying securities and ETF, respectively. $BidRet_{t+1}^{Und}$ and $BidRet_{t+1}^{ETF}$ measure the percentage change of the best bid price for the underlying securities and ETF, respectively. $DolAsk_t^{Und}$ and $DolBid_t^{Und}$ represent the market-weighted average dollar-value of the best ask and bid quotes at the end of period t. Similarly, $DolAsk_t^{ETF}$ and $DolBid_t^{ETF}$ are the dollar value of the best quotes available for the ETF. $MisAsk_t^{Und}$ and $MisBid_t^{Und}$ are the percentage of ask and bid, for the underlying securities that are classified as missing, according to the approach described in Appendix B, at the end of period t. $MisAsk_t^{ETF}$ and $MisBid_t^{ETF}$ are dummy variables set to one whenever the ETF ask or bid quote is missing. All observations are designated as $Arb_t^{EB>UA}$, $Arb_t^{UA>EB>UM}$, $Arb_t^{UM>EA>UB}$ or $Arb_t^{UB>EA}$, in accordance with Figure 1, or classified as $NoArb_t$ when none of these conditions is satisfied. Coefficients marked *, ** and *** are significant at the 10%, 5% and 1% level, respectively, and t-statistics are reported in parenthesis.

Table V—Continued

Panel A: Future underlying volume difference, $VolDiff_{t+1}^{Und}$, as the dependent variable						
	1-Minute Windows		15-Minute Windows		30-Minute Windows	
$VolDiff_t^{Und}$	0.0712*** (34.64)	0.0712*** (34.66)	0.0567*** (9.033)	0.0566*** (8.847)		
$VolDiff_{t-1}^{Und}$	0.0393*** (37.40)	0.0392*** (37.42)				
$VolDiff_{t-2}^{Und}$	0.0282*** (38.22)	0.0281*** (38.24)				
$VolDiff_{t-3}^{Und}$	0.0218*** (33.54)	0.0217*** (33.53)				
$VolDiff_{t-4}^{Und}$	0.0214*** (35.55)	0.0213*** (35.56)				
$VolDiff_t^{ETF}$	-0.00841*** (-11.32)	-0.00831*** (-11.20)	0.000105 (0.179)	2.19e-05 (0.0368)	-0.000392 (-0.414)	-0.000468 (-0.473)
$AskRet_t^{Und}$	5.598*** (8.155)	5.583*** (8.153)	1.200*** (7.419)	1.193*** (7.408)	1.008*** (7.877)	1.002*** (7.824)
$BidRet_t^{Und}$	4.991*** (7.828)	4.979*** (7.830)	0.924*** (6.142)	0.921*** (6.175)	0.809*** (7.404)	0.808*** (7.434)
$AskRet_t^{ETF}$	-0.000542* (-1.955)	-0.000542* (-1.960)	0.00470 (0.359)	0.00457 (0.284)	-0.0136 (-0.799)	-0.0133 (-0.780)
$BidRet_t^{ETF}$	0.000415 (1.213)	0.000415 (1.219)	-0.00572 (-0.427)	-0.00561 (-0.341)	0.0128 (0.746)	0.0126 (0.729)
$\ln(DolAsk_t^{Und})$	-0.707*** (-12.43)	-0.705*** (-12.43)	-0.346*** (-4.408)	-0.342*** (-4.375)	-0.222 (-1.411)	-0.218 (-1.387)
$\ln(DolBid_t^{Und})$	0.851*** (14.20)	0.847*** (14.18)	0.453*** (3.368)	0.449*** (3.332)	0.338 (1.708)	0.335 (1.687)
$\ln(DolAsk_t^{ETF})$	-0.0619*** (-10.80)	-0.0688*** (-12.43)	-0.0483*** (-6.624)	-0.0553*** (-7.159)	-0.0317*** (-3.324)	-0.0373*** (-3.538)
$\ln(DolBid_t^{ETF})$	0.0765*** (12.68)	0.0825*** (14.09)	0.0516*** (9.553)	0.0579*** (10.07)	0.0396*** (5.287)	0.0452*** (5.566)
$MisAsk_t^{Und}$	0.716 (0.873)	0.436 (0.466)	0.914 (0.162)	0.530 (0.0904)	7.586 (1.095)	7.245 (1.021)
$MisBid_t^{Und}$	-0.362 (-0.442)	-0.0799 (-0.0857)	1.114 (0.200)	1.499 (0.258)	-5.339 (-0.784)	-4.998 (-0.717)
$MisAsk_t^{ETF}$	-0.0352 (-0.309)	-0.0171 (-0.143)	-0.295 (-0.625)	-0.267 (-0.557)	0.134 (0.222)	0.158 (0.259)
$MisBid_t^{ETF}$	-0.00771 (-0.0680)	-0.0276 (-0.233)	0.102 (0.222)	0.0676 (0.145)	-0.277 (-0.479)	-0.307 (-0.528)
$Arb_t^{EB>UA}$		-0.0292 (-0.765)		0.0219 (0.316)		0.00940 (0.108)
$Arb_t^{UA>EB>UM}$		0.244*** (8.454)		0.346*** (8.385)		0.343*** (5.722)
$Arb_t^{UM>EA>UB}$		-0.287*** (-10.80)		-0.366*** (-7.033)		-0.282*** (-4.204)
$Arb_t^{UB>EA}$		-0.0410 (-1.251)		-0.0303 (-0.285)		0.0309 (0.348)
Daily ETF Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.047	0.047	0.123	0.123	0.172	0.173
Observations	93,066,569		5,801,571		2,659,058	

Table V—Continued

Panel B: Future ETF volume difference, $VolDiff_{t+1}^{ETF}$, as the dependent variable						
	1-Minute Windows		15-Minute Windows		30-Minute Windows	
$VolDiff_t^{Und}$	0.00171***	0.00170***	0.00516***	0.00513***	0.00334**	0.00331**
	(5.587)	(5.576)	(7.416)	(7.370)	(2.679)	(2.714)
$VolDiff_t^{ETF}$	0.0324***	0.0325***	0.0121**	0.0120**		
	(23.88)	(23.90)	(2.523)	(2.520)		
$VolDiff_{t-1}^{ETF}$	0.0264***	0.0264***				
	(30.63)	(30.75)				
$VolDiff_{t-2}^{ETF}$	0.0229***	0.0229***				
	(32.04)	(32.24)				
$VolDiff_{t-3}^{ETF}$	0.0197***	0.0197***				
	(30.15)	(30.34)				
$VolDiff_{t-4}^{ETF}$	0.0179***	0.0179***				
	(31.06)	(31.32)				
$AskRet_t^{Und}$	0.197***	0.194***	0.0841	0.0839	0.128**	0.129**
	(3.226)	(3.224)	(1.621)	(1.638)	(2.234)	(2.244)
$BidRet_t^{Und}$	0.246***	0.245***	0.269***	0.270***	0.294***	0.297***
	(4.307)	(4.363)	(4.911)	(4.976)	(4.090)	(4.110)
$AskRet_t^{ETF}$	-0.000300***	-0.000286***	-0.00474	-0.00624	-0.0162	-0.0166
	(-3.295)	(-3.174)	(-0.662)	(-0.927)	(-1.541)	(-1.318)
$BidRet_t^{ETF}$	0.000312***	0.000300***	0.00615	0.00763	0.0176	0.0180
	(2.988)	(2.867)	(0.844)	(1.114)	(1.648)	(1.414)
$\ln(DolAsk_t^{Und})$	0.0240**	0.0257**	0.114***	0.115***	0.114*	0.115*
	(2.109)	(2.266)	(3.480)	(3.480)	(1.943)	(1.928)
$\ln(DolBid_t^{Und})$	0.0503***	0.0480***	0.132***	0.130***	0.156**	0.156**
	(3.893)	(3.737)	(3.543)	(3.473)	(2.317)	(2.316)
$\ln(DolAsk_t^{ETF})$	0.0895***	0.0825***	0.111***	0.104***	0.0870***	0.0824***
	(16.31)	(16.37)	(10.66)	(10.81)	(4.311)	(4.232)
$\ln(DolBid_t^{ETF})$	-0.0888***	-0.0819***	-0.107***	-0.101***	-0.0786***	-0.0744***
	(-15.81)	(-15.87)	(-8.233)	(-8.214)	(-4.980)	(-4.532)
$MisAsk_t^{Und}$	0.0435	-0.181	1.089	0.879	-0.579	-0.718
	(0.103)	(-0.403)	(0.517)	(0.410)	(-0.199)	(-0.247)
$MisBid_t^{Und}$	-0.115	0.107	-1.270	-1.030	0.123	0.271
	(-0.278)	(0.241)	(-0.614)	(-0.490)	(0.0433)	(0.0954)
$MisAsk_t^{ETF}$	-0.138*	-0.125	-0.0507	-0.0371	0.00321	0.0156
	(-1.898)	(-1.609)	(-0.105)	(-0.0750)	(0.00419)	(0.0202)
$MisBid_t^{ETF}$	0.00697	-0.00866	-0.189	-0.198	-0.297	-0.306
	(0.0952)	(-0.110)	(-0.384)	(-0.392)	(-0.386)	(-0.395)
$Arb_t^{EB>UA}$		0.346***		0.474***		0.531***
		(9.466)		(6.769)		(5.312)
$Arb_t^{UA>EB>UM}$		0.182***		0.0905**		0.0384
		(7.429)		(2.135)		(0.757)
$Arb_t^{UM>EA>UB}$		-0.176***		-0.205***		-0.0855
		(-7.700)		(-3.834)		(-1.209)
$Arb_t^{UB>EA}$		-0.350***		-0.691***		-0.640***
		(-9.456)		(-8.040)		(-6.155)
Daily ETF Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.029	0.030	0.098	0.098	0.129	0.129
Observations	93,066,569		5,801,571		2,659,058	

Table VI

Determinants of Daily Creation/Redemption and Arbitrage Opportunities

The dependent variable in the first specification, $\Delta ShrOut_d$, defined in Equation (5), is the change in ETF shares outstanding on day d. Next, the dependent variable in the second specification, $ArbSum_d$, defined in Equation (6), represents the direction and severity of arbitrage opportunities throughout the trading day. $DiscPrem_d$ represents the daily discount or premium based on the NAV reported by the fund sponsor. Ret_d^{Und} and Ret_d^{ETF} are the cumulative intraday, open to close, returns for the underlying portfolio and ETF respectively. $VolDiff_d^{Und}$ is the difference in the underlying portfolio's total dollar buy and sell volume during day d divided by the portfolio's daily average total volume over the previous 200 days. Similarly, $VolDiff_d^{ETF}$ captures the direction of trading volume for the ETF. OLS standard errors are triple clustered by ETF, yearly permno and date using the Cameron, Gelbach and Miller (2011) multi-way clustering procedure. Coefficients marked *, ** and *** are significant at the 10%, 5% and 1% level, respectively, and t-statistics are reported in parenthesis.

Table VI—(continued)

	$\Delta ShrOut_d$		$ArbSum_d$	
	Coefficient	T-stat	Coefficient	T-stat
$\Delta ShrOut_d$			6.58e-05	(1.439)
$\Delta ShrOut_{d-1}$	0.0537***	(7.628)	7.91e-05*	(1.926)
$\Delta ShrOut_{d-2}$	0.0353***	(6.038)	7.12e-05*	(1.904)
$\Delta ShrOut_{d-3}$	0.0227***	(3.989)	2.75e-05	(0.745)
⋮	⋮	⋮	⋮	⋮
$\Delta ShrOut_{d-7}$	0.0100*	(1.894)	3.78e-06	(0.104)
$\Delta ShrOut_{d-8}$	0.00953**	(1.984)		
$ArbSum_d$	0.494*	(1.733)		
$ArbSum_{d-1}$	0.749***	(2.760)	0.0182***	(3.380)
$ArbSum_{d-2}$	0.654**	(2.329)	0.0159***	(2.890)
$ArbSum_{d-3}$	0.388	(1.641)	0.00969*	(1.888)
⋮	⋮	⋮	⋮	⋮
$ArbSum_{d-7}$	-0.152	(-0.684)	0.00256	(0.580)
$ArbSum_{d-8}$			0.00365	(0.810)
$DiscPrem_d$	2.84e-05	(0.204)	7.30e-07	(0.757)
$DiscPrem_{d-1}$	-5.48e-05	(-0.464)	4.36e-06	(1.047)
$DiscPrem_{d-2}$	5.58e-05	(0.652)	-5.11e-06	(-0.820)
⋮	⋮	⋮	⋮	⋮
$DiscPrem_{d-7}$	-0.000121	(-0.795)	2.14e-07	(0.535)
Ret_d^{Und}	0.560***	(3.717)	0.0200***	(7.575)
Ret_{d-1}^{Und}	0.161	(1.565)	-0.000649	(-0.439)
Ret_{d-2}^{Und}	0.163**	(2.080)	-0.00187	(-1.406)
⋮	⋮	⋮	⋮	⋮
Ret_{d-7}^{Und}	0.0425	(0.484)	-0.000139	(-0.105)
Ret_d^{ETF}	-0.0824	(-0.946)	-0.0234***	(-8.603)
Ret_{d-1}^{ETF}	0.125	(1.373)	0.00257*	(1.940)
Ret_{d-2}^{ETF}	0.0472	(0.611)	0.00255*	(1.917)
⋮	⋮	⋮	⋮	⋮
Ret_{d-7}^{ETF}	0.0267	(0.393)	0.000376	(0.286)
$VolDiff_d^{Und}$	1.090*	(1.739)	-0.00950	(-1.259)
$VolDiff_{d-1}^{Und}$	1.298**	(2.205)	0.0105	(1.645)
$VolDiff_{d-2}^{Und}$	0.236	(0.411)	0.00827	(1.393)
⋮	⋮	⋮	⋮	⋮
$VolDiff_{d-7}^{Und}$	-0.704	(-1.339)	-0.00113	(-0.190)
$VolDiff_d^{ETF}$	1.060***	(9.643)	0.0115***	(13.34)
$VolDiff_{d-1}^{ETF}$	1.062***	(12.30)	0.00318***	(5.586)
$VolDiff_{d-2}^{ETF}$	0.478***	(9.306)	0.00208***	(4.255)
⋮	⋮	⋮	⋮	⋮
$VolDiff_{d-7}^{ETF}$	0.210***	(5.413)	0.00110**	(2.124)
Date Fixed Effects	Yes		Yes	
Yearly ETF Fixed Effects	Yes		Yes	
R-squared	0.101		0.069	
Observations	217,664		222,362	

Table VII

Daily Return and Volume Regressions for Control Vairables

The dependent variable in the first two specifications are Ret_d^{Und} and Ret_d^{ETF}, the cumulative intraday, open to close, returns for the underlying portfolio and ETF respectively. The dependent variable in the third specification is $VolDiff_d^{Und}$, the difference in the underlying portfolio's total dollar buy and sell volume during day d divided by the portfolio's daily average total volume over the previous 200 days. Finally, the dependent variable in the fourth specification is $VolDiff_d^{ETF}$, which captures the direction of trading volume for the ETF divided by the fund's daily average total volume over the previous 200 days. $\Delta ShrOut_d$, defined in Equation (5), is the change in ETF shares outstanding on day d. $ArbSum_d$, defined in Equation (6), represents the direction and severity of arbitrage opportunities throughout the trading day. $DiscPrem_d$ represents the daily discount or premium based on the NAV reported by the fund sponsor. OLS standard errors are triple clustered by ETF, yearly permno and date using the Cameron, Gelbach and Miller (2011) multi-way clustering procedure. Coefficients marked *, ** and *** are significant at the 10%, 5% and 1% level, respectively, and t-statistics are reported in parenthesis.

Table VII—(continued)

	Ret_d^{Und}		Ret_d^{ETF}		$VolDiff_d^{Und}$		$VolDiff_d^{ETF}$	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
$\Delta ShrOut_d$	0.000419***	(3.110)	-6.40e-05	(-0.622)	2.42e-05	(1.326)	0.00421***	(5.273)
$\Delta ShrOut_{d-1}$	-1.17e-05	(-0.122)	-5.62e-05	(-0.565)	1.03e-05	(0.520)	-3.60e-05	(-0.183)
$\Delta ShrOut_{d-2}$	-0.000113	(-1.004)	3.94e-05	(0.391)	1.61e-06	(0.107)	-0.000151	(-0.935)
$\Delta ShrOut_{d-3}$	-8.45e-05	(-0.990)	-3.06e-05	(-0.354)	5.97e-06	(0.367)	2.55e-05	(0.190)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
$\Delta ShrOut_{d-7}$	6.78e-05	(0.666)	-0.000146*	(-1.718)	8.20e-06	(0.565)	0.000361**	(2.475)
$ArbSum_d$	0.117***	(7.646)	-0.159***	(-8.307)	-0.00164	(-1.232)	0.367***	(10.24)
$ArbSum_{d-1}$	-0.0125	(-1.618)	0.0109	(1.170)	-0.00172	(-1.454)	0.0721***	(4.350)
$ArbSum_{d-2}$	-0.00424	(-0.509)	0.00509	(0.581)	0.000330	(0.271)	0.0413***	(2.904)
$ArbSum_{d-3}$	-0.00841	(-1.128)	0.0146*	(1.727)	-0.000764	(-0.666)	0.0232	(1.407)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
$ArbSum_{d-7}$	-0.00926	(-1.291)	0.00782	(0.887)	-0.00198	(-1.549)	0.0383**	(2.557)
$DiscPrem_d$	-9.67e-06	(-1.031)	1.09e-05	(1.030)	-1.93e-07	(-0.324)	2.08e-05**	(2.351)
$DiscPrem_{d-1}$	-6.80e-06	(-0.836)	9.29e-06	(0.901)	7.48e-09	(0.0327)	-2.55e-07	(-0.0239)
$DiscPrem_{d-2}$	8.16e-06	(0.704)	-8.86e-06	(-0.723)	-4.61e-08	(-0.0944)	-5.62e-06	(-1.080)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
$DiscPrem_{d-7}$	-2.72e-06	(-1.233)	7.64e-07	(0.166)	-9.56e-08	(-0.315)	-2.69e-06	(-0.526)
Ret_d^{Und}			0.921***	(89.46)	0.0103***	(9.264)	-0.00451	(-0.541)
Ret_{d-1}^{Und}	0.0655***	(7.414)	-0.0778***	(-8.493)	0.000773	(0.818)	0.0260***	(3.621)
Ret_{d-2}^{Und}	0.0445***	(6.305)	-0.0524***	(-6.761)	-0.000240	(-0.416)	0.0265***	(3.617)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Ret_{d-7}^{Und}	0.0273***	(5.337)	-0.0298***	(-5.343)	0.000252	(0.383)	0.0114	(1.590)
Ret_{d-8}^{Und}	0.00230	(0.857)						
Ret_d^{ETF}	0.795***	(47.68)			0.000632	(0.844)	0.0479***	(6.178)
Ret_{d-1}^{ETF}	-0.0665***	(-8.369)	0.0731***	(8.176)	-0.000716	(-0.944)	0.0137*	(1.960)
Ret_{d-2}^{ETF}	-0.0420***	(-6.688)	0.0478***	(6.494)	-0.000152	(-0.298)	0.000205	(0.0318)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Ret_{d-7}^{ETF}	-0.0234***	(-5.325)	0.0275***	(5.257)	-6.65e-05	(-0.121)	-0.00448	(-0.709)
Ret_{d-8}^{ETF}			0.00779***	(3.689)				
$VolDiff_d^{Und}$	0.358***	(8.542)	0.0246	(0.865)			0.277***	(6.663)
$VolDiff_{d-1}^{Und}$	-0.0433	(-1.553)	-0.0428*	(-1.721)	0.127***	(14.79)	0.0940**	(2.380)
$VolDiff_{d-2}^{Und}$	0.0190	(0.862)	-0.0362	(-1.624)	0.0403***	(5.246)	0.0257	(0.641)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
$VolDiff_{d-7}^{Und}$	0.0533**	(2.431)	-0.00928	(-0.457)	0.0174***	(2.739)	0.0651	(1.559)
$VolDiff_{d-8}^{Und}$					0.00934	(1.351)		
$VolDiff_d^{ETF}$	-0.000851	(-0.508)	0.0102***	(5.885)	0.00145***	(5.407)		
$VolDiff_{d-1}^{ETF}$	0.00247*	(1.721)	-0.00486***	(-2.752)	0.000160	(0.692)	0.106***	(19.39)
$VolDiff_{d-2}^{ETF}$	-0.000917	(-0.697)	-0.00122	(-0.770)	0.000421*	(1.780)	0.0572***	(12.85)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
$VolDiff_{d-7}^{ETF}$	-0.000998	(-0.718)	-0.000562	(-0.345)	-0.000198	(-0.875)	0.0124***	(3.230)
$VolDiff_{d-8}^{ETF}$							0.0128***	(3.546)
Date Fixed Effects	Yes		Yes		Yes		Yes	
Yearly ETF Fixed Effects	Yes		Yes		Yes		Yes	
R-squared	0.943		0.935		0.394		0.180	
Observations	222,362		222,362		222,247		222,362	

