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Arbitrage and Liquidity: Evidence from a Panel of Exchange Traded Funds[1]

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Abstract

Market liquidity is expected to facilitate arbitrage, which in turn should affect the liquidity of the assets traded by arbitrageurs. We study this relationship using a unique dataset of equity and bond ETFs compiled from big trade-level data. We find that liquidity is an important determinant of the efficacy of the ETF arbitrage. For less liquid bond ETFs, Granger-causality tests and impulse responses suggest that this relationship is stronger and more persistent, and liquidity spillovers are observed from portfolio constituents to ETF shares. Our results inform the design of synthetic securities, especially when derived from less liquid instruments.

Keywords: Exchange traded funds, ETF, market liquidity, law of one-price, arbitrage, ETF premium.

JEL classification: G12, G14.

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1 Introduction

Liquidity is an important topic for regulators, academics and practitioners alike. Absence of arbitrage, on the other hand, is at the hart of our modern understanding of financial markets. Scholars recognize that trading frictions, like those associated with the presence of positive bid-ask spread, are related to deviation from the no arbitrage benchmark. Recent papers have found that arbitrage, in turn, affects market liquidity of stocks and currencies (Roll, Schwartz and Subrahmanyam 2007, Foucalt, Kozhan and Tham 2016, Rösch 2018). But the relationship between liquidity and arbitrage involving fixed income securities remains largely unexplored. Our paper aims to fill this gap in the literature, presenting new evidence about the relationship between arbitrage and liquidity from a panel of Exchange Traded Funds (ETFs), spanning funds that invest in stocks and corporate bonds.

Scholars are interested in understanding the relationship between arbitrage and liquidity in fixed-income markets. In fact, in the seminal paper in this literature, Roll, Schwartz and Subrahmanyam (2007) suggested this extension to the literature. Moreover, this extension of the literature is relevant for practitioners given the prominence of derivative and structured products involving government bonds, corporate bonds, and mortgage-backed securities, among others. Furthermore, the role of these structures in the financial crisis of 2007-08 has renewed the attention of academics and policy makers about their role in financial markets.

Furthermore, ETFs have attracted the interest of economists as they represent one of the most important financial innovations in decades (Lettau and Madhavan 2018). In fact, from the beginning of 2000 to the end of 2017, assets under management of domestic ETFs have increased from \$26 billions to \$3.5 trillions, according to data from Morningstar. ETFs offer a proportional share in a portfolio like mutual funds, but their shares trade in exchanges, where their price and liquidity are determined. These institutional features naturally give rise to the following questions: how well do ETFs track their underlying portfolio?, what are the determinants of the liquidity of ETF shares?, does ETF arbitrage links the liquidity of ETF shares and ETF constituents?

The structure of ETFs is particularly suitable for our analysis. First, ETFs invest in both relatively liquid equity securities and relatively illiquid fixed income securities, allowing us to compare these two asset classes under the same institutional setting. Second, the *ETF arbitrage mechanism* allows arbitrageurs to do in-kind conversions between ETF shares and ETF portfolio constituents. As we describe in section 2, in-kind conversions allow arbitrageurs to close their positions, attenuating the concern that our results are confounded by omitted variables associated with the risks of maintaining open arbitrage positions. Finally, ETFs issue and withdraw shares typically in response to arbitrage activity, allowing us to empirically validate the use of ETF mispricing as a proxy for arbitrage activity.

In this paper, we compile a unique database of equity and bond ETFs using big trade-level data on both stocks and bonds. Liquidity of ETF shares and ETF constituents, at daily frequency, is proxied with effective spreads. We calculate effective spreads for stocks using Daily NYSE Trade and Quotes (DTAQ) and for bonds using FINRA Trade Reporting and Compliance Engine (TRACE). In this way, we obtain effective spreads for ETF shares, which trade as stocks in the U.S. In addition, we use ETF portfolio composition files from Markit North America, Inc. to compute portfolio-level effective spreads from portfolio constituents spreads calculated from DTAQ and TRACE. We supplement this information with data on the ETF premium—the difference between the ETF price and its net-asset value (NAV). Since arbitrageurs can profit from large ETF premia and discounts, we consider the absolute value of the premium, which we refer to as ETF mispricing. Our final sample contains over 400,000 observations from February 1, 2012 to December 28, 2017 for 584 domestic ETFs: 509 domestic equity ETFs and 75 domestic bond ETFs.

Using this information, we first examine the relationship between the liquidity of ETF shares and ETF constituents and the efficacy of the ETF arbitrage mechanism, measured by the speed of adjustment of mispricing. We find that ETF mispricing reverts to zero relatively fast, with the average speed of mean-reversion implying a mispricing half-life of 0.44 days. This result is consistent with previous work that argues for the efficacy of the ETF arbitrage mechanism given the small and transient nature of ETF mispricing (Engle and Sarkar 2006). Moreover, we document that the average speed of adjustment of mispricing is slower for bond ETFs, relative to equity ETFs, with half-lives of 1.36 and 0.37 days, respectively. The fact that bond ETFs, which invest in more illiquid corporate bonds, exhibit a slower speed of adjustment illustrates that constituents' liquidity is an important consideration for arbitrageurs whose trades extinguish the mispricing. In fact, at the ETF level we find a strong negative correlation between the mispricing speed of adjustment and average ETF portfolio spreads. The illiquidity of ETF shares also is negatively correlated with the speed of adjustment when we consider only equity ETFs. Together these results show that liquidity affects the efficacy of arbitrage.

Next, we study the joint dynamics of ETF mispricing and liquidity in our sample of 584 ETFs, relating these variables in panel vector autoregressions (PVARs) for equity and bond ETFs separately. Our endogenous variables are ETF spreads, ETF portfolio spreads, and ETF mispricing. To avoid the possibility of spurious results these series are expunged of trends and calendar regularities. Our PVAR approach builds on Roll, Schwartz and Subrahmanyam (2007), who used a VAR to relate the dynamics of arbitrage and liquidity, using the NYSE composite index and future contracts on this index. By contrast, we consider a panel of ETFs. As these authors, we consider mispricing as a proxy for arbitrage activity and measure the illiquidity of the portfolio associated with a derivative asset—ETF shares in our case—using bid-ask spreads. Relative to these authors, we expand the analysis to also consider the liquidity of the derivative, allowing us to analyze the joint dynamic of arbitrage and the liquidity of the derivative, in addition to the liquidity of the associated portfolio as previously done. ETFs are a relatively new product, so the time series dimension of our sample is relatively shorter, but the panel dimension increases the power of the statistical analyses allowing us for the possibility of reliable conclusions. Our analysis yields the following results.

First, liquidity and arbitrage display a statistically significant two-way relation, both in the case of equity and bond ETFs. In fact, for both asset classes there is two-way Granger causality between ETF mispricing and the effective spreads of both ETF shares and ETF portfolios. Second, the effect of arbitrage on liquidity, and of liquidity on arbitrage, is larger and more persistent in the case of bond ETFs. In fact, in the case of bond ETFs, a shock to the ETF or portfolio spread predicts larger and more persistent responses of mispricing, and similarly, a shock to mispricing predicts larger and more persistent responses of spreads. Finally, liquidity spillovers are statistically significant in some cases, with shocks to bond portfolio spreads predicting future spreads to bond ETF shares.

We contribute new evidence from a panel of ETFs to the literature that analyzes the relationship between arbitrage and liquidity. The theoretical literature proposes different mechanism through which arbitrage can affect liquidity. Holden (1995) presents a model where arbitrageurs equate net order imbalances across markets, acting as cross-sectional market makers. Kummar and Seppi (1994) present a model where trades by informed cross-market arbitrageurs can have nonmonotone effects on liquidity. Foucalt, Kozhan and Tham (2016) argue that arbitrage can be "toxic" as it can lead market makers to charge higher bid-ask spread to compensate for the expected losses from trades with informed arbitrageurs.

Empirical studies have scrutinized the relationship between arbitrage and liquidity in equity and currency markets. Our paper builds on Roll, Schwartz and Subrahmanyam (2007), who study this relationship, using the NYSE composite index and future contracts on this index. Deville and Riva (2007) study arbitrage and liquidity using data from the French index options market. Rösch (2018) investigate the relationship between arbitrage and liquidity using American Depositary Receipts of stocks traded in foreign markets. Foucalt, Kozhan and Tham (2016) document the presence of toxic arbitrage at intraday frequency in currency markets. Our paper present new evidence about the relationship between arbitrage and liquidity for a panel of ETF spanning both equity and bond securities.

The growth of ETFs led to important questions about their impact on financial markets. The evidence on their impact on stock market liquidity is mixed. Hamm (2014) and Israeli, Lee and Sridharan (2017) argue that they reduce the liquidity of stocks. On the other hand, Sağlam, Tuzun and Wermers (2018) provide evidence for ETFs improving the liquidity of stocks. There is also an important debate on the impact of ETFs on the informativeness of stock prices. Israeli, Lee and Sridharan (2017) argue that ETFs reduce the sensitivity of stocks to their earnings news. On the other hand, Glosten, Nallareddy and Zou (2016) suggest that ETFs increase the informational efficiency of stocks with respect to systematic component of their earnings news. Hasbrouck (2003) and Madhavan and Sobczyk (2016) showed that ETFs play an important role in price discovery. In addition, many studies (such as Da and Shive (2012) and Israeli, Lee and Sridharan (2017)) find evidence that ETFs increase the correlation of returns between their underlying assets. Bhattacharya and O'Hara (2017) argues that ETFs could distort the pricing efficiency of underlying securities, because market makers in individual securities learn from ETF prices, which include idiosyncratic information of other securities. In addition, ETFs can attract short-horizon uninformed traders, which increases the non-fundamental price volatility of the underlying stocks (Ben-David, Franzoni and Moussawi 2018). Danhauser (2017) finds that ETFs lead to long-term positive valuations for their underlying corporate bonds. Finally, Pan and Zeng (2017) show that the creation and redemption of ETF shares is affected by bond-dealer inventories. The difference between these recent papers on ETFs and ours is that we analyze the joint liquidity dynamics of ETFs and their portfolios.

The rest of the paper is organized as follows. Section 2 presents some background on the ETF arbitrage mechanism that are relevant for our analysis. Section 3 describes the data and the calculations of our arbitrage and liquidity measures. Section 4 analyzes the relationship of liquidity and the speed of adjustment of mispricing. Section 5 presents our PVAR analysis relating liquidity and arbitrage. Section 6 offer some conclusions. Appendices provide additional detail about the calculation of our variables.

2 Background: ETF Arbitrage Mechanism

Exchange-traded funds (ETFs) are pooled investment vehicles, which offer a proportional share in a portfolio like mutual funds.[1] Similar to close-end funds, ETFs and their constituents are listed on exchanges and trade at prices determined in markets. Market prices for ETF shares and constituents determine the ETF premium: the difference between the ETF share price and its net-asset value (NAV), i.e., the per share market value of the ETF portfolio.

Although there are similarities with close-end funds, ETFs are different because they allow shares to be created and redeemed through the *ETF arbitrage mechanism*.[2] This mechanism allows arbitrageurs to close their positions, facilitating the arbitrage of ETF mispricings. In fact, Engle and Sarkar (2006) find that the arbitrage mechanism limits the size and persistence of ETF premia, relative to close-end funds.

In a nutshell, the ETF arbitrage mechanism works as follows. Arbitrageurs create and redeem ETF shares in exchange for pre-specified baskets of constituent securities. Each ETF establishes contractual relationships with a set of trading firms, known as Authorized Participants (APs), specifying the process for creating and redeeming ETF shares. But, any interested arbitrageur, like broker/dealers or trading firms, can place creation and redemption orders through APs, so in our analysis we consider that these creation and redemption orders are placed by generic arbitrageurs, as opposed to solely by APs.

Some aspects of this process are common across ETFs. For instance, ETFs are required, before each trading day, to make available a portfolio composition file that describes the makeup of the creation and redemption baskets during the trading day. So, the composition of the creation and redemption baskets is known in advance to arbitrageurs.[3] By contrast, other aspects of the creation and redemption process are ETF specific. For

[1] Most domestic ETFs are registered as investment companies under the Investment Company Act of 1940 and regulated by the Securities Exchange Commission (SEC).

[2] For a more comprehensive description of the arbitrage mechanism see, for instance, Lettau and Madhavan (2018) and Antoniewicz and Heinrichs (2014).

[3] The portfolio composition file is transmitted the previous day, but revisions can take place until noon of a given trading day (see Antoniewicz and Heinrichs 2014).

example, when most constituent securities are eligible to settle through National Securities Clearing Corporation (NSCC), creations and redemptions are settled through NSCC, who acts as the central counterparty. Alternatively, creation and redemption orders can be settled directly between APs and ETFs, in which case APs may be required to pledge collateral while the order is being settled.

Our use of trade-level data to compute effective spreads for ETF constituents naturally makes most of the constituents for the ETFs in our sample to be NSCC eligible, so we focus on the rules that apply in this case. Several of these rules are relevant for our analysis.

First, APs can convert creation and redemption baskets for ETF shares as pre-specified in the portfolio composition file.[4] These conversions take place at the end of the trading session *in-kind* allowing arbitrageurs to lock-in profits before the actual creation/redemption takes place at the end of the trading day. To illustrate this, consider the case of the creation order depicted in Figure 1. The figure shows that at 10:00 am ETF shares were valued at 100, while the ETF NAV was 98. At that point an arbitrageur buys the creation basket for 98 and shorts the ETF shares at 100, earning the ETF premium of 2 per share. The arbitrageur's position is exposed to market risk, as its mark-to-market value fluctuates. But, once the arbitrageur has bought the creation basket and shorted the ETF shares, the arbitrageur can put a creation order that will allow her to exchange the creation basket *in-kind* for the corresponding ETF shares. This closes the arbitrageur position as she transfers her long ETF portfolio position and obtains the ETF shares to deliver on her short sale. If the ETF premium was negative (ETF was trading at a discount), then the arbitrageur can trade in the opposite direction, redeeming ETF shares. Therefore, the absolute value of ETF premium—or ETF mispricing—should be a good proxy for arbitrage trades between the ETF shares and the ETF constituents.

The ability to convert ETF shares to redemption baskets and to convert creation baskets to ETF shares makes ETFs a good laboratory to study the relationship between arbitrage and liquidity. In fact, previous and contemporary investigations of this relationship consider similar settings. Rösch (2018) considers American Depositary Receipts, or ADRs, which typically can be converted to shares in the home country, and vice versa. Roll, Schwartz and Subrahmanyam (2007) study this relationship considering future contracts on the NYSE composite index. In the case of future contracts, arbitrageurs can only lock-in profits at the expiration of the future contract. By contrast, the ETF arbitrage

[4] APs have the option to accumulate creation and redemption orders during the day and can use opposing orders to offset them.

mechanism grant arbitrageurs the option to exchange ETF shares and ETF constituents at any point after the arbitrage position is taken. Thus, for the same constituent portfolio the ETF arbitrage is expected to carry lower costs and risks relative to index arbitrage, using futures.

Second, transaction cost are bore by arbitrageurs affecting their profits and incentives.[5] For example, Flannery, Nimalendran, Ray, and Yousefi (2017) use ETF premia to get a measure of corporate bond liquidity. To illustrate the impact of trading costs consider the previous example, but where arbitrageurs can trade at the prevailing bid and ask quotes. Figure 2 depicts this case. If arbitrageurs were to purchase the ETF portfolio at the prevailing ask quote, and short the ETF shares at the prevailing bid quote, then their profits will be equal to the ETF portfolio ask quote minus the ETF share bid quote. That is, ceteris paribus, transaction costs lower the profits earned from ETF arbitrage. In practice, arbitrageurs can obtain more favorable prices but we will still expect that higher trading costs would reduce arbitrage incentives, as trading costs may be related to the price impact of trades, influencing the effective prices at which securities are traded, or may be related to the difficulty of locating thinly traded securities.

It is worth noting that the arbitrage of ETF mispricing involves additional risks and costs. Arbitrageurs are exposed to liquidity risk given uncertainty about their price impacts, availability of securities for shorting, and adverse price movements before all trades are completed. In addition, arbitrageurs may have to pay fees associated with the creation/redemption process to the ETF manager or the AP.

Third, APs and arbitrageurs are not required to create or redeem shares, but they do so when it is in their own interest. For example, an arbitrageur interested in profiting from the discrepancy between the prices of an ETF and its constituents may place a creation/redemption order through an AP. Alternatively, APs may use the creation/redemption mechanism to fulfill large orders for their institutional clients.

Finally, the creation and redemption basket need not be "equal" to the ETF portfolio. That is, the creation or redemption baskets may not be proportional to the ETF portfolio, or tracking basket.[6] In choosing securities for creation and redemption baskets, ETF managers have the flexibility to deviate from the ETF tracking basket. For instance,

[5]A consequence of the design of the arbitrage mechanism is that trading costs are externalized from the ETF investors perspective. In fact, the creation and redemption of ETF shares are recorded by the ETF at NAV (and take place in-kind).

[6]Tracking basket is not the same thing as the index tracked by the ETF. Tracking basket is the basket of securities from which NAV is calculated to track the value of the ETF portfolio.

managers might substitute illiquid or hard to find securities with more liquid alternatives including cash in order to facilitate the creation and redemption process; or they might want to use different baskets to rebalance their portfolio holdings.

This practice of using different baskets is more common in fixed income ETFs in our data. Using Markit data (described in the next section), we compute for each ETF the fraction of days where the creation, redemption, and tracking basket are equal. Considering the 527 domestic equity ETFs in the data we calculate the distribution of the fraction of days that all three baskets are equal. Figure 3a shows that for 97 percent of domestic equity ETFs these baskets are equal at least 9 out of 10 days, i.e., the fraction of days is at least 0.9. In fact, for 57 percent of ETF these three baskets are equal, i.e., the fraction of days is 1. By contrast, considering the 76 bond ETFs in the data we observe a different pattern (Figure 3b). Only 54 percent of bond ETFs have all three baskets the same at least 9 out of 10 days, and there is a 25 percent of bond ETFs that have these baskets being different at least on 1 out of 10 days. Figure 3 also depict in red the fraction of times within each fraction-of-days bin when only the creation and redemption baskets are equal. For domestic equity ETFs, the creation and redemption baskets are almost always the same, so red bars are of the same height as the blue bars. By contrast, for bond ETFs, we see that even in the cases that the three baskets are different most days, more than 30 percent of times the creation and redemption baskets were the same. We will use this fact to motivate our definition of the ETF portfolio effective spread, described in the next section.

3 Data Description

We combine information from four main sources for trading days between 02/01/2012 and 12/31/2017. First, we use data from Markit North America, Inc. for daily portfolio composition files that are used to link portfolio constituents to ETFs. In addition, we use two sources of transaction level data to compute security-level effective spreads. For domestic stocks—including ETF shares—we use New York Stock Exchange, Daily TAQ (DTAQ); and for domestic corporate bonds we use FINRA Trade Reporting and Compliance Engine (TRACE). Finally, we use Morningstar to supplement our data with fund level information.

We use Morningstar data to classify ETFs in two major asset classes: domestic equity and domestic corporate bonds, see Appendix A for details.

3.1 ETF Premium

From Morningstar, we obtain daily ETFs' closing prices and net asset values (NAV). The NAV corresponds to the per share value of the ETF tracking portfolio. Markit ETF data allows us to compute NAV from constituent-level information. But this alternative is less reliable compared to NAV information from Morningstar, which is reported by ETF sponsors as a requirement to get exemption relief by the SEC.

For ETF i on day t, we denote by p_{it} the log of the ETF closing price and n_{it} the log of the NAV computed using closing prices. We compute the ETF premium as the difference between the ETF price and its NAV; and the ETF mispricing as the absolute value of this difference. That is,

$$Premium_{it} = (p_{it} - n_{it}) \times 10^4 \qquad \text{and} \qquad Mispricing_{it} = |p_{it} - n_{it}| \times 10^4 \ , \tag{1}$$

where the factor 10^4 expresses the premium in basis points of the NAV.

Since arbitrageurs are incentivized by both large premia or discounts, i.e., negative premia, in most of our analysis we consider the *Mispricing*, which is equal to the absolute value of the ETF premium (equation (1)). Roll, Schwartz and Subrahmanyam (2007) interpret mispricing as a proxy for arbitrage activity. By contrast, Rösch (2018) interprets mispricing as a proxy for impediments to arbitrage. Both interpretations are testable in the context of the ETF arbitrage mechanism, as arbitrage activity expands and contracts the number of ETF shares outstanding. Under the former a large premium should predict ETF share creations, whereas under the latter a large premium should not be associated with ETF share creation. The same being true for ETF discounts and ETF share redemptions. Unreported results show that the ETF premium predicts ETF share creation and redemption activity, so we follow Roll, Schwartz and Subrahmanyam (2007) and interpret mispricing as a proxy for arbitrage activity.[7]

In the case of international securities or securities that have not traded recently the calculation of NAV may consider stale prices, or prices inferred from comparable securities, so the premium will not reflect arbitrage incentives so accurately. This concern is largely absent for domestic equities but could influence our premium measure for bond ETFs.

[7]Specifically, we relate the ETF premium and arbitrage activity in a panel vector-autoregression, with arbitrage activity computed as the ratio of the value of the change in outstanding shares and the fund's lagged netassets. Both for equity and bond ETFs, Granger-causality tests reject that the ETF premium do not Granger-cause arbitrage activity.

3.2 ETF and Portfolio Effective spread

We calculate the effective spreads of ETFs and their stocks constituents from the DTAQ, which covers the intraday transactions and quotes of U.S. stocks and U.S. ETFs. Similar to Lee and Ready (1991), we classify each trade as buy or sell by comparing it to the prevailing quotes. We compare each transaction price with the midpoint of one millisecond prior best bid and ask quotes to determine whether a transaction is a buy or sell. The effective spreads for ETFs and stock constituents are calculated as twice the difference between the execution price and the midpoint of the best bid and ask as a fraction of the midpoint. Daily effective spread corresponds to the volume-weighted average of effective spreads in that day. On day t, we denote with $\textit{ETF Spread}_{it}$ the effective spread of ETF i and with $\textit{Constituent Spread}_{jt}$ the effective spread of stock constituent j. (See Appendix C.1 for details.)

For corporate bond constituents, we use TRACE data to compute the effective spread. TRACE reports corporate bond transactions dealer-to-dealer and costumer-to-dealer. We use only the customer-to-dealer trades, i.e., when the buyer or seller has been identified as a customer.[8] Effective spreads of corporate bonds are calculated as the difference between the volume-weighted buy prices and the volume-weighted sell prices as a fraction of the volume-weighted prices. We denote with $\textit{Constituent Spread}_{jt}$ the effective spread of bond constituent j on day t. (See Appendix C.2 for details.)

Markit ETF contains cusips for ETF shares and ETF constituents. We use this data to create daily links between ETF cusips and the cusips of its constituents. These links are used to merge fund-level information with constituents' information. We use the constituent information to calculate the effective spread of a portfolio corresponding to a single share of an ETF basket.

To describe the weights used to aggregate constituent spreads, it is useful to introduce the following notation. Let b index the three ETF baskets, $\{C, R, T\}$, let $\mathcal{J}_{ibt}$ be the set of constituents of basket b of ETF i on day t, let p_{jt} be the close price of constituent j on day t, let u_{ibjt} be constituent j units in basket b of ETF i on day t, and x_{ibt} be the number of ETF shares in basket b of ETF i on day t. The latter is sometimes referred to as the size of the creation-redemption basket and typically equals 50,000 shares. The identity that NAV

[8] TRACE data is pre-filtered following the procedure developed in Dick-Nielsen (2012).

equals the per share value of a portfolio motivates the following constituent weights

$$w_{ibjt} = \frac{u_{ibjt}\, p_{j,t-1}}{x_{ibt}\, n_{i,t-1}}\ . \tag{2}$$

In fact, the NAV identity implies that $n_{it}x_{ibt} = \sum_{j\in\mathcal{J}_{ibt}} p_{jt}u_{ibjt}$, that is the value of the constituents of basket b of ETF i on date t equals the NAV of basket b. We use the one day lag of constituent prices and NAV to avoid introducing spurious dependence between portfolio spreads that will be computed with these weights and premia that depends negatively on NAV.

We construct effective spread measure for each ETF basket portfolio as the weighted sum of their constituents' effective spreads. That is, for basket b of ETF i on day t,[9]

$$\mathit{Portfolio\ Spread}_{ibt} = \sum_{j\in\mathcal{J}_{ibt}} \omega_{ibjt}\mathit{Constituent\ Spread}_{jt}\ . \tag{3}$$

In practice, basket weights could be unavailable reflecting that constituent price information is unavailable from TAQ or TRACE (equation (2)). Thus, the calculation of portfolio spreads for each basket assumes that the effective spread of constituents for which the portfolio weights are missing equal the average effective spread for the constituents with available weights. This assumption should bias our calculated basket-level effective spreads down, if price information is less likely to be obtained for more illiquid securities. This could be the case if, for instance, less liquid securities trade less frequently, explaining the missing price information. This feature of the data should bias our results towards not being able to elicit a relationship between (il)liquidity and mispricing, as we are not be able to measure the illiquidity of securities that do not trade on a given day.

As described in section 2, for arbitrageurs the relevant portfolio spreads are for the creation and redemption baskets when the ETF premium is positive and negative, respectively. In order to account for this institutional aspects and based on the evidence about the relationship of the creation and redemption portfolios presented in section 2, we define the ETF portfolio effective spread as the average of the creation and redemption basket spreads. That is,

$$\mathit{Portfolio\ Spread}_{it} = \frac{\mathit{Portfolio\ Spread}_{iCt} + \mathit{Portfolio\ Spread}_{iRt}}{2}\ . \tag{4}$$

[9] In order to have reliable liquidity measures for ETF baskets we only consider basket-level effective spreads when our basket weights ω_{ibjt} add up to at least 0.5 and to at most 1.25 (see Appendix B).

An alternative to equation (4) would have been to define portfolio spread as the portfolio spread of the creation basket when the premium is positive and as the portfolio spread of the redemption basket when the premium is negative. But this alternative could introduce a mechanical relationship between premium and portfolio spread.

We note that in light of the fact that within domestic equity the creation and redemption baskets are identical on almost all days, our definition only affects portfolio spreads for bond ETFs.

Our final sample filters observations according to data availability and to ensure accuracy of our portfolio spread measures (see Appendix B). Moreover, to reduce the influence of outliers in our analysis we winsorize ETF mispricing, and ETF and portfolio effective spreads at the 1^{st} and 99^{th} percentiles. Our final sample contains over 400,000 observations for 584 domestic ETFs: 509 domestic equity ETFs and 75 domestic bond ETFs.

Table 1 presents descriptive statistics for *Mispricing*, *ETF Spread*, and *Portfolio Spread* computed according to the aforementioned conventions over our final sample. Considering all ETFs, average portfolio spreads are 16 basis points, whereas average ETF spreads are 12 basis points, and average mispricing is 11 basis points.

Both portfolio spreads and mispricing are higher on average for bond relative to equity ETFs. Considering only domestic equity ETFs, we observe tighter portfolio spreads with an average of 11 basis points. In contrast, for domestic bond ETFs, portfolio spreads are almost 60 basis points, reflecting the illiquidity of corporate bonds. Average mispricing displays a similar pattern with an average of 8 and 31 for equity and bond ETFs, respectively. Higher mispricing of bond ETFs may not be surprising if high portfolio spreads impede arbitrage. However, it is interesting to note that despite these facts, average ETF spreads for both equity and bond ETFs are similar taking values of 12 and 14 basis points, respectively.

Figures 4 and 5 presents the median, 25^{th} and 75^{th} percentiles of the distribution of daily values for ETF mispricing, and ETF and portfolio spreads in our sample of equity and bond ETFs, respectively. We see that over our sample these series exhibit mild trends and some deterministic patterns, something that we further investigate below.

4 Liquidity and the Speed of Adjustment of Mispricing

We begin our analysis inspecting the relationship between the speed of adjustment of mispricing and the market liquidity of both ETF shares and ETF constituents. Our null hypothesis is that the speed of adjustment is independent of market liquidity. This could be the case, because either mispricing does not incentivize arbitrage, so the speed of adjustment is independent of the mispricing. Or this could be the case, because liquidity is not an important consideration for arbitrageurs, so the speed of adjustment is independent of liquidity.

Our alternative hypothesis is that the speed of adjustment depends on market liquidity. This could be the case if ETF mispricing gives arbitrageurs an incentive to take offsetting positions in ETF shares and ETF constituents to earn the price differential. As arbitrageurs take these positions, ETF mispricing should shrink. And given that market liquidity facilitates arbitrageurs' trades, the speed of adjustment of ETF mispricing should depend on market liquidity.

In order to measure how fast ETF mispricing mean revert, we calculate a measure of the speed of adjustment of ETF mispricing by running the following regression for each of the 584 ETFs in our sample, separately:

$$\Delta Mispricing_{it} = \alpha_i + \mu_i \, Mispricing_{i,t-1} + \epsilon_{it} \ , \tag{5}$$

where $Mispricing_{it}$ is the absolute value of the log difference between the ETF i's price and its NAV, α_i and μ_i are coefficients to be estimated, and ϵ_{it} are zero mean disturbances. The coefficient μ_i characterizes the speed of mean-reversion of ETF mispricing. In fact, ignoring the constant, it is easy to show that the half-life of mispricing is given by $-\ln(2)/\ln(1+\mu_i)$.

Panel A of Table 2 reports the average and standard deviation of the estimates for μ_i across our sample of 584 ETFs. For the entire sample of ETFs, the average mean-reversion coefficient is -0.79, or a half-life of 0.44 days. Once we separate the equity and bond ETFs, a clear distinction appears. The mean-reversion coefficient for domestic equity ETFs is -0.85 whereas it is -0.40 for bond ETFs, i.e., a half-life of 0.37 and 1.36 days, respectively. The larger absolute value of the mean-reversion coefficient indicates that the mispricing of equity ETFs disappears faster, likely reflecting a more effective ETF arbitrage activity. By contrast, the mispricing of bond ETFs disappears slower. The fact that bond ETFs, which invest in more illiquid corporate bonds, exhibit a slower speed of adjustment suggests that constituents' liquidity is an important consideration for arbitrageurs whose trades extinguish the mispricing.

We further investigate the role of ETF shares' or ETF constituents' liquidity play in the effectiveness of arbitrage by computing the correlation of the speed of adjustment and liquidity at the ETF level. Panel B of table 2 report the correlation of our estimates for

μ_i with ETF and portfolio spreads across ETFs. Considering all ETFs, these correlation coefficients are both positive and statistically significant, rejecting our null hypothesis in favor of our alternative hypothesis. The fact that the correlation is larger for ETF portfolio spreads is consistent with the view that liquid ETF constituents enable more effective arbitrage and a faster speed of adjustment of ETF mispricing. The fact that the correlation is positive and statistically significant for the spread of ETF shares, indicates that ETF liquidity also enables arbitrage. But the small correlation suggests a lesser role for ETF shares' liquidity in explaining the cross sectional variation in arbitrage effectiveness, likely reflecting the smaller dispersion of ETF spreads in our data.

The correlation coefficients when we consider only equity and bond ETFs are different. Considering equity ETFs, the correlation coefficient with the ETF spread is positive whereas the correlation coefficient with portfolio spread is not statistically significant. In contrast, for bond ETFs, the correlation coefficient with portfolio spread is positive, whereas it is not statistically significant for ETF spread. These findings suggest that with respect to the effectiveness of arbitrage, there are important differences between equity and bond ETFs. For equity ETFs, the effectiveness of arbitrage is linked to the liquidity of ETFs whereas for bond ETFs, it is related to the portfolio liquidity.

Together these results show that liquidity affects the efficacy of arbitrage. Yet, it is important to point out that arbitrage may also feedback into market liquidity. In the next section, we analyze the joint dynamics of liquidity and arbitrage activity in our panel of ETFs.

5 Joint Dynamics of Arbitrage and Liquidity

We continue our analysis studying the joint dynamics of mispricing and the liquidity of ETF shares and ETF constituents. Before analyzing this joint dynamics, we expunge our variables of common regularities and trends to minimize the possibility of spurious conclusions. Then, we related the adjusted variables in a panel vector autoregression (PVAR) analysis.

5.1 Adjustment Regressions

Before we estimate the PVAR, we aim to remove the common regularities and trends from the variables to avoid the possibility of spurious results. We follow Roll, Schwartz and Subrahmanyam (2007) and use adjustment regressions to remove the deterministic components in ETF spread, portfolio spread and mispricing. We run these regressions separately for equity and bond ETFs to account for possible differences between these asset classes. The rationale for removing deterministic components in these series comes from previous research that have found that spreads exhibit time trends and calendar regularities (see Chordia, Roll and Subrahmanyam 2001). This, in turn, suggests that mispricing might also exhibit these deterministic components. In fact, Roll, Schwartz and Subrahmanyam (2007) find time trends and calendar regularities for the futures-cash basis, i.e., the difference between the NYSE composite index and the price for this index implied by futures contract associated with it. Since trends and calendar regularities of ETF premia and spreads have largely been unexplored, our analysis is of independent interest.

We regress the raw spreads for ETF shares and ETF portfolios on the following variables: (i) time trend and square of the time trend; (ii) day-of-the-week dummies; (iii) pre-holiday dummy which indicates a day before a holiday;[10] (iv) monthly dummies; and (v) ETF fixed effects. We regress the raw ETF mispricing on the same set of variables, but consider only a Friday dummy, instead of the day-of-the-week dummies. The Friday dummy is expected to account for the increased cost of holding arbitrage inventory over the weekend.

Table 3 presents the results of these adjustment regressions for equity ETFs. Large majority of the estimated coefficients are statistically significant, confirming the deterministic variation in ETF spread, portfolio spread, and mispricing. For the ETF spread, the estimated coefficients for trend and trend^2 are negative and imply a decreasing trajectory for the spread over our sample period. This could reflect a secular decline in ETF spreads due to survivorship bias—only ETFs that attract more investors interest are likely to remain in business. In the case of portfolio spread, the estimated coefficients for trend and trend^2 are positive and statistically significant. Together they imply a non-monotone trend over our sample period, with average portfolio spreads decreasing mildly in the first quarter of our sample and increasing thereafter. For the mispricing regression, trend and trend^2 coefficients are statistically significant and imply a decreasing trend for mispricing over our sample.

Monthly dummies, which omit January, are negative. That is, ETF spreads are gener-

[10]We consider holidays that did not fall on a Monday from the list maintained by SIFMA, https://www.sifma.org/resources/general/us-holiday-archive/.

ally higher in January. Similarly, mispricing and portfolio spreads also display a January effect, but on average they are higher in December. The presence of a January effect for spreads is largely consistent with the evidence of Roll, Schwartz and Subrahmanyam (2007), who consider the weighted average quoted and effective spread for the constituents of the NYSE composite index.

For all of the three regressions, the pre-holiday dummy is positive and significant, suggesting that ETFs and their constituents are less liquid, and mispricing is higher, prior to a holiday. Friday dummy is positive and significant for the ETF mispricing. This is consistent with the idea that arbitrageurs may require additional compensation if they will have to hold their positions over the weekend. Portfolio spreads tend to be highest on Fridays, which could be related to the previous finding. However, ETF spreads tend to be highest on Mondays, as implied by the negative coefficients on the day-of-week dummies in this case.

Table 4 summarizes the results of the adjustment regressions for bond ETFs. Similar to equity ETFs, for ETF spread trend and trend^2 coefficients are negative and statistically significant. However, in this case, the estimated coefficients imply an inverted U-shape trend: mildly increasing in the first quarter of the sample and decreasing thereafter. Both in the case of portfolio spread and mispricing the coefficients are statistically significant and their values imply a decreasing and convex trend over our sample period. Unlike equity ETFs, spreads of bond ETFs do not seem to display a January effect. The monthly dummies do not lend themselves to a clear interpretation: on average, bond-ETF spreads are highest in July, portfolio spreads are highest in December, and misprincings are highest in February.

In the case of bond ETFs, spreads for both ETF shares and ETF constituents are higher in the days preceding a holiday, but for mispricing the positive estimated pre-holiday effect can not be rejected to be different than zero. Also, Friday dummy in the mispricing regression is positive, but not significant, which suggests that the forced holding of bond positions over the weekend is not a major consideration for bond arbitrageurs. As with equity ETFs, for bond ETFs the spread of ETF shares appears higher on Monday. By contrast, for portfolio spreads we see a different pattern between equity and bond ETFs. For bond ETFs portfolio spreads are lower in the later days of the week, whereas for equity ETFs portfolio spreads were highest on Friday.

Before turning to our PVAR analysis we analyze the stationarity and correlation of our adjusted series, i.e., the residuals from the regressions presented in Tables 3 and 4. We denote the adjusted series by *ETF Spread**, *Portfolio Spread**, and *Mispricing**.

To assess the stationarity of the residuals from the adjustment regressions, we perform a panel unit root test based on Phillip-Perron for these adjusted series. These tests strongly reject the existence of unit root for all three panel time series at p-values less than 0.001.

Table 5 report the cross correlations of our adjusted series. All pairwise correlations are statistically significant at the 1 percent level. For both asset classes the correlation between ETF spreads and mispricing is the highest with values above 0.4. This correlation is followed in magnitude by the correlation of ETF and portfolio spreads for equity ETFs, with a value of 0.22, and portfolio spread and mispricing for bond ETFs, with a value of 0.28. Finally, the lowest correlation for equity ETFs is between portfolio spread and mispricing, with a value of 0.16, whereas for bond ETFs it is between ETF spread and portfolio spread, with a value of 0.11. These correlations and their statistical significance suggest the presence of multivariate causality among mispricing and the liquidity of both ETF shares and ETF portfolio constituents.

5.2 PVAR Analysis

We examine the joint dynamics of ETF mispricing and liquidity in our sample of 584 ETFs, relating these variables in separate PVARs for equity and bond ETFs respectively. Our input variables are the residuals from the adjustment regressions: *Mispricing*$^*_{it}$, *ETF Spread*$^*_{it}$, and *Portfolio Spread*$^*_{it}$. Our use of a PVAR approach is motivated by the multivariate causality among these variables suggested by the statistically significant cross-correlations reported in Table 5. Intuitively, when financial markets are illiquid, it could be harder to arbitrage mispricings away. Conversely, arbitrage may create imbalances in order flows and market makers' inventories increasing illiquidity in both the market for ETF shares and ETF constituents. This feedback loop between ETF shares' and ETF constituents' liquidity, or the participation of the same investors or market-markers in the markets for ETF shares and ETF constituents, can introduce bivariate causality among these securities' liquidity.

Our PVAR approach builds on Roll, Schwartz and Subrahmanyam (2007), who used a VAR to relate the dynamics of arbitrage and liquidity, using the NYSE composite index and future contracts on this index. By contrast, we consider a panel of ETFs. As these authors, we consider mispricing as a proxy for arbitrage activity and the spread of the portfolio associated with a derivative asset. But, we expand the analysis to also consider the liquidity of the derivative—ETF shares in our case. This allows us to analyze the join dynamic of arbitrage and the liquidity of the derivative, in addition to the liquidity of the associated portfolio as previously done. ETFs are a relatively new product, so the time series dimension of our sample is relatively short, but the panel dimension increases the power of the statistical analyses allowing us for the possibility of reliable conclusions.

We examine the joint dynamics of our variables of interest, stacking them in the vector $Y_{it} = (Mispricing^*_{it}, ETF\ Spread^*_{it}, Portfolio\ Spread^*_{it})$, where i index the different ETFs and $t \in T_i$ index trading days where ETF i is observed in our unbalanced panel.

More specifically, we model this relationship as:

$$Y_{it} = Y_{it-1}A_1 + \ldots + Y_{it-p}A_p + e_{it} \ , \tag{6}$$

where $\{A_j\}_{j=1}^{p}$ are 3-by-3-coefficient matrices to be estimated and e_{it} are 3-dimensional vectors with zero mean. The PVAR is specified with 5 autoregressive terms.

Table 6 reports the results of the PVAR for equity ETFs. The estimated coefficients of all variables on their own lags are positive, statistically significant, and decay over time almost monotonically. The latter confirms the absence of unit roots, as indicated by the Phillip-Perron tests reported in subsection 5.1, and it suggests some persistence of these variables. The cross-effects between these variables are generally positive and statistically significant, suggesting that all variables are interrelated. That is, there are liquidity spillovers from ETF shares to portfolio constituents, and vice versa; and there is a bivariate causality between mispricing, representing arbitrage activity, and the liquidity of both ETF shares and ETF portfolios. Moreover, the relative magnitude of the estimated coefficients and t-statistics suggests a stronger relationship between mispricing and ETF shares' spread. These results are in line with the values for the cross-correlations reported in the previous subsection.

Table 7 reports the PVAR results for bond ETFs. Similar to equity ETFs, for all variables the estimated coefficients on their own lags are positive, statistically significant, and decay over time. In this case, the cross-effects are generally positive but most are not statistically significant. Lagged ETF spreads do not seem to affect current portfolio spreads, but the statistical significance of the cross-effects for the other pairs of variables suggest the presence of liquidity spillovers from bond portfolios into bond ETF spreads, and a bivariate causality between mispricing and both liquidity measures.

Table 8 reports the correlations of innovations, i.e., residuals, from the three PVAR equations for our two asset classes. As it was the case for the adjusted series, the correlation for the innovations is highest between the mispricing and ETF spread for both equity and bond ETFs, with values of 0.08 and 0.09, respectively. Also in line with the previous evidence, for equity ETFs, the second largest correlation is between both spreads, with a value of 0.03, followed by the correlation of portfolio spread and mispricing, with a value of 0.01. For bond ETFs, the correlation of portfolio spread with both mispricing and ETF spread is 0.01. This contrast with the evidence for the adjusted series, where portfolio spreads and mispricing exhibited a higher correlation.

Next, we perform Granger-causality tests for the separately estimated PVARs for equity and bond ETFs. Panel A of Table 9 reports the chi-square statistics and p-values for equity ETFs and Panel B reports the same statistics for bond ETFs. The null hypothesis is that the variables listed in the rows do not Granger-cause the variables listed in the columns.

For equity ETFs, all three variables Granger-cause one another. In all cases the test that row variables do not Granger-cause column variables is rejected at the 1 percent level. This is consistent with liquidity influencing arbitrage and arbitrage, in turn, influencing liquidity for both ETF shares and ETF constituents. The Granger-causality relationship between ETF spread and mispricing appears to be the strongest, in line with the evidence from the correlations of adjusted series and PVAR innovations presented above. This finding is interesting as the previous study by Roll, Schwartz and Subrahmanyam (2007) did not provide evidence on the relationship of arbitrage and the liquidity of the derivative. In our case, the ETF share corresponds to the the derivative, and it exhibits the strongest relation with arbitrage.

For bond ETFs, mispricing and ETF spread are Granger-caused by the other two variables in our system. However, in the case of portfolio spread, only mispricing Granger-causes it. In other words, the mispricing provides information about the future portfolio spreads, but the test cannot reject that the ETF spread does not Granger-cause the portfolio spread. The latter suggests that there are no direct liquidity spillovers from bond ETF shares into bond ETF constituents. But it does not rule out that ETF spreads can indirectly affect the spreads of bond ETF constituents, as ETF spreads influence mispricing which in turn influences portfolio spreads.

To analyze the impact of a shock to one variable on the other variables in the system, we compute the impulse response functions (IRF) implied by our PVAR. The IRFs account for both the direct and indirect effects from the shock to an individual variable. In order to isolate the effect of a shock to a single variable, we orthogonalize the residuals from the PVAR using the inverse of the Cholesky decomposition of the residual covariance matrix. Unlike the PVAR estimated coefficients and, thus, the Granger-casuality test, the IRFs depend on the ordering of the endogenous variables used for the Cholesky decomposition. We report the results when the variable ordering is: *Mispricing**, *ETF Spread** and *Portfolio Spread**.[11] Our conclusions are largely robust to the ordering of these variables.

Figure 6 plots the impulse response functions for equity ETFs with 95 percent confidence bands using 1,000 Monte Carlo replications. All of the three variables display some persistence, so a shock to a given variable provide information about the future value of the same variable, especially over the next few trading days.

Next, we inspect the interrelation between portfolio spread and mispricing, which we can compare to the evidence presented in Roll, Schwartz and Subrahmanyam (2007). As these authors we find that shocks to the mispricing help to predict portfolio spreads over the next couple of days. That is, the ETF arbitrage affects the liquidity of the ETF portfolio constituents. Roll, Schwartz and Subrahmanyam (2007) find weak predictability, in the reverse direction, from the average spread of NYSE composite index constituents to mispricing. By contrast, we find that shocks to the ETF portfolio spread seem to have explanatory power on ETF mispricing over the next two weeks, with the effect of portfolio spread on mispricing manifesting after a couple of days. We note that the two set of results are not expected to coincide. First, the two studies use different constituent samples. Roll, Schwartz and Subrahmanyam (2007) consider the constituents of the NYSE composite index from 1988 to 2002, whereas we consider the portfolio constituents of 509 domestic equity ETFs from 2012 to 2017. Second, our study includes the liquidity of the derivative security in the PVAR system, so the predictability of mispricing from shocks to portfolio spreads could reflect the indirect effects through the ETF spread. We continue the inspection of the IRFs by looking at the effect of ETF spread shocks on mispricing and vice versa. Studying this relationship is interesting because, for one, little is known about the effect of arbitrage on derivates' liquidity. For another, this relationship appeared empirically relevant based on the inference from the correlations of adjusted variables and PVAR innovations and the Granger-causality tests. The IRFs confirm the empirical relevance of the relation between ETF spread and mispricing. Mispricing shocks have a relatively large and persistent effect on the ETF spread (bottom left panel), and the same is true in the reverse direction (top right panel). These results suggest that illiquidity shocks

[11]We order mispricing first to facilitate comparisons with the reported results in Roll, Schwartz and Subrahmanyam (2007).

especially in ETF shares reduce arbitrage incentives in equity ETFs. Hence, ETF spreads are important for the law of one price.

The aforementioned results are insensitive to the relative ordering of spreads and mispricing, but the relative ordering of ETF spread and portfolio spread affects the IRF from ETF spread shocks on portfolio spreads, and vice versa. The reported IRFs exhibit a a significant albeit short-lived effect from ETF spreads shocks on portfolio spreads, whereas the effect of portfolio spread shocks appears statistically insignificant on ETF shares. These IRFs, together with the correlation analysis and Granger-causality tests, suggests that ETF and portfolio spreads are jointly determined for equity ETFs.

Little is known about the relationship between arbitrage and liquidity for fixed income securities, so the IRFs for bond ETFs are of special interest. Figure 7 plots the IRFs for bond ETFs with 95 percent confidence bands using 1,000 Monte Carlo replications. It should be noted that these IRFs are plotted over a much larger time range, considering 100 trading days, instead of 20 as for equity ETFs. This fact underscores the richer and more persistent dynamics among our variables of interest for bonds ETFs. As with equity ETFs, shocks to a bond ETF variable are informative in predicting the future values of the same variable, with shocks to bond portfolio spreads and mispricing being relatively more persistent. The latter is consistent with the results of section 4 that showed that for bond ETFs mispricing is more persistent.

We proceed to inspect these IRFs in the same order as for equity ETFs, beginning with the relationship between portfolio spread and mispricing. We find a positive, significant, and very persistent effect of shocks to mispricing on bond portfolio spreads, and we find the same properties in the response of mispricing to portfolio spread shocks. These results are striking compared to the previous evidence for equity ETFs, where these IRFs reflected smaller and shorter lived responses. In the case of bond ETFs, the effect of a shock to portfolio spread or mispricing helps predict the value of the other variable even after 100 trading days after the shock! These more persistent dynamics suggests the presence of a reinforcing feedback between portfolio spreads and mispricing. As portfolio spreads widen arbitrage incentives decrease making mispricing more persistent, as suggested by the analysis of section 4. Larger mispricing appears to feed back into wider portfolio spreads. This feedback likely reflect the action of dealers, who make markets for the bond constituents. Based on our evidence, we can only speculate over the economic incentives driving the response of dealers. One explanation could be that dealers set larger bid-ask spreads in response to order imbalances caused by arbitrage activity incentivized by a wider mispricing. But this explanation seems at odds with the fact that arbitrage for bond ETFs appeared less effective (section 4), if the effectiveness of arbitrage is related to the number of arbitrage trades. Another explanation is simply that dealers have market power and are able to extract arbitrage rents by widening bond bid-ask spreads. Additional research should further scrutinize dealers' economic incentives in the context of ETF arbitrage for bond ETFs.

We continue inspecting IRFs for bond ETFs, looking at the effect of ETF spread shocks on mispricing and vice versa. Inference from Granger-causality tests and correlations reported in Tables 5 and 8 make us expect a strong relationship between these variables. In fact, mispricing shocks have a significant and persistent effect on the ETF spread (bottom left panel), the same being true in the reverse direction (top right panel). These results, in line with the results for equity ETFs, suggest that ETF shares' liquidity is important for arbitrage incentives in bond ETFs. We conclude that ETF spreads (in both asset classes) are important for the efficacy of the ETF arbitrage mechanism.

Finally we inspect the relationship between the liquidity of bond ETFs and their constituents. Inference from previous results suggested the absence of a direct effect of ETF spreads on bond-ETF portfolio constituents. The IRF in the top middle panel of Figure 7 supports the absence of both a direct and an indirect effect of shocks to ETF spreads on the spread bond constituents. That is, we do not find liquidity spillovers from bond ETFs into their constituent bonds. By contrast, liquidity shocks to bond ETF portfolios do affect the subsequent liquidity of bond ETF shares (left middle panel). In the case of bond ETFs all results are insensitive to the ordering of variables assumed to compute the IRFs.

Differences in our results for equity and bond ETFs are interesting, as they shed light on the role of the liquidity of the portfolio constituents on the dynamic relation between arbitrage and liquidity. Figure 8 compares the IRFs for both equity and bond ETFs, considering 25-basis-point shocks to our three endogenous variables. This comparison shows that, generally, the response of our endogenous variables for the same shock is larger and more persistent for bond ETFs. The discrepancy is stark when we consider the relationship between portfolio spread and arbitrage, with the IRFs for bond ETFs being larger and more persistent. When we consider the relationship between mispricing and ETF spread, we see also larger and more persistent effects for shocks to ETF spread on mispricing; however, for shocks of mispricing on ETF spread the effects upon impact is larger for equity ETFs, with the effect still being more persistent for bond ETFs. Together the evidence lead us to conclude that the more illiquidity the constituents the stronger and more persistent is the relationship between arbitrage and liquidity. Finally, we compare the IRFs that capture the liquidity spillovers between ETF shares and ETF constituents. As discussed above, for equity ETFs the direction for liquidity spillovers was sensitive to the assumed ordering of the variables in the PVAR. By contrast, for bond ETFs the IRFs suggested that there are liquidity spillovers from bond portfolios to bond ETF shares, but not the other way around. These results suggests that liquidity spillovers from ETF shares to ETF constituents are weaker when constituents are less liquid.

6 Conclusions

In this paper, we present new evidence about the relationship between arbitrage and liquidity using a panel of ETFs, spanning both domestic equities and bonds. To study the relationship between arbitrage and liquidity, we compile a unique ETF dataset from big trade-level data. To the best of our knowledge, our paper is the first to dynamically relate mispricing to endogenous liquidity measures, such as effective spreads, when fixed-income securities are involved.

Our results indicate that the liquidity of ETF shares and ETF constituents promotes the efficacy of the ETF arbitrage mechanism. For equity ETFs, the average speed of adjustment implies an ETF mispricing half-life of 0.37 days. The fast speed of reversion to zero suggests an effective ETF arbitrage mechanism (Engle and Sarkar 2006). For bond ETFs, the average speed of convergence implies an ETF mispricing half-life of 1.36 days. The less effective arbitrage of bond ETF mispricing is associated to the lower liquidity, on average, of bond ETF constituents. Liquidity of ETF shares is also associated to the efficacy of arbitrage, but only within equity ETFs.

Our analysis finds weak liquidity spillovers between ETF shares and ETF constituents. In most cases, Granger-causality tests indicate that one effective spread have predictive power over the other spread. But, only shocks to bond portfolio spreads have predictive power over future bond ETF spreads.

Our findings support the presence of a robust interrelationship between liquidity and arbitrage, when the securities involved are either equities or bonds. These findings, on the one hand, provide additional supporting evidence for this interrelationship when equities are involved (Roll, Schwartz and Subrahmanyam 2007, Rösch 2018). On the other hand, these findings suggests that the effect of arbitrage on liquidity, and of liquidity on arbitrage, is larger and more persistent when less liquid bond securities are involved.

Our results also give insights about some important aspects of synthetic securities derived from illiquid assets. The liquidity of these synthetic securities seems sensitive to the liquidity shocks to their underlying investments. Hence, the liquidity of synthetic securities are not independent of their illiquid investments. If the liquidity of their investments becomes more illiquid, the liquidity of the synthetic security may also dry up. On the other hand, we cannot find evidence suggesting that the liquidity of underlying illiquid investments dries up when the synthetic security becomes more illiquid.

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Appendix

A ETF Categories

This appendix describes the definition of our 2 ETF asset classes using Morningstar information.

Funds classified in *domestic equities* correspond to equity funds that are not international funds. Equity funds correspond to funds where variable 'global broad category group' equals 'Equity' or where variable 'morningstar category' equals 'Preferred Stock'. We consider equity funds to invest internationally if 'group US category' equal 'International Equity', or if 'category morningstar' contains any of the following strings: 'US Fund China', 'US Fund Diversified Emerging Markets', or if 'category morningstar institutional' contains any of the following strings: 'Emerging Europe', 'Latin America', 'Pacific/Asia', 'India', 'Diversified Emerging Markets,' 'World', 'Foreign'.

Domestic bond funds are comprised of investment grade and high yield bond funds. The former we identify with the funds where variable 'category Morningstar' contains any of the following strings: 'US Fund Short-Term Bond', 'US Fund Ultrashort Bond', 'US Fund Intermediate-Term Bond', 'US Fund Long-Term Bond', 'US Fund Corporate Bond'. The latter corresponds to funds with 'category Morningstar' equal to 'US Fund High Yield Bond'.

B Calculation of Basket-level Effective Spreads

We use Markit ETF data to link portfolio constituents and ETFs. From Markit ETF we obtain daily portfolio composition files that, for each ETF, list the units of each security in basket $b = T, C, R$. Considering he notation introduced in the paper we introduce the following filters to ensure that effective spreads for each basket and ultimately our ETF portfolio measure are good proxies of the actual effective spreads that prevailed on a given day. Let $\Omega_{ibt} = \sum_{j \in \mathcal{J}_{ibt}} \omega_{ibjt}$, i.e., the sum of portfolio weights defined in equation (2). Missing weights are ignored or treated as zeroes. Missing weights may reflect that constituent price information is unavailable from TAQ or TRACE, or that we can not compute NAV as the ratio of assets under management and shares outstanding using Markit ETF information. Our first filter is that we drop basket-level effective spreads if $\Omega_{ibt} < 0.5$ or $\Omega_{ibt} > 1.25$. In addition, let $\overline{\Omega}_{it} = (\Omega_{iCt} + \Omega_{iRt})/2$, i.e., the average sum of weights for the creation and redemption baskets. Then, our second filter is that we drop observations were this average sum of weights $\overline{\Omega}_{it} < 0.75$ or $\overline{\Omega}_{it} > 1.25$.

In addition, we filter ETFs with less than 35 days in our sample after filtering on $\overline{\Omega}_{it}$ and requiring that information is available for the ETF premium, the ETF effective spread, and the ETF portfolio spread.

C Calculation of Securities' Effective Spreads

This appendix provides additional details about how effective spreads are calculated for individual securities: ETF shares and ETF constituents.

C.1 Effective Spread of ETFs and Stock Constituents

We treat both ETF and stock constituents as stocks to compute their effective spreads. Information on secondary market stock transactions is from DTAQ. First, we sign each trade aggressive and passive based on the Lee and Ready (1991) algorithm by choosing contemporaneous best bid and best ask prices one millisecond prior. Second, we compute the effective *half* spread as the difference between the transaction price and the mid-point of the best bid and ask prices as a ratio of the mid-point of the best bid and ask prices:

$$BuySideHalfSpread = \frac{TransactionPrice - MidPointPrice}{MidpointPrice} \tag{C.7}$$

$$SellSideHalfSpread = \frac{MidPointPrice - TransactionPrice}{MidpointPrice} \tag{C.8}$$

Our stock effective spread measure is twice the daily volume-weighted average of these effective *half* spreads.

$$EffectiveSpread_{Stock} = 2 * \frac{\sum_i^n Size_i \times HalfSpread_i}{Volume} \tag{C.9}$$

where $Size_i$ is the size of the transaction i and volume is the sum of all daily transaction volume.

C.2 Effective Spread of Bond Constituents

Information of corporate bond transactions is from the Enhanced TRACE. After we clean the Enhanced Trace following Dick-Nielsen (2012), we select the customers-to-dealer and dealer-to-dealer trades. First, we compute the dollar effective spreads as daily volume-weighted prices of customer buy and customer sell transactions. Second, we compute the inter-dealer transaction prices as daily average price of dealer-to-dealer transactions. Our corporate bond effective spread measure is the ratio of dollar effective spreads to the inter-dealer transaction prices.

$$EffectiveSpread_{Bond} = \frac{CustomerBuyPrice - CustomerSellPrice}{InterDealerTransactionPrice} \tag{C.10}$$

Tables and Figures

Table 1: Summary Statistics

	Mean	Std	Min	Max	ETFs	Obs
ALL						
Portfolio Spread	15.57	18.84	1.41	165.38	584	408,960
ETF Spread	12.28	13.26	1.08	111.11	584	408,960
Mispricing	10.84	14.96	0.00	141.08	584	408,960
Domestic Equity						
Portfolio Spread	10.72	7.46	2.86	43.98	509	366,069
ETF Spread	12.07	12.83	1.22	89.17	509	366,069
Mispricing	8.44	10.47	0.00	58.34	509	366,069
Bond ETFs						
Portfolio Spread	56.96	31.55	1.41	165.38	75	42,891
ETF Spread	14.04	16.37	1.08	111.11	75	42,891
Mispricing	31.26	27.05	0.00	141.08	75	42,891

The table reports the summary statistics of ETF spread, portfolio spread and mispricing for U.S. ETFs. As defined in equation 2, portfolio spread is the weighted effective spreads of ETF constituents. For bond constituents, FINRA TRACE is used to calculate the effective spreads. Effective spread of bonds are simple the volume-weighted difference of customer buy and sell transactions as a percent of inter-dealer transaction prices. For stocks constituents and ETF Spreads, NYSE DTAQ is used to calculate the effective spreads by following Lee-Ready algorithm. ETF mispricing is the absolute value of the difference between ETF market price and ETF netasset value from Morningstar Direct. All variables are in basis points.
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Table 2: Mean-reversion of ETF Mispricing

Panel A: Basic Statistics

	μ_i		
	All ETFs	Equity ETFs	Bond ETFs
Mean	-0.79	-0.85	-0.40
Std	0.19	0.11	0.19
ETFs	584	509	75

Panel B: Correlation of μ_i with Illiquidity

	All ETFs	Equity ETFs	Bond ETFs
ETF Spread	0.08	0.13	-0.09
	(0.07)	(0.00)	(0.45)
Portfolio Spread	0.63	-0.03	0.22
	(0.00)	(0.48)	(0.05)

We estimate the mean-reversion coefficient, μ_i, of ETF Mispricing from the below regression for each ETF:

$$\Delta Mispricing_{it} = \alpha_i + \mu_i Mispricing_{i,t-1} + \epsilon_{it}$$

where $Mispricing_{it}$ is the absolute value of the log difference between price and NAV of ETF i. Number in parenthesis report the significance level of each correlation coefficient.
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Table 3: Pre-Filtering Regressions: Equity ETFs

	ETF Spread		*Portfolio Spread*		*Mispricing*	
	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
Trend	-0.71	-23.62	0.05	3.60	-2.32	-83.96
Trend^2	-0.20	-5.44	0.05	2.92	0.34	9.94
Pre-holiday Dummy	1.11	8.56	1.60	25.65	0.65	5.45
Tuesday	-0.85	-17.01	0.10	4.17		
Wednesday	-0.71	-14.32	0.15	6.09		
Thursday	-0.77	-15.37	0.12	4.91		
Friday	-0.55	-10.97	1.97	81.87	0.15	4.31
February	-0.28	-3.27	-0.77	-18.88	-0.38	-4.83
March	-0.72	-9.00	-0.90	-23.48	-0.55	-7.40
April	-0.61	-7.23	-0.74	-18.47	-0.36	-4.68
May	-0.80	-9.74	-0.70	-17.81	-0.31	-4.12
June	-0.43	-5.18	-0.71	-17.99	0.49	6.46
July	-0.61	-7.43	-0.63	-16.06	-0.78	-10.36
August	-0.75	-9.03	-0.70	-17.55	-0.57	-7.45
September	-0.90	-11.01	-0.94	-24.01	-0.12	-1.54
October	-0.51	-6.23	-0.58	-14.66	-0.07	-0.94
November	-0.30	-3.49	-0.01	-0.27	-0.26	-3.33
December	-0.25	-3.05	0.26	6.67	0.31	4.09
ETF Fixed Effects	Yes		Yes		Yes	
# of ETFs	509		509		509	
# of obs	366,069		366,069		366,069	
Adj R-squared	0.46		0.63		0.31	

The table reports the regression results of the filtering regressions on the variables for equity ETFs. Trend is a time-trend variable going from -1 at the beginning of the sample to 1 at the end of the sample and quadratic time trend variable is equal to $(\text{Trend}^2 - 1)/2$. Pre-holiday is a dummy variable, taking a value of 1 if it is one business day before a holiday. Tuesday, Wednesday, Thursday, Friday, February, March, April, May, June, July, August, September, October, November, December are day and month dummy variables.
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Table 4: Pre-Filtering Regressions: Bond ETFs

	ETF Spread		*Portfolio Spread*		*Mispricing*	
	Coeff.	t-statistic	Coeff.	t-statistic	Coeff.	t-statistic
Trend	-3.57	-29.04	-16.98	-96.15	-12.76	-51.99
$Trend^2$	-3.38	-25.07	5.94	30.67	3.09	11.46
Pre-holiday Dummy	1.22	2.75	2.19	3.44	0.89	1.01
Tuesday	-0.54	-3.12	0.42	1.70		
Wednesday	-0.29	-1.69	-1.09	-4.41		
Thursday	-0.21	-1.20	-1.63	-6.57		
Friday	0.03	0.16	-1.46	-5.88	0.18	0.66
February	0.98	3.14	2.89	6.43	2.44	3.92
March	0.11	0.39	1.96	4.66	2.13	3.65
April	-0.63	-2.08	-0.68	-1.56	-0.41	-0.67
May	-0.41	-1.40	-0.42	-1.01	-1.97	-3.39
June	1.60	5.44	3.36	7.92	0.60	1.02
July	1.82	6.20	2.50	5.91	1.52	2.59
August	0.43	1.47	3.42	8.07	0.30	0.52
September	0.77	2.57	0.82	1.90	0.42	0.70
October	0.77	2.57	1.00	2.31	-0.43	-0.71
November	0.54	1.70	1.49	3.27	-1.63	-2.59
December	1.59	5.20	4.12	9.39	-0.28	-0.46
ETF Fixed Effects	Yes		Yes		Yes	
# of ETFs	75		75		75	
# of obs	42,891		42,891		42,891	
Adj R-squared	0.54		0.74		0.32	

The table reports the regression results of the filtering regressions on the variables for bond ETFs. Trend is a time-trend variable going from -1 at the beginning of the sample to 1 at the end of the sample and quadratic time trend variable is equal to $(\text{Trend}^2 - 1)/2$. Pre-holiday is a dummy variable, taking a value of 1 if it is one business day before a holiday. Tuesday, Wednesday, Thursday, Friday, February, March, April, May, June, July, August, September, October, November, December are day and month dummy variables.
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Table 5: Correlation Coefficients of Adjusted Variables

Equity ETFs			
	*Mispricing**	*Portfolio Spread**	*ETF Spread**
*Mispricing**	1.00		
*Portfolio Spread**	0.16	1.00	
*ETF Spread**	0.45	0.22	1.00

Bond ETFs			
	*Mispricing**	*Portfolio Spread**	*ETF Spread**
*Mispricing**	1.00		
*Portfolio Spread**	0.28	1.00	
*ETF Spread**	0.41	0.11	1.00

The table reports the correlation coefficients of the ETF variables after the filtering regressions.
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Table 6: PVAR: Domestic Equity ETFs

	Domestic Equity					
	*Mispricing**		*Portfolio Spread**		*ETF Spread**	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
*Mispricing**						
L1.	0.10	32.66	0.00	2.24	0.04	14.81
L2.	0.08	25.80	0.00	1.28	0.03	9.17
L3.	0.07	23.17	0.00	1.09	0.02	8.32
L4.	0.07	23.93	0.00	-3.31	0.02	6.05
L5.	0.07	22.37	0.00	-3.18	0.02	6.90
*Portfolio Spread**						
L1.	0.00	0.25	0.27	79.59	0.01	1.53
L2.	0.00	0.23	0.18	57.06	0.00	0.59
L3.	0.01	2.18	0.15	51.56	0.00	-0.37
L4.	0.00	0.89	0.14	50.71	-0.02	-3.33
L5.	0.01	2.23	0.10	33.92	-0.01	-1.06
*ETF Spread**						
L1.	0.03	11.94	0.00	1.15	0.12	34.33
L2.	0.03	12.89	0.00	2.06	0.10	30.65
L3.	0.03	11.42	0.00	-3.13	0.09	25.41
L4.	0.02	8.50	0.00	-3.49	0.08	24.30
L5.	0.03	10.17	0.00	0.39	0.08	25.04
# obs			366,069			
ETFs			509			
Average # of days for an ETF			719.19			

The table reports the estimation results for equity ETFs from the PVAR analysis described in equation 6.
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Table 7: PVAR: Bond ETFs

	Bond ETFs					
	*Mispricing**		*Portfolio Spread**		*ETF Spread**	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
*Mispricing**						
L1.	0.36	43.08	0.02	3.62	0.02	3.97
L2.	0.20	24.27	0.00	0.92	0.01	1.16
L3.	0.13	15.70	0.00	0.41	0.01	1.31
L4.	0.08	9.96	0.00	0.06	0.00	0.41
L5.	0.09	11.47	0.01	1.96	0.00	-0.25
*Portfolio Spread**						
L1.	0.02	2.86	0.28	33.65	0.01	2.07
L2.	0.00	-0.58	0.19	24.70	0.00	1.02
L3.	0.00	0.48	0.16	20.48	0.00	0.67
L4.	0.01	1.24	0.13	17.52	0.00	-0.50
L5.	0.01	1.94	0.17	22.06	0.00	0.93
*ETF Spread**						
L1.	0.05	3.78	0.01	1.01	0.25	21.97
L2.	0.01	0.82	-0.01	-0.79	0.15	13.32
L3.	0.03	2.02	0.00	-0.72	0.11	10.78
L4.	0.00	0.27	0.01	1.12	0.09	9.12
L5.	0.00	0.08	-0.01	-1.57	0.09	8.59
# obs			42,891			
ETFs			75			
Average # of days for an ETF			571.88			

The table reports the estimation results for bond ETFs from the PVAR analysis described in equation 6.
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Table 8: Correlation Coefficients of Innovations from PVAR

Equity ETFs			
	*Mispricing**	*Portfolio Spread**	*ETF Spread**
*Mispricing**	1.00		
*Portfolio Spread**	0.01	1.00	
*ETF Spread**	0.08	0.03	1.00

Bond ETFs			
	*Mispricing**	*Portfolio Spread**	*ETF Spread**
*Mispricing**	1.00		
*Portfolio Spread**	0.01	1.00	
*ETF Spread**	0.09	0.01	1.00

The table reports the correlation coefficients for the orthogonalized innovations from the PVAR analysis described in equation 6.
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Table 9: Granger Causality

Panel A: Domestic Equity ETFs

	*Mispricing**		*Portfolio Spread**		*ETF Spread**	
	Chi Square	p-value	Chi Square	p-value	Chi Square	p-value
*Portfolio Spread**	15.51	0.01			16.27	0.01
*ETF Spread**	460.81	0.00	30.40	0.00		
*Mispricing**			30.47	0.00	420.55	0.00
ALL	472.67	0.00	62.41	0.00	456.28	0.00

Panel B: Bond ETFs

	*Mispricing**		*Portfolio Spread**		*ETF Spread**	
	Chi Square	p-value	Chi Square	p-value	Chi Square	p-value
*Portfolio Spread**	27.98	0.00			19.84	0.00
*ETF Spread**	19.33	0.00	5.47	0.36		
*Mispricing**			55.14	0.00	66.51	0.00
ALL	46.88	0.00	62.26	0.00	109.64	0.00

The table reports the Granger-causality test results from the PVAR analysis described in equation 6. The null hypothesis is that the row variable does not Granger-cause the column variable.
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Figure 1: ETF Arbitrage without Transaction Costs.

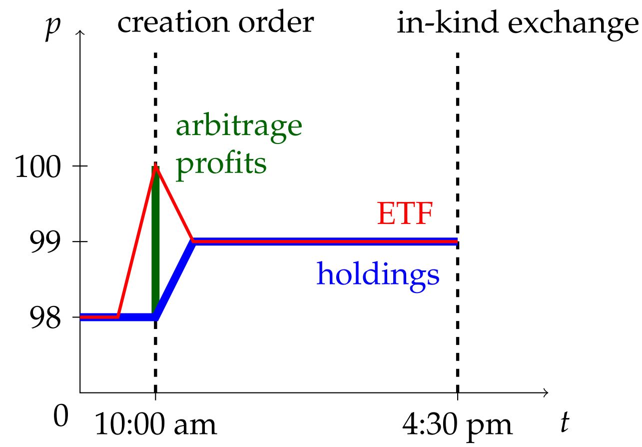


Figure 2: ETF Arbitrage with Transaction Costs.

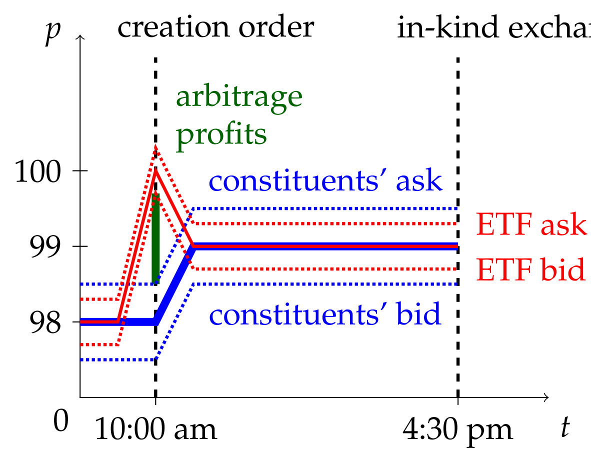
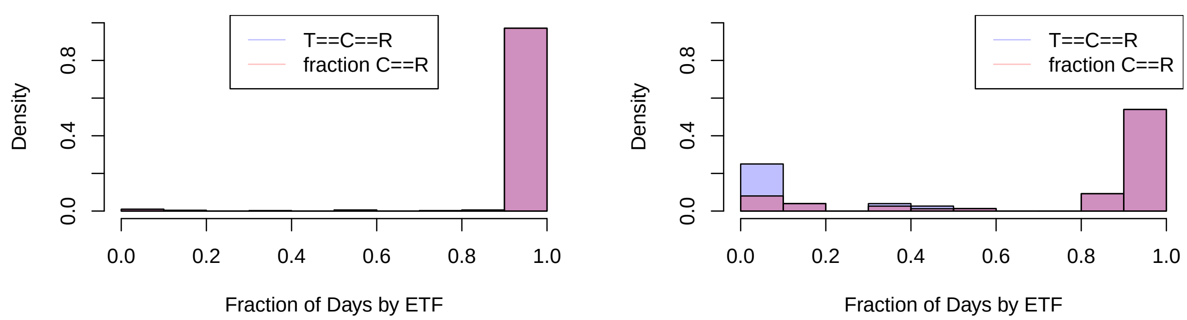


Figure 3: Distribution of Fraction of Days with Equal Baskets

(a) Equity ETFs

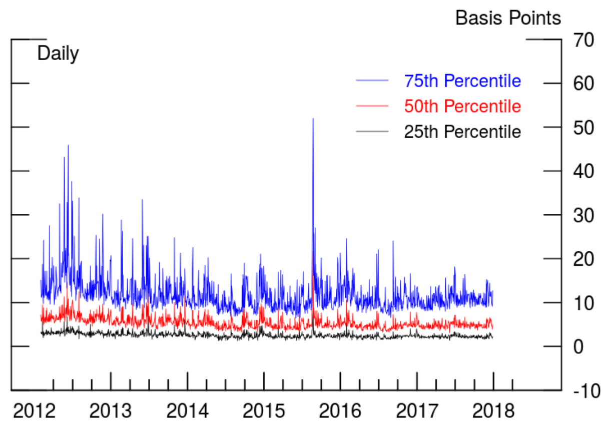
(b) Bond ETFs



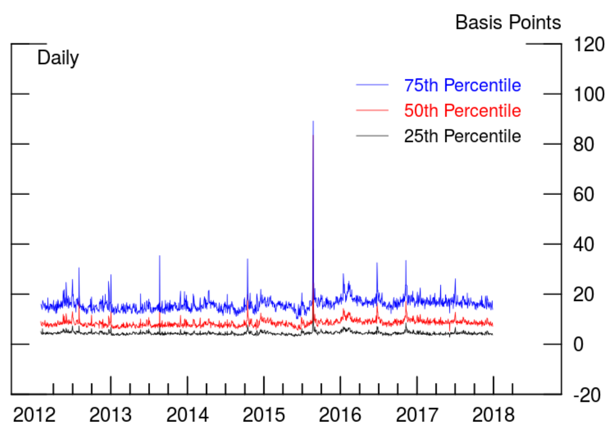
Blue bars denote the distribution of the fraction of days the creation (C), redemption (R), and tracking (T) baskets are all equal. Red bars represent the fraction of these observations where the C and R baskets are equal.
Source: Own elaboration based on Markit North America, Inc.

Figure 4: Domestic Equity: Distribution of ETF Premium, and ETF and Portfolio Spreads

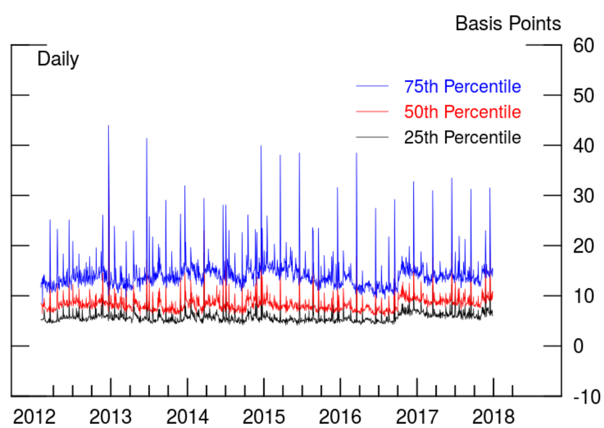
(a) ETF Mispricing



(b) ETF Spread



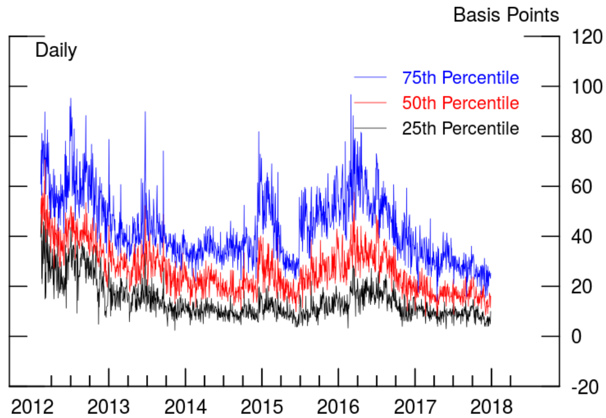
(c) Portfolio Spread



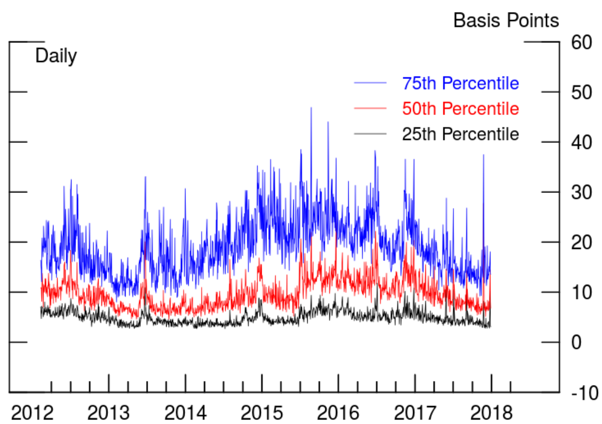
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Figure 5: Domestic Bonds: Distribution of ETF Premium, and ETF and Portfolio Spreads

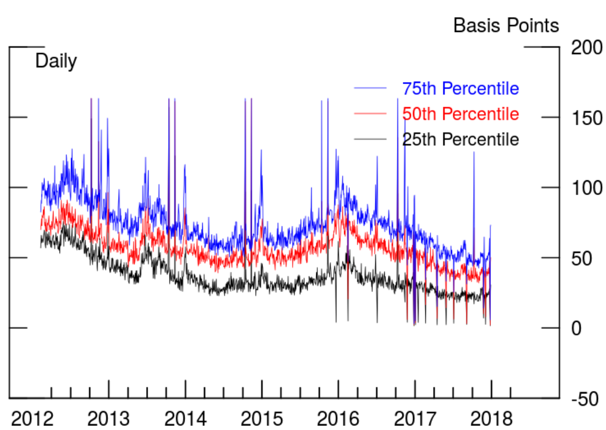
(a) ETF Mispricing



(b) ETF Spread

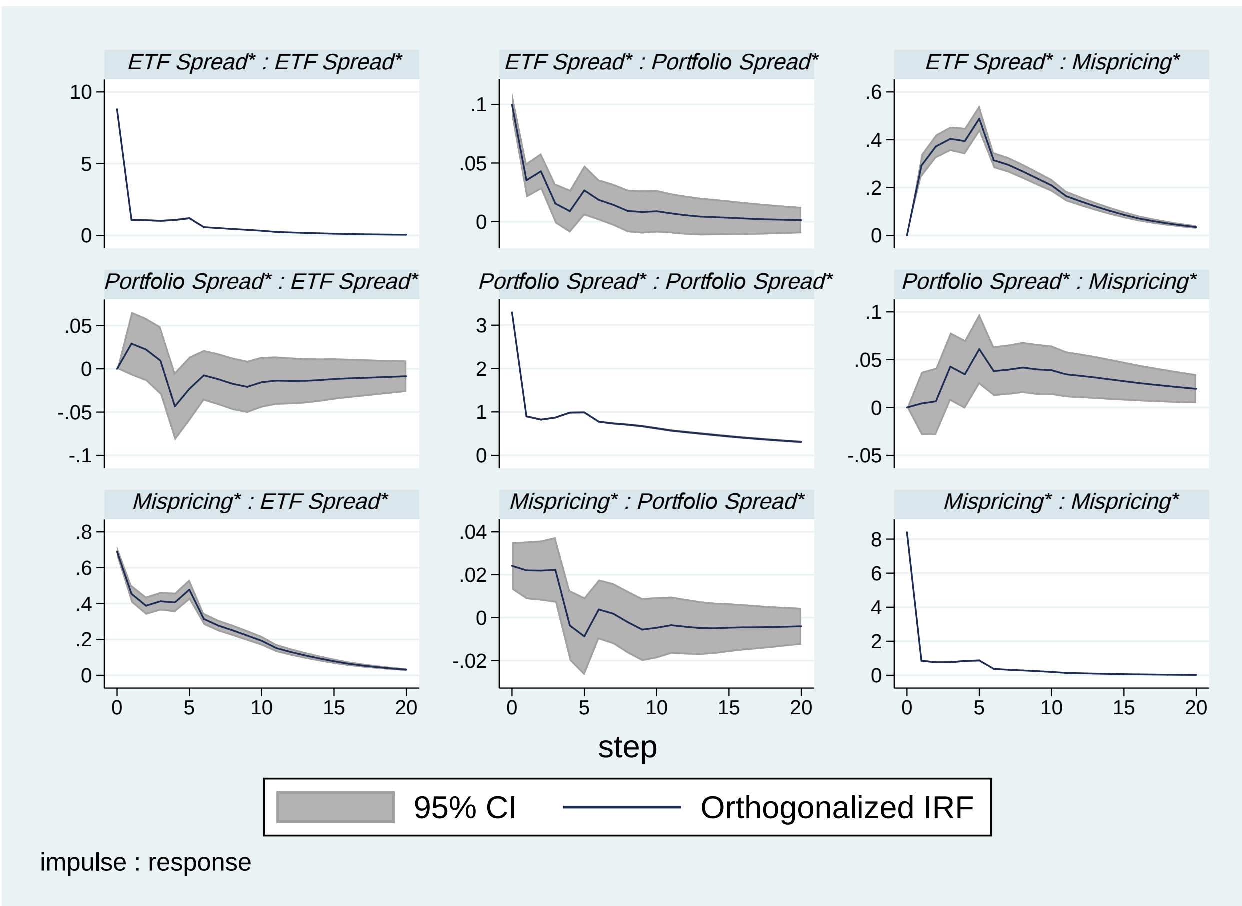


(c) Portfolio Spread



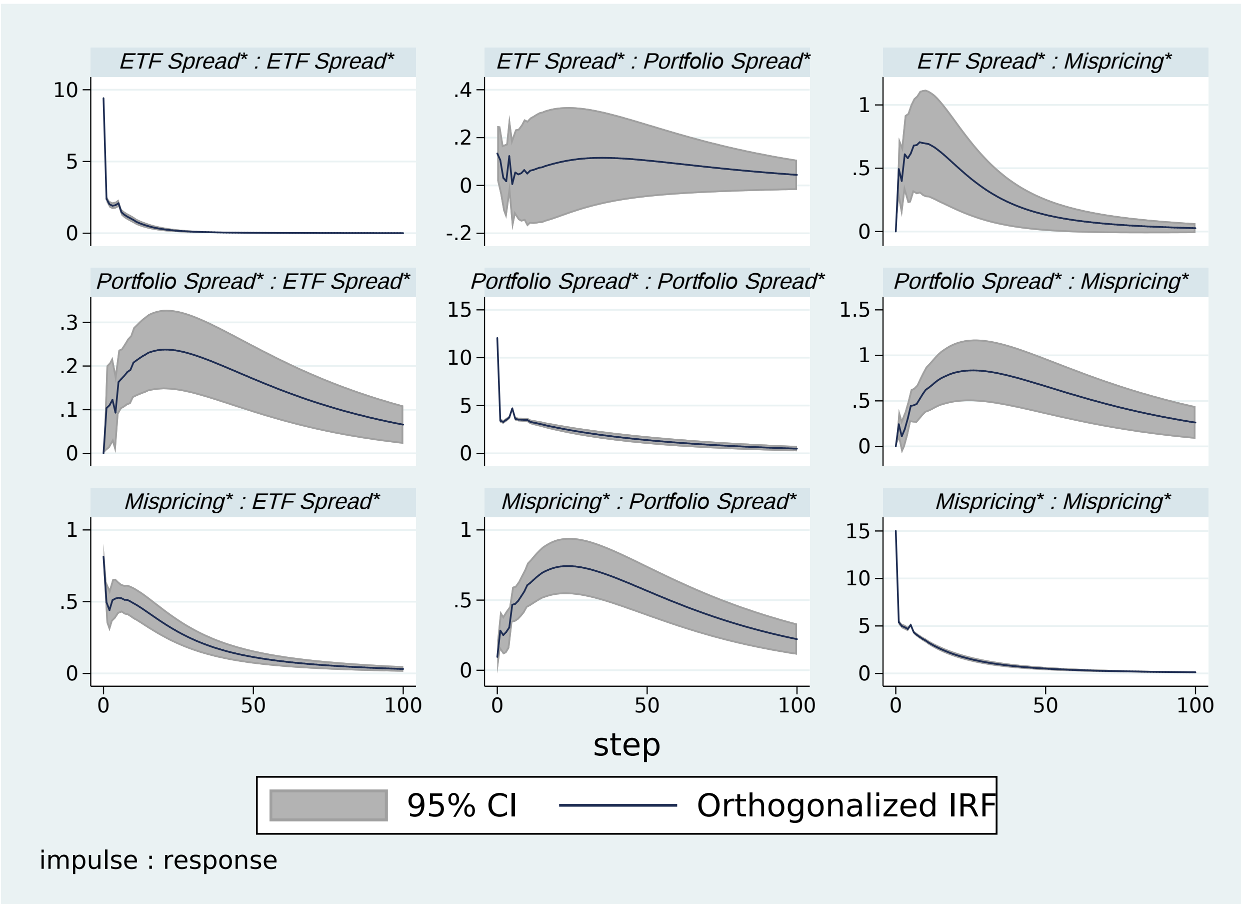
Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.

Figure 6: Equity ETFs: Impulse Response Functions



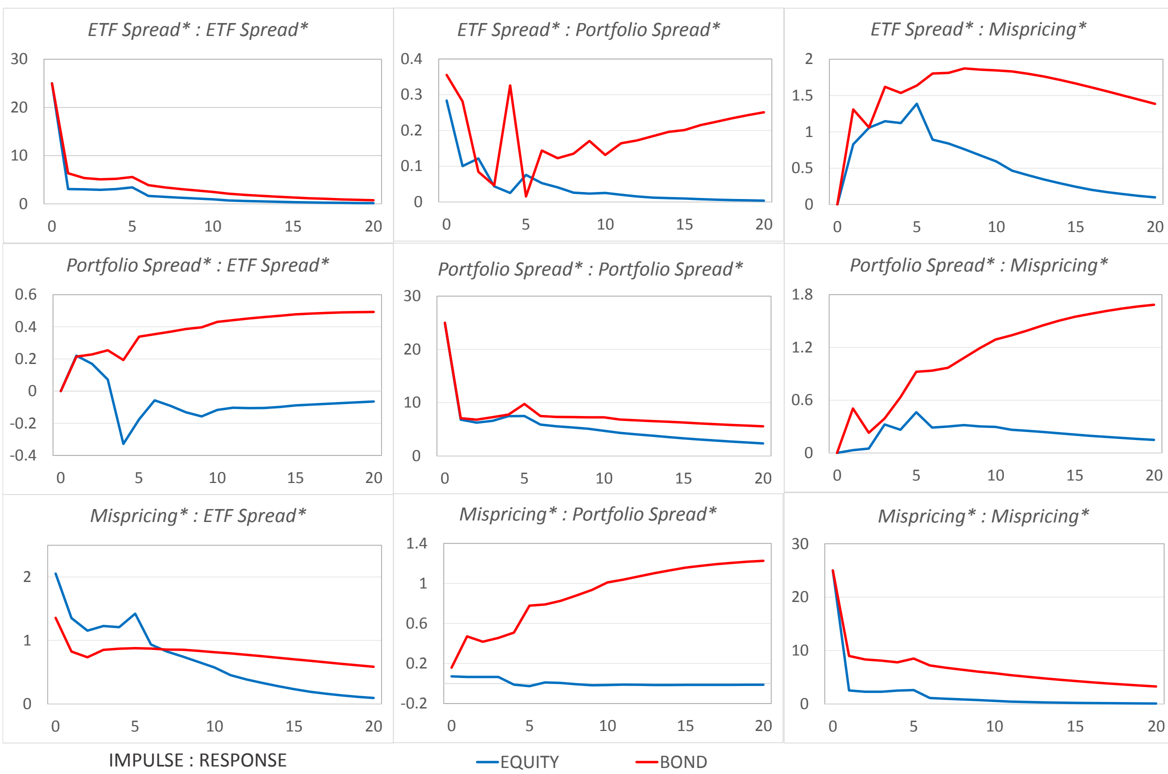
The figure reports the orthogonalized impulse-response functions for equity ETFs from the PVAR analysis described in equation 6. Shaded areas represent the 95 percent confidence bands using 1,000 Monte Carlo replications.
Source: Own elaboration based on IHS Markit ETF, TAQ, TRACE, and Morningstar.

Figure 7: Bond ETFs: Impulse Response Functions



The figure reports the orthogonalized impulse-response functions for bond ETFs from the PVAR analysis described in equation 6. The shaded areas represent the 95 percent confidence bands using 1,000 Monte Carlo replications. Source: Own elaboration based on IHS Markit ETF, TAQ, TRACE, and Morningstar.

Figure 8: IRF: Comparison of Equity and Bond ETFs



The figure reports the orthogonalized impulse-response functions for equity (blue) and bond (red) ETFs from the PVAR analysis described in equation 6. Source: Own elaboration based on Markit North America, Inc., DTAQ, TRACE, and Morningstar.