Do ETFs Increase Stock Volatility?

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Abstract

We study whether exchange traded funds (ETFs)—an asset of increasing importance—impact the volatility of the underlying stocks. Using identification strategies based on the variation in ETF ownership, as well as on variation in ETF mispricing and flows, we present evidence that stocks owned by ETFs exhibit 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.

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1 Introduction

With $2 trillion of assets under management globally (July 2013), 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 regulators' attention with regard to the hidden risks to which ETF investors are exposed and the threat that ETFs pose to market stability.[1] 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 reviewing the evidence for role of ETFs in increasing volatility in the market.[2] Regulators are wary of high frequency volatility as it may reduce participation of long term investors.[3] Despite these concerns, however, there is scant systematic evidence about the relation between the presence of ETFs and the volatility of the underlying securities.

In this paper, we test whether ETFs lead to an increase in the volatility of the underlying securities. 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.[4] Our results suggest that ETF ownership contributes to increase stock volatility through the arbitrage trades between the ETF and the underlying stocks and, to a lesser extent, as a result of the flows into and out of ETFs.

[1] 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)).

[2] 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.

[3] See 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."

[4] 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".

In an efficient market, the price of an ETF should equal the price of its underlying portfolio, up to transaction costs, as 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).[5] 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 describe the mechanics of this effect, consider for example a large liquidity sell order of ETF shares by an institutional trader. As 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 demands are not perfectly elastic and they require compensations in terms of positive expected returns. Hence, the selling activity leads to downward price pressure on the underlying portfolio. As a result, 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, arbitrageurs' activity induces propagation of liquidity shocks from the ETF to the underlying securities.

We begin our analysis with exploring the relation between stock volatility and ETF ownership. ETFs aim at replicating the performance of the index. Therefore, they tend to hold stocks in the same proportion as in the index that they track. However, some ETFs only hold a subset of the constituents of the index to minimize costs. Also, the same stock appears with different weights in different indexes. Furthermore, ETF ownership as a fraction of stock market capitalization depends also on the size of the ETF 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 strategy as 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., macro-related news); however, it is less likely that fundamental reasons generate an effect that is stronger for

[5] 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 creating and redeeming ETF shares on a continuous basis.

stocks with higher ETF ownership, as ETF ownership is to a large extent mechanically determined by the factors listed above.

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 and with an increase of 16% of a standard deviation in daily turnover. The volatility survives also 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 in general less economically significant for smaller stocks, consistent with the idea that ETF arbitrageurs concentrate 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 that are consistent with the theoretical story outlined above. ETF arbitrage occurs at different frequencies and in two different fashions. First, at high frequencies, typically intraday, arbitrageurs respond to discrepancies in the price of the ETF with respect to the Net Asset Value (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, on average one day out of four, ETF market makers (Authorized Participants (APs)) create and redeem ETF shares in response to large demand imbalances in the ETF market. These flows, which involve 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 in which 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 and turnover effects are even stronger for those underlying stocks for which arbitrage activity is less restricted, i.e., with lower arbitrage costs. In particular, the effects are more intense for stocks with small bid-ask spreads and with low share lending fees.

With regard to the creation/redemption channel, we use the same identification technique (variation in ETF ownership across stocks) and find that ETF flows impact the volatility and turnover 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 the results that we present are generated by a fundamental shock that impacts the value of the ETFs and the underlying securities, as opposed to 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 e.g. Greenwood (2005)), whereas fundamental shocks would leave price at the new level. Our results show clear evidence of 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 stock 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 issue is whether the presence of ETFs increases the basket securities' overall exposure to liquidity trading. Our evidence suggests that this is the case. First, we show that investors in ETFs have a significantly lower investment horizon than the investors in the underlying stocks. Specifically, the churn ratio of ETF investors (measured as in Cella, Ellul, and Giannetti (2011)) is significantly higher than the churn ratio of investors in common stocks in the S&P 500. Thus, the ETFs' clientele is different from the clientele of the securities in the ETF baskets. Second, using the same identification as for the volatility effect, we show that stocks with higher ETF ownership have significantly higher turnover. This finding supports the conclusion that the high turnover clientele of ETFs is inherited by the underlying stocks through the channels of arbitrage and flows.

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) have voiced 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 ETFs trading to the Flash Crash. In work subsequent to the present paper, Da and Shive (2013) find a positive effect of ETF ownership 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), Cella, Ellul, and Giannetti (2011), Chang and Hong (2011), Greenwood and Thesmar (2011), Lou (2011), and Jotikasthira, Lundblad, and Ramadorai (2012)). The recent paper by Basak and Pavlova (2013) makes the theoretical point, related to our empirical claim, that the inclusion of asset in an index tracked by institutional investors increases the non-fundamental volatility in that assets' prices.

The theoretical framework is provided by 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 following 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 impact 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 more 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 exploded to more than 1,000 ETFs by the end of 2011, 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, consider the descriptive statistics of ETF ownership for S&P 500 and Russell 3000 stocks provided in Table 1. Due to the expansion of the ETF market, ETF's ownership of individual stocks increased dramatically over the last decade. The table shows that the number of ETFs tracking the S&P 500 grew to over 50 in the years 2008 to 2011. The average assets under management (AUM) of these ETFs is $3bn to $4bn. The average ownership of ETFs in S&P 500 stocks is above 3% in recent years. The statistics for the Russell 3000 paint a similar picture. The number of ETFs tracking the Russell 3000 is close to 30 in recent years. The average AUM is about $3bn, and percent ownership of ETFs in firms is above 3.5% in recent years.

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. For example, we leave aside leveraged and inverse ETFs that use derivatives to deliver the performance of the index, which in any case do not represent more than 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.[6] However, unlike closed-end funds, new ETFs shares can be created and redeemed. Because the price of ETF shares is determined by the demand and supply in the secondary market, it may diverge from the value of the underlying securities (the NAV). Some institutional investors (called "authorized participants," APs), which are typically market makers or specialists, 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.[7]

To illustrate the arbitrage process through creation/redemption of ETF shares, we focus on 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 decreases 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.[8] 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 that are involved. This fee would amount to about 3.4 bps for a single creation unit in the SPY (that is, 50,000 shares, which are worth about $8.8 million as of October 2013), or 0.6 bps for five creation units. In our sample period (2000-2012), share creation/redemption

[6] 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.

[7] Creation and redemption in cash is especially common in ETFs on foreign assets or for illiquid assets, e.g., fixed income ETFs.

[8] See http://ftalphaville.ft.com/blog/2009/03/12/53509/the–curious–case–of–etf–nav–deviations/ for a description of trading strategies by APs.

occurs on average on 71% of the trading days. For the largest ETF, the SPY, in the year 2012, flows into and out of the fund occurred almost every day (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.[9] 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 prices can also be arbitraged against other ETFs (see Marshall, Nguyen, and Visaltanachoti (2010)) or against futures contracts (see Richie, Daigler, and Gleason (2008)).[10] Given the fleeting nature of profit opportunities in this line of business, ETF arbitrage is carried out mostly at high frequencies by hedge funds doing statistical arbitrage.[11,12]

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 returns swaps and other derivatives. As a result, creation and redemption occur in cash. However, the secondary market arbitrage still involves transactions in the underlying securities. So, the potential for a liquidity shock to affect the price of the underlying securities is present also in the case of synthetic ETFs.

Finally, while we limit our analysis to ETFs that track stock indexes, the arbitrage process is an inherent characteristics of all types of ETFs. As a consequence, one should expect the effects of ETFs that we describe in this paper to involve other asset classes as well.

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[9] 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.

[10] 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.

[11] 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/.

[12] To be precise, although these trading strategies involve claims on the same cash flows, they may not be arbitrages in the strict sense as they may involve some amount of risk. In particular, market frictions might introduce noise into the process. For example, execution may not be immediate, or 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, as we discuss ETF arbitrage, we are implying the broader definition of "risky arbitrage."

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. Then, total volatility of the underlying securities can increase as a result of ETF ownership.

Greenwood's (2005) model with risk averse market makers is useful to explain the channel of shock transmission that we wish to identify. To exemplify, let us start from 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, we imagine a non-fundamental shock, such as an exogenous increase in demand, hitting the ETF market. This could happen, for example, if some large institution receives inflows and scales up its existing ETF allocation. Market makers absorb the liquidity demand by shorting the ETF. Because they are risk averse, they require a 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, market makers 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 market makers who require a compensation for holding assets in the two markets. To provide the market makers 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 (that is, 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 ETF price and NAV can be present at any time. As a result, a strict adherence to the model would prevent the ETF price from ever diverging from the NAV. Then, while 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. Moreover, market makers for one asset are allowed to observe realizations of prices of the other asset.

Due to the synchronicity of trading by all investors classes, price discrepancies between two identical assets cannot emerge even in the Cespa and Foucault (2012) model. Still, one can conceive a dynamic extension of this 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 arbitrageurs' trading also occurs in the second period and it brings about price convergence between the two assets. In this extended framework, the prices of two identical assets can temporarily differ (in the first period). Also, arbitrageurs' risk aversion and hedging trades are still crucial for the transmission of liquidity shocks between two markets.

The mechanism described above can be contrasted against a scenario in which fundamental information is only gradually impounded into the prices of the securities in an ETF basket. In this scenario, prices behave similarly to the description in Figure 1, but the trigger is a fundamental shock, not a liquidity shock. In particular, it is possible that price discovery takes place in the ETF market first, for example, because it is more liquid. Then, when fundamental information arrives ETF prices adjust immediately, while the underlying securities' prices remain temporarily fixed ('stale pricing'). The later adjustment of the NAV can generate a sequence of price moves that resembles the one described above. 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 can 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 that we wish to identify (Figure 1) and the price discovery scenario with stale pricing (Figure 2) is that non-fundamental liquidity shocks induce a reversal in stock prices (Figure 1d). Greenwood's (2005) model predicts that after the initial liquidity shock prices revert to fundamental value over some future horizon. This does not happen if the initial shock is a fundamental one, as in the price discovery scenario. Hence, in our empirical analysis we will provide evidence of price reversal for the underlying securities to corroborate our conjecture that arbitrage trading can transfer liquidity shocks across markets.

A different issue concerns the counterfactual to our claim that the presence of ETFs magnifies the exposure of the underlying securities to liquidity shocks. Our conjecture that liquidity shocks are propagated from ETF prices to the NAV, even if correct, would be void of implications if, in the absence of ETFs, the liquidity shocks would still hit the underlying securities. For example, some of the traders that invest in ETFs and may potentially induce liquidity shocks would invest directly in the underlying securities if ETFs did not exist.

Our response to this objection relies on the conjecture that ETFs attract a new clientele of investors with significantly higher turnover than the original investors in the underlying shocks. These traders impound liquidity shocks at a higher frequency in the ETF prices. Then, via arbitrage, these shocks are transmitted to the underlying securities. The generation of a new clientele of investors happens because of the low transaction costs permitted by ETFs and the new trading strategies that are connected with them. In particular, ETFs have allowed a strategy based on the exploitation of ETF mispricing. This strategy is inherent to the fact that ETFs are derivatives. The smooth functioning of arbitrage is what allows the ETF sponsors to tout the low tracking error of these instruments. This explains why ETF sponsors facilitate arbitrageurs' activity by disseminating NAV values at the fifteen-second frequency throughout the trading day. As a result of the low trading costs and availability of information, arbitraging ETFs against the NAV has become a very popular business among hedge funds and high frequency traders in the latest years (Marshall, Nguyen, and Visaltanachoti (2010)).[13]

[13] Also see: http://ftalphaville.ft.com/2011/05/18/572086/how-profitable-is-etf-arbitrage/

Because we claim that the low trading costs of ETFs attract high-frequency traders, our argument is analogous and symmetric to the stance of those authors who suggest 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)) and ultimately it is an empirical question whether lower transaction costs attract a clientele of high frequency traders.

To support our conjecture, in Section 5 we provide evidence consistent with the claim that ETF investors have higher turnover than common stock investors. Also, we show that ETF ownership positively affects stock turnover, especially in connection with arbitrage activity, suggesting the high frequency clientele is inherited by the securities in the ETF basket via the channel of arbitrage.

3 Data

3.1 Data Sources

We use Center for Research in Security Prices (CRSP), Compustat, 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 the 1,261 securities that have the historical share code of 73, which defines exclusively ETFs in the CRSP universe. We then screen all U.S.-traded securities in Compustat XpressFeed and OptionMetrics data, identifying ETFs using the security-type variables.[14] We then merge the CRSP data with the data we extract from the latter two databases. Shares outstanding data in Compustat are updated on a daily basis but are sparse before 2000, so we fill the gaps in the daily shares outstanding data using the OptionMetrics total shares outstanding figures, which are available from 1996. OptionMetrics is then used to complement the ETF series and extract the daily-level shares outstanding. The total shares outstanding allow us to compute the daily market capitalization and measures of net share creations/redemptions of each ETF.[15]

[14] Note that the CRSP-Compustat merged product does not have correct links between 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.

[15] We use short sale data from Compustat. We notice that short selling of ETFs is prevalent by hedge funds and other sophisticated investors as part of their hedging and market timing bets (see

Net asset value (NAV), in addition to fund styles (objectives) and other characteristics, are extracted from the CRSP Mutual Fund, Lipper, and Morningstar databases. This information is available from September 1998. 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. Daily NAV returns are computed from daily NAVs. 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 calculate the mispricing using 4:00 pm ETF prices drawn from the intraday Trade and Quote data (TAQ), as the last trade in the ETF at or before 4:00 pm. Furthermore, we restrict our analysis to U.S. ETFs that hold U.S. equities.

The Thomson-Reuters Mutual Fund holdings database allows us to construct ETF holdings for each stock at the end of every month. 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. We use these data to align ETF ownerships 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.

3.2 Descriptive Statistics

The unrestricted sample consists of 1,146 distinct ETFs, with 1,065,832 daily observations with complete data from September 2, 1998 to March 31, 2011. Figure 3 illustrates the growth of ETFs over our sample period. Table 1, Panel A, gives information on the growth of the assets in the ETF sector, showing that the average assets under management (AUM) in U.S. ETFs have grown from $9 billion in 29 ETFs during 1998 to more than $1 trillion in 986 ETFs in March 2011. ETF growth in terms of assets and the number of ETFs picked up sharply after 2004. Panel B of Table 1 breaks down the ETFs in March 2011 by their Lipper objective code (for categories with more than $1 billion of AUM). The largest category by AUM contains the ETFs that track the S&P 500, including $95.6 billion in AUM and four ETFs, one of which is the SPY that we study in the Flash Crash analysis. The last column shows the fund objectives that

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http://www.marketwatch.com/story/short-interest-in-etfs-down; for example, when the iShares Lehman 20+ Year Treasury Bond Fund (TLT) had a whopping 235% of shares outstanding in short interest as of October 2004, the short interest ratio for TLT was 15,669,711, while the total shares outstanding for this ETF were 4,000,000).

we include in the equity ETF group in some of the regressions. From this group, we also exclude leveraged or short equity ETFs in order to focus on plain vanilla equity ETFs.

Table 2 reports summary statistics for the variables that are used in the regressions. Panel A presents summary statistics for the churn-ratio analysis (which is carried out in Table 4). Panel B presents summary statistics for the cross-sectional regressions for ETFs (Tables 4, 6, and 7). Panel C shows summary statistics for the time-series analysis (Table 6). Panel D shows summary statistics for stock-month-level data (Table 9). We defer further description of these variables until we use them in the analysis.

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. We implement the test by exploiting the variation in ETF ownership across stocks.

Variation in ETF ownership primarily comes from three sources. First, stocks are typically part of multiple indices; e.g., a stock might be part of S&P 500, S&P 500 Value, Russell 3000, and sector indices. Second, there is variation in ETFs assets under management; thus the amount the ETFs invest across stocks varies. Third, there is variation in weighting schemes. In particular, the S&P 500 and many other indexes are capitalization-weighted, while the Dow Jones is price-weighted. Fourth, some ETFs hold a subset of the stocks that participate in the index, as opposed to the entire set of stocks that compose the index. It is likely that stocks are selected based on their correlation with the index as ETFs attempt to minimize the tracking error. Our identifying assumption is that variation in ETF ownership resulting from these four 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. Given that firms do not choose whether to participate in an index or not, and given that they have no control on investors' demand of ETFs or the way that indices are calculated, we believe that the identifying assumption is well founded.

To further ensure that our results are driven by exogenous variation in ETF ownership, we provide results that control for stock-level fixed effects. In these regressions, the variation in ETF ownership is within the stock, i.e., derived primarily by time variation in ETF ownership, while controlling for unobservables that could make a stock, for example, a more likely candidate for an index and that are correlated with volatility.

The regressions in Table 3 help to illustrate the determinants of ETF variation across stocks. At the monthly frequency, we regress stock-level ETF ownership (in % of market capitalization) on the logarithm of market capitalization, the number of ETFs holding the stock, the logarithm of the assets under management of all the ETFs holding the stock, and the average weight of the stock in all the ETFs in which it appears. The regressors are standardized to have zero mean and unit standard deviation. Different combinations of time and stock fixed effects are included and standard errors are clustered at the stock level. Columns (1) to (3) restrict the sample to S&P 500 stocks, while Columns (4) to (6) extend it to all stocks in the Russell 3000 index. In all regressions, size is negatively correlated with ownership, suggesting that the dollar value of ETF ownership scales less than proportionally with market capitalization. Considering that market capitalization is negatively correlated with volatility, 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, in our analysis we always include controls for market capitalization. Controlling for stock size, the evidence in Table 3 is that ETF ownership correlates significantly with the three other regressors, which are arguably exogenous with respect to stock volatility. The number of ETFs, which is a likely proxy for the number of indices in which a company appears, is the most important determinant. Notice that the R-squared in all regressions is fairly high, suggesting that, outside the set of included regressors, the omitted determinants of ETF ownership are of reduced importance and unlikely to make ownership a largely endogenous variable.

Overall, the evidence in Table 3 corroborates our assumption that, controlling for size and stock fixed effects, ETF ownership is an exogenous variable with respect to volatility and turnover. This conclusion legitimates the identification strategy that we use in the rest of the analysis.

4.2 ETF Ownership, Intraday Volatility, and Turnover

In line with regulators' concerns that the recent wave of financial innovation may impact high-frequency volatility, we start from looking for an impact of ETF ownership 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 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 in percent. 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 our claim is that the additional volatility coming from ETF ownership is due to the trading of 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 dependent variable and compute it 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 4, Columns (1) and (2). The regressions show that intra-day volatility is significantly related to ETF ownership. In light of the identification strategy described above, we can assert that these estimates establish the causal link between ETFs ownership and stock volatility. From Column (2), a one-standard deviation increase in ETF ownership is associated with higher volatility by 21% of a standard deviation. The effect seems economically important.

In Columns (3) and (4) of Table 4, we explore whether ETF ownership affects stock turnover as well. The estimates reveal a positive and significant relation between ETF ownership and turnover. From Column (4), a one-standard deviation increase in ETF ownership is associated with higher turnover by about 16% of a standard deviation. Again, the effect seems economically large.

In Columns (5) to (8) of Table 4 we repeat these tests for the sample of Russell 3000 stocks. Once we control for stock fixed effects, we find again the significant relation between ETF ownership and stock volatility. In both turnover specifications, the estimates remain statistically significant. In this sample, however, the effects are substantially smaller than for large stocks. For example, from Column (6), a one-standard deviation increase in ETF ownership raises intraday volatility by about 8% of a standard deviation. Quite plausibly, arbitrageurs rely less on small stocks to replicate ETF baskets. Hence, small stocks' prices and volume are less impacted by ETF ownership.

The results in Table 4 provide the main evidence in the paper that volatility and turnover are significantly related to ETF ownership. Because of the identification strategy discussed above, we can 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 interpretations to the estimates in Table 4. Overall, this analysis contributes to establish ETFs as catalysts for demand shocks that ultimately impact the underlying securities.

4.3 Effects of ETF Ownership on Daily Return Volatility

Our previous results show that ETF ownership is associated with higher return volatility with the day (Table 4). A legitimate concern is that, while it is possible ETFs impact the micro-structure of trading for the underlying securities, these effects are washed out in longer horizons. To entertain this possibility, we study whether the effects that we identify are a short-lived phenomenon (e.g., induced by high-frequency traders) or, rather, whether these effects exist also at frequencies that are relevant for long-term investors. To this purpose we use the monthly frequency for the explanatory variables and measure the dependent variable, volatility, using the daily return observations within a month.

The specification that we explore in Table 5 is a regression of stock volatility in a given month on the average ETF ownership of the stock within the month. As suggested by the discussion above, stock-level controls are in order 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 4. We cluster standard errors both at the date and the stock levels. In addition, time 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 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. The economic significance is therefore large. Extending the universe to smaller stocks (Column (4)), the effect is diluted, amounting to about 6% of a standard deviation. This finding confirms the evidence for intra-day volatility in Table 4.

Next, we wish to provide a preview on 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 represent arbitrage opportunities, we compute its volatility, which treats positive and negative mispricing equally.[16] 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)), the results reveal a stronger effect in the sample of large stocks (Column (2)) than for smaller stocks (Column (5)). For S&P 500 stocks, a one-standard deviation increase in the explanatory variable (0.044) raises stock volatility by about 22% of a standard deviation. The effect is smaller at 5.5% of a standard deviation in the sample of Russell 3000 stocks. Especially for large stocks, the economic significance of the impact of ETF arbitrage on stock volatility 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) allocated to a given stock across all the ETFs holding the stock, as a fraction of the stock's market

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[16] Similar results obtain if we use the average of absolute mispricing as explanatory variable.

capitalization. Again, we take the volatility of this variable to avoid averaging positive and negative flows (the sum of absolute flows gives similar results). The results are consistent with the conjecture that the creation/redemption activity exerts price 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 effects reduces to 3.4% of a standard deviation.

Overall, our findings demonstrate that the effect of ETFs on volatility persists beyond the intra-day horizon. The daily volatility that is studied in this section is relevant for those 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 for the impact of ETF ownership on stock volatility.

5 Exploring the Arbitrage Channel

As discussed in Section 2, our conjecture is that ETFs propagate demand shocks to the underlying securities. This fact results in a new layer of liquidity shocks hitting 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. Also, we show that the ETF average mispricing and flows within a month affect daily stock volatility. In this section, the goal is to expand the analysis of the arbitrage channel.

5.1 Stock Volatility, ETF Ownership, and Non-Fundamental Trades

5.1.1 Arbitrage Trades following ETF Mispricing

We mentioned that 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. Focusing more closely on the APs' activities, we also measure arbitrage trading using creation and redemption of ETF shares. Thus, in a second set of tests we proxy arbitrage activity with stock-level ETF flows.

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

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

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 it is measured using closing prices.

Our regression specification is:

$$\begin{aligned} Volatility_{i,t} &= \alpha + \beta_1\ abs\left(ETF\ mispricing_{i,t-1}\right) * ETF\ ownership_{i,t-1} + \\ &\beta_2\ abs\left(ETF\ mispricing_{i,t-1}\right) + \beta_3\ ETF\ ownership_{i,t-1} \\ &+\beta_4\ Controls_{i,t-1} + Stock\ FE + Day\ FE + \varepsilon_{i,t} \end{aligned} \tag{2}$$

We run a similar specification using stock turnover as dependent variables. The controls are the same as in Table 4 and standard errors are clustered at the stock level.

Our variable of interest is the interaction between ownership and mispricing. We conjecture and test 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 it proxies for arbitrage that takes place during day *t*. Using day-*t* mispricing instead does not materially affect the results.

Table 6, Panel A, presents the regressions. In Column (1), we observe that intraday volatility increases with the absolute ETF ownership. The effect, however, is significantly stronger for stocks with high ETF mispricing, as reflected in the interaction between the absolute ETF mispricing and ETF ownership. For stocks that have no ETF ownership, the effect of ETF mispricing is minimal. A one standard deviation increase in abs(ETF mispricing) is associated with an increase of 0.06% standard deviations in volatility. However, if ETF ownership is at its mean (2.8%), then the effect is much larger: a one-standard deviation increase in abs(ETF mispricing) is associated with an increase of 15.77% standard deviations in volatility.[17]

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 0.03% standard deviations. However, when ETF ownership is at its mean, intraday turnover is higher by 4.08% standard deviations.[18]

While 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. These results suggest that the arbitrage of ETF mispricing is an important channel in the increase of volatility by ETF ownership, especially for large stocks.

5.1.2 Arbitrage Activity by APs

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

$$abs\left(ETF\ Flows_{i,t}\right) = \sum_{j=1}^{J} \frac{\sum_{j=1}^{J} \left|\frac{Fund\ flows_{j,t}}{AUM_{j,t-1}}\right| * ETF\ owernship_{i,j,t}}{\sum_{j=1}^{J} ETF\ owernship_{i,j,t}} \tag{3}$$

i.e., for each stock *i* and day *t* we sum the product of percentage 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 (3) we take the absolute value of the flows.

The specification that we bring to the data resembles equation (2), but we replace $abs\left(ETF\ Flows_{i,t}\right)$ for $abs\left(ETF\ mispricing_{i,t-1}\right)$. Table 6, 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

[17] (0.006 * 0.002 + 42.035* 0.002 * 0.028) / 0.015 = 0.1577 (non-rounded numbers were used).
[18] (0.207 * 0.002 + 896.893 * 0.002 * 0.028) / 0.946 = 0.0408 (non-rounded numbers were used).

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 to higher volatility by 5.23% standard deviations.[19]

The effect of flows with respect to ETF ownership on stock turnover is similar in magnitude (Column (2)). Without ETF ownership, the relation between absolute flows and turnover is negative and statistically insignificant. For the mean value of ETF ownership, however, a one standard deviation increase in absolute ETF flows is associated with turnover higher by 6.57% standard deviations.[20]

Columns (3) and (4) presents similar regressions for the Russell 3000. Here the results are weaker, although in the same direction as in the S&P 500 sample. When there is no ETF ownership, the effect of flows on volatility and turnover is zero or negative, respectively. When ETF ownership is at its mean level, then the effect of absolute ETF flows on volatility and turnover is positive. A one standard deviation increase in absolute ETF flows translates to an increase of 2.34% standard deviations in intraday volatility[21] and of 18.59% standard deviations in intraday turnover.[22]

In sum, our findings demonstrate that the channels through which ETF ownership increases volatility and turnover are related to arbitrage by market participants and by APs.

5.2 Evidence for Price Reversals of Underlying Stocks

As discussed in the theoretical framework section (Section 2.2), a distinct feature of arbitrage trades and of APs' trades is that they are motivated by non-fundamental information and therefore are expected to generate price reversals in the following periods. This prediction is a key differentiator between the trades that are based on non-fundamentals (arbitrage trades and APs' trades following fund flows) and trades that are performed in response to fundamental information that spread gradually across the ETFs and the underlying securities.

[19] (-0.009 * 0.010 + 3.197 * 0.028 * 0.010) / 0.015 = 0.0523 (non-rounded numbers used).
[20] (-0.090 * 0.010 + 232.101 * 0.028 * 0.010) / 0.946 = 0.0657 (non-rounded numbers used).
[21] (-0.000 * 0.083 + 0.141 * 0.031 * 0.083) / 0.016 = 0.0234 (non-rounded numbers used).
[22] (-0.129 * 0.083 + 70.306 * 0.031 * 0.083) / 0.920 = 0.1859 (non-rounded numbers used).

5.2.1 Price Reversals following Arbitrage Trades

The arbitrage mechanism that discussed before is based on the model of Greenwood (2005). Adapting the model to our framework, one could imagine an asset that is well priced (e.g., the stock), and the other asset in premium (e.g., the ETF). Traders attempt to arbitrage the two, thus taking long positions in the stock and short positions in the ETF. In the short term, the prices will move towards convergence: the stock's price will increase and the ETF's price will decrease. However, in the longer term, prices will move towards fundamentals, i.e., the stock will decrease in price, back to the fundamental price.

Hence, the prediction is that on days in which the ETF is in premium relative to the stock, the price of the stock will increase. This effect is expected to be stronger for stocks that have higher ETF ownership. In the following days, the stock should move back towards its fundamental value, i.e., decrease in price. When the ETF is in discount relative to the stock, the directions of the effects are in reverse.

We test this prediction in Table 7. In Panel A the sample is limited to S&P 500 firms and in Panel B the sample is limited to Russell 3000 firms. Our core specification is:

$$\begin{aligned} Ret(t_1,t_2)_{i,t} &= \alpha + \beta_1 ETF\ Ownership_{i,t} \\ &+\beta_2\ ETF\ Ownership_{i,t} * ETF\ Discount\ (or\ premium)_{i,t} \\ &+ \beta_3\ ETF\ Discount\ (or\ premium)_{i,t} + \beta_4\, Stock\ controls_{i,t} \\ &+ Stock\ FE + Day\ FE + \varepsilon_i \end{aligned} \tag{4}$$

where $Ret(t_1,t_2)$ is the stock return measured over days t_1 to t_2.

The empirical prediction is that in the current day of the trade ($t_1 = t_2 = 0$), the stock will react to the market impact of the arbitrage trades. I.e., when it is in a discount relative to the ETF, arbitrageurs take a long position in the stock; and when the stock is in premium – short positions. Hence, at times when the ETF is in premium relative to the stock (i.e., the ETF discount/premium is positive), the return on the stock is positive. We observe evidence for this effect in Table 7, Panel A, Column (1). We observe that the main effect of the ETF discount/premium is positive, and that this correlation becomes even more strongly positive when ETF ownership is high (i.e., the interaction between ETF ownership and ETF discount has a positive coefficient).

The magnitude of the effect can be calculated as following (for the S&P 500 sample in Column (1) and for the Russell 3000—in Column (5)). When ETF ownership is zero, and ETF mispricing is one standard deviation higher than zero, stock experience a return that higher by XXX. The effect for the Russell 3000 is statistically indistinguishable different from zero. This is likely to be due magnitude of arbitrage trades in the Russell 3000 seem to be relatively small (see Section 5.1.1).

In the days following the trade, we expect to observe a reversal in prices. I.e., at times that the ETF is in premium relative to the stock, there is a drift of the stock price downwards to back to the original level of prices. This is what we observe in Columns (2) to (4). For windows of 5 to 20 days, stock returns are negatively correlated with the ETF discount/premium, as predicted. The correlation is significantly more negatively correlated with the ETF discount/premium when ETF ownership is greater.

The economic magnitude of the reversal is large. Consider the month-long window (Column (4)). When ETF ownership is nonexistent, one standard error in ETF mispricing on day $t = 0$ is the reversal amounts to a reversal of XXX in the next month. When ETF ownership is at its mean, however, the effect increases to XXX.

We observe similar patterns for the Russell 3000 sample, in Panel B of Table 7. The only difference is that the on the current day (Column (1)), the coefficients are not significantly different from the zero.

5.2.2 Price Reversals due to Fund Flows to ETFs

We measure also the price reversals following the redeeming and creation of ETF units by APs. When there a flow of funds into an ETF, APs purchase the underlying securities and convert them into ETF units. When there are outflows, APs convert ETF units into the underlying securities and sell them in the market. In both cases there could be a price impact on the underlying securities.

We explore this mechanism in Table 7, Panel B. When fund flows are positive, there is a positive pressure on the price of the stock (Column (1)), and it reverses in the following days (Columns (2) to (4)). Column (1) shows that in the absence of ETF ownership, a one standard deviation increase of ETF fund flows is associated with lower current returns of XXX. Although this figure is statistically significant, it is economically small. When ETF ownership is at its mean, ETF ownership that is one standard deviation away from zero is associated with current returns of XXX.

In the following days following the APs' trades, stock returns revert. When ETF ownership is zero, one standard deviation of ETF flows is correlated with next-month returns of XXXX. When ETF ownership at the level of one standard deviation, then the magnitude of the reversion is XXX in the following month.

Columns (5) to (8) presents the effects for Russell 3000 stocks. Here, there is no effect on returns in the absence of ETF ownership. When ETF ownership is one standard deviation away from zero, the return on the fund flows experienced by APs is XXX, and in the following month it is XXX.

To sum these findings we document that stocks exhibit returns that are consistent with arbitrage trades and trades by APs following fund flows. These returns appear as a current price impact and future reversal. Our results show that the effect is materially larger for S&P 500 stocks than for the Russell 3000. A potential reason for this is that Russell 3000 stocks are subject to greater limits to arbitrage. We provide cross-sectional tests for the prominence of limits of arbitrage in the following subsection.

5.3 Limits to Arbitrage

To further understand the nature of the effects of arbitrage trading between ETFs and stocks, we explore how the effects of volatility and turnover are modified by of limits to arbitrage. The theory suggests that arbitrage trades should be less frequent when limits to arbitrage are present. We explore two proxies for limits to arbitrage: bid-ask spread and lending fees.

Wide bid-ask spreads reflect high limits to arbitrage. When the spread is wide, traders refrain from engaging in arbitrage trades since they cannot secure a profit. The prediction is, therefore, that the volatility and turnover of stocks with high bid-ask spread exhibit weaker sensitivity to ETF ownership. In Table 8, Panel A, we split the sample according to the lagged bid-ask spread of the stocks, and rerun the analysis from Table 4. The panel shows that across the board the sensitivity of both volatility and turnover to the interaction of absolute mispricing and ETF ownership is higher for stocks with low bid ask spread. For the same level of mispricing and ETF ownership, the impact on intraday volatility and turnover is lesser for high bid-ask spread stocks. This is apparent for S&P 500 stocks (Columns (1) to (4)), and for Russell 3000 stocks (Columns (5) to (8)).

Next, we split the sample by rebate rate. When the rebate rate is high, arbitrageurs are less likely to engage in arbitrage transactions, as the transaction costs associated with short selling shares are higher, hence reducing the profitability of trades. Also, high rebate rates may reflect shortage in shares for lending, meaning that some arbitrageurs may not have access to shares for lending through their brokers. The implication is that the effects of intraday volatility as well as turnover are expected to be stronger when rebate rates are low.

Table 8, Panel B, presents evidence for this effect. For both intraday volatility and turnover, the effect of absolute mispricing is weaker with respect to ETF ownership when rebate rates are high. In other words, when stock rebate rate is high, ETF ownership does not increase intraday volatility as much when mispricing is high.

These results reflect the importance of limits of arbitrage on the ability and desire of arbitrageurs to engage in arbitrage trades. On explanation is that when limits to arbitrage are high, arbitrageurs are more likely to sit on the sidelines waiting to the mispricing to widen (see Ben-David and Roulstone 2010).

5.4 ETF Ownership and Stock Clientele

An important question in our analysis of the role of ETFs in increasing stocks’ volatility and turnover is whether ETFs added to the volatility of stocks relative to a situation in which ETFs did not exist. One could argue that in the absence of ETFs, investors would directly invest in the underlying stocks. For example, in this scenario, arbitrageurs might engage in arbitrage trades of the stocks relative to other assets (e.g., futures, or mutual funds). Similarly, instead of APs converting their fund flows into stock trades, investors would invest directly in the underlying stocks. Hence, perhaps the price impact due to arbitrage trades and fund flows are not evitable? Alternatively, perhaps ETF investors just migrated from existing closed-end funds.

It is hard to fully respond this question, however, we can provide some evidence that ETFs introduces a new class of investors. To answer this question, we examine the ownership composition of ETFs and compare it to the ownership composition of the underlying stocks. We argue that the introduction of ETFs answered a need of speculators (traders with relatively high turnover) for a tool that allows taking market positions at low transaction costs. Consistent with this conjecture, ETF sponsors indeed testify that their clientele is composed of such institutional traders (CITE XXXX).

In Table 9, we test whether investors in ETFs have higher churn that investors in the underlying stocks. The sample that we study n Columns (1) to (4) is composed of the S&P 500 stock-quarters together with ETF-quarters and closed-fund-quarters that are based on the S&P 500 index. In parallel fashion, the sample in Columns (5) to (8) is composed of Russell 3000 stock-quarters and Russell 3000 ETF-quarters. The dependent variables are variations of measures of investor churn ratio. The variables of interest are dummy variables indicating whether the security is an ETF or a closed-end fund.

XXX Francesco – can you please help on this; I copied your comment from the Excel here XXX. The measures of investor turnover are the following. First, churn ratio (CR) is measured as XXX. Second, CRR measures are weighted with the quintile rank of CR of each institution (-2 Low CR and +2 for highest CR quintile, within each quarter). Third, IT is a turnover measure calculated as the median of three turnover measures: (a) min(Buys, Sales), (b) min(Buys, Sales) + abs(Flows), and (c) Buys + Sales – abs(Flows). XXX Is this based on other people's work? We need to cite XXX Fourth, the ITR measure are weighted with the quintile rank of IT of each institution (-2 Low IT and +2 for highest IT quintile, within each quarter).

The results uniformly show that the churn ratios of investors in the ETF securities are significantly higher than those of investors in the underlying stocks as well as investors in closed-end funds (the difference between the ETF indicator and the closed end fund indicator is statistically different in all regressions with $p < 0.01$).

These results show that investors in ETFs have a higher churn ratio than investors in stocks and closed end funds. This evidence is consistent with the idea that ETFs attract a new class of investors, e.g., hedge funds and investment firms that would not have invested in stocks otherwise. XXX Is this really the conclusion? XXX

8 Conclusion

ETF prices are tied by arbitrage activity to the prices of the securities in their basket. In this paper we show that arbitrage activity between the two types of securities leads to an increase in the volatility of the underlying securities. We use samples of S&P 500 and Russell 3000 to demonstrate that stock volatility and turnover tightly increase with ETF ownership.

We present evidence that the economic channel relates to arbitrage and price impact of fund flows. When the ETF and the underlying basket divert in prices, there is a stronger incentive for market participants to arbitrage the difference in prices. The effect is expected to increase with ETF ownership. We show that stock volatility and turnover indeed increase with the magnitude of the arbitrage opportunity and ETF ownership. Similarly – for fund flow into ETFs. When flows are high and ETF ownership is high, there is a high impact on stock volatility and turnover. We also find that these patterns command a reversal in prices at later dates, as the theory predicts.

These results emphasize a side effect financial innovation. New securities with values that are derived by existing securities call for arbitrage trades. The arbitrage trades generate a price impact on both securities, which translates to higher volatility, higher turnover, and price reversals.

Overall, we provide support for theories on the limits of arbitrage. Arbitrageurs do not only adjust the prices of mispriced securities, but they can also move the price of securities that are correctly priced. Thus, the large amount of capital that is employed in arbitrage trading strategies does not necessarily improve the efficiency of prices if arbitrage is limited (e.g., Shleifer and Vishny (1997), and Gromb and Vayanos (2012)).

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Table 1. ETF Ownership Statistics

The table presents descriptive statistics for ETFs ownership of stocks. For each year, we average the number of ETFs across months, average their assets under management (AUM), average the weight of each stock in the ETF, and average the total percentage ownership of ETFs in each stocks. 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 sample (daily sample), and for the stock-month sample (monthly sample). Variable definitions are provided in the Appendix.

Panel A: Daily Frequency Sample Statistics

S&P 500

	N	Mean	Std Dev	Min	Median	Max
Intraday volatility (%)	638,211	0.020	0.015	0.005	0.015	0.123
Intraday turnover (%)	638,211	1.230	0.946	0.053	0.946	6.520
ETF ownership	638,211	0.028	0.013	0.001	0.027	0.113
ETF mispricing	638,211	0.001	0.002	0.000	0.001	0.132
ETF flows	638,211	0.009	0.010	0.000	0.007	0.756
log(Mktcap ($m))	638,211	9.160	0.875	5.440	9.140	11.300
1/Price	638,211	0.040	0.036	0.006	0.029	0.629
Amihud	638,211	0.000	0.000	0.000	0.000	0.017
Bid-ask spread	638,211	0.001	0.001	0.000	0.001	0.015
Lending fee (%; average 7 day)	638,211	18.1	71.3	-8.6	8.7	1650.0

Russell 3000

	N	Mean	Std Dev	Min	Median	Max
Intraday volatility	3,937,169	0.024	0.016	0.005	0.019	0.123
Intraday volatility	3,937,169	0.991	0.920	0.046	0.710	6.520
ETF ownership	3,937,169	0.031	0.018	0.001	0.028	0.113
ETF mispricing	3,937,169	0.002	0.063	0.000	0.001	42.300
ETF flows	3,937,169	0.015	0.083	0.000	0.009	87.600
log(Mktcap ($m))	3,937,169	6.960	1.400	4.180	6.770	11.300
1/Price	3,937,169	0.075	0.077	0.006	0.049	0.629
Amihud	3,937,169	0.013	0.029	0.000	0.003	0.313
Bid-ask spread	3,937,169	0.002	0.002	0.000	0.001	0.015
Lending fee (%; average 7 day)	3,937,169	45.6	144	-8.63	11.6	1651.0

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 3. Determinants of ETF Ownership in Stocks

Dependent variable:	ETF ownership in stock-month					
Sample:	S&P 500			Russell 3000		
	(1)	(2)	(3)	(4)	(5)	(6)
# ETFs owning stock	1.056***	0.911***	0.499***	1.357***	1.043***	0.409***
	(56.186)	(10.580)	(9.215)	(75.049)	(41.954)	(16.504)
log(Total AUM of ETFs)	0.317***	0.395***	0.187***	0.292***	-0.090***	0.183***
	(28.625)	(9.882)	(9.750)	(37.811)	(-5.336)	(9.879)
Average weight of stock in ETFs	0.371***	0.430***	0.231***	0.264***	0.263***	0.222***
	(12.905)	(13.386)	(7.385)	(12.906)	(12.814)	(10.054)
log(Mktcap (t-1))	-0.608***	-0.652***	-0.413***	-1.035***	-0.752***	-0.484***
	(-18.773)	(-17.645)	(-9.448)	(-57.960)	(-34.692)	(-16.803)
Stock Effects	No	No	Yes	No	No	Yes
Time Effects	No	Yes	Yes	No	Yes	Yes
Observations	63,479	63,479	63,479	365,317	365,317	365,317
Adjusted R-squared	0.630	0.672	0.851	0.503	0.565	0.787

Table 4. ETF Ownership, Intraday Stock Volatility, and Turnover (Daily Sample)

The table presents evidence regarding the relation between intra-day stock volatility and ETF ownership. Columns (1) to (4) use a sample of S&P 500 stocks and Columns (5) to (8) use a sample of Russell 3000 stocks. Samples are at the day-stock level. Intraday stock volatility and intraday stock turnover are computed using second-by-second data from NYSE TAQ database. All regressions are OLS regressions. Standard errors are clustered at the stock level. Variable definitions are provided in the Appendix. *t*-statistics are presented in parentheses. ***, **, * represent statistical significance at the 1%, 5%, or 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 5. ETF Ownership and Daily Stock Volatility (Monthly Sample)

The table presents evidence regarding the relation between daily stock volatility and ETF ownership. Columns (1) to (3) use a sample of S&P 500 stocks (month-stock observations) and Columns (4) to (6) use a sample of Russell 3000 stocks (month-stock observations). Daily stock volatility is computed using daily data within the period of a calendar month. All regressions are OLS regressions. Standard errors are clustered at the stock level. Variable definitions are provided in the Appendix. *t*-statistics are presented in parentheses. ***, **, * represent statistical significance at the 1%, 5%, or 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 6. Stock Volatility, ETF Ownership, and Arbitrage

The table presents evidence regarding the relation between stock volatility and turnover and variables that proxy the extent of non-fundamental shocks interacted with ETF ownership (a proxy for the exposure of stock to the non-fundamental shocks). 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. In both panels, Columns (1) and (2) use a sample of S&P 500 stocks and Columns (3) and (4) use a sample of Russell 3000 stocks. Samples are at the day-stock level. Intraday stock volatility and intraday stock turnover are computed using second-by-second data from NYSE TAQ database. All regressions are OLS regressions. Standard errors are clustered at the stock level. Variable definitions are provided in the Appendix. *t*-statistics are presented in parentheses. ***, **, * represent statistical significance at the 1%, 5%, or 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 6. 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 7. Price Reversals

The table presents evidence exploring future return patterns following arbitrage opportunities between the stock and ETFs and following fund flows to the ETFs. 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. In both panels, Columns (1) and (2) use a sample of S&P 500 stocks and Columns (3) and (4) use a sample of Russell 3000 stocks. Samples are at the day-stock level. Intraday stock volatility and intraday stock turnover are computed using second-by-second data from NYSE TAQ database. All regressions are OLS regressions. Standard errors are clustered at the stock level. Variable definitions are provided in the Appendix. *t*-statistics are presented in parentheses. ***, **, * represent statistical significance at the 1%, 5%, or 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 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)
× ETF ownership (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 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)
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 7. 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 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)
× ETF ownership (t-1)	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 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)
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 8. Evidence from Limits to Arbitrage

XXX

The table presents regressions using ETF-day-level data. The sample is all equity ETFs between 2001 and 2010. In Panel A, the dependent variable is the daily rate of change in ETF shares (in %). The independent variables include: lagged NAV return, lagged ETF return, and lagged ETF mispricing. Panel B explores the relation between ETF mispricing and the buy-sell order imbalance on the ETF and underlying stocks. The table focuses on the buy-sell order imbalance at the ETF level (Columns (1) to (3)) and the underlying security level (Columns (4) to (6)) on past ETF mispricing and past ETF order imbalance. Panel C presents regressions of future stock returns on current ETF mispricing interacted with stock characteristics: the log of market capitalization, the beta relative to the S&P 500, and idiosyncratic volatility from a one-factor model. The sample is restricted to stocks that are included in the S&P 500 index. The dependent variable is stock returns (%). All regressions are OLS regressions. Variable definitions are provided in the Appendix. *t*-statistics are presented in parentheses. ***, **, * represent statistical significance at the 1%, 5%, or 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)
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)
× ETF Ownership (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)
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)
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 8. 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)
abs(Flows (t-1))	-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)
× ETF Ownership (t-1)	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)
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)
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 8. 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)
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)
× ETF Ownership (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)
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)
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 8. 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)
abs(Flows (t-1))	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)
× ETF Ownership (t-1)	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)
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)
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

Table 9. Clientele Difference between ETFs and Stocks

The table presents regressions using second-level data. Panel A presents regressions of second-level S&P 500 returns on May 6, 2010 on lagged variables: SPY mispricing, S&P 500 return, SPY return, and E-mini futures return, as well as cumulative returns. In Panel B, the independent variable is order imbalance (calculated using the Lee and Ready (1991) algorithm). In Panel C, the independent variable is average short selling volume in the following 5 seconds. All regressions are OLS regressions. Calendar day fixed effects are included in all regressions, and ETF fixed effects are included in Columns (2), (4), (6), and (8). Variable definitions are provided in the Appendix. *t*-statistics are presented in parentheses. ***, **, * represent statistical significance at the 1%, 5%, or 10% levels, respectively.

ETFOWN is the % ownership by ETFs. All ETF variables are weighted by the ETF ownership of each stock. CR is the churn ratio. IT is the turnover measure (median of three measures: Turnover #1 (min(Buys,Sales)), Turnover #2 (min(Buys,Sales)+abs(Flows)), Turnover #3 (Buys+Sales-abs(Flows))) _CR measures are weighted by actual CR value of each institution that owns the stock. _CRR measures are weighted with the quintile rank of CR of each institution (-2 Low CR and +2 for highest CR quintile). CR_LOWQ is the ownership by bottom CR quintile CR_HGHQ is the ownership by highest CR quintile institutions same applies for IT measures.

Sample:	S&P 500				Russell 3000			
Dependent variable:	Churn ratio	CRR	IT	ITR	Churn ratio	CRR	IT	ITR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Security is ETF	0.169***	0.807***	0.088***	0.739***	0.143***	0.700***	0.070***	0.624***
	(15.670)	(21.291)	(13.259)	(20.055)	(12.250)	(15.774)	(9.697)	(14.676)
Security is Closed-end Fund	0.074***	0.426***	0.029***	0.347***	0.044***	0.260***	0.010***	0.181***
	(13.102)	(17.168)	(13.377)	(15.540)	(7.786)	(10.268)	(5.317)	(8.182)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135,958	135,958	135,958	135,958	453,277	453,277	453,277	453,277
Adjusted R^2	0.278	0.242	0.225	0.204	0.209	0.155	0.182	0.122

Figure 1: Non-Fundamental Shocks Are Propagated via Arbitrage

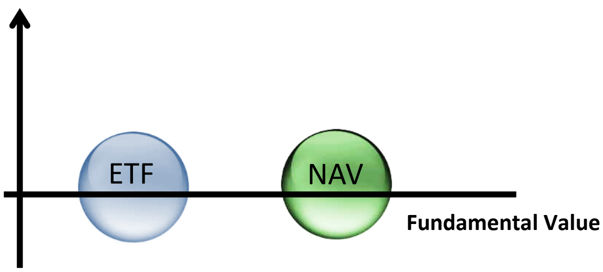


Figure 1a. Initial equilibrium

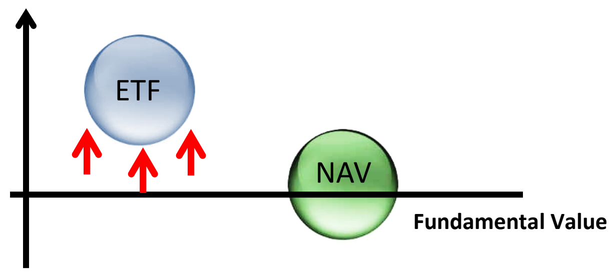


Figure 1b. Non-fundamental shock to ETF

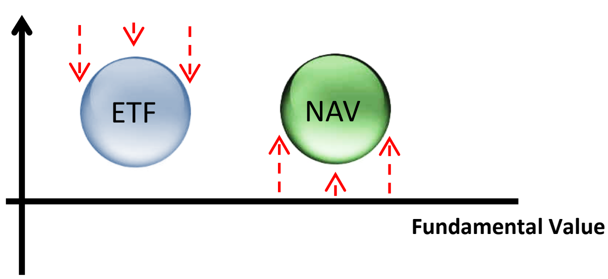
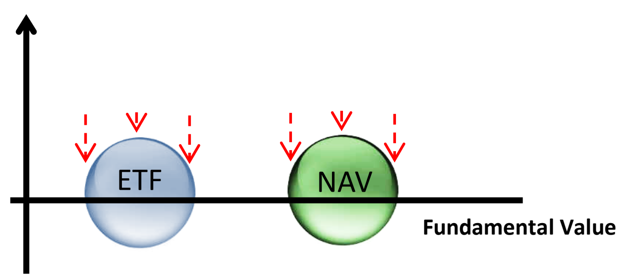


Figure 1c. Initial outcome of arbitrage: the non–fundamental shock is propagated to the NAV, the ETF price starts reverting to the fundamental value.



.value
after a delay
Figure 1d. Re-establishment of equilibrium: after some time, both the

Figure 2: Fundamental Shock with Price Discovery Occurring in the ETF Market: The ETF Moves First, the NAV Follows with Some Delay

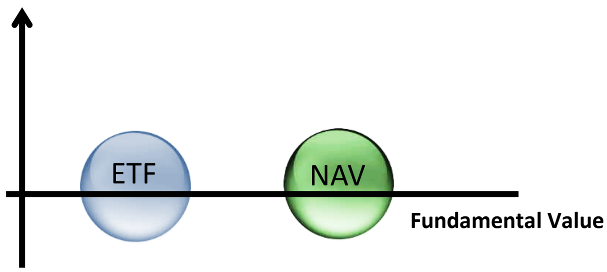


Figure 2a. Initial equilibrium

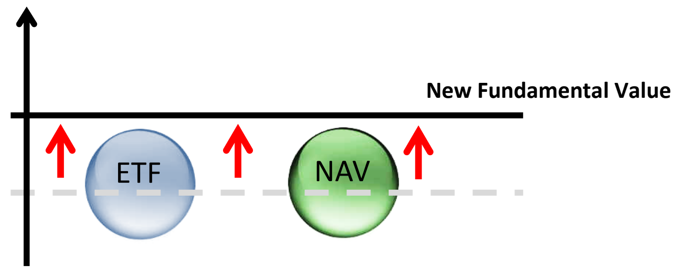


Figure 2b. Shock to fundamental value

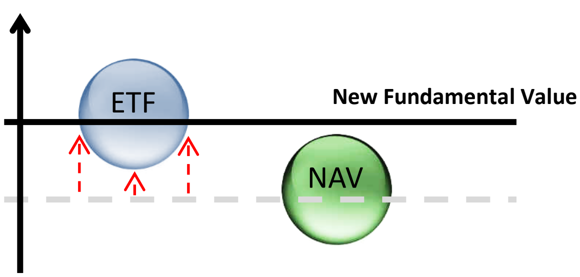


Figure 2c. The ETF price moves to the new fundamental value.

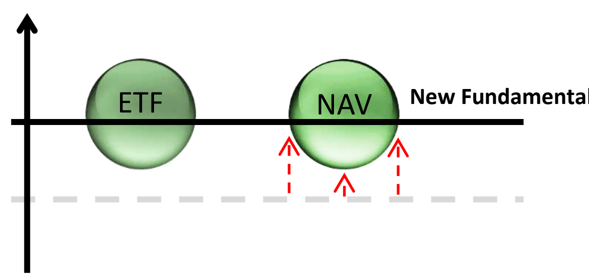


Figure 2d. After a delay, the NAV catches up with the new fundamental.