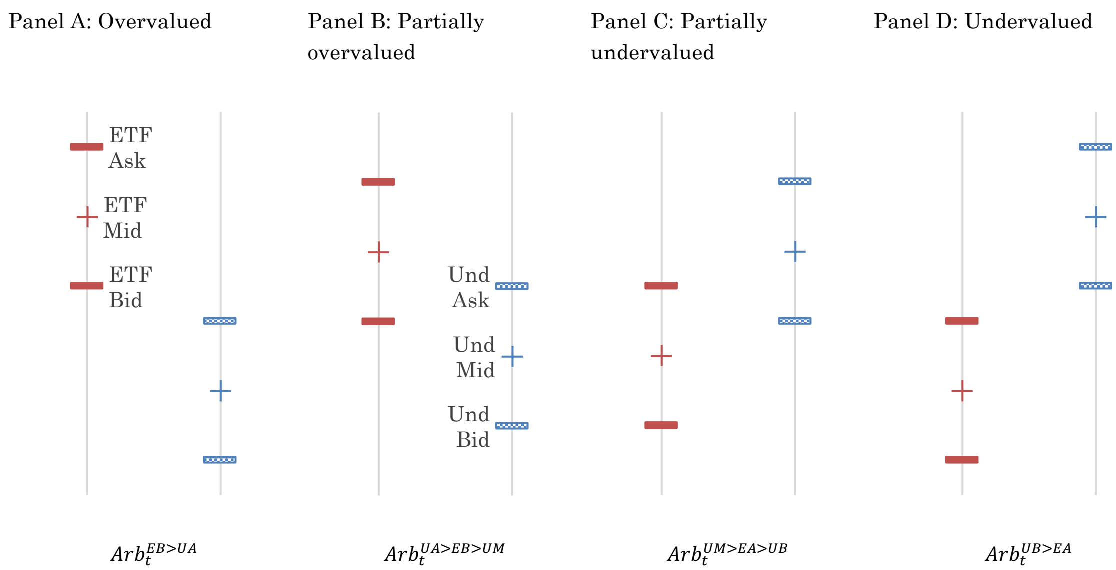
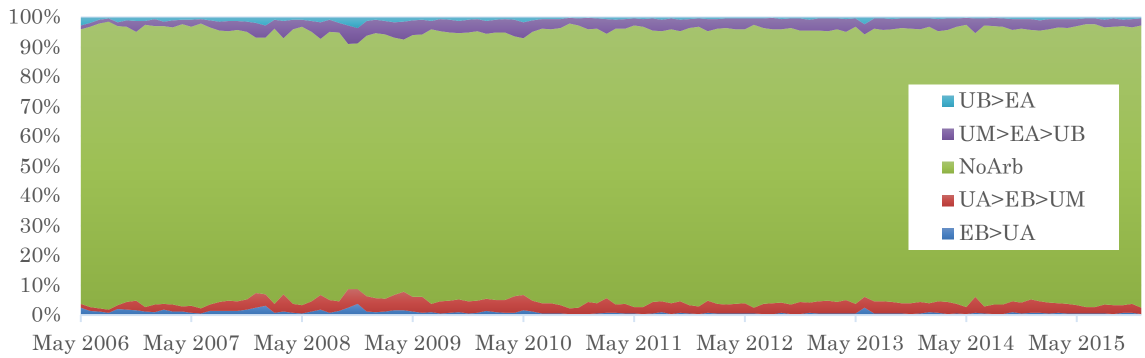


Figure 1. Arbitrage opportunities

Panel A: Frequency of arbitrage opportunities



Panel B: Magnitude of arbitrage opportunities

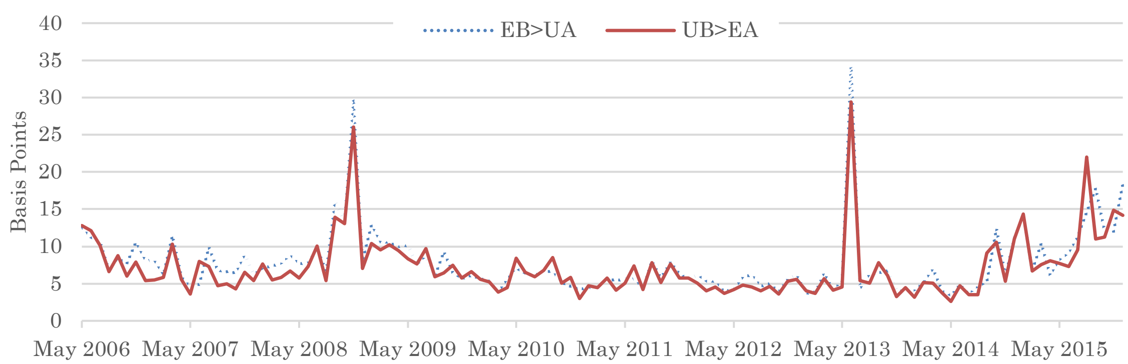
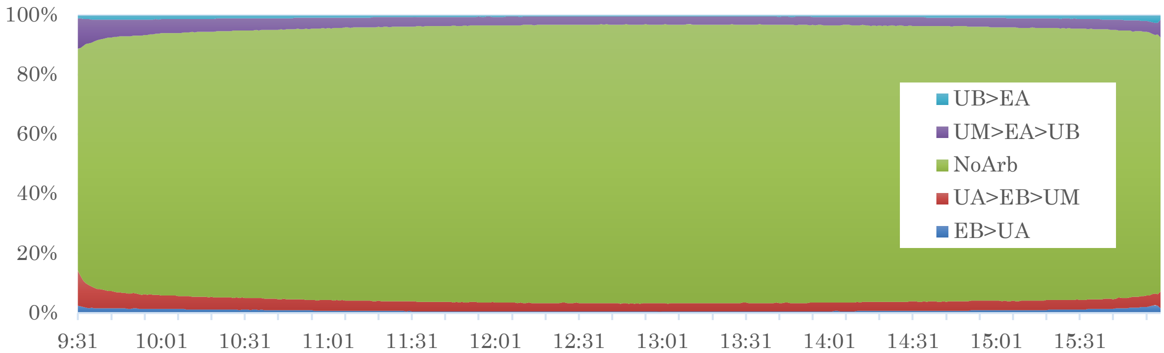


Figure 2. Frequency and magnitude of arbitrage opportunities over time

The shaded region of Panel A (Panel B) describes the frequency (magnitude) of arbitrage opportunities over the sample period, classified according to the four mispricing associations presented in Figure 1, or as $NoArb_t$ when none of these conditions is satisfied. Magnitude is defined as the absolute value percentage difference between the ETF Bid and Underlying Ask when the ETF is overvalued (EB>UA) or the Underlying Bid and ETF Ask when the ETF is undervalued (UB>EA).

Panel A: Frequency of arbitrage opportunities



Panel B: Magnitude of arbitrage opportunities

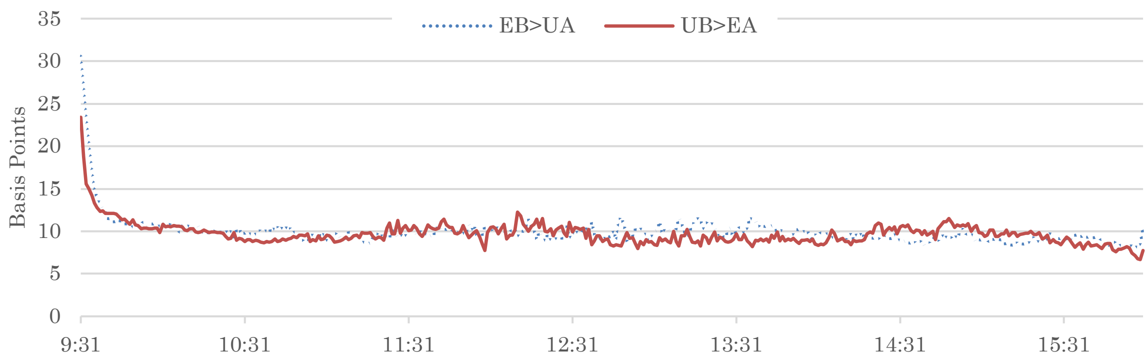


Figure 3. Frequency and magnitude of arbitrage opportunities during trading day

The shaded region of Panel A (Panel B) describes the frequency (magnitude) of arbitrage by time of day, classified according to the four mispricing associations presented in Figure 1, or as $NoArb_t$ when none of these conditions is satisfied. Magnitude is defined as the absolute value percentage difference between the ETF Bid and Underlying Ask when the ETF is overvalued (EB>UA) or the Underlying Bid and ETF Ask when the ETF is undervalued (UB>EA).

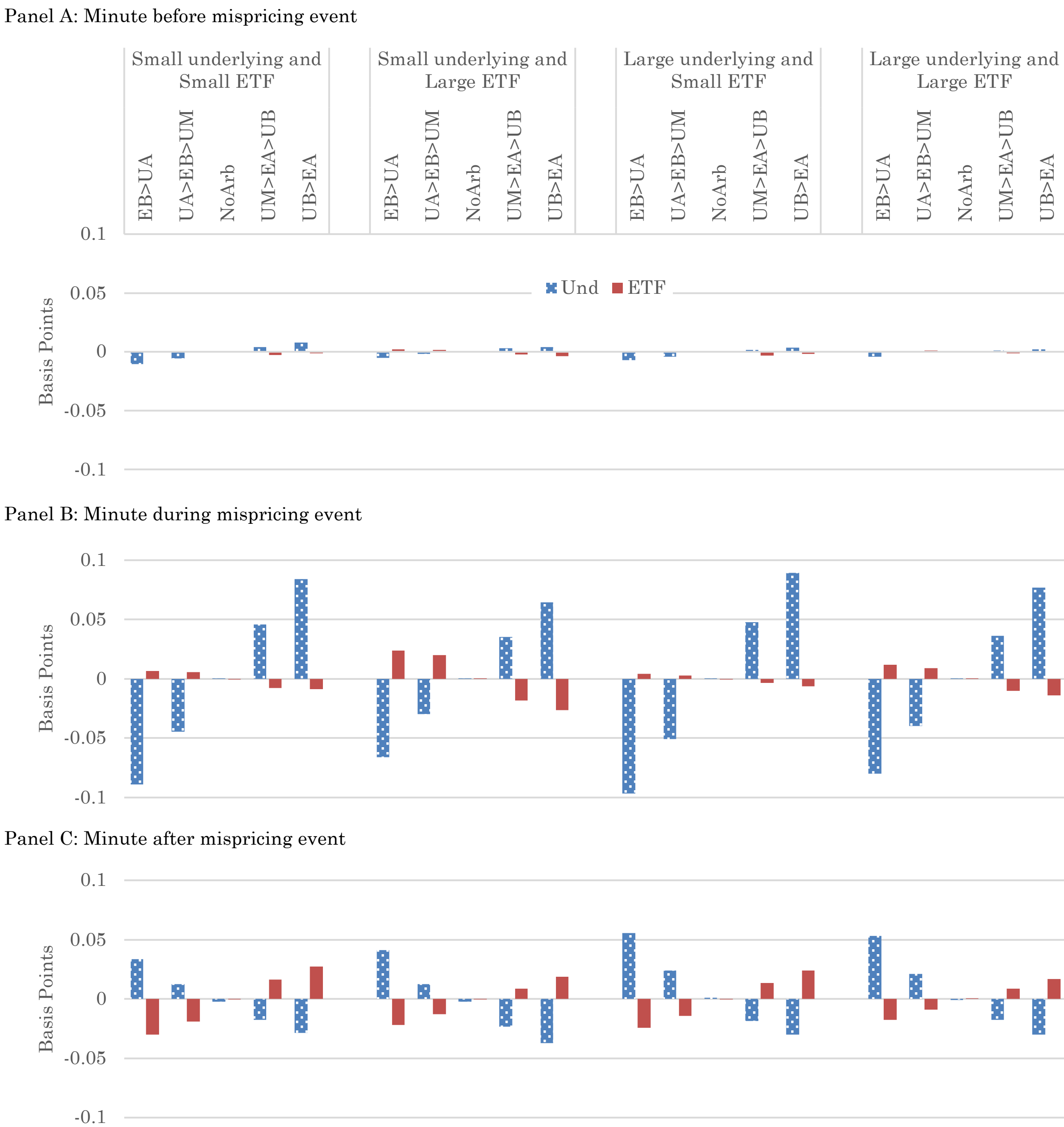
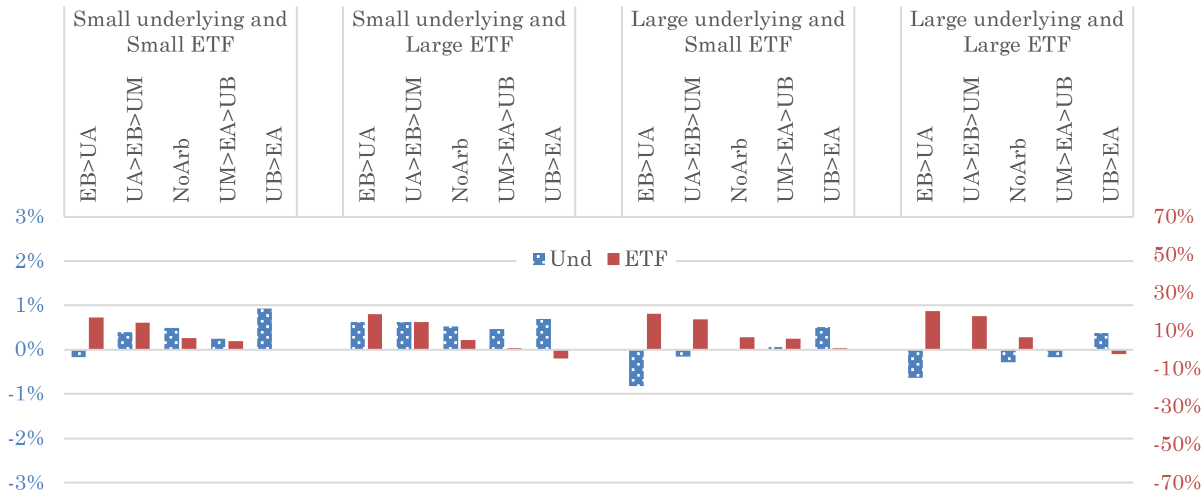


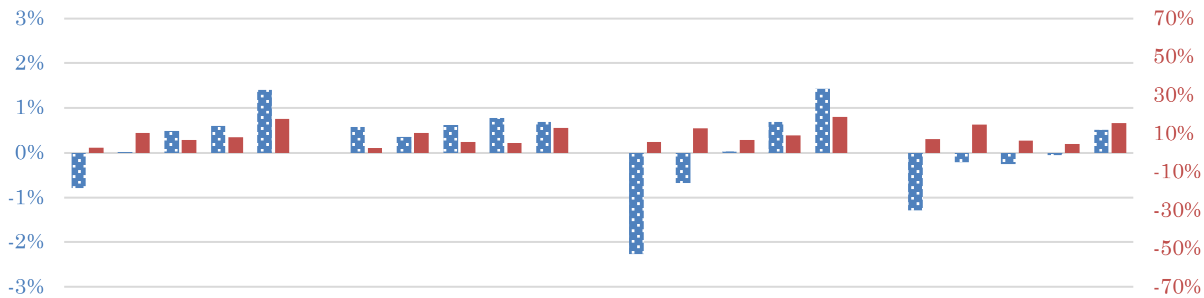
Figure 4. Average midpoint returns around arbitrage opportunities

This figure describes average midpoint returns for ETFs and constituents in the three minutes around arbitrage. Returns are Winsorized across the entire sample at the 1st and 99th percentiles. Panel A reports average midpoint returns during the minute $t-2$ to $t-1$, Panel B reports returns during minute $t-1$ to t and Panel C describes returns during minute t to $t+1$. The results are classified according to the four mispricing associations described in Figure 1, or as $NoArb_t$ when none of these conditions is satisfied, as well as by the size of the ETF and underlying. ETFs are considered large when their mean daily market capitalization falls in the top tercile of our sample during a particular month, whereas the underlying is considered large when average market capitalization of the holdings falls in the top tercile of ETFs for a given month.

Panel A: Minute before mispricing event



Panel B: Minute during mispricing event



Panel C: Minute after mispricing event

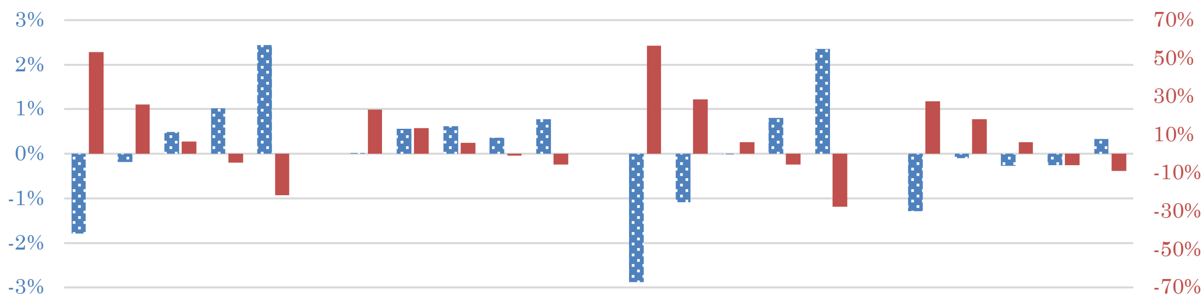


Figure 5. Average directional volume around arbitrage opportunities

This figure describes average directional volume for ETFs and constituents in the three minutes around arbitrage. ETF volume is presented in solid bars with the right vertical axis. Dollar directional volume is classified as buy (sell) volume if trades occur at prices above (below) the prevailing midpoint during minute t. Directional volume is Winsorized across the entire sample at the 1st and 99th percentiles. Panel A reports average directional volume during the minute $t-2$ to $t-1$, Panel B reports directional volume during minute $t-1$ to t and Panel C describes directional volume during minute t to $t+1$. The results are partitioned according to the four mispricing associations described in Figure 1, or as $NoArb_t$ when none of these conditions is satisfied, as well as by the size of the ETF and underlying, described in Figure 4.

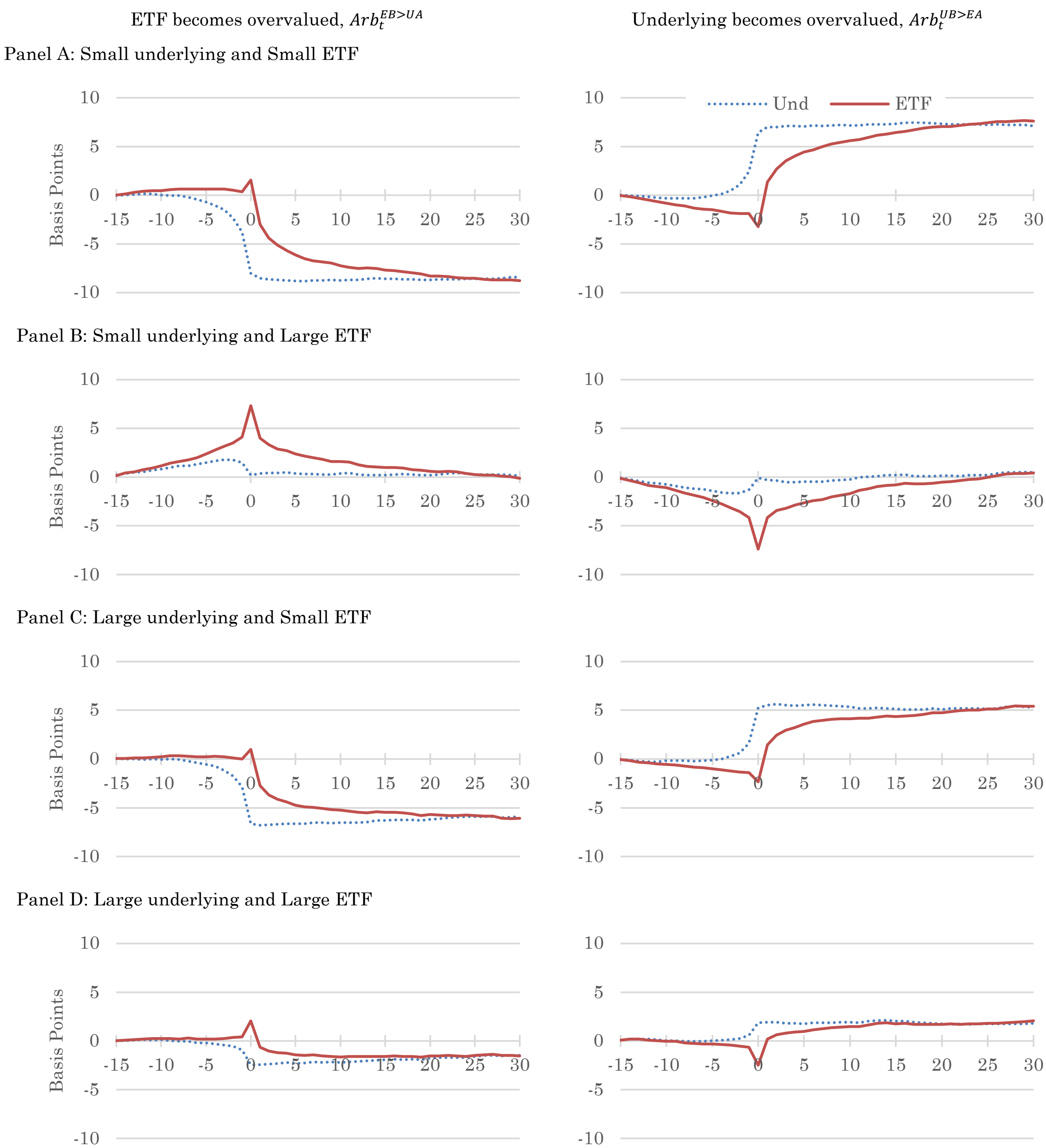
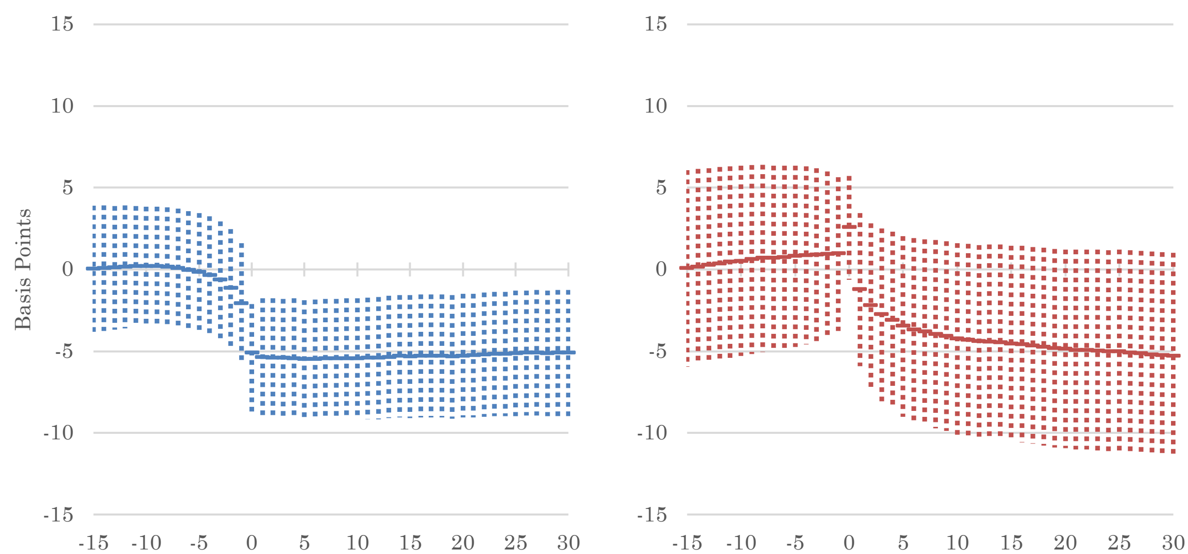


Figure 6. Average midpoint returns around arbitrage opportunities

This figure describes average midpoint returns for ETFs and constituents in a 45-minute window around arbitrage. Each panel presents average midpoint returns based on the size of the ETF and underlying portfolio, as described in Figure 4. The results are partitioned using the two clear arbitrage opportunities presented in Figure 1 (i.e. when the ETF bid exceeds the underlying ask or when the underlying bid exceeds the ETF ask).

Underlying ETF

Panel A: ETF becomes overvalued, $Arb_t^{EB>UA}$



Panel B: Underlying becomes overvalued, $Arb_t^{UB>EA}$

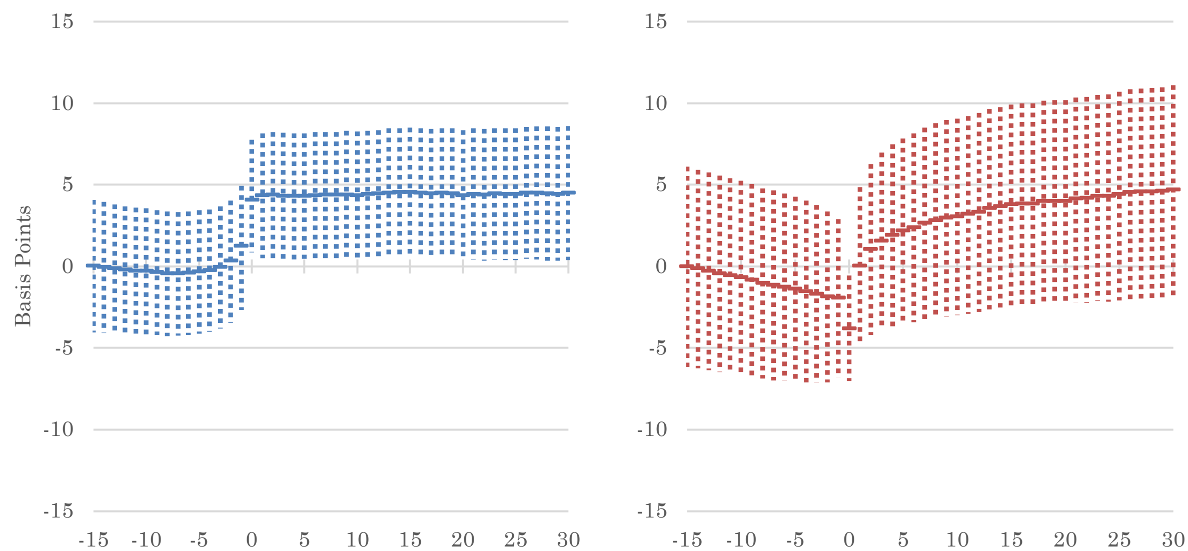


Figure 7. Cumulative bid and ask return around arbitrage opportunities

This figure presents cumulative bid and ask returns for ETFs and constituents in the 45-minute window around arbitrage, classified using the two clear arbitrage opportunities presented in Figure 1 (i.e. when the ETF bid exceeds the underlying ask or when the underlying bid exceeds the ETF ask).

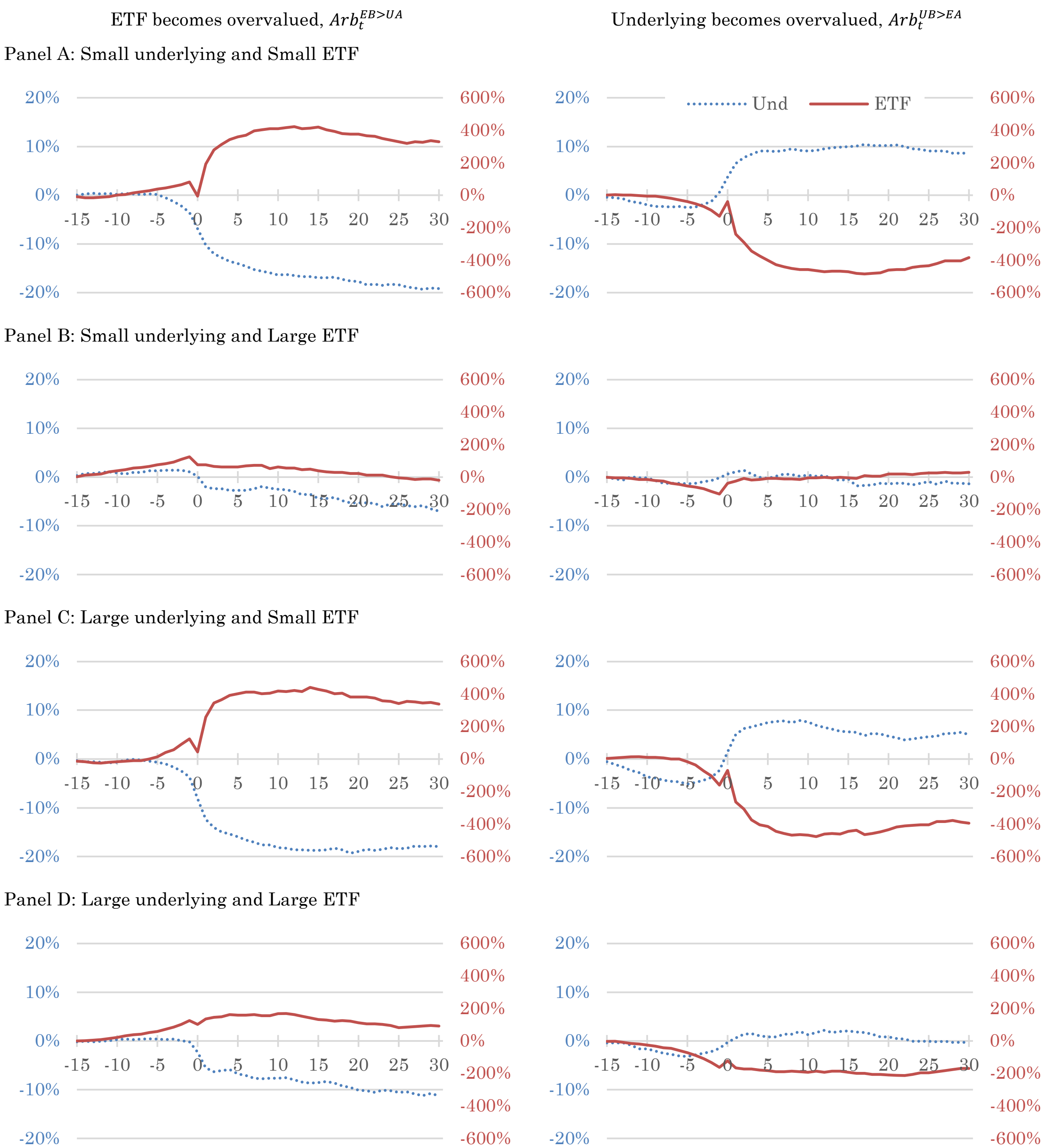


Figure 8. Average on-balance volume around arbitrage opportunities

This figure describes average on-balance volume for ETFs and constituents in a 45-minute window around arbitrage. Each panel presents average on-balance volume based on the size of the ETF and the underlying, as described in Figure 4. The results are partitioned using the two clear arbitrage opportunities presented in Figure 1 (i.e. when the ETF bid exceeds the underling ask or when the underlying bid exceeds the ETF ask).

A. Replicating ETF Portfolios

The CRSP Survivor-Bias-Free US Mutual Fund Database provides a list of historical holdings and total net asset values for a number of publicly traded open-end mutual funds. For our purposes, however, the database also reports the monthly holdings for 2,007 unique ETFs between 2006 and 2015, 1,459 of which are passively managed index funds.[17] From summary statistics reported in Box, Davis and Fuller (2018), these funds should approximate the universe of all U.S.-listed ETFs during this time period. Our goal is to estimate the intraday intrinsic value of an ETF based on how many shares of each security a fund holds multiplied by the national best bid and offer prices for those securities reported by the Trades and Quotes (TAQ) Database. Errors in the replication of these constituent portfolios would make it difficult to identify intraday arbitrage opportunities. Therefore, we verify the accuracy of each holding reported in the Mutual Fund Database by corroborating the value of that position using another source.

The Mutual Fund Database summarizes constituent value in three ways: the dollar value, the percent market value and the number of shares held in each position. Fund holdings are self-reported by each ETF sponsor. However, the values implied by these three measures are often inconsistent. For instance, the percentage market

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[17] ETFs have an ETF flag recorded as "F," and pure index funds have an Index Fund flag equal to "D."

values often sum to a number other than 100%, and the sum of all holdings' market values rarely equals the total net asset value reported by the fund.

To first deal with inconsistencies in reported total net asset values, we calculate the implied total net asset value, $iTNAV_{fp}$, of each fund f based on the percent market value, $\%Val_{fp}$, of a position, p, and its reported dollar value, $DolVal_{fp}$:

$$iTNAV_{fp} = \frac{DolVal_{fp}}{\%Val_{fp}}. \tag{7}$$

If an ETF consists of 300 holdings, equation (7) gives us 300 estimates of the fund's total net asset value. To minimize the impact of outliers on our final estimate, we choose the median $iTNAV_{fp}$ to represent the actual total net asset value of the fund.

The majority of funds hold at least some foreign assets, derivatives or fixed income securities. To generate a sample of funds that hold only U.S. equities, we attempt to find matches for each fund's reported holdings in the CRSP Daily Stock File.[18] The Mutual Fund Database provides five identifiers, PERMNO, CUSIP, ticker, PERMCO and security name, for all ETF constituents. To ensure our sample

[18] From our sample of ETF holdings, we also remove any observations where the reported coupon rate is greater than 0 or the maturity date is not missing. This filter should remove most fixed income securities.

is as accurate as possible, we merge the Mutual Fund Database and the Daily Stock File independently on all five identifiers.[19]

It is not uncommon that a single holding matches up with multiple equity securities depending on which identifier is used, so we verify that the reported value of each holding is consistent with the closing stock price recorded in the Daily Stock File. Our value comparisons are based on two different combinations of the Mutual Fund Database and the Daily Stock File. First, we calculate an estimate of each position's dollar value based on the sponsor-reported number of shares held and the closing stock price of each potential match from the Daily Stock File. Next, we estimate each position's percentage value by dividing our estimated dollar value by the fund's median $iTNAV_{fp}$. For matches based on each of the five identifiers, we compare our estimates of dollar value and percent market value with those reported by the fund sponsors. We remove all matches where either estimate of value differs from its corresponding reported value by more than 10%. If any individual holdings are still matched with multiple securities in the Daily Stock File, we choose the one whose estimated dollar value is closest to what was reported by the fund.[20]

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[19] ETFs often hold small amounts of cash between dividend distributions, so we retain all positions in the Mutual Fund Database with the security name "USD CASH," and we assume that those securities have a closing price of $1 on the close of each reporting date.

[20] It is not uncommon for funds to report multiple positions in the same security. In these cases, we only retain the position with the highest reported market value.

Having removed all of the positions in foreign assets, derivatives and fixed income securities, we next compare the combined value of our matched holdings to the total net asset value of the fund. Once again, we rely on each fund's median $iTNAV_{fh}$ and the percentage market values calculated from Daily Stock File closing prices. Specifically, we require that the sum of estimated percent market values falls somewhere between 97% and 103% of $iTNAV_{fh}$ during each reporting date. As a final check on our portfolio replication, we compare the total number of matched holdings to the number of holdings originally reported in the Mutual Fund Database. Here, we only retain portfolios whose matched holdings account for at least 97% of the total holdings reported. The filtering process described above leaves us with 423 passively managed U.S. equity funds that have replicable holdings for at least one reporting date during our sample period.

The monthly reporting frequency of the Mutual Fund Database prevents us from knowing the size of each position during non-reporting trading sessions. Furthermore, we observe significant variation in the absolute size of ETF holdings from one month to the next as ETF shares are created and redeemed. Fortunately, constraining the sample to passively managed funds ensures that the relative allocations between each position do not change from one day to the next as long as index membership is held constant. The stability of portfolio composition allows us to interpolate the number of shares held in each security throughout the month.

The Mutual Fund Database provides closing daily net asset values for each ETF, f, in our sample. The sponsor calculates this measure by dividing the fund's total net asset value by the number of ETF shares outstanding, $ShrOut_f$:

$$DNAV_f = \frac{\sum_p Price_p \times Shares_{fp}}{ShrOut_f}, \tag{8}$$

where $Price_p$ is the daily closing price of each position, p, and $Shares_{fp}$ is the size of each position within the fund. To verify the accuracy of share interpolation, we create our own proxy for daily net asset value. Each time that ETF shares are created or redeemed, the denominator on the right side of Equation (8) adjusts accordingly. The total net asset value, the numerator of Equation (8), also changes when the number of ETF shares outstanding changes between reporting dates. However, our estimates of total net asset value are based on share counts for individual positions that are fixed between reporting dates which may not line up with the dates of ETF share creation or redemption.

Our solution to this problem is based on the observation that, while market weightings for individual portfolio holdings change constantly, the share weights of those holdings never change within a trading day. With this in mind, we multiply both sides of the Equation (8) by the ratio of ETF shares outstanding and the sum of constituent shares:

$$DNAV_f \times \frac{ShrOut_f}{\sum_p Shares_{fp}} = \sum_p \frac{Price_p \times Shares_{fp}}{\sum_p Shares_{fp}}, \tag{9}$$

For an ETF whose relative composition is constant between monthly reporting dates, the relationship between $ShrOut_f$ and $\sum_p Shares_{fp}$ will also remain constant across trading days. Therefore, changes in daily net asset value, $DNAV_f$, should be perfectly correlated with changes in the share-weighted price of underlying holdings, $\sum_p[(Price_p \times Shares_{fp})/\sum_p Shares_{fp}]$.

Even though changes in the size of an ETF portfolio preserve the correlation between daily net asset value and share-weighted price, adjustments to the relative composition of an ETF portfolio can spoil this relation. While changes in composition are infrequent for passively managed funds, their holdings must be adjusted anytime their underlying benchmarks are reconstituted. In Panel A of Figure A-1 we illustrate a hypothetical ETF portfolio that exchanges 500 shares of stock ABC for 300 shares of XYZ thirteen trading days after they last reported holdings. Panel B describes a common approach to share interpolation in the mutual fund literature (e.g., Wermers (2000), Cremers and Petajisto (2009)), whereby share counts are assumed to remain constant until the following report date. In this case, we should not expect perfect correlation between reported daily net asset value and share-weighted price because the former is based on the holdings in Panel A, whereas the latter is based on the composition assumed in Panel B.

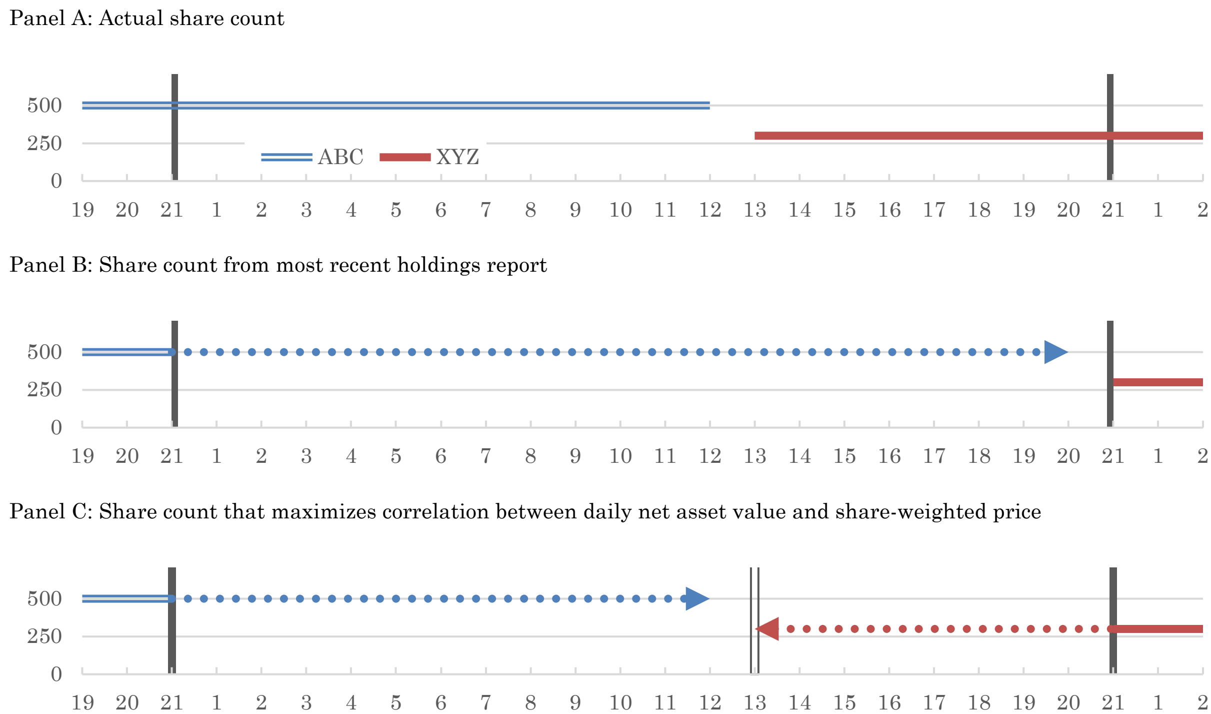


Figure A-1. Share count interpolation example

To account for changes in portfolio holdings between reporting dates, we maximize the correlation between daily net asset value, $DNAV_f$, and share-weighted price, $\sum_p[(Price_p \times Shares_{fp})/\sum_p Shares_{fp}]$, by varying the date for which we assume these portfolio changes occurred. Thus, for a month containing twenty-one trading days, we compute twenty-one different month-long series of share-weighted price. If the portfolio's composition changes on day thirteen, as in Figure A-1, the share-weighted price series with day thirteen as the assumed reallocation date will have the highest correlation with daily net asset value.

To calculate correlations, we require the ETFs in our sample to have consecutive months of replicable portfolio holdings. To ensure that our replicated portfolios accurately represent the underlying holdings of each fund, we only retain fund-months where the correlation between reported daily net asset value and estimated share-weighted price is greater than 99.5%. The final sample contains 12,170 fund-months and preserves at least one month of holdings for all 423 ETFs.

B. TAQ Filters

To identify arbitrage opportunities, we compare the quoted price of an ETF to the price of its underlying portfolio inside of each trading day. From the portfolio replication and interpolation processes described in Appendix A, we are given a list of share-weights for 241,810 fund-days during our sample period. We combine these holdings with intraday prices from TAQ to compute the end-of-minute bid and ask quotes for each ETF portfolio.

Most analyses of TAQ data rely on a fairly standard set of filters (Huang and Stoll (1996), Bessembinder (1999), (2003a), (2003b)) to mitigate the impact of erroneous quotes and outliers. For our study, however, it is critical that we simulate the experience of a potential arbitrage trader that is interacting with the market in real-time. We worry that excessive filtering could lead to optimistic appraisals of available liquidity. To be sure that an arbitrage trader could, for instance, profitably buy an ETF while selling its underlying portfolio, we retain the original quotes whenever possible and document their removal in extreme cases where filtering becomes necessary.

We begin by removing quotes with conditions 1, 2, 6, 10, 12, and 23. Next, we identify the subset of best bid and ask prices whose quoted spreads, defined as the difference between each price scaled by their midpoint, are greater than zero but less than 50%. From this subset, we calculate the daily median midquote for every ETF and underlying stock that appears in our sample. These median midquotes represent the "typical" trade price for a security within each trading session. To identify quotes that diverge dramatically from typical prices, we flag the bid or ask as missing if the quote exceeds the daily median midquote by more than a factor of five.

For quotes with spreads that are less than zero or greater than 50%, we attempt to document an explanation for the quoted spread's irregularity. For instance, we classify either the bid or ask as missing when no price is recorded in TAQ. When both prices are available, we classify the ask as missing if the quote is at least 25% larger than the previous midquote. Likewise, we flag the bid as missing when the quote is 25% smaller than the previous midquote. Whenever the quoted spread is negative, we record both the bid and ask as missing.

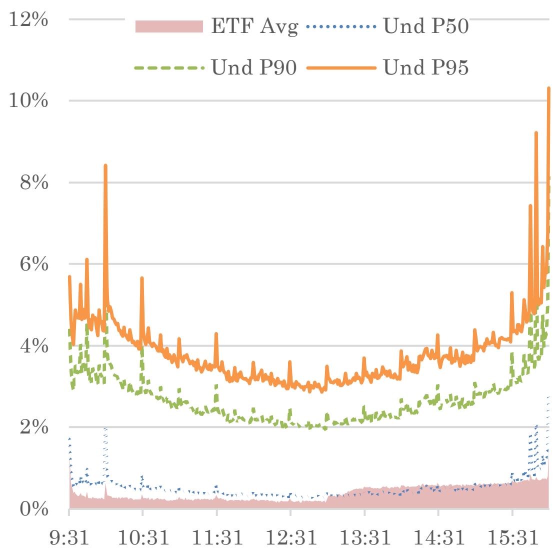
For all quotes that are flagged as missing, the most recent satisfactory quote is recorded in its place. However, the quote is not replaced entirely, unless both the bid and ask prices are classified as missing. Unlike removing these observations entirely, our approach allows for the preservation of a reasonable bid quote in situations where the accompanying ask quote has deviated, and vice versa. If the replacement quote results in a spread that also violates our zero or 50% bounds, we flag both the bid and ask as missing and replace them with the most recent satisfactory observations.

Across our sample period, one-minute best bid and ask quotes are flagged as missing 0.519% and 0.515% of the time, respectively, for our entire sample of ETFs and underlying securities. For observations where either the bid or the ask is missing, 85.89% are missing because their quoted spread is negative or greater than 50% of the quoted midpoint.[21] 12.72% are missing because one of the quotes did not have a recorded price in TAQ. Only 2.48% are flagged because they exceed the daily median midquote by a factor of five.

We calculate the weighted average proportion of missing or inferred bid, $MisBid_t^{Und}$, and ask, $MisAsk_t^{Und}$, quotes in the underlying portfolio for each fund-day and minute t in our sample. Similarly, the binary variables $MisBid_t^{ETF}$ and $MisAsk_t^{ETF}$ equal one whenever the fund's bid and ask prices are either missing or inferred. Panels A and B of Figure B-1 describe the 50th, 90th and 95th percentile of $MisAsk_t^{Und}$ and $MisBid_t^{Und}$, as well as the average of $MisBid_t^{ETF}$ and $MisAsk_t^{ETF}$, during each minute of the trading day. According to Figure B-1, the proportion of missing or

[21] Even allowing for a relatively wide range of acceptable quotes, we still observe a missing bid or ask in approximately 1 out of 100 minutes. To get a sense of how this magnitude might affect our results, consider an ETF with 100 holdings. If the likelihood that quotes are missing is not correlated across securities, an admittedly bold assumption, then the probability that none of the securities had a missing ask, for instance, would be approximately $0.99^{100} = 36.6\%$. Thus, at least one stock in the portfolio would have a missing ask observation $1 - 0.366 = 63.4\%$ of the time. This implies that arbitrage traders would be unable to purchase the entire underlying portfolio most of the time.

Panel A: Minute-by-minute percentiles for $MisBid_t^{Und}$ and averages for $MisBid_t^{Und}$



Panel B: Minute-by-minute percentiles for $MisAsk_t^{Und}$ and averages for $MisAsk_t^{Und}$

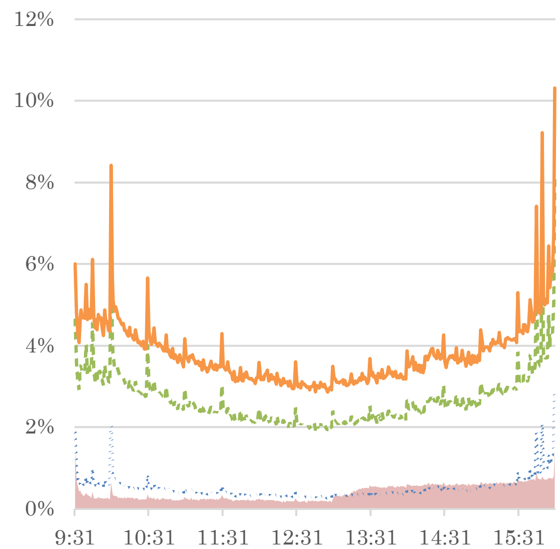


Figure B-1. Percentage of missing NBBO quotes during the trading day

This figure describes the 50th, 90th and 95th percentile of $MisAsk_t^{Und}$ and $MisBid_t^{Und}$, as well as the average of $MisBid_t^{ETF}$ and $MisAsk_t^{ETF}$, during each minute of the trading day. $MisBid_t^{Und}$ ($MisBid_t^{ETF}$) and $MisAsk_t^{Und}$ ($MisAsk_t^{ETF}$) are the weighted average proportion of missing or inferred bid, and ask, quotes in the underlying portfolio (ETF), respectively, for each fund-day and minute t in the sample.

inferred quotes is highest at market open and close, rising above 10% for some underlying portfolios by the end of the day.

Typical TAQ filters eliminate all observations where quoted spreads exceed some threshold, resulting in a smooth sequence of prices that are always within certain bounds. In reality, these quotes may or may not represent liquidity that was actually available in the market. Our process of replacing divergent quotes still produces a dataset where average spreads are artificially low and prices are less volatile than those that would be observable in real time. However, flagging these quotes allows us to acknowledge them in our statistical inferences.

C. Intraday Quotes

With an accurate record of daily underlying share-weightings for each ETF, along with minute-by-minute bid and ask prices for each holding, we can calculate quoted prices for each portfolio. In most contexts, estimating the value of an ETF portfolio would simply require calculating the closing market-weighted average price for each of the individual constituents. However, variation in intraday prices cause the relative market-weights of these constituents to change constantly throughout the day.

Once again, our solution to this problem is based on the relationship described by Equation (9). Even if relative market-weights adjust with quoted prices, variation in a fund's net asset value is perfectly correlated with changes in the share-weighted price of the underlying holdings. Therefore, the intraday underlying bid, Und_f^{Bid}, and ask, Und_f^{Bid}, price for fund f can be represented as follows:

$$\begin{aligned} Und_f^{Bid} \times \frac{ShrOut_f}{\sum_p Shares_{fp}} &= \sum_p \frac{Bid_p \times Shares_{fp}}{\sum_p Shares_{fp}} \\ Und_f^{Ask} \times \frac{ShrOut_f}{\sum_p Shares_{fp}} &= \sum_p \frac{Ask_p \times Shares_{fp}}{\sum_p Shares_{fp}}, \end{aligned} \tag{10}$$

where Bid_p and Ask_p are the quoted bid and ask prices of each position p. However, to compare Und_f^{Bid} and Und_f^{Ask} with quoted ETF prices, we also need the ratio of fund shares outstanding to the sum of constituent shares, $ShrOut_f / \sum_p Shares_{fp}$.

The ratio of shares outstanding to the sum of constituent shares is difficult to estimate because of intra-month variations in $\sum_p Shares_{fp}$. Here, we rely on the equilibrium relationship between an ETF's quoted price and its intrinsic value. In the absence of tradeable arbitrage opportunities, all three of the following conditions should hold:

$$
\begin{aligned}
&1.\quad ETF_f^{Ask} \geq Adj_{Max} \times \sum_p \frac{Bid_p \times Shares_{fp}}{\sum_p Shares_{fp}} \\
&2.\quad ETF_f^{Bid} \leq Adj_{Min} \times \sum_p \frac{Ask_p \times Shares_{fp}}{\sum_p Shares_{fp}} \\
&3.\quad \frac{ETF_f^{Bid}}{\sum_p \frac{Ask_p \times Shares_{fp}}{\sum_p Shares_{fp}}} = Adj_{Min} \leq \left(\frac{ShrOut_f}{\sum_p Shares_{fp}}\right)^{-1} \leq Adj_{Max} = \frac{ETF_f^{Ask}}{\sum_p \frac{Bid_p \times Shares_{fp}}{\sum_p Shares_{fp}}},
\end{aligned}
\tag{11}
$$

where Adj_{Max} and Adj_{Min} represent the upper and lower bounds for the inverse of $ShrOut_f / \sum_p Shares_{fp}$.

At the end of every fund-day-minute in our sample, we calculate the midpoint between both bounds. Next, we find the median daily midpoint, Adj_{Med}, for each fund. Finally, we multiply this median midpoint by the intraday share-weighted bid and ask prices to generate estimates of Und_f^{Bid} and Und_f^{Ask}. To ensure that underlying quotes are comparable to ETF bids and asks, Und_f^{Bid} and Und_f^{Ask} are also rounded to the nearest penny. The daily median midpoint, Adj_{Med}, provides an adjustment factor for share-weighted price that minimizes the frequency of perceived arbitrage opportunities. Thus, our approach makes us more likely to underestimate the total number of tradeable price discrepancies in our sample.

We also attempt to estimate Und_f^{Bid} and Und_f^{Ask} by comparing the market closing prices of each underlying security to the daily net asset value, $DNAV_f$, reported by the fund sponsor. Rearranging Equation (9), gives:

$$\frac{ShrOut_f}{\sum_p Shares_{fp}} = \frac{\sum_p Price_p \times \frac{Shares_{fp}}{\sum_p Shares_{fp}}}{DNAV_f}. \tag{12}$$

All of the inputs on the right-hand side remain fixed within each trading session because creations and redemptions only occur after the market has closed. Therefore, the ratio of $DNAV_f$ to share-weighted closing price can be used to calculate Und_f^{Bid} and Und_f^{Ask} from share-weighted bid and ask prices.

Unfortunately, the procedure for calculating $DNAV_f$ can vary across funds. For instance, some funds may choose the prevailing market price at 4:00pm, while others base security prices on the closing auction. Due to narrow spreads in the ETF and underlying portfolios, even small errors in the estimation of underlying bid and ask prices can lead to a dramatic increase in the misclassification of arbitrage opportunities. When $DNAV_f$ are used to calculate Und_f^{Bid} and Und_f^{Ask}, we classify 13.15% of fund-day-minutes as tradeable arbitrage opportunities. When median midpoints, Adj_{Med}, are used instead, we only recognize mispricing in 1.66% of our observations.