Do ETFs Increase Volatility?

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Abstract

Due to their exceptional liquidity, ETFs are likely to be a catalyst for noise traders. This noise can propagate to the underlying securities through the arbitrage channel. Therefore, we explore whether ETFs increase the non-fundamental volatility of the securities in their baskets. We exploit exogenous changes in index membership, and find that stocks with higher ETF ownership display significantly higher volatility. ETF ownership is also related to significant departures of stock prices from a random walk at the intraday and daily frequencies. Additional time-series evidence suggests that ETFs introduce new noise into the market, as opposed to just reshuffling existing noise across securities.

Keywords: ETFs, volatility, arbitrage, fund flows

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1 Introduction

Passive investing is gaining popularity in the asset management industry. While almost all mutual funds followed active strategies in 1980, by the end of 2014, 30% of assets were in passive allocations (Morningstar, 2015). Exchange Traded Funds (ETFs) are at the forefront of this trend in the U.S., as well as globally (Cheng, Massa, and Zhang, 2015). The first ETF started trading in the U.S. in 1993. At the end of 2014, exchanged traded passive vehicles had a market capitalization of $2 trillion, which is almost half of the passive mutual fund industry.[1] Some authors believe that the shift to passive investing is welfare improving, given the drop in intermediation fees and the improvement in portfolio diversification that index funds provide (French, 2008). Furthermore, Stambaugh (2014) argues that the rise in passive investing is symptomatic of improved market efficiency, as profit opportunities for active managers are shrinking.

However, because of their peculiar characteristics, ETFs do not conform to the traditional view of passive funds as buy and hold investors. For example, ETFs provide intraday liquidity to their investors. As a result, they attract high-frequency demand, which translates into price pressure on the underlying securities, due to the arbitrage relation between the ETF and its basket. This trading activity is potentially destabilizing for the underlying securities' prices because it likely reflects non-informational motives. (Arguably, traders who have company-specific information exploit their advantage by exchanging individual securities, as opposed to index products, such as ETFs.) To compound this effect, the lower trading costs of ETFs relative to the underlying securities can increase the rate of arrival of demand shocks to the market. Specifically, trading strategies that were previously too expensive suddenly become affordable thanks to the availability of ETFs. Noise trading can therefore leave a bigger footprint on security prices because of these instruments, suggesting that ETFs may pose new challenges to the efficient pricing of the underlying securities.

Despite the ways in which ETFs differ from traditional passive funds, and despite their prominent role in today's investment space, there has been virtually no large sample study

[1] ETFs, along with other exchange traded products (ETPs), have reached $2.8 trillion of assets under management (AUM) globally as of December 2014 (BlackRock, December 2014). Also important, ETPs are involved in an increasing share of transactions in equity markets. For example, in August 2010, exchange traded products accounted for about 40% of all trading volume in U.S. markets.

exploring the causal effect of ETFs on the noise in the underlying securities' prices.[2] This paper aspires to fill this gap. We investigate whether the prices of the securities with higher ownership by ETFs display higher volatility and are more likely to depart from a random walk. The analysis focuses on plain vanilla ETFs that physically replicate U.S. stock indexes, which hold the large majority of assets in the industry (81% of AUM in U.S. ETFs).

The conjectured channel of noise propagation is arbitrage trading. The demand shocks in the ETF market put pressure on ETF prices. To the extent that the ETF price deviates from the net asset value (NAV) of the portfolio holdings, arbitrageurs trade the underlying securities in the same direction as the initial price pressure. Thus, arbitrage can transfer price pressure from the ETF market to the portfolio holdings. This effect is similar to that of mutual fund flows on the prices of the portfolio holdings (Coval and Stafford, 2007; Lou, 2012; Hombert and Thesmar, 2014; Cella, Ellul, and Giannetti 2013; and in the general context of large trades: Ellul, 2006). The main difference relative to mutual funds is that transactions in ETFs, as well as arbitrage activity, take place continuously throughout the day. This fact makes ETFs a more rapid conduit for the propagation of demand shocks than other managed portfolios.

Our empirical analysis starts by showing that ETFs attract short-term investors, whose demand shocks could ultimately result in price pressure in the underlying securities (similar to the effects documented in Cella, Ellul, and Giannetti 2013). ETFs are, on average, significantly more liquid than the basket of underlying securities in terms of bid-ask spread, price impact, and turnover. For example, the value-weighted portfolio of all equity-based ETFs in the U.S. trades at a bid-ask spread that is 20 basis points (bps) lower than the spread for the equivalent portfolio of underlying stocks. Theories positing that short-horizon clienteles self-select into assets with lower trading costs (Amihud and Mendelson, 1986) suggest that ETFs should be the preferred habitat of high-turnover investors. Indeed, using 13-F institutional holdings data, we find that the institutions holding ETFs have a significantly shorter horizon than those holding the underlying securities. We take this evidence as satisfying a necessary condition for the argument that ETFs are more

[2] A few papers test whether ETFs have a destabilizing effect, but most of them focus on specific types of ETFs or specific events. Cheng and Madhavan (2009) and Trainor (2010) investigate whether the daily rebalancing of leveraged and inverse ETFs increases stock volatility; they find mixed evidence. Bradley and Litan (2010) voice concerns that ETFs may drain the liquidity of already illiquid stocks and commodities. Madhavan (2012) relates market fragmentation in ETF trading to the Flash Crash of 2010. Instead, Da and Shive (2015) and Israeli, Charles, and Sridharan (2015) are large sample studies, like our paper. The results in these papers support our main claim, while differing in the identification strategy. A discussion follows below.

appealing than stocks for noise traders who wish to express their views at a low cost and high frequency.

In the core of our analysis, we test whether there is a positive causal link between ETF ownership and noise in stock prices. ETF ownership is the total fraction of a stock's capitalization that is held by ETFs. Using the annual reconstitution of the Russell indexes, as in Chang, Hong, and Liskovich (2015) and Appel, Gormley and Keim (2015) and others, we find evidence of a causal effect of ETF ownership on volatility. In addition, prices of stocks with higher ETF ownership display stronger deviations from a random walk at the intraday and daily frequencies, which is consistent with the increase in volatility being due to noise

We start by providing simple OLS evidence on the association between daily volatility and ETF ownership, at the stock level and at a monthly frequency. In this analysis, a one-standard-deviation increase in ETF ownership is associated with a statistically significant increase in daily volatility that ranges between 7% and 13% of a standard deviation, for S&P 500 stocks. The effect is, therefore, economically significant. The magnitude is less than half, but still statistically significant, when we extend the sample to a universe that includes smaller firms (Russell 3000). The effect is weaker for these stocks, probably because ETF arbitrageurs focus on the largest stocks in each basket when trading the replicating portfolios, in order to minimize transaction costs and to achieve larger profits.

The observed increase in volatility is consistent with greater noise in stock prices. However, it could also reflect higher investor attention, which makes prices react more strongly to fundamental information, as shown by Andrei and Hasler (2015). To investigate whether the increased volatility reflects an increase in noise, we measure the impact of ETFs on the mean-reverting component of prices. First, we construct the absolute difference from one of intraday and daily variance ratios of stock returns.[3] We find that the deviation in the variance ratios of stock returns from unity increases with ETF ownership, suggesting a link between the presence of ETFs and lower price efficiency of the underlying securities. We also estimate predictive regressions of stock returns as a function of ETF flows at the stock level and daily frequency. We find that almost

[3] When the variance ratio equals one, prices follow a random walk. See, e.g., Lo and MacKinlay, 1988; O'Hara and Ye, 2011.

half of the contemporaneous positive impact of flows reverts over the next twenty days, confirming that the presence of ETFs is significantly related to the mean-reverting component of prices.

Our main empirical strategy aims at identifying truly exogenous variation in ETF ownership. Although the OLS regressions control for observable stock characteristics and include stock fixed effects, there is a legitimate concern that ETF ownership is an endogenous variable.[4] To address this concern, we rely on the natural experiment provided by the annual reconstitution of the Russell indexes. We follow closely the approach in Appel, Gormley and Keim (2015) who run an instrumental variable (IV) regression exploiting the mechanical rule allocating stocks between the Russell 1000 (top 1000 stocks by market capitalization) and the Russell 2000 (next 2000 stocks by market capitalization) indexes in June of each year. Due to the large difference in index weights, the top stocks in the Russell 2000 receive significantly larger amounts of passive money than do the bottom stocks in the Russell 1000. The identifying assumption is that, after controlling for market capitalization, which determines index assignment, a switch to either index generates exogenous variation in ETF ownership. Hence, we use the index-switch as an instrument to identify the effect of ETF ownership on volatility. In addition, we also control for lagged volatility, which is positively correlated with the probability of switching and could, therefore, lead us to find a spurious effect.

This methodology confirms that the impact of ETF ownership on volatility is positive and strongly statistically significant. The IV estimates exceed those from the OLS regressions, averaging around 32% of a standard deviation, which suggests a negative omitted variable bias in the OLS specifications. The replication of the variance ratio exercise within the IV context also confirms the sign and significance of the OLS results with a larger magnitude. To make sense of the larger IV coefficients, we also note that the IV slopes measure a local average treatment effect (LATE), which is the weighted average effect across the units in the sample, giving more weight to units that are more likely to receive treatment (the 'index switchers', in our context). Hence, for stocks far away from the cutoff, which are less likely to switch, the effect is probably closer to the smaller OLS estimates.

[4] For example, new ETFs might track investment themes that have gained popularity among investors. The stocks in these segments of the market might be more volatile because of the attention they already receive, not because ETFs attract noise trading. This mechanism would generate a positive bias in the OLS estimates. Alternatively, higher ETF ownership may signal companies that belong to multiple indexes, which have less volatile stocks because they are more established companies. This fact would lead to a negative omitted variable bias.

We provide additional evidence on the channel that drives the effect of ETFs on volatility. According to the main hypothesis of the paper, the impact of noise traders on ETF prices propagates to the prices of the underlying securities because arbitrageurs take hedging positions in portfolios replicating the ETF basket. These trades occur whenever the ETF price diverges from the NAV. To test this channel, we ask whether the impact of ETF arbitrage activity on stock prices is weaker for securities that display higher arbitrage costs. Indeed, we find that a proxy for arbitrage activity (the difference between the ETF price and the NAV, labeled 'mispricing') has a smaller effect on volatility and noise for stocks in the top half the distribution of the bid-ask spread and of share-lending fees, i.e., for stocks with higher limits to arbitrage. Moreover, strongly supporting the arbitrage channel, the coefficient on share-lending fees is significant only in the subsample for which the arbitrage trades involve shorting the stock (that is, when mispricing is negative).

Thanks to the possibility of identifying exogenous variation in ETF ownership, we can conclude that ETFs increase noise in the prices of the stocks that they own. This result is sufficient to establish a new dimension along which institutional trading can destabilize prices, and it runs contrary to the belief that the rise in passive investing is unambiguously related to increased pricing efficiency.

This cross-sectional evidence, however, could follow from a migration of noise traders from securities with low ETF ownership to those with high ownership. Therefore, in the last part of our analysis, we address the question of whether ETFs induce an increase in the overall noise in the stock market, as opposed to just a redistribution of noise across securities. ETFs can attract new noise traders because of their innovative characteristics. Specifically, relative to standard mutual funds, which clear trades once a day, ETFs permit continuous intraday trading at low cost. In addition, ETFs provide a variety of investment themes previously not offered by mutual funds. Finally, ETFs allow the expression of negative views through short selling, which is not possible with mutual funds. In general, it is plausible that ETFs enable investors to take long and short positions at higher frequency and lower cost, on a wider range of asset classes. Consequently, noise trading has the potential to leave a bigger footprint in the market thanks to the introduction of ETFs.

In support of this conjecture, we provide suggestive time-series evidence that the average share of ETF ownership in the market is positively associated with average stock volatility. The effects persists when we control for aggregate ownership by other mutual funds and include a time trend, which helps to absorb omitted factors. Although the identification strategy does not allow us to make unambiguous causal inference from these times-series estimates, the finding is fully consistent with the view that ETFs attract non-fundamental demand that would not otherwise reach the stock market if ETFs did not exist. In other words, the overall noise appears to increase because of ETFs.

Our study relates to different strands of the literature. There is mounting evidence on the role of institutions in impounding non-fundamental shocks into asset prices as a result of flows from their investors (Brunnermeier and Nagel, 2004; Coval and Stafford, 2007; Ben-David, Franzoni, and Moussawi 2012; Cella, Ellul, and Giannetti, 2013; Hombert and Thesmar, 2014; Lou, 2012; Vayanos and Woolley, 2013). We highlight a previously unexplored channel that is typical of a new class of institutional portfolios: arbitrage activity between ETFs and the underlying baskets. Our paper indirectly relates to the rich literature on the effect of indexing (Shleifer, 1986; Barberis, Shleifer, and Wurgler, 2005; Greenwood, 2005; Wurgler, 2011; Chang, Hong, and Liskovich, 2015). The trigger for the effect that we measure is trading in ETFs, as opposed to index reconstitution. Index membership matters only in defining the stocks that are affected by ETFs. Moreover, by documenting an effect of institutional ownership on volatility, we join a body of work that focuses on the impact of institutions on the second moments of returns (Greenwood and Thesmar, 2011; Anton and Polk, 2014; Lou and Polk, 2014). Closely related, Basak and Pavlova (2013a, 2013b) argue theoretically that the inclusion of an asset in an index tracked by institutional investors increases the non-fundamental volatility in that asset's prices.

A few recent studies also focus on the effect of ETFs on second moments, but use different empirical approaches. Da and Shive (2015) find that ETFs ownership is associated with higher comovement of the underlying securities. This idea is subsumed by our results: ETFs impound the same shocks into all the stocks in their basket and, therefore, make them comove. Hence, the empirical challenge, as taken on here, is to show that ETFs indeed *cause* price variation in the underlying stocks. If the causal link exists, then comovement is a by-product of this effect. Our identification strategy allows us to draw causal inference. Simply showing comovement is not by itself sufficient because of the potential endogeneity of ETF ownership with respect to stocks with similar characteristics. Similarly, the recent paper by Israeli, Lee, and Sridharan (2015) makes the claim that increased ETF ownership can lead to higher trading costs and lower benefits from information acquisition, a combination which results in less informative security prices for the component firms. While their results supports our conclusions, once again, the evidence in our paper relies on exogenous variation in ETF ownership to draw a causal link from ETF ownership to security prices. Finally, Leippold, Su, Ziegler (2015) develop a theoretical model that is fully consistent with our empirical findings. In time-series tests, they show that the impact of ETFs on return correlations exceeds the effect of futures, which is a core prediction of their theory.

Another theme in the literature that our study relates to is the long-running debate on the effect of derivatives on the quality of the underlying securities' prices. On one side of the debate is the concern that liquidity shocks in derivatives markets can trickle down to the cash market, adding noise to prices. For example, Stein (1987) shows that imperfectly informed speculators in futures markets can destabilize spot prices. Among the supporters of the alternative view, Grossman (1989) argues that the existence of futures provides additional market-making power to absorb the impact of liquidity shocks. As a result, volatility in the spot market is reduced (see also Danthine, 1978; Turnovsky, 1983).[5] We contribute to this literature by providing systematic evidence from ETFs, an asset class that has a similar flavor to futures, but is potentially more attractive to noise traders due to the lack of margin requirements and absence of roll over risk. In December 2014, the assets under management in ETFs tