Do ETFs Increase Volatility?

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April 2014

Abstract

We study whether exchange traded funds (ETFs)—an asset of increasing importance—impact the volatility of their underlying stocks. Using identification strategies based on the mechanical variation in ETF ownership, we present evidence that stocks owned by ETFs exhibit significantly higher intraday and daily volatility. We estimate that an increase of one standard deviation in ETF ownership is associated with an increase of 16% in daily stock volatility. The driving channel appears to be arbitrage activity between ETFs and the underlying stocks. Consistent with this view, the effects are stronger for stocks with lower bid-ask spread and lending fees. Finally, the evidence that ETF ownership increases stock turnover suggests that ETF arbitrage adds a new layer of trading to the underlying securities.

Keywords: ETFs, stocks, volatility, mispricing, fund flow

JEL Classification: G12, G14, G15

We are especially grateful to Robin Greenwood (AFA discussant) and Dimitri Vayanos. We thank George Aragon, Chris Downing, Andrew Ellul, Vincent Fardeau, Thierry Foucault, Rik Frehen, Denys Glushkov, Jungsuk Han, Harald Hau, Augustin Landier, Ananth Madhavan, David Mann, Rodolfo Martell, Albert Menkveld, Robert Nestor, Marco Pagano, Alberto Plazzi, Scott Richardson, Anton Tonev, Tugkan Tuzun, Scott Williamson, Hongjun Yan, and participants at seminars at SAC Capital Advisors, the University of Lugano, the University of Verona, the fourth Paris Hedge Funds Conference, the fifth Paul Woolley Conference (London School of Economics), the eighth Csef-IGIER Symposium (Capri), the fifth Erasmus Liquidity Conference (Rotterdam), the first Luxembourg Asset Pricing Summit, the Geneva Conference and Liquidity and Arbitrage, the 20th Annual Conference of the Multinational Finance Society, and the Swedish House of Finance seminar for helpful comments and suggestions. Ben-David acknowledges support from the Neil Klatskin Chair in Finance and Real Estate and from the Dice Center at the Fisher College of Business. An earlier version of this paper was circulated under the title "ETFs, Arbitrage, and Shock Propagation".

1 Introduction

With $2.5 trillion of assets under management globally as of October 2013,[1] exchange traded funds (ETFs) are rising steadily among the big players in the asset management industry. This asset class is also capturing an increasing share of transactions in financial markets. For example, in August 2010, exchange traded products represented about 40% of all trading volume in U.S. markets (Blackrock (2011)). This explosive growth has attracted the attention of regulators, who have begun to look at the hidden risks to which ETF investors are exposed and the threat that ETFs pose to market stability. For example, Ramaswamy (2011) voices the concern that ETFs may add to the buildup of systemic risks in the financial system. In addition, the U.S. Securities and Exchange Commission (SEC) has begun to review whether ETFs play a role in increasing volatility in the market. Regulators are wary of high frequency volatility because it can reduce participation of long-term investors.[2] Despite these concerns, there is scant systematic evidence about the relation between ETF ownership and the volatility of the underlying securities.

In this paper, we test whether ETFs lead to an increase in the volatility of the securities in their baskets. We use variation in ETF ownership across stocks, as well as variation in ETF mispricing and ETF flows, to measure the effects of ETFs on the volatility of the underlying securities.[3] Our results suggest that ETF ownership increases stock volatility through the

[1] See http://www.hedgefundfundamentals.com/wp-content/uploads/2012/08/HFF_Hedge_Funds_101_10-2013FINAL.pdf

[2] In more detail, the risks to ETF investors relate to their potential illiquidity, which manifested during the Flash Crash of May 6, 2010, when 65% of the cancelled trades were ETF trades. Also worthy of note, regulators have taken into consideration the potential for counterparty risk, which seems to be operating in the cases of both synthetic replication (as the swap counterparty may fail to deliver the index return) and physical replication (as the basket securities are often loaned out). Moreover, concerns have been expressed that a run on ETFs may endanger the stability of the financial system (Ramaswamy (2011)).
With regard to the SEC ETF-related concerns, see "SEC Reviewing Effects of ETFs on Volatility" by Andrew Ackerman, Wall Street Journal, 19 October 2011, and "Volatility, Thy Name is E.T.F.", by Andrew Ross Sorkin, New York Times, October 10, 2011.
With regard to the SEC focus on short-term volatility, see the SEC Concept release No. 34-61358: "[S]hort term price volatility may harm individual investors if they are persistently unable to react to changing prices as fast as high frequency traders. As the Commission previously has noted, long-term investors may not be in a position to access and take advantage of short-term price movements. Excessive short-term volatility may indicate that long-term investors, even when they initially pay a narrow spread, are being harmed by short-term price movements that could be many times the amount of the spread."

[3] In this paper, we label ETF "mispricing" the difference between the market price of the ETF and the Net Asset Value of the ETF (NAV). This definition does not mean to imply that either the ETF or the NAV are correctly priced, while the other is not. We are just complying with the standard jargon in the industry and taking a shortcut with respect to the more cumbersome label of "discount/premium."

arbitrage trades between the ETF and the underlying stocks and, to a lesser extent, through the flows into and out of ETFs.

In an efficient market, the price of an ETF should equal the price of its underlying portfolio, up to transaction costs, because the two assets have the same fundamental value. The fact that new shares of ETFs can be created and redeemed almost continuously facilitates arbitrage so that, on average, the ETF price cannot diverge consistently and substantially from its net asset value (NAV).[4] However, due to their popularity among retail and institutional investors for speculative and hedging purposes, ETFs are increasingly exposed to non-fundamental demand shocks. If arbitrage is limited, these shocks can propagate from the ETF market to the underlying securities.

To understand the mechanics of this effect, consider a large liquidity sell order of ETF shares by an institutional trader. As described in the models of Greenwood (2005) and Gromb and Vayanos (2010), arbitrageurs buy the ETF and hedge this position by selling the underlying portfolio. If arbitrageurs have limited risk-bearing capacity, their demand is not perfectly elastic, and they require compensation in terms of positive expected returns. Hence, the selling activity leads to downward price pressure on the underlying portfolio. Consequently, the initial liquidity shock at the ETF level is propagated to the underlying securities, whose prices fall for no fundamental reason. In this sequence of events, arbitrageur activity induces propagation of liquidity shocks from the ETF to the underlying securities.

We begin our analysis by exploring the relation between stock volatility and ETF ownership. The majority of ETFs aim to replicate the performance of the index. Therefore, they tend to hold stocks in the same proportion as in the index that they track. The identification comes from the fact that variation in ETF ownership, across stocks and over time, depends on factors that are exogenous with respect to our dependent variable of interest. Specifically, the same stock appears with different weights in different indexes. Furthermore, the fraction of ETF ownership in a firm depends also on the size of the ETF (i.e., its assets under management) relative to that of the company. Thus, the variation in the fraction of stock ownership by ETFs, across and within stocks, is largely exogenous. Throughout the study, we use this identification

[4] Unlike premia and discounts in closed-end funds (e.g., Lee, Shleifer, and Thaler (1991), Pontiff (1996)), mispricing between ETF prices and the NAV can more easily be arbitraged away thanks to the possibility of continuously creating and redeeming ETF shares.

strategy because it allows us to rule out effects based on fundamental information. For example, it is possible that flows into ETFs are correlated with fundamental information regarding the underlying stocks (e.g., sector-related news), but it is less likely that fundamental reasons produce an effect on volatility that is stronger for stocks with higher ETF ownership, because ETF ownership depends mechanically on factors that are unrelated to stock volatility.

Our first set of results shows that intraday volatility (calculated based on second-by-second returns) increases with ETF ownership. For S&P 500 stocks, a one standard deviation increase in ETF ownership is associated with a 21% standard deviation increase in intraday volatility. The volatility also survives in daily returns. At this frequency, the effect of a one standard deviation increase in ETF ownership is about 16% of a standard deviation of daily volatility. The effects are generally less economically significant for smaller stocks, consistent with ETF arbitrageurs concentrating on a subset of more liquid stocks to replicate the ETF baskets.

We investigate the economic channels for the propagation of demand shocks from the ETF market to the prices of the underlying securities. ETF arbitrage occurs at different frequencies and in two different ways. First, at high frequencies, typically intraday, arbitrageurs respond to discrepancies in the price of the ETF with respect to the NAV by taking long and short positions in the ETF and the underlying securities. This buying and selling activity can propagate demand shocks from the ETF price to the basket stocks. Second, ETF market makers (Authorized Participants (APs)) create and redeem ETF shares in response to large demand imbalances in the ETF market, which happens on 71% of the trading days in our sample, on average. These flows, which involve the buying or selling of the underlying securities, can also generate price pressure on the underlying basket.

Consistent with the first channel of ETF arbitrage, we document that volatility and turnover increase on days when arbitrage is more likely to occur, that is, when the divergence between the ETF price and the NAV (i.e., the mispricing) is large. Adhering to our identification strategy, we show that this effect is significantly stronger for stocks with high ETF ownership. Further supporting the arbitrage channel, we show that the volatility effect is even stronger among those stocks for which arbitrage activity is less restricted (i.e., those with lower arbitrage costs). The effects are more intense for stocks with small bid-ask spreads and for those with low share lending fees.

With regard to the creation/redemption channel, we again look at variation in ETF ownership across stocks and find that ETF flows impact the volatility of the underlying stocks. Our results show that stock volatility increases with flows to ETFs and that this effect is stronger for stocks with high ETF ownership.

To further rule out the concern that our results are generated by a fundamental shock that impacts the value of the ETFs and the underlying securities rather than by the propagation of liquidity shocks, we examine the behavior of prices in the aftermath of arbitrage and flows. Specifically, we look for evidence of return reversal after the initial price jump associated with ETF arbitrage and flows. Price reversals are evidence of liquidity shocks (see, for example, Greenwood (2005)), whereas fundamental shocks would leave prices at the new level. Our results provide clear evidence of the reversal of the initial price shocks associated with ETF arbitrage and flows, consistent with the conjecture that these channels allow propagation of liquidity shocks.

The evidence of increased exposure of the stocks in the ETF baskets to liquidity shocks would be irrelevant if, in the absence of ETFs, liquidity traders invested directly in the underlying securities. Hence, an important question is whether the presence of ETFs increases the basket securities' overall exposure to liquidity trading. Our evidence suggests that this is the case. Using the same identification as for the volatility effect, we show that stocks with higher ETF ownership have significantly higher turnover. In particular, a one standard deviation increase in ETF ownership is associated with an increase of 16% of a standard deviation in daily turnover. Also, the higher turnover is linked to the same arbitrage channels that are driving the volatility effect. This finding suggests that the high turnover clientele of ETFs is inherited by the underlying stocks as a result of arbitrage. Also, it rules out the explanation that ETFs are merely replacing investors that without the ETFs would trade directly in the stocks.

A few other studies discuss the potentially destabilizing effects of ETFs. Cheng and Madhavan (2009) and Trainor (2010) investigate whether the daily rebalancing of leveraged and inverse ETFs increases stock volatility and find mixed evidence. Bradley and Litan (2010) voice concerns that ETFs may drain the liquidity of already illiquid stocks and commodities, especially if a short squeeze occurs and ETF sponsors rush to create new ETF shares. Madhavan (2011) relates market fragmentation in ETF trading to the Flash Crash of 2010. In work that is more recent than our paper, Da and Shive (2013) find that ETF ownership has a positive effect on the comovement of stocks in the same basket. This result is a direct implication of our finding. We show that ETF ownership increases stock volatility via the propagation of liquidity shocks. Because the stocks in the same basket are going to be affected by the same liquidity shocks, their covariance increases as a result.

More generally, this paper relates to the empirical and theoretical literature studying the effect of institutions on asset prices. There is mounting evidence of the effect of institutional investors on expected returns (Shleifer (1986), Barberis, Shleifer, and Wurgler (2005), Greenwood (2005), Coval and Stafford (2007), and Wurgler (2011) for a survey) and on correlations of asset returns (Anton and Polk (2010), Chang and Hong (2011), Greenwood and Thesmar (2011), Lou (2011), and Jotikasthira, Lundblad, and Ramadorai (2012)). Cella, Ellul, and Giannetti (2013) show that institutional investors' portfolio turnover is an important determinant of stock price resiliency following adverse shocks. Related to our empirical claim, Basak and Pavlova (2013) make the theoretical point that the inclusion of an asset in an index tracked by institutional investors increases the non-fundamental volatility in that asset's prices.

The theoretical framework for the shock propagation effect that we describe is based on the literature on shock propagation with limited arbitrage. Shock propagation can occur via a number of different channels, including portfolio rebalancing by risk-averse arbitrageurs (e.g., Greenwood (2005)), wealth effects (e.g., Kyle and Xiong (2001)), and liquidity spillovers (e.g., Cespa and Foucault (2012)). The mechanism that most closely describes our empirical evidence is the one by Greenwood (2005). Also related to our paper in terms of showing contagion with limited arbitrage, Hau, Massa, and Peress (2010) find that a demand shock stemming from a global stock index redefinition impacts both the prices of the stocks in the index and the currencies of the countries in which these stocks trade.

The paper proceeds as follows. Section 2 provides institutional details on ETF arbitrage and the theoretical framework for the effects that we study. Section 3 describes the data. Section 4 provides the main evidence of the effects of ETF ownership on stock volatility and turnover. Section 5 explores the channels through which ETFs affect volatility. Section 6 concludes.

2 ETF Arbitrage: Institutional Details and Theoretical Framework

2.1 Mechanics of Arbitrage

Exchange traded funds (ETFs) are investment companies that typically focus on one asset class, industry, or geographical area. Most ETFs track an index, very much like passive funds. Unlike index funds, ETFs are listed on an exchange and trade throughout the day. ETFs were first introduced in the late 1980s and became popular with the issuance in January 1993 of the SPDR (Standard & Poor's Depository Receipts, known as "Spider"), which is an ETF that tracks the S&P 500 (which we label "SPY," from its ticker). In 1995, another SPDR, the S&P MidCap 400 Index (MDY) was introduced, and subsequently the number of ETFs exploded to more than 1,600 by the end of 2012, spanning various asset classes and investment strategies. Other popular ETFs are the DIA, which tracks the Dow Jones Industrials Average, and the QQQ, which tracks the Nasdaq-100.

To illustrate the growing importance of ETFs in the ownership of common stocks, we present descriptive statistics for S&P 500 and Russell 3000 stocks in Table 1. Due to the expansion of this asset class, ETF ownership of individual stocks has increased dramatically over the last decade. For S&P 500 stocks, the average fraction of a stock's capitalization held by ETFs has risen from 0.27% in 2000 to 3.78% in 2012. The table shows that the number of ETFs in which the average S&P500 stock appears has grown from just above 2 to about 50 during the same period. The average assets under management (AUM) for ETFs holding S&P 500 stocks in 2012 was $5bn. The statistics for the Russell 3000 stocks paint a similar picture.

In our analysis, we focus on ETFs that are listed on U.S. exchanges and whose baskets contain U.S. stocks. The discussion that follows applies strictly to these "plain vanilla" exchange traded products that do physical replication, that is, they hold the securities of the basket that they aim to track. We omit from our sample leveraged and inverse ETFs that use derivatives to deliver the performance of the index, which represent at most 2.3% of the assets in the sector (source: BlackRock). These more complex products are studied by Cheng and Madhavan (2009), among others.

Similar to closed-end funds, retail and institutional investors can trade ETF shares in the secondary market.[5] However, unlike closed-end funds, new ETF shares can be created and redeemed. Because the price of ETF shares is determined by the demand and supply in the secondary market, it can diverge from the value of the underlying securities (the NAV). Some institutional investors (called "authorized participants," APs), which are dealers that have signed an agreement with the ETF provider, can trade bundles of ETF shares (called "creation units," typically 50,000 shares) with the ETF sponsor. An AP can create new ETF shares by transferring the securities underlying the ETF to the ETF sponsor. These transactions constitute the primary market for ETFs. Similarly, the AP can redeem ETF shares and receive the underlying securities in exchange. For some funds, ETF shares can be created and redeemed in cash.[6]

To illustrate the arbitrage process through creation/redemption of ETF shares, we distinguish the two cases of (i) ETF premium (the price of the ETF exceeds the NAV) and (ii) ETF discount (the ETF price is below the NAV). In the case of an ETF premium, APs have an incentive to buy the underlying securities, submit them to the ETF sponsor, and ask for newly created ETF shares in exchange. Then the AP sells the new supply of ETF shares on the secondary market. This process puts downward pressure on the ETF price and, potentially, leads to an increase in the NAV, reducing the premium. In the case of an ETF discount, APs buy ETF units in the market and redeem them for the basket of underlying securities from the ETF sponsor. Then the APs can sell the securities in the market. This generates positive price pressure on the ETF and possibly negative pressure on the NAV, which reduces the discount.

Creating/redeeming ETF shares has limited costs in most cases, especially for equity-focused funds. These costs include the fixed creation/redemption fee plus the costs of trading the underlying securities. Petajisto (2013) describes the fixed creation/redemption costs as ranging in absolute terms from $500 to $3,000 per creation/redemption transaction, irrespective of the number of units involved. This fee would amount to about 3.4 bps for a single creation unit in the SPY (that is, 50,000 shares worth about $8.8 million as of October 2013), or 0.6 bps for five creation units. During our sample period (2000–2012), share creation/redemption occurs, on

[5] Barnhart and Rosenstein (2010) examine the effects of ETF introductions on the discount of closed-end funds and conclude that market participants treat ETFs as substitutes for closed-end funds.
[6] Creation and redemption in cash is especially common with ETFs on foreign assets or for illiquid assets, e.g., fixed income ETFs.

average, on 71% of the trading days. For the largest ETF, the SPY, flows into and out of the fund occurred almost every day in 2012 (99.2% of the trading days).

Arbitrage can be undertaken by market participants who are not APs and without creation/redemption of ETF shares. Because both the underlying securities and ETFs are traded, investors can buy the inexpensive asset and short sell the more expensive one. For example, in the case of an ETF premium, traders buy the underlying securities and short sell the ETF. They hold the positions until prices converge, at which point they close down the positions to realize the arbitrage profit. Conversely, in the case of an ETF discount, traders buy the ETF and short sell the individual securities. ETF sponsors facilitate arbitrageur activity by disseminating NAV values at a 15-second frequency throughout the trading day. They do so because the smooth functioning of arbitrage is what brings about the low tracking error of these instruments. As a result of the low trading costs and availability of information, arbitraging ETFs against the NAV has become popular among hedge funds and high-frequency traders in recent years (Marshall, Nguyen, and Visaltanachoti (2010)). ETF prices can also be arbitraged against other ETFs (Marshall, Nguyen, and Visaltanachoti (2010)) or against futures contracts (Richie, Daigler, and Gleason (2008)).[7,8]

These institutional details, with some modifications, also apply to synthetic ETFs, which are more prevalent in Europe. These products replicate the performance of the index using total return swaps and other derivatives. As a result, creation and redemption are handled in cash. However, the secondary market arbitrage still involves transactions in the underlying securities. So, the potential for propagation of demand shocks from the ETF market to the underlying securities via arbitrage is also present among synthetic ETFs.

[7] See http://www.indexuniverse.com/publications/journalofindexes/joi–articles/4036–the–etf–index–pricing–relationship.html for a description of trading strategies that eliminate mispricing between ETFs and their underlying securities. Also see: http://ftalphaville.ft.com/2011/05/18/572086/how-profitable-is-etf-arbitrage/. See, e.g., http://ftalphaville.ft.com/blog/2009/07/30/64451/statistical–arbitrage–and–the–big–retail–etf–con/ and http://ftalphaville.ft.com/blog/2011/06/06/584876/manufacturing–arbitrage–with–etfs/. See http://seekingalpha.com/article/68064–arbitrage–opportunities–with–oil–etfs for a discussion of a trading strategy to exploit a mispricing between oil ETFs and oil futures.

[8] To be precise, although these trading strategies involve claims on the same cash flows, they may not be arbitrages in the strict sense because they can involve some amount of risk. In particular, market frictions can introduce noise into the process. For example, execution may not be immediate, shares may not be available for short selling, or mispricing can persist for longer than the arbitrageurs' planned horizon for the trade. In the remainder of the paper, when we refer to ETF arbitrage, we are implying the broader definition of "risky arbitrage."

Finally, although we limit our analysis to ETFs that track equity indexes, the arbitrage process is an inherent characteristic of all types of ETFs. As a consequence, one should expect the effects of ETFs that we describe in this paper to play out for types of underlying assets as well.

2.2 Theoretical Framework

We conjecture that the arbitrage between ETFs and the securities in their baskets can propagate a liquidity shock from the ETF market to the prices of these securities. The arrival of liquidity shocks in the ETF market adds a new layer of non-fundamental volatility to the prices of the basket securities. As a consequence, total volatility of the underlying securities can increase due to ETF ownership.

We use Greenwood's (2005) model with risk-averse market makers to explain the channel of shock transmission that we wish to identify. The market makers in the model can be thought of as the Authorized Participants or, more generally, the arbitrageurs in the ETF market. We apply this model to two assets with identical fundamentals: the ETF and the basket of underlying securities (whose market value is the NAV of the ETF). To illustrate, we imagine a situation in which the ETF price and the NAV are aligned at the level of the fundamental value of the underlying securities, as in Figure 1a. Then, a non-fundamental shock, such as an exogenous increase in demand, hits the ETF market. This type of shock could happen, for example, if a large institution receives inflows and scales up its existing ETF allocation. Arbitrageurs absorb the liquidity demand by shorting the ETF. Because they are risk averse, the arbitrageurs require compensation for the (negative) inventory in the ETF that they are holding. Hence, the ETF price has to rise (Figure 1b). At the same time, to hedge their short ETF position, arbitrageurs take a long position in the securities in the ETF basket. This buying activity puts upward pressure on the prices of the basket securities, as in Figure 1c. Eventually, as in the last period of Greenwood's (2005) model, prices revert back to fundamentals (Figure 1d).

In this sequence of events, shock transmission results from the trading of risk-averse investors who require compensation for holding assets in the two markets. To provide the investors with the required risk premium, prices have to adjust in both markets.

In Greenwood's (2005) model, the long and short hedging trades happen simultaneously (i.e., the movements in Figures 1b and 1c happen at the same time). Moreover, given that there is a unique market maker, two assets with identical payoffs always end up having the same price, and no discrepancy between the ETF price and the NAV can be present at any time. As a result, a strict adherence to the model would prevent the ETF price from ever deviating from the NAV. Although this simple theoretical framework allows us to describe the mechanism for liquidity shock transmission, we need a richer model to capture the fact that in reality the ETF price and the NAV can diverge for some time.

Cespa and Foucault (2012) provide a useful framework with multiple investor classes and some degree of market fragmentation. They assume three types of traders: liquidity demanders, who submit market orders in one of two markets, and two types of liquidity suppliers: market makers, who are specialized in one asset class, and cross-market arbitrageurs, who trade securities in both markets. Arbitrageurs respond to misalignments in the prices of the assets in the two markets. The model is static in the sense that all investor classes trade in the same period. As a result, even with this model, price discrepancies between two identical assets cannot emerge.

One can conceive a dynamic extension of the Cespa and Foucault (2012) framework in which trade occurs sequentially. In the first period, there is a liquidity shock in one of the two assets that is accommodated by market makers via a price adjustment. In the next period, the market makers for the second asset observe the price realization of the first asset and adjust their own price. Cross-market arbitrageur trading also occurs in the second period, bringing about price convergence between the two assets. In this dynamic framework, the prices of two identical assets can temporarily differ (in the first period). In this modified framework, arbitrageurs' risk aversion and hedging trades are still crucial for the transmission of liquidity shocks between the two markets.

The mechanism that we have just described generates predictions that partly overlap with those from an alternative scenario positing gradual price discovery after a shock to fundamentals. According to this alternative view, prices behave similarly to the description in Figure 1, but the trigger is a fundamental shock rather than a liquidity shock. Specifically, it is possible that price discovery takes place in the ETF market first, for example, because it is more liquid. Then, when fundamental information gets to the market, ETF prices adjust immediately, but the underlying securities' prices remain temporarily fixed ("stale pricing"). The slow adjustment of the NAV generates a sequence of price moves that resembles those in Figure 1. This situation is illustrated in Figure 2. The initial equilibrium (Figure 2a) is perturbed by a shock to the fundamental value of the ETF components (Figure 2b). If price discovery takes place in the ETF market, the ETF price moves first (Figure 2c) and the prices of the underlying securities move with a delay (Figure 2d).

Because stale pricing could be a relevant phenomenon, especially for the more illiquid underlying securities, we need to show that liquidity shock propagation does take place. The crucial distinction between the liquidity shock propagation mechanism that we wish to identify (Figure 1) and the alternative scenario with stale pricing (Figure 2) is that non-fundamental shocks induce a reversal in stock prices (Figure 1d). This does not happen if the initial shock is a fundamental one, as in the price discovery scenario. Hence, in our empirical analysis, we provide evidence of price reversal for the underlying securities to corroborate our conjecture that arbitrage trading can transfer liquidity shocks across markets.

The claim that ETF ownership increases volatility faces the challenge of clearly specifying the counterfactual. Our view is that in the absence of ETFs, the underlying stocks would be less affected by liquidity shocks because of the lower incidence of arbitrage trading. Specifically, we posit that ETFs attract a new clientele with significantly higher turnover than the original investors in the underlying stocks. Theoretical support for our conjecture comes from Amihud and Mendelson (1986) who posit that investors with shorter holding periods self-select into assets with lower trading costs. In the specific case of ETFs, this theory implies that the low transaction costs of these securities attract a new clientele of high-turnover investors. These traders impound liquidity shocks at a higher frequency in the ETF prices. In our story, these shocks are then transmitted to the underlying securities via arbitrage. [9]

A different view is that, if ETFs were not available, the same investors would directly trade the underlying securities. According to this argument, ETFs are simply another vehicle through which the same clientele trades in the underlying securities. The implication of this logic

[9] Because we claim that the low trading costs of ETFs attract high-frequency traders, our stance is analogous and symmetric to the argument that transaction taxes can deter short-term investors from affecting asset prices (Stiglitz (1989), Summers and Summers (1989)). The literature is split on this issue (Jones and Seguin (1997)).

is that, in the absence of ETFs, the non-fundamental shocks would hit directly the underlying securities' prices and their volatility would still be impacted. A prediction of this argument is that ETFs are a replacement for the underlying securities, as far as trading volume is concerned. Grossman (1989) makes a related point about futures. He argues that the volatility of the prices of the underlying assets would be even higher in the absence of futures, because future markets, being more liquid, are better suited to absorb non-fundamental shocks.

Ultimately, whether low transaction costs of ETFs attract a clientele of high-frequency traders that increase the exposure of the underlying securities to non-fundamental shocks is an empirical question. A prediction of our claim, which separates it from the alternative view, is that ETF ownership is related to higher turnover in the underlying securities. This consideration motivates us to use turnover as an additional dependent variable, besides volatility, in our empirical tests. Specifically, using an identification strategy based on the exogenous variation in ETF stock ownership, we intend to show that the presence of ETFs is related to higher stock turnover. Also, to further support our claim, the empirical analysis aims to draw a positive link between stock turnover and proxies for ETF arbitrage activity.

3 Data

We use Center for Research in Security Prices (CRSP), Compustat, Bloomberg, and OptionMetrics data to identify ETFs traded on the major U.S. exchanges and to extract returns, prices, and shares outstanding. To identify ETFs, we first draw information from CRSP for all 1,554 securities that have the historical share code of 73, which exclusively defines ETFs in the CRSP universe. We then screen all U.S.-traded securities in the Compustat XpressFeed and OptionMetrics data, identifying ETFs using the security-type variables, and merge this sample with the CRSP ETF sample.[10] Our initial sample consists of 1,883,124 daily observations for 1,673 ETFs between 1993 and 2012. Because very few ETFs traded in the 1990s, we restrict the sample to the 2000–2012 period. Among other statistics, Table 1 reports stock-level averages of the number of ETFs and of the AUM of the ETFs, broken down by the S&P 500 and Russell 3000 universes. The table shows that the number of ETFs holding the average stock increased

[10] Note that at the time of the first draft of this paper in 2011, the CRSP-Compustat merged product did not correctly link ETF securities in the CRSP and Compustat universes. For this reason, we use historical CUSIP and ticker information to map securities in the CRSP, Compustat, and OptionMetrics databases.

dramatically since the year 2000, for both S&P 500 and Russell 3000 stocks. In 2000, there were two ETFs per stock in both universes, on average, compared to 49 and 27 in 2012 for the average S&P 500 and Russell 3000 stock, respectively. Furthermore, as the total market capitalization of ETFs increased, the average ownership of ETFs per stock increased from 0.3% in 2000 to 3.8% in 2012.

We use total shares outstanding at day-end to compute the daily market capitalization of each ETF and to measure the net share creations/redemptions of each ETF at the daily level. Because CRSP shares outstanding figures are stale during the month, we assessed the accuracy of three databases that provide shares outstanding data at a daily frequency: Bloomberg, Compustat, and OptionMetrics. Thanks to direct validation by BlackRock, we concluded that Bloomberg is more timely in updating ETF shares outstanding when newly created or redeemed shares are cleared with the Depository Trust & Clearing Corporation (DTCC). On many occasions, Compustat and OptionMetrics shares outstanding data lag Bloomberg by up to three and sometimes five days. Therefore, Bloomberg is our primary source for shares outstanding and the related net flow measures. We use Compustat and OptionMetrics to complement the ETF series when there are gaps in the Bloomberg data.

We then obtain net asset value (NAV), in addition to fund styles (objectives) and other characteristics, from the CRSP Mutual Fund and Morningstar databases. Our initial ETF sample consists of 1,673 ETFs, many of which invest in various asset classes and non-U.S. securities. To examine how arbitrage amplifies liquidity shocks to underlying securities through creating/redeeming ETF shares and secondary market arbitrage, we restrict our sample to ETFs that invest primarily in U.S. domestic equity stocks, because they are not plagued with stale pricing issues (global equity or bond ETFs) or other issues (short bias, volatility, and futures-based ETFs, commodities, etc.). Therefore, we exclude leveraged, short equity ETFs, and all ETFs that invest in international or non-equity securities, or in futures and physical commodities. We also eliminate hedge and long/short ETFs as well as dedicated short bias funds and focus on plain vanilla U.S. domestic long equity ETFs. To do so, we use both CRSP Style Codes and Lipper prospectus objective codes in the CRSP Mutual Fund Database to restrict our sample to the fund objectives that span broad-based U.S. Diversified Equity funds and U.S. sector ETFs that invest in equities (e.g., U.S. companies investing in oil and natural resources vs. those investing in oil or commodity futures).[11] We end up with 660 U.S. equity ETFs, for which we obtain quarterly holdings information using Thomson-Reuters Mutual Fund holdings database. ETFs are subject to Investment Company Act reporting requirements, and similar to mutual funds, they have to disclose their portfolio holdings at the end of each fiscal quarter.[12] We use these data to align ETF ownership every month using the most recently reported holdings. Then, for every stock, we sum the total ownership by various ETFs to construct our ETF holdings measure.

We use Trade and Quote database (TAQ) data to compute stock-level volatility at a daily frequency from second-by-second data. For each stock, we compute a return in each second during the day using the last trade price at the end of each second during market hours (between 9:30 am and 4:00 pm). Then, we compute the standard deviation of those second-by-second returns as the intraday volatility measure.[13] Daily turnover is computed as CRSP volume divided by shares outstanding.

Using TAQ, we extract the ETF end-of-day prices exactly at 4:00 pm to ensure that ETF prices and the underlying NAV are computed at the same time. Some ETFs are traded until 4:15 pm (Engle and Sarkar (2006)), but the major U.S. stock markets close at 4:00 pm; thus, we use 4:00 pm ETF prices drawn from the intraday TAQ feed as the last trade in the ETF at or before 4:00 pm. Then, we compute ETF mispricing as the difference between the ETF share price and the NAV of the ETF portfolio at day close. Mispricing is expressed as a fraction of the ETF price. Part of our analysis is carried out at a monthly frequency. To this end, we compute volatility at a monthly frequency from the standard deviation of daily returns within the month.

[11] The Lipper Asset Code is not sufficient to accurately filter for U.S. domestic equity funds, because the Equity Funds code comprises of a wide array of U.S. and global funds that implement various direct investment or alternative/inverse strategies. Instead, we use Lipper Objective Code classifications that are assigned by Lipper to a specific population of equity funds and are based on how the fund invests by looking at the actual holdings of the fund to determine market cap and style versus a benchmark. We restrict our sample to the following Lipper Objective Codes: Board Based U.S. Equity: S&P 500 Index Objective Funds, Mid-Cap Funds, Small-Cap Funds, Micro-Cap Funds, Capital Appreciation Funds, Growth Funds, Growth and Income Funds, and Equity Income Funds ('CA' ,'EI' ,'G' ,'GI' ,'MC' ,'MR' ,'SG' ,'SP' respectively). We also include Sector Funds that invest in U.S. companies: Basic Materials, Consumer Goods, Consumer Services, Financial Services, Health/Biotechnology, Industrials, Natural Resources, Real Estate, Science and Technology, Telecommunications, Specialty/Miscellaneous Funds, and Utilities (BM, CG, CS, FS, H, ID, NR, RE, TK, TL, S, and UT, respectively).

[12] We find that Thomson Mutual Fund Ownership data is more reliable and more complete than CRSP Mutual Fund Holdings until mid-2010.

[13] We also compute intraday volatility using intraday returns based on NBBO midpoints, and the results are similar.

We extract stock lending fees from the Markit Securities Finance (formerly Data Explorers) database. The database contains about 85% of the OTC security lending market, with historical data going back to 2002. In constructing the aggregate security loan fee, Markit extracts the agreed fees from contract-level information and constructs a fee value that is the volume weighted average of each contract-level security loan fee. We use the variable that reports the average lending fee over the prior seven days.

Table 2 reports summary statistics for the variables that we use in the regressions. Panel A presents summary statistics for the day-stock level sample. Panel B presents summary statistics for the month-stock level sample. Panel C presents a correlation table for the variables in the daily-frequency sample. We further describe these variables in later sections.

4 The Effect of ETF Ownership on Volatility and Turnover

4.1 Identification

Our objective is to test whether ETF ownership leads to an increase in the volatility of the underlying securities. To this end, we exploit the variation in ETF ownership across stocks and over time.

ETF ownership of stock *i* at time *t* is defined as the sum across ETFs holding the stock of the dollar value of holdings divided by the stock's capitalization. We write this as

$$ETF\ owernship_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} AUM_{j,t}}{Mkt\ Cap_{i,t}}, \qquad (1)$$

where *J* is the set of ETFs holding stock *i*; $w_{i,j,t}$ is the weight of the stock in the portfolio of ETF *j*; and $AUM_{j,t}$ is the assets under management of ETF *j*.

From Equation (1), it appears that variation in ETF ownership across stocks and over time primarily comes from three sources. First, stocks are typically part of multiple indices (e.g., a stock might be part of the S&P 500, the S&P 500 Value, the Russell 3000, and sector indices). Second, there is variation in ETFs' assets under management; thus, the dollar amount that the ETFs invest across stocks varies. Third, there is variation in weighting schemes. The S&P 500 and many other indexes are capitalization-weighted, but the Dow Jones is price-weighted. Our identifying assumption is that variation in ETF ownership resulting from these three sources is exogenous with respect to our dependent variables of interest, stock volatility and turnover, especially when stock-level controls (such as market capitalization and liquidity) are included in the regression. Conditioning on a given universe, such us the S&P 500 and the Russell 3000, characteristics like volatility and turnover play no role in determining the sub-index to which a stock belongs (e.g., S&P 500 Growth or Value or sector indices). Also, investors' demand for ETFs, which determines AUM, and the way in which indices are calculated are exogenous with respect to the dependent variables. Given these considerations, we believe that the identifying assumption is well founded.

To further ensure that our results are driven by exogenous variation in ETF ownership, in our preferred specifications we control for stock-level fixed effects. In these regressions, the variation in ETF ownership is for the same stock over time, and we control for unobservables that are potentially correlated with the dependent variable.

Based on Equation (1), we can anticipate that there is a mechanical negative correlation between ETF ownership and stock capitalization. This can happen if the weights at the numerator do not grow fast enough with capitalization to compensate for the increase in the denominator. The summary statistics in Table 2 confirm that ETF ownership and market capitalization are unconditionally negatively correlated. Considering that market capitalization is negatively correlated with volatility (Table 2), which is one of the main dependent variables of interest in our analysis, the negative relation between ownership and size could induce a spurious positive relation between ownership and volatility. To filter out this mechanical link, we include controls for market capitalization in all of our analyses.

Overall, these arguments suggest that there is exogenous variation in ETF ownership that can be used to identify the effect of ETFs on volatility. We isolate this exogenous component of ETF ownership by controlling for stock size and fixed effects.

4.2 ETF Ownership, Intraday Volatility, and Turnover

In line with regulators' concerns that the recent wave of financial innovation may affect high-frequency volatility, we start by looking at whether ETF ownership has an impact on intraday volatility. Using daily stock-level observations, we regress intraday volatility, computed using second-by-second returns from TAQ, on prior-day ETF ownership as well as on prior-day controls for size and liquidity. The controls for liquidity are the inverse of the stock price, the Amihud (2002) measure of price impact, and the bid-ask spread expressed as a percentage. We also include day fixed effects in all regressions and add stock fixed effects in even numbered columns. Standard errors are clustered at the stock level.

Because we argue that the additional volatility coming from ETF ownership stems from trading by a high-turnover clientele, we also study the effect of ETF ownership on stock turnover. In specifications that mirror those for volatility, we use stock turnover as the dependent variable, computed as the CRSP dollar volume divided by market capitalization.

First, we limit our sample to the S&P 500 stock universe. The volatility results are presented in Table 3, Columns (1) and (2). The regressions show that intraday volatility is significantly related to ETF ownership. In light of the identification strategy described above, we assert that these estimates establish a causal link between ETF ownership and stock volatility. Column (2) indicates that a one standard deviation increase in ETF ownership is associated with higher volatility by 19% of a standard deviation.[14] The effect seems economically important.

In Columns (3) and (4) of Table 3, we explore whether ETF ownership also affects stock turnover. The estimates reveal a positive and significant relation between ETF ownership and turnover. Column (4) shows that a one standard deviation increase in ETF ownership is associated with higher turnover by about 19% of a standard deviation.[15] Again, the effect seems economically large and supports the view that ETFs attract a high-turnover clientele.

In Columns (5) to (8), we repeat these tests for the sample of Russell 3000 stocks. After controlling for stock fixed effects, we again find a significant relation between ETF ownership and stock volatility. In both turnover specifications, the estimates are statistically significant. In this sample, however, the effects are substantially smaller than for large stocks. For example, Column (6) shows that a one standard deviation increase in ETF ownership raises intraday volatility by about 8% of a standard deviation. Quite plausibly, arbitrageurs are less likely to rely

[14] (0.243 * 0.014) / 0.018 = 0.1890.
[15] (11.631 * 0.014) / 0.853 = 0.1909.

on small stocks to replicate ETF baskets. Hence, small stocks' prices and volume are less impacted by ETF ownership.

The results in Table 3 provide our primary evidence that volatility and turnover are significantly related to ETF ownership. Because of our identification strategy, we consider variation in ETF ownership as exogenous with respect to the dependent variables, especially after controlling for stock characteristics and fixed effects. Hence, we feel that we can attribute a causal interpretation to the estimates in Table 3. Overall, this analysis helps to establish that ETFs are catalysts for demand shocks that ultimately affect the underlying securities.

4.3 Effects of ETF Ownership on Daily Return Volatility

Our results in Table 3 show that ETF ownership is associated with higher return volatility within the day. However, a legitimate concern is that while it is possible that ETFs affect the microstructure of trading for the underlying securities, these effects are washed out over longer horizons. To examine this possibility, we study whether the effects that we identify are a short-lived phenomenon (e.g., induced by high-frequency traders) or whether these effects also exist at frequencies that are relevant for long-term investors. We define our explanatory variables at the monthly frequency and construct the dependent variable, volatility, using the daily return observations within a month. In this way, we can study whether ETF ownership impacts the volatility of daily returns.

Table 4 shows a regression of daily stock volatility in a given month on the average ETF ownership of the stock within the month. We use stock-level controls to absorb effects that could induce a mechanical link between ownership and our dependent variable. To this purpose, we include (the logarithm of) the market capitalization of the stock as well as the same controls for liquidity as in Table 3. We cluster standard errors both at the date and the stock levels. In addition, date and stock fixed effects are included in all the specifications.

In Columns (1) to (3), we limit the sample to S&P 500 stocks, and in Columns (4) to (6), we extend it to Russell 3000 stocks. The regressions in Columns (1) and (4) show that stock volatility is positively related to ETF ownership and that the effect is stronger for large stocks. In Column (1), a one standard deviation increase in stock ownership for S&P 500 stocks (1.44%) is associated with a 20 bps increase in daily volatility, which represents 16% of the standard deviation of the dependent variable.[16] The economic significance is therefore large. Extending the universe to smaller stocks (Column (4)), the effect is diluted, amounting to about 5% of a standard deviation.[17] This finding confirms the evidence for intraday volatility in Table 3.

Next, we preview the arbitrage channels through which ETF ownership affects stock volatility. These effects are studied in more detail in Section 5. In Table 4, Columns (2) and (5), the explanatory variable is the volatility of stock-level mispricing within a given month. Mispricing is the value-weighted average of the mispricing of the ETFs holding the stock. The weights are proportional to the dollar holdings of the stock by a given ETF. Rather than averaging daily stock-level mispricing, which would conceal the fact that both positive and negative mispricing provides arbitrage opportunities, we compute its volatility, which treats positive and negative mispricing equally.[18] This variable is meant to capture the extent of arbitrage opportunities emerging during a month. In both samples of stocks, our proxy for arbitrage opportunities has a positive and significant relation with stock-level volatility. Consistent with the effects of ETF ownership (Columns (1) and (4)), we find a stronger effect in the sample of large stocks (Column (2)) than smaller stocks (Column (5)). For S&P 500 stocks, a one standard deviation increase in the explanatory variable (0.003) raises stock volatility by about 22% of a standard deviation.[19] The effect is smaller at 5.2% of a standard deviation in the sample of Russell 3000 stocks.[20] Especially among large stocks, the economic significance of the impact on stock volatility of the proxy for ETF arbitrage seems large even at this lower frequency.

Our second measure of arbitrage focuses more closely on the creation/redemption channel. In Columns (3) and (6), the explanatory variable is the volatility of stock-level flows, which are the sum of ETF flows (that is, the dollar value of creations/redemptions, scaled by the lagged ETF market capitalization) allocated to a given stock across all the ETFs holding the stock, as a fraction of the stock's market capitalization. Again, we take the volatility of this variable to avoid averaging positive and negative flows (the sum of absolute flows gives similar

[16] (0.144 * 1.440) / 1.290 = 0.1607.
[17] (0.041 * 1.730) / 1.490 = 0.0476.
[18] We obtain similar results if we use the average of absolute mispricing as the explanatory variable.
[19] (94.223 * 0.003) / 1.290 = 0.2190.
[20] (25.973 * 0.003) / 1.490 = 0.0522.

results). The results are consistent with our prediction that the creation/redemption activity exerts pressure on the prices of the underlying securities, which translates into higher stock volatility. Like in the previous regressions, the impact of flows on volatility is stronger for S&P 500 stocks, amounting to 13% of a standard deviation for a one standard deviation increase in the explanatory variable. For Russell 3000, the effect is weaker, at 3.4% of a standard deviation.[21]

Overall, the evidence suggests that the effect of ETFs on volatility persists beyond the intraday horizon. The daily volatility we study in this section is relevant for investors, such as mutual funds, that do not trade at high frequencies but still reallocate their portfolio on a daily basis. The next section extends the analysis of the arbitrage channel and the impact of ETF ownership on stock volatility.

5 Exploring the Arbitrage Channel

As discussed in Section 2, we posit that ETFs propagate demand shocks to the underlying securities. Consequently, a new layer of liquidity shocks hit the basket securities. In Section 4, we provide evidence consistent with this conjecture by showing that stocks with higher ETF ownership display higher volatility and turnover. We also show that both the ETF average mispricing and flows within a month affect daily stock volatility. In this section, we look more closely at the arbitrage channel.

[21] For S&P500 stocks: (3.757 * 0.045) / 1.290 = 0.131; for Russell 3000 stocks: (0.939* 0.055) / 1.490 = 0.034.

5.1 Stock Volatility, ETF Ownership, and Arbitrage Activity

Arbitrage occurs in two ways. At high frequencies, arbitrageurs take long and short positions in ETFs and the underlying baskets and wait for price convergence. At lower frequencies, Authorized Participants create and redeem ETF shares to profit from mispricing. In both cases, arbitrageurs and APs react to price discrepancies between the ETF price and the NAV (ETF mispricing). Hence, in our first set of tests, we use stock-level mispricing as a proxy for arbitrage trading. Then, focusing more closely on AP activities, we also measure arbitrage trading using creation and redemption of ETF shares. Thus, in a second set of tests, we use stock-level ETF flows as a proxy for arbitrage activity.

5.1.1 Arbitrage Trades following ETF Mispricing

Stock-level absolute mispricing is the value-weighted average of the absolute value of the mispricing of the ETFs holding the stock. The absolute value is motivated by the fact that arbitrage responds to both positive and negative levels of mispricing. The weights are proportional to the fraction of the stock owned by each ETF (i.e., ETF ownership). For stock *i* on day *t*, mispricing is defined as

$$abs\left(ETF\ mispricing_{i,t}\right) = \frac{\sum_{j=1}^{J} \left|Mispricing_{j,t}\right| * ETF\ owernship_{i,j,t}}{\sum_{j=1}^{J} ETF\ owernship_{i,j,t}}, \tag{2}$$

where *J* is the set of ETFs holding stock *i* at time *t*, and $Mispricing_{j,t}$ is the difference between the ETF price and its NAV, scaled by the ETF price and measured using closing prices.

Then, our regression specification is

$$\begin{aligned} Volatility_{i,t} &= \alpha + \beta_1\ abs\left(ETF\ mispricing_{i,t-1}\right) * ETF\ ownership_{i,t-1} + \\ &\beta_2\ abs\left(ETF\ mispricing_{i,t-1}\right) + \beta_3\ ETF\ ownership_{i,t-1} \\ &+\beta_4\ Controls_{i,t-1} + Stock\ FE + Day\ FE + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

We run a similar specification using stock turnover as the dependent variable. We use the same controls as in Table 3, and standard errors are clustered at the stock level.

Our variable of interest in equation (3) is the interaction between ownership and mispricing. We posit that because of arbitrage, the effect of ownership on volatility and turnover is stronger for stocks that are held by ETFs with larger mispricing. We use lagged end-of-day mispricing to test this supposition because it proxies for arbitrage that takes place during day *t*. Using day-*t* mispricing instead does not materially affect the results.

Table 5, Panel A, presents the regressions. In Column (1), we observe that intraday volatility increases with the absolute ETF ownership. As expected, the effect is significantly stronger for stocks with high ETF mispricing, which is reflected in the slope on the interaction between the absolute ETF mispricing and ETF ownership. For stocks that have close to zero ETF ownership, the effect of ETF mispricing is minimal. A one standard deviation increase in abs(ETF mispricing) is associated with an increase of 0.4% of a standard deviation in volatility.[22] However, if ETF ownership is at its mean (1.9%), the effect is much larger: a one standard deviation increase in abs(ETF mispricing) is associated with an increase of 85.4% of a standard deviation in volatility.[23]

The effect on intraday turnover is large as well (Column (2)). In the absence of ETF ownership, a one standard deviation increase in lagged absolute mispricing is associated with higher intraday turnover by 0.3% of a standard deviation.[24] However, when ETF ownership is at its mean, intraday turnover is higher by 26.3% of a standard deviation.[25]

Although the results for the S&P 500 sample are very strong both statistically and economically, the corresponding results for the Russell 3000 are not significantly different from zero, confirming the prior evidence of a weaker effect on smaller stocks. Overall, these results suggest that the arbitrage of ETF mispricing is an important channel to explain the impact of ETF ownership on volatility, especially for large stocks.

5.1.2 Arbitrage Activity by APs

Next, we more directly test the impact of ETF arbitrage through creation and redemption activity by APs. We measure stock-level flows using the following definition:

[22] 0.006 * 0.013 / 0.018 = 0.0043.
[23] (0.006 * 0.013 + 42.035* 0.013 * 0.019) / 0.018 = 0.8543.
[24] (0.207 * 0.013) / 0.853 = 0.0032.
[25] (0.207 * 0.013 + 896.893 * 0.013 * 0.019) / 0.853 = 0.2628.

$$abs\left(ETF\ Flows_{i,t}\right) = \sum_{j=1}^{J} \frac{\sum_{j=1}^{J} \left| \frac{Fund\ flows_{j,t}}{AUM_{j,t-1}} \right| * ETF\ owernship_{i,j,t}}{\sum_{j=1}^{J} ETF\ owernship_{i,j,t}}. \tag{4}$$

For each stock *i* and day *t*, we sum the product of the percentage of flows into the ETFs that own the stock and the percentage ownership of the ETF in the stock. For example, if ETF j experiences a flow of 1% and owns 10% of stock *i*, the stock is likely to experience a demand for 1% * 10% = 0.1% of its shares. Because both positive (share creation) and negative (share redemption) flows represent arbitrage activity, in equation (4) we take the absolute value of the flows.

Our specification resembles equation (3), but we replace $abs\left(ETF\ Flows_{i,t}\right)$ with $abs\left(ETF\ mispricing_{i,t-1}\right)$. Table 5, Panel B, presents the results of the regressions. We first consider the S&P 500 sample (Columns (1) and (2)). The main effect of ETF ownership on stock volatility (Column (1)) remains positive and significant. Moreover, the effect is magnified for stocks with higher flows. When ETF ownership is at its mean, a one standard deviation increase in absolute ETF flows translates into volatility that is higher by 3.7% of a standard deviation.[26]

The effect of ETF ownership interacted with flows on stock turnover is similar in magnitude and significance (Column (2)). For the mean value of ETF ownership, a one standard deviation increase in absolute ETF flows is associated with turnover higher by 6.6% of a standard deviation.[27]

Columns (3) and (4) present similar regressions for the Russell 3000 sample. Here, the results are in the same direction as in the S&P 500 sample. They are weaker for volatility and stronger for turnover. For stocks at the mean level of ownership, a one standard deviation increase in absolute ETF flows translates into an increase of 1.2% of a standard deviation in intraday volatility[28] and of 12.3% of a standard deviation in intraday turnover.[29]

In sum, our findings support the conjecture that ETF ownership also increases volatility and turnover through the channel of share creation/redemption by market makers (APs). The

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[26] (-0.009 * 0.013 + 3.197 * 0.019 * 0.013) / 0.018 = 0.0373.
[27] (-0.090 * 0.013 + 232.101 * 0.019 * 0.013) / 0.853 = 0.0534.
[28] (0 * 0.080 + 0.141 * 0.021 * 0.080) / 0.020 = 0.0118.
[29] (-0.129 * 0.080 + 70.306 * 0.021 * 0.080) / 0.875 = 0.1227.

importance of this channel, however, seems smaller in magnitude than the effect originating from ETF mispricing arbitrage.

5.2 Evidence of Price Reversals for the Underlying Stocks

Our conjecture is that arbitrage trades between ETFs and their replicating portfolios are able to cause an increase in non-fundamental volatility of the underlying stocks. To corroborate this prediction, it is crucial to provide evidence consistent with the propagation of non-fundamental shocks by ETF arbitrage.

The alternative scenario to our conjecture is one in which trading in the underlying securities is motivated by fundamental information. The fundamental news is impounded in the ETF price first and then, with a delay, into the prices of the underlying securities (stale pricing). This view can also explain the observed correlation between arbitrage trades and stock volatility if the new information generates both increased trading activity and higher volatility.

In Section 2.2, we argue that a key distinction between these two scenarios is whether, following the initial price impact of arbitrage trades, stock prices revert toward the initial equilibrium (as in Figure 1) or whether they remain at the new level (as in Figure 2). In the first case, consistent with our conjecture, one can conclude that the price change following arbitrage trades is, at least in part, due to a non-fundamental shock.

As in Section 5.1, we use mispricing and flows to identify arbitrage trades. In this case, however, the sign of these variables matters for the direction of the price impact and the subsequent reversal. Specifically, positive mispricing (i.e. an ETF premium) triggers purchases of the underlying stocks. Hence, on the first day in which arbitrage trades occur, we expect a positive price impact on the underlying stocks. In the next days, we expect a reversal if the arbitrage-triggering shock is non-fundamental (as in Figure 1). Similarly, positive flows (share creation) involve purchases of the underlying securities. Hence, on the first day, we expect a positive price impact and a reversal in the following days.

To test this conjecture, we first use mispricing as a signal for arbitrage trades and adopt the following specification:

$$Ret(t_1, t_2)_{i,t} = \alpha + \beta_1 ETF\ Ownership_{i,t-1}$$
$$+\beta_2\ ETF\ Ownership_{i,t-1} * ETF\ mispricing_{i,t-1} + \beta_3\ ETF\ mispricing_{i,t-1} \quad (5)$$
$$+\ \beta_4\ Stock\ controls_{i,t-1} + Day\ FE + \varepsilon_{i,}$$

where $Ret(t_1, t_2)$ is the stock return measured between days t_1 to t_2. When $t_1 = t_2 = t$, we use the returns on the same day that the arbitrage trades take place. In this case, we expect β_2 to be positive. To test for reversal, we let $t_1 = t + 1$ and $t_1 = t + K$ (with K = 5, 10, 20 days) and expect β_2 to be negative and significant. We use day-stock level observations and cluster the standard errors at the stock level to control for the autocorrelation of residuals induced by overlapping observations for multiday returns.

The evidence in Table 6, Panel A, is broadly consistent with our expectation that arbitrage propagates non-fundamental shocks. In Column (1), we observe that the first-day effect of ETF mispricing is positive and significant, and it is magnified by ETF ownership. The magnitude of the effect can be calculated as follows. For the S&P 500 sample (Column (1)), a one-standard deviation move in ETF mispricing, for stocks with the mean level of ETF ownership (0.019), brings about an increase in daily returns of 0.085%.[30] This seems like a large effect given that the mean daily return in the sample is 0.053%.

For completeness, we report the estimate for Russell 3000 stocks (Column (5)). In this sample, the main effect of mispricing is not significant, while the sign on the interaction between ownership and mispricing is actually negative, which confirms the evidence from the previous sections that ETF arbitrage plays a less significant role in this universe.

In the days following the trade, we expect prices to revert. For example, at times when the ETF trades at a premium relative to the NAV, after the initial positive impact on the NAV, we expect to see a downward drift in stock prices. This prediction is confirmed in Columns (2) to (4). For windows of 5 to 20 days, stock returns are negatively correlated with the ETF mispricing, as predicted. This correlation is more negative for stocks with higher ETF ownership.

The economic magnitude of the reversal is large. Consider the month-long window (Column (4)) for the S&P 500 sample. A one standard deviation increase in mispricing at $t = 0$, for stocks with ETF ownership at its mean (0.019), is associated with lower returns of –0.344%

[30] (1.043 * 0.012 + 321.266 * 0.019 * 0.012) = 0.0857%.

over the next trading month.[31] Given that mispricing is persistent, this large reversal, exceeding in magnitude the first day price impact, can be the result of the unwinding of the price impacts from days prior to day $t = 0$. For the Russell 3000 (Column (8)), the effect is close to zero and is statistically insignificant, which is consistent with the evidence from the prior tables of a weaker effect of flows on smaller stocks.

We also measure the behavior of prices following the redemption/creation of ETF units by APs, which is the other channel through which arbitrage can propagate non-fundamental shocks, according to our conjecture. Inflows into ETFs emerge if APs purchase the underlying securities and convert them into ETF units. ETF outflows result from APs converting ETF units into the underlying securities, which are sold in the market. Because the price impact on the underlying stocks is different as a function of the direction of the flows, the sign of the flows is now important and the explanatory variable is net flows, as opposed to absolute flows.

Table 6, Panel B, estimates the one- and multiple-day price reaction to ETF flows. Focusing on S&P 500 stocks, consistent with our conjecture, an increase in flows on day $t = 0$ generates positive pressure on the same day (Column (1)), and it reverts in the following days (Columns (2) to (4)). From Column (1), a one-standard deviation increase in ETF flows, for stocks at the mean level of ownership, is associated with higher returns by 0.01%.[32] Then, comparing the first-day price impact in Panels A and B of Table 6, we conclude that the effect of flows is significant, but less economically large than the effect of mispricing arbitrage, which is consistent with the evidence in Table 5.

Column (5) of Panel B, Table 6, shows that the first-day impact for Russell 3000 stocks, contrary to our expectation, is negative. This finding confirms that the evidence for smaller stocks is less robust. Also possible, because of the lower liquidity in this universe of stocks, APs start trading the underlying securities a few days before creation/redemption. As a result, on day $t = 0$, the price impact has already started to revert.

In the days following $t = 0$, prices revert, consistent with our conjecture. For the S&P 500 sample, when ETF ownership increases from zero to the mean level, a one-standard

[31] (–1.671 * 0.012 – 1421.138 * 0.019 * 0.012) = –0.3440%.
[32] (0.255 * 0.019 + 16.245 * 0.019 * 0.019) = 0.0107%.

deviation increase in ETF flows is correlated with next-20-day returns of –0.156%.[33] Columns (5) to (8) present the effects for Russell 3000 stocks. Here, the reversal effect is also significant, but smaller in magnitude.

In sum, we show that stocks prices follow a patter which is consistent with arbitrage having a role in propagating non-fundamental shocks. Our results show that the effect is stronger for S&P 500 stocks than for Russell 3000 stocks. One potential reason for the less significant role of arbitrage trades in the Russell 3000 universe is that smaller stocks are subject to greater limits of arbitrage. We explore this possibility in the next sub-section.

5.3 Limits to Arbitrage

To validate the conjecture that the effects we identify operate through the arbitrage channel, we introduce interactions with proxies for limits to arbitrage. Our prior is that arbitrage trading should be less important when limits to arbitrage are more binding. We use two proxies for limits to arbitrage: the stock-level bid-ask spread and stock lending fees.

Because ETF arbitrage involves a roundtrip transaction in the stock, a large stock-level bid-ask spread reduces the profitability of arbitrage trades and the incidence of arbitrage trading in a given stock. The prediction is, therefore, that the volatility and turnover of stocks with high bid-ask spreads are less sensitive to proxies of ETF arbitrage. In Table 7, Panel A, we split the sample according to the median percentage bid-ask spread in the cross-section of stocks in the prior day and re-run the analysis from Table 3. The panel shows that overall the sensitivity of both volatility and turnover to the interaction of absolute mispricing and ETF ownership is higher for stocks with a low spread. For the same level of mispricing and ETF ownership, the impact on intraday volatility and turnover is lower for high bid-ask spread stocks. The only exception to this pattern comes from the turnover of S&P 500 stocks.

We find additional evidence consistent with our conjecture when examining the effects on intraday volatility and turnover of ETF flows (Table 7, Panel B). Similar to Panel A, we regress intraday volatility and turnover on ETF ownership interacted with absolute ETF flows, as well as main effects, controls, and fixed effects. We are interested in the way the coefficient on

[33] (-4.062*0.019-222.293*0.019*0.019) = –0.1566%.

the interaction varies across columns. The sample is split by bid-ask spread, with odd columns containing stocks with below-median spreads and even columns containing stocks with above-median spreads. The results show that in most regression pairs, the effects are stronger for the low bid-ask spread sample than for the high bid-ask spread sample. These results are consistent with the idea that APs are reluctant to create/redeem shares when the costs of the transactions are too high.

Next, we use stock lending fees as a proxy for limits to arbitrage. When the lending cost is high, arbitrageurs are less likely to engage in arbitrage transactions, because the transaction costs associated with short selling shares are higher, hence reducing the profitability of trades. Also, a high lending fee can reflect a shortage in shares for lending, meaning that some arbitrageurs may simply not be able to carry out the trade. Our prior is that the effects of arbitrage trades on intraday volatility and turnover are expected to be stronger when lending fees are lower.

Table 7, Panel C, presents evidence of this effect. For both intraday volatility and turnover, the effect of absolute mispricing is weaker, for a given level of ETF ownership, when lending fees are higher (even-numbered columns). In other words, when stock lending fees are high, ETF ownership does not increase intraday volatility as much for a given level of mispricing.

To provide evidence that APs' trades are also affected by the cost of shorting, we split the sample by lending fees and repeat the tests for fund flows. The results are presented in Table 7, Panel D. Again, we are interested in the coefficient on the interaction between ETF ownership and the absolute measure of fund flows. Consistent with our prior, the results show that in all specifications the effect is stronger for the subsample that has low lending fees (odd-numbered columns).

Overall, these results validate our claim that arbitrage is the channel through which ETFs impact stock volatility and turnover. Whenever arbitrage is more costly, as signaled by a higher bid-ask spread or steeper stock lending fees, the impact of our arbitrage proxies is reduced.

6 Conclusion

ETF prices are tied through arbitrage to the prices of the securities in their baskets because they represent claims to the same stream of cash flows. In this paper, we present evidence that arbitrage activity between ETFs and the stocks in their baskets leads to an increase in stock volatility. We conclude that the liquidity shocks in the ETF market are propagated via arbitrage trades to the prices of underlying securities, adding a new layer of non-fundamental volatility.

Our identification strategy is based on the cross-sectional and time series variation in ETF stock ownership. This variation is exogenous with respect to the variables of interest because it arises from the mechanical weighting schemes of the indexes that are tracked by ETFs and from the fact that assets under management change over time and across ETFs.

Our main finding is that stocks with higher ETF ownership display higher volatility and turnover. A one standard deviation increase in ETF ownership raises daily volatility and turnover by about 16%. We explore the economic channel behind these effects using two proxies for arbitrage trading. First, when the price of ETFs and the underlying baskets diverge, there is a stronger incentive for market participants to arbitrage the difference in prices. We show that stock volatility and turnover indeed increase with the magnitude of this arbitrage opportunity. Second, we use ETF share creation/redemption as a proxy for arbitrage trades. The rationale is that market makers in the ETF market profit from deviations between the ETF price and the NAV by changing the supply of ETF shares. We find that when ETF shares change in either direction, there is a positive impact on stock volatility and turnover. Moreover, the effect of arbitrage trades on the variables of interest is weaker for stocks that are harder to arbitrage, that is, those with higher bid-ask spreads and higher costs of shorting. This evidence corroborates the arbitrage channel as an explanation for the impact of ETFs on the underlying stocks. Finally, we show that the price impact of ETF arbitrage reverts over a multiday horizon, consistent with the initial trigger of the price move being, at least in part, a liquidity shock.

These results emphasize an unintended consequence of financial innovation. New securities with values that are derived from existing securities, such as ETFs, are attractive for arbitrage trades. Liquidity trading in the ETFs generates volatility that is passed down via arbitrage to the underlying securities. While the effects that we point out are obtained in the universe of U.S. stocks, we believe that they can be extended to other asset classes. In this sense, our work relates to a growing literature highlighting the role of index trading in generating non-fundamental volatility and comovement (e.g., Basak and Pavlova (2013)).

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Appendix. Variable Description

Variable	Description	Source
Daily Sample		
ETF ownership	The sum of the ownership by all ETFs holding the stock, using the most recent quarterly investment company reports for equity ETFs.	Thomson-Reuters
log(Mktcap)	The logged market capitalization of the stock (in $ millions) at the end of the day.	CRSP
1/Price	The inverse of the nominal share price at the end of the day.	CRSP
Amihud ratio	Absolute return scaled by dollar volume in $million.	CRSP
Bid-ask spread	The quoted spread divided by the bid-ask midpoint.	CRSP
Intraday volatility	Standard deviation of second-by-second intraday returns.	TAQ
Daily turnover	Total share volume scaled by period-end shares outstanding, after adjusting both volume and shares outstanding for splits and similar events.	CRSP
abs(ETF mispricing)	Stock-day level measure. Weighted average of the absolute percentage difference between the ETF Price and the NAV across the ETFs holding the stock (using the ETF price and NAV at 4:00 pm). The weight is ETF ownership of the stock.	TAQ, Bloomberg, Compustat
abs(ETF flows)	Stock-day level measure. Weighted average of the absolute percentage change in ETF shares outstanding across the ETFs holding the stock. The weight is ETF ownership of the stock.	Bloomberg, Compustat
Ret(t_1, t_2)	The total return of the stock between the close of t_1 and the close of t_2.	CRSP
Lending Fee	Loan fee aggregated at the security level, 7-day average.	Markit
Monthly Sample		
ETF mispricing volatility (within the month)	Standard deviation of day-end ETF mispricing (using the ETF price and NAV at 4:00 pm).	TAQ, Bloomberg, Compustat
ETF flow volatility (within the month)	Standard deviation of the relative change in daily ETF shares outstanding during the month.	Bloomberg, Compustat
log(Mktcap)	The logged market capitalization of the stock (in $ millions) at the end of the month.	CRSP
1/Price	The inverse of the nominal share price at the end of the month.	CRSP
Amihud	Absolute return scaled by dollar volume in $million, average.	CRSP
Bid-ask spread	The quoted spread divided by the bid-ask midpoint.	CRSP

Table 1. ETF Ownership Statistics

The table presents descriptive statistics for ETF ownership of stocks. For each year, across months and stocks, we average the number of ETFs, their assets under management (AUM), the weight of each stock in the ETF, and the percentage of each stocked owned by ETFs. We present statistics for S&P 500 stocks (left columns) and for Russell 3000 stocks (right columns).

	S&P 500				Russell 3000			
Year	#ETFs	Average ETF AUM ($m)	Average stock weight in ETF (%)	Average ownership of ETF in firm (%)	#ETFs	Average ETF AUM ($m)	Average stock weight in ETF (%)	Average ownership of ETF in firm (%)
2000	2.45	5627.93	0.64	0.27	2.41	5129.91	0.53	0.30
2001	13.45	2173.41	0.42	0.63	8.91	1053.93	0.16	0.37
2002	15.47	2798.87	0.45	0.88	10.18	1185.35	0.14	0.71
2003	15.95	3542.45	0.45	1.00	10.42	1465.49	0.14	0.85
2004	21.40	3451.84	0.47	1.06	14.30	1702.26	0.14	1.11
2005	24.74	3756.30	0.49	1.37	15.73	2040.02	0.16	1.37
2006	25.80	4337.34	0.51	1.68	16.81	2447.86	0.17	1.85
2007	36.04	4082.81	0.64	1.97	22.60	2438.93	0.24	2.17
2008	50.61	2980.85	0.69	2.69	30.26	1789.13	0.28	2.81
2009	53.19	2733.88	0.67	3.11	31.30	1710.54	0.26	3.41
2010	52.04	3261.34	0.68	3.16	30.08	2311.04	0.27	3.60
2011	52.77	3977.15	0.67	3.52	28.87	2937.45	0.27	3.77
2012	48.59	5026.84	0.68	3.78	26.93	3434.84	0.26	3.82
Average	30.43	3547.27	0.57	1.90	20.01	2045.99	0.21	2.10

Table 2. Summary Statistics

The table presents summary statistics for the variables used in the study. Panels A and B show summary statistics for the stock-day and for the stock-month samples, respectively. Panel C shows summary statistics for the return regressions (returns are in percentages). Panel D provides correlations. All panels distinguish between the S&P 500 and the Russell 3000 samples.

Panel A: Daily Frequency Sample Statistics

S&P 500

	N	Mean	Std Dev	Min	Median	Max
Intraday volatility (%)	1,480,640	0.022	0.018	0.004	0.016	0.147
Intraday turnover (%)	1,480,640	0.970	0.853	0.031	0.700	6.230
ETF ownership	1,480,640	0.019	0.014	0.000	0.016	0.092
abs(ETF mispricing)	1,480,640	0.002	0.013	0.000	0.001	3.960
abs(ETF flows)	1,480,640	0.008	0.025	0.000	0.005	7.370
log(Mktcap ($m))	1,480,640	9.270	1.130	5.040	9.170	13.400
1/Price	1,480,640	0.041	0.038	0.001	0.031	0.870
Amihud	1,480,640	0.0004	0.0009	0.0000	0.0002	0.0315
Bid-ask spread	1,480,640	0.003	0.006	0.000	0.001	0.098

Russell 3000

	N	Mean	Std Dev	Min	Median	Max
Intraday volatility (%)	7,712,862	0.025	0.020	0.004	0.019	0.147
Intraday turnover (%)	7,712,862	0.874	0.875	0.029	0.596	6.230
ETF ownership	7,712,862	0.021	0.018	0.000	0.016	0.092
abs(ETF mispricing)	7,712,862	0.009	0.055	0.000	0.001	42.300
abs(ETF flows)	7,712,862	0.013	0.080	0.000	0.006	87.600
log(Mktcap ($m))	7,712,862	7.000	1.540	0.616	6.760	13.400
1/Price	7,712,862	0.081	0.117	0.000	0.050	40.000
Amihud	7,712,862	0.020	0.055	0.000	0.003	0.965
Bid-ask spread	7,712,862	0.004	0.006	0.000	0.002	0.379

Panel B: Monthly Frequency Sample Statistics

S&P 500

	N	Mean	Std Dev	Min	Median	Max
Daily stock volatility (%)	51,349	2.080	1.290	0.612	1.730	10.800
ETF ownership (%; average within the month)	51,349	2.110	1.440	0.050	1.760	9.360
ETF flows volatility (within the month)	51,349	0.045	0.045	0.001	0.033	0.433
ETF mispricing volatility (within the month)	51,349	0.003	0.003	0.000	0.002	0.021

Russell 3000

	N	Mean	Std Dev	Min	Median	Max
Daily stock volatility (%)	311,079	2.610	1.490	0.612	2.240	10.800
ETF ownership (%; average within the month)	311,079	2.320	1.730	0.017	1.880	9.380
ETF flows volatility (within the month)	311,079	0.062	0.055	0.001	0.047	0.435
ETF mispricing volatility (within the month)	311,079	0.003	0.003	0.000	0.003	0.021

Table 2. Summary Statistics (Cont.)

Panel C: Summary Statistics for Return Regressions

S&P 500

	N	Mean	Std Dev	Min	Median	Max
Ret(t)	1,444,095	0.053	2.152	-9.442	0.015	10.388
Ret(t+1,t+5)	1,444,095	0.203	4.655	-19.902	0.220	21.317
Ret(t+1,t+10)	1,444,095	0.386	6.304	-23.861	0.462	25.227
Ret(t+1,t+20)	1,444,095	0.750	8.858	-31.429	0.960	33.667
net(ETF Mispricing)	1,444,095	0.000	0.012	-0.908	0.000	3.919
net(ETF Flows)	1,444,095	0.001	0.019	-9.000	0.000	0.897

Russell 3000

	N	Mean	Std Dev	Min	Median	Max
Ret(t)	7,265,787	0.051	2.526	-9.443	0.000	10.388
Ret(t+1,t+5)	7,265,787	0.177	5.432	-19.902	0.147	21.318
Ret(t+1,t+10)	7,265,787	0.347	7.310	-23.862	0.351	25.227
Ret(t+1,t+20)	7,265,787	0.670	10.317	-31.429	0.749	33.668
net(ETF Mispricing)	7,265,787	-0.007	0.057	-42.325	0.000	27.620
net(ETF Flows)	7,265,787	0.001	0.051	-9.000	0.000	0.917

Panel D: Correlation Table

S&P 500

	Intraday volatility	Intraday turnover	ETF ownership	abs(ETF mispricing)	abs(ETF flows)	log(Mktcap)	1/Price	Amihud
Intraday volatility	1.000							
Intraday turnover	0.390	1.000						
ETF ownership	-0.011	0.375	1.000					
abs(ETF mispricing)	0.046	-0.006	-0.071	1.000				
abs(ETF flows)	0.026	0.023	-0.011	0.047	1.000			
log(Mktcap)	-0.086	-0.217	-0.067	-0.022	0.008	1.000		
1/Price	0.436	0.141	-0.030	0.013	-0.003	-0.391	1.000	
Amihud	0.175	-0.076	-0.192	0.031	0.010	-0.484	0.393	1.000
Bid-ask spread	0.213	-0.151	-0.409	0.048	0.016	-0.167	0.199	0.403

Russell 3000

	Intraday volatility	Intraday turnover	ETF ownership	abs(ETF mispricing)	abs(ETF flows)	log(Mktcap)	1/Price	Amihud
Intraday volatility	1.000							
Intraday turnover	0.271	1.000						
ETF ownership	-0.070	0.180	1.000					
abs(ETF mispricing)	-0.014	-0.037	-0.075	1.000				
abs(ETF flows)	0.015	0.004	-0.016	0.184	1.000			
log(Mktcap)	-0.273	0.119	0.006	-0.068	-0.035	1.000		
1/Price	0.440	-0.044	-0.025	0.003	0.006	-0.393	1.000	
Amihud	0.271	-0.210	-0.157	0.011	0.007	-0.436	0.419	1.000
Bid-ask spread	0.279	-0.177	-0.326	0.082	0.008	-0.256	0.312	0.478

Table 3. ETF Ownership, Intraday Stock Volatility, and Turnover (Daily Sample)

The table reports estimates from OLS regressions of intraday volatility and daily turnover on ETF ownership and controls. In Columns (1) to (4), the sample consists of S&P 500 stocks, and in Columns (5) to (8) the sample consists of Russell 3000 stocks. The frequency of the observations is daily. Intraday stock volatility is computed using second-by-second data from the TAQ database, and daily turnover is computed as daily volume from CRSP divided by shares outstanding. Variable descriptions are provided in the Appendix. Standard errors are clustered at the stock level. *t*-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Sample:	S&P 500				Russell 3000			
Dependent variable:	Intraday volatility		Intraday turnover		Intraday volatility		Intraday turnover	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF ownership (t-1)	0.333***	0.243***	18.869***	11.631***	-0.009	0.069***	7.624***	4.026***
	(9.613)	(7.461)	(7.976)	(8.773)	(-1.360)	(8.883)	(14.875)	(10.027)
log(Mktcap (t-1))	0.003***	0.004***	-0.171***	-0.194***	-0.001***	-0.003***	0.034***	0.077***
	(8.781)	(5.356)	(-10.524)	(-5.552)	(-12.372)	(-10.781)	(6.106)	(9.068)
1/Price (t-1)	0.219***	0.195***	2.826***	1.202**	0.059***	0.032***	0.534***	-0.044
	(20.998)	(12.929)	(6.106)	(2.263)	(26.912)	(12.631)	(12.861)	(-1.048)
Amihud (t-1)	-0.243	-0.333	-158.086***	-123.183***	0.015***	0.020***	-2.551***	-1.141***
	(-0.554)	(-1.038)	(-7.861)	(-7.548)	(6.206)	(8.656)	(-26.777)	(-15.669)
Bid-ask spread (t-1)	-0.124	-0.119*	-9.143***	-7.636***	-0.033	-0.006	-12.764***	-10.096***
	(-1.496)	(-1.872)	(-4.773)	(-5.516)	(-1.211)	(-0.264)	(-12.396)	(-13.161)
Stock fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,472,346	1,472,346	1,472,346	1,472,346	7,687,652	7,687,652	7,687,652	7,687,652
Adjusted R^2	0.425	0.466	0.282	0.464	0.367	0.451	0.123	0.381

Table 4. ETF Ownership and Daily Stock Volatility (Monthly Sample)

The table reports estimates from OLS regressions of daily volatility on ETF ownership, ETF mispricing volatility, and ETF flow volatility. In Columns (1) to (3), the sample consists of S&P 500 stocks, and in Columns (4) to (6), the sample consists of Russell 3000 stocks. The frequency of the observations is monthly. Daily stock volatility is computed using daily returns within a month. Variable descriptions are provided in the Appendix. Standard errors are clustered at the date and stock levels. *t*-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Daily stock volatility (computed within the month)					
Sample:	S&P 500			Russell 3000		
	(1)	(2)	(3)	(4)	(5)	(6)
ETF ownership (average within the month)	0.144***			0.041***		
	(8.190)			(7.051)		
ETF mispricing volatility (within the month)		94.223***			25.973***	
		(12.654)			(10.378)	
ETF flow volatility (within the month)			3.757***			0.939***
			(11.170)			(9.953)
log(Mktcap (t-1))	-0.159***	-0.159***	-0.170***	-0.259***	-0.258***	-0.261***
	(-2.917)	(-3.069)	(-3.168)	(-12.444)	(-12.544)	(-12.666)
1/Price (t-1)	6.494***	6.180***	6.431***	2.750***	2.693***	2.695***
	(7.250)	(7.074)	(7.237)	(11.937)	(11.802)	(11.764)
Amihud (t-1)	87.364***	85.146***	84.791***	0.453*	0.518*	0.503*
	(4.256)	(4.297)	(4.226)	(1.646)	(1.891)	(1.833)
Bid-ask spread (t-1)	23.586**	38.094***	21.167**	3.692	5.364	3.336
	(2.454)	(4.359)	(2.156)	(1.078)	(1.583)	(0.969)
Stock Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,349	51,349	51,349	311,079	311,079	311,079
Adjusted R^2	0.630	0.638	0.630	0.557	0.557	0.557

Table 5. Stock Volatility, ETF Ownership, and Arbitrage

The table reports estimates from OLS regressions of intraday volatility and daily turnover on ETF ownership, variables that proxy for ETF arbitrage, and controls. In Columns (1) to (2), the sample consists of S&P 500 stocks, and in Columns (3) to (4), the sample consists of Russell 3000 stocks. The frequency of the observations is daily. Intraday stock volatility is computed using second-by-second data from the TAQ database, and daily turnover is computed as daily volume from CRSP divided by shares outstanding. In Panel A, the variable of interest is the interaction of lagged absolute ETF mispricing and ETF ownership. In Panel B, the variable of interest is the interaction of lagged absolute ETF fund flows and ETF ownership. Variable descriptions are provided in the Appendix. Standard errors are clustered at the stock level. *t*-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Effect of ETF Mispricing on Volatility and Turnover

Sample:	S&P 500		Russell 3000	
Dependent variable:	Intraday volatility	Intraday turnover	Intraday volatility	Intraday turnover
	(1)	(2)	(3)	(4)
ETF ownership (t-1)	0.186***	10.371***	0.068***	4.005***
	(5.814)	(8.038)	(8.633)	(9.949)
× abs(ETF mispricing (t-1))	42.035***	896.893***	-0.113	-2.660
	(9.876)	(6.860)	(-0.417)	(-0.350)
abs(ETF mispricing (t-1))	0.006***	0.207**	-0.005	-0.085
	(2.749)	(2.459)	(-0.943)	(-0.811)
log(Mktcap (t-1))	0.004***	-0.198***	-0.003***	0.071***
	(5.351)	(-5.658)	(-11.660)	(8.253)
1/Price (t-1)	0.193***	1.145**	0.032***	-0.062
	(12.832)	(2.148)	(12.693)	(-1.454)
Amihud (t-1)	-0.306	-122.456***	0.020***	-1.153***
	(-0.960)	(-7.536)	(8.404)	(-15.860)
Bid-ask spread (t-1)	-0.096	-7.187***	0.004	-9.967***
	(-1.595)	(-5.328)	(0.187)	(-13.096)
Stock fixed effects	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes
Observations	1,471,139	1,471,139	7,679,072	7,679,072
Adjusted R^2	0.470	0.465	0.452	0.381

Table 5. Stock Volatility, ETF Ownership, and Arbitrage (Cont.)

Panel B: Effects of Fund Flows on Volatility and Turnover

Sample:	S&P 500		Russell 3000	
Dependent variable:	Intraday volatility	Intraday turnover	Intraday volatility	Intraday turnover
	(1)	(2)	(3)	(4)
ETF ownership (t-1)	0.229***	10.305***	0.068***	3.328***
	(7.003)	(7.996)	(8.846)	(8.269)
× abs(ETF flows (t))	3.197***	232.101***	0.141*	70.306***
	(5.861)	(5.988)	(1.688)	(8.298)
abs(ETF flows (t))	-0.009***	-0.090	-0.000*	-0.129***
	(-4.521)	(-1.491)	(-1.893)	(-3.466)
log(Mktcap (t-1))	0.004***	-0.198***	-0.003***	0.073***
	(5.240)	(-5.709)	(-11.581)	(8.520)
1/Price (t-1)	0.194***	1.120**	0.032***	-0.063
	(12.769)	(2.130)	(12.692)	(-1.490)
Amihud (t-1)	-0.302	-121.598***	0.020***	-1.137***
	(-0.951)	(-7.525)	(8.458)	(-15.699)
Bid-ask spread (t-1)	-0.112*	-7.565***	0.003	-9.946***
	(-1.792)	(-5.532)	(0.119)	(-13.088)
Stock fixed effects	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes
Observations	1,471,139	1,471,139	7,679,072	7,679,072
Adjusted R^2	0.467	0.466	0.452	0.381

Table 6. Price Reversals

The table reports estimates from OLS regressions of one- and multiday returns on ETF ownership, variables that proxy for ETF arbitrage, and controls. In Columns (1) to (4), the sample consists of S&P 500 stocks, and in Columns (5) to (8), the sample consists of Russell 3000 stocks. The frequency of the observations is daily. Returns are in percent. In Panel A, the variable of interest is the interaction of ETF mispricing and ETF ownership. In Panel B, the variable of interest is the interaction of ETF fund flows and ETF ownership. Variable descriptions are provided in the Appendix. Standard errors are clustered at the stock level. *t*-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Price Reversals Following ETF Mispricing

	S&P 500				Russell 3000			
	Ret(t)	Ret(t+1,t+5)	Ret(t+1,t+10)	Ret(t+1,t+20)	Ret(t)	Ret(t+1,t+5)	Ret(t+1,t+10)	Ret(t+1,t+20)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF ownership (t-1)	0.662***	-2.630***	-5.866***	-10.678***	0.013	-0.487	-0.792	-0.709
	(3.410)	(-2.901)	(-3.316)	(-3.048)	(0.184)	(-1.642)	(-1.360)	(-0.615)
× ETF mispricing (t-1)	321.266***	-492.213***	-308.665	-1,421.138**	-8.326***	-15.234	-17.098	-19.997
	(3.615)	(-2.929)	(-1.061)	(-2.519)	(-3.599)	(-1.345)	(-0.766)	(-0.486)
ETF mispricing (t-1)	1.043***	0.232	-1.614***	-1.671**	-0.000	-0.158	-0.390	-0.793
	(3.843)	(0.593)	(-3.331)	(-2.359)	(-0.007)	(-1.021)	(-1.188)	(-1.237)
log(Mktcap (t-1))	0.014***	-0.038***	-0.079***	-0.142***	0.014***	0.004	0.011**	0.025**
	(6.339)	(-4.608)	(-4.749)	(-4.327)	(13.903)	(1.291)	(1.970)	(2.219)
1/Price (t-1)	-1.025***	1.053***	2.201***	5.919***	-0.615***	-0.324***	-0.496***	-0.322
	(-9.677)	(2.838)	(2.965)	(4.105)	(-20.951)	(-5.709)	(-4.604)	(-1.520)
Amihud (t-1)	28.351***	-19.831	-48.022*	-50.814	0.099***	-1.377***	-2.530***	-4.371***
	(6.601)	(-1.567)	(-1.874)	(-1.095)	(2.864)	(-12.425)	(-12.094)	(-10.679)
Bid-ask spread (t-1)	2.025***	1.423	4.986	10.859	2.159***	-2.294**	-2.840	-5.372
	(3.363)	(0.625)	(1.128)	(1.299)	(6.012)	(-1.986)	(-1.337)	(-1.312)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,426,141	1,426,141	1,426,141	1,426,141	7,090,277	7,090,277	7,090,277	7,090,277
Adjusted R^2	0.325	0.299	0.278	0.281	0.281	0.246	0.223	0.223

Table 6. Price Reversals (Cont.)

Panel B: Price Reversals Following Fund Flows to ETFs

	S&P 500				Russell 3000			
	Ret(t)	Ret(t+1,t+5)	Ret(t+1,t+10)	Ret(t+1,t+20)	Ret(t)	Ret(t+1,t+5)	Ret(t+1,t+10)	Ret(t+1,t+20)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF ownership (t-1)	0.612***	-2.453***	-5.658***	-10.313***	0.070	-0.382	-0.648	-0.482
	(3.124)	(-2.705)	(-3.186)	(-2.941)	(0.999)	(-1.289)	(-1.113)	(-0.419)
× ETF flows (t)	16.245*	-134.935***	-237.910***	-222.293***	-49.383***	-46.006***	-40.958***	-58.873***
	(1.878)	(-5.034)	(-8.528)	(-5.830)	(-14.948)	(-8.489)	(-6.047)	(-6.711)
ETF flows (t)	0.255*	-1.689***	-2.894***	-4.062***	0.067***	-0.117***	-0.087*	-0.036
	(1.942)	(-3.104)	(-5.232)	(-4.629)	(3.743)	(-3.081)	(-1.795)	(-0.558)
log(Mktcap (t-1))	0.015***	-0.039***	-0.079***	-0.144***	0.014***	0.003	0.009*	0.022**
	(6.870)	(-4.665)	(-4.774)	(-4.389)	(13.831)	(0.972)	(1.673)	(2.013)
1/Price (t-1)	-1.003***	1.016***	2.148***	5.752***	-0.616***	-0.326***	-0.500***	-0.333
	(-9.568)	(2.744)	(2.897)	(4.007)	(-20.987)	(-5.750)	(-4.638)	(-1.574)
Amihud (t-1)	30.337***	-17.901	-44.859*	-45.831	0.098***	-1.396***	-2.557***	-4.423***
	(7.039)	(-1.408)	(-1.727)	(-0.990)	(2.850)	(-12.642)	(-12.265)	(-10.843)
Bid-ask spread (t-1)	1.826***	1.298	4.924	11.176	2.107***	-2.160*	-2.547	-4.910
	(3.047)	(0.574)	(1.120)	(1.338)	(5.835)	(-1.871)	(-1.201)	(-1.201)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,419,903	1,419,903	1,419,903	1,419,903	7,078,529	7,078,529	7,078,529	7,078,529
Adjusted R^2	0.326	0.299	0.279	0.281	0.281	0.246	0.223	0.223

Table 7. Evidence from Limits-to-Arbitrage

The table reports estimates from OLS regressions of intraday volatility and daily turnover on ETF ownership, variables that proxy for ETF arbitrage, and controls. In Columns (1) to (4), the sample consists of S&P 500 stocks, and in Columns (5) to (8), the sample consists of Russell 3000 stocks. The frequency of the observations is daily. Intraday stock volatility is computed using second-by-second data from the TAQ database, and daily turnover is computed as daily volume from CRSP divided by shares outstanding. In Panels A and C, the variable of interest is the interaction of lagged absolute ETF mispricing and ETF ownership. In Panels B and D, the variable of interest is the interaction of lagged absolute ETF fund flows and ETF ownership. The sample is split by the lagged bid-ask spread (Panels A and B) or the lagged stock lending fee (Panels C and D). Variable descriptions are provided in the Appendix. Standard errors are clustered at the stock level. *t*-statistics are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Mispricing and Bid-Ask Spread

Sample:	S&P 500				Russell 3000			
Dependent variable:	Intraday volatility		Intraday turnover		Intraday volatility		Intraday turnover	
Bid-ask spread (t-1):	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF ownership (t-1)	0.142***	0.168***	10.017***	8.286***	0.094***	0.066***	3.564***	4.195***
	(4.833)	(4.169)	(7.050)	(5.462)	(8.944)	(7.257)	(6.480)	(9.764)
× abs(ETF mispricing (t-1))	50.828***	17.244***	750.869***	764.789***	0.736***	-0.197	21.775**	-11.773*
	(12.241)	(5.869)	(5.204)	(5.591)	(3.767)	(-0.955)	(2.227)	(-1.956)
abs(ETF mispricing (t-1))	0.003	0.001	0.204**	-0.266	-0.016***	-0.003	-0.429***	-0.007
	(1.388)	(0.189)	(2.149)	(-1.487)	(-4.880)	(-0.753)	(-3.018)	(-0.118)
log(Mktcap (t-1))	0.005***	0.002**	-0.186***	-0.295***	0.000*	-0.005***	-0.037***	0.083***
	(4.044)	(2.541)	(-5.012)	(-7.028)	(1.780)	(-15.029)	(-2.982)	(8.354)
1/Price (t-1)	0.082***	0.190***	-0.985	0.363	0.062***	0.026***	-1.590***	0.028
	(3.555)	(12.505)	(-1.327)	(0.679)	(10.606)	(10.371)	(-6.486)	(0.804)
Amihud (t-1)	-0.467	-0.222	-213.891***	-98.507***	0.048***	0.014***	-3.218***	-0.937***
	(-0.866)	(-0.524)	(-7.192)	(-6.234)	(7.150)	(6.353)	(-10.700)	(-16.194)
Bid-ask spread (t-1)	-0.641***	0.119**	-14.885***	-3.711**	-0.685***	0.081***	-10.460***	-6.150***
	(-5.013)	(2.500)	(-5.906)	(-2.471)	(-8.990)	(3.718)	(-4.387)	(-9.479)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	735,570	735,569	735,570	735,569	3,839,536	3,839,536	3,839,536	3,839,536
Adjusted R^2	0.488	0.522	0.544	0.436	0.407	0.474	0.401	0.362

Table 7. Evidence from Limits to Arbitrage (Cont.)

Panel B: Fund Flows and Bid-Ask Spread

Sample:	S&P 500				Russell 3000			
Dependent variable:	Intraday volatility		Intraday turnover		Intraday volatility		Intraday turnover	
Bid-ask spread (t-1):	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF ownership (t-1)	0.205***	0.169***	9.918***	7.760***	0.099***	0.064***	3.023***	3.562***
	(6.813)	(4.262)	(6.834)	(5.344)	(9.495)	(7.130)	(5.581)	(8.188)
× abs(ETF flows (t))	4.231***	2.648***	275.046***	197.370***	-0.096	0.239**	74.942***	55.122***
	(7.632)	(4.580)	(9.243)	(4.609)	(-0.979)	(2.456)	(12.255)	(6.068)
abs(ETF flows (t))	-0.010***	-0.004**	-0.095	-0.037	0.000*	-0.001***	0.018	-0.133***
	(-4.051)	(-2.004)	(-1.606)	(-0.404)	(1.691)	(-2.949)	(1.536)	(-9.671)
log(Mktcap (t-1))	0.005***	0.002**	-0.186***	-0.294***	0.001*	-0.005***	-0.034***	0.084***
	(3.997)	(2.547)	(-5.094)	(-7.066)	(1.898)	(-14.978)	(-2.725)	(8.478)
1/Price (t-1)	0.086***	0.190***	-0.949	0.338	0.062***	0.026***	-1.590***	0.026
	(3.633)	(12.430)	(-1.284)	(0.637)	(10.610)	(10.370)	(-6.478)	(0.764)
Amihud (t-1)	-0.484	-0.204	-213.397***	-97.238***	0.047***	0.014***	-3.147***	-0.928***
	(-0.868)	(-0.481)	(-7.212)	(-6.185)	(7.068)	(6.410)	(-10.486)	(-16.103)
Bid-ask spread (t-1)	-0.683***	0.116**	-15.357***	-3.831**	-0.695***	0.080***	-10.444***	-6.132***
	(-5.086)	(2.440)	(-5.970)	(-2.569)	(-9.083)	(3.689)	(-4.357)	(-9.464)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	735,568	735,571	735,568	735,571	3,839,536	3,839,536	3,839,536	3,839,536
Adjusted R^2	0.482	0.522	0.545	0.438	0.407	0.474	0.401	0.362

Table 7. Evidence from Limits to Arbitrage (Cont.)

Panel C: Mispricing and Lending Fees

Sample:	S&P 500				Russell 3000			
Dependent variable:	Intraday volatility		Intraday turnover		Intraday volatility		Intraday turnover	
Lending fees:	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF ownership (t-1)	0.085***	0.026*	6.587***	5.601***	0.037***	0.044***	2.813***	1.969***
	(5.327)	(1.854)	(5.845)	(5.076)	(8.026)	(7.162)	(6.827)	(4.164)
× abs(ETF mispricing (t-1))	21.480***	18.856***	1,467.626***	783.211***	2.221***	-0.536***	324.516***	-2.942
	(5.072)	(4.503)	(5.320)	(3.807)	(2.606)	(-2.767)	(3.950)	(-0.557)
abs(ETF mispricing (t-1))	-0.157*	-0.224***	-16.278***	-8.800**	-0.035*	0.002***	-7.344***	0.019
	(-1.657)	(-2.952)	(-2.904)	(-2.084)	(-1.772)	(3.862)	(-3.835)	(1.079)
log(Mktcap (t-1))	0.000	0.001	-0.464***	-0.566***	-0.004***	-0.006***	-0.007	0.033*
	(0.525)	(1.214)	(-11.998)	(-10.087)	(-14.197)	(-16.838)	(-0.391)	(1.772)
1/Price (t-1)	0.187***	0.204***	0.038	1.338	0.035***	0.015***	-0.416***	-0.064
	(13.798)	(15.204)	(0.058)	(1.254)	(12.870)	(5.077)	(-4.354)	(-1.058)
Amihud (t-1)	-0.491	-0.662	-273.758***	-407.072***	-0.010***	-0.018***	-1.437***	-1.435***
	(-0.693)	(-0.848)	(-5.798)	(-6.412)	(-3.445)	(-5.086)	(-10.874)	(-10.162)
Bid-ask spread (t-1)	1.777***	2.183***	47.114***	44.975***	1.026***	1.372***	-13.974***	-15.849***
	(3.117)	(4.903)	(4.595)	(3.088)	(11.298)	(13.376)	(-6.540)	(-5.944)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	366,618	366,618	366,618	366,618	2,088,566	2,088,563	2,088,566	2,088,563
Adjusted R^2	0.518	0.582	0.504	0.524	0.477	0.520	0.458	0.428

Table 7. Evidence from Limits to Arbitrage (Cont.)

Panel D: Fund Flows and Lending Fees

Sample:	S&P 500				Russell 3000			
Dependent variable:	Intraday volatility		Intraday turnover		Intraday volatility		Intraday turnover	
Lending fees:	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ETF ownership (t-1)	0.107***	0.047***	7.899***	6.312***	0.034***	0.040***	2.321***	1.200**
	(6.442)	(3.128)	(7.013)	(5.739)	(7.370)	(6.541)	(6.005)	(2.510)
× abs(ETF flows (t))	0.953	0.263	98.639**	48.965	0.684***	0.375***	100.294***	83.037***
	(1.639)	(0.753)	(2.485)	(1.234)	(7.212)	(4.292)	(12.066)	(6.767)
abs(ETF flows (t))	0.039**	0.046***	1.079	2.848***	-0.002	-0.001***	-0.856***	-0.250***
	(2.560)	(4.979)	(0.977)	(2.781)	(-0.612)	(-3.837)	(-3.278)	(-7.415)
log(Mktcap (t-1))	0.000	0.001	-0.467***	-0.564***	-0.004***	-0.006***	-0.005	0.036*
	(0.404)	(1.257)	(-12.144)	(-10.088)	(-14.128)	(-16.803)	(-0.305)	(1.948)
1/Price (t-1)	0.187***	0.204***	0.015	1.323	0.035***	0.015***	-0.411***	-0.064
	(13.694)	(15.195)	(0.023)	(1.248)	(12.857)	(5.076)	(-4.336)	(-1.059)
Amihud (t-1)	-0.474	-0.627	-272.455***	-404.583***	-0.010***	-0.018***	-1.430***	-1.433***
	(-0.665)	(-0.795)	(-5.891)	(-6.440)	(-3.409)	(-5.074)	(-10.902)	(-10.234)
Bid-ask spread (t-1)	1.764***	2.154***	46.079***	42.960***	1.026***	1.374***	-14.022***	-15.321***
	(3.068)	(4.840)	(4.403)	(2.967)	(11.271)	(13.377)	(-6.622)	(-5.800)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	366,618	366,618	366,618	366,618	2,088,566	2,088,563	2,088,566	2,088,563
Adjusted R^2	0.518	0.582	0.503	0.524	0.477	0.520	0.459	0.429

Figure 1: Illustration of the Propagation of Non-fundamental Shocks Via Arbitrage

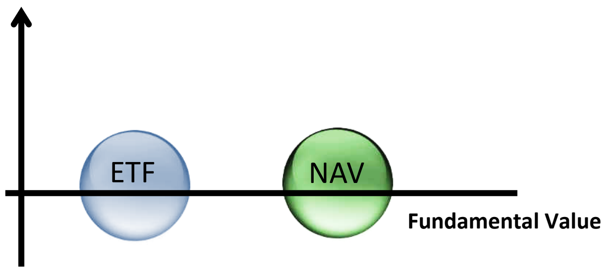

Figure 1a. Initial equilibrium

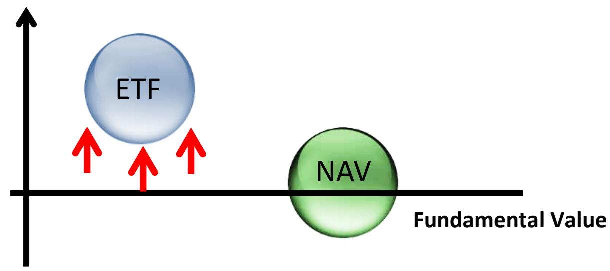

Figure 1b. Non-fundamental shock to ETF

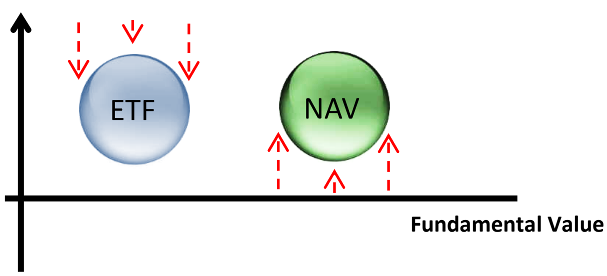

Figure 1c. Initial outcome of arbitrage: the non-fundamental shock is propagated to the NAV, and the ETF price starts reverting to the fundamental value.

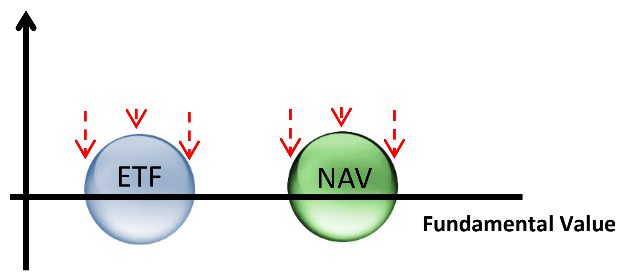

Figure 1d. Re-establishment of equilibrium: after some time, both the ETF price and the NAV revert to the fundamental value.

Figure 2: Illustration of the Propagation of a Fundamental Shock with Price Discovery Occurring in the ETF Market

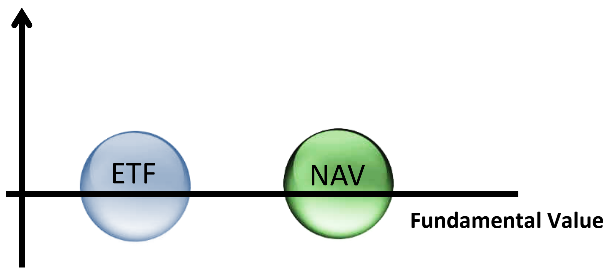

Figure 2a. Initial equilibrium

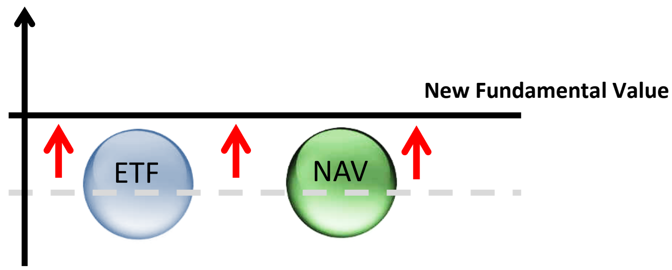

Figure 2b. Shock to fundamental value

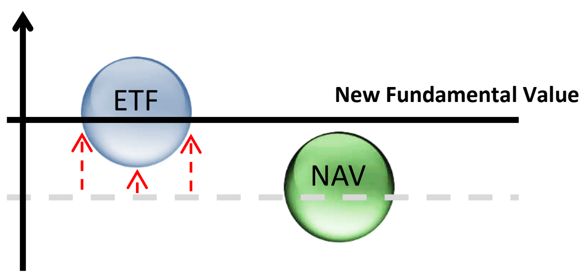

Figure 2c. Price discovery takes place in the ETF market. The ETF price moves to the new fundamental value.

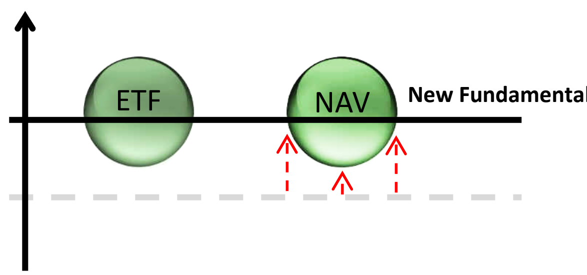

Figure 2d. After a delay, the NAV catches up with the new fundamental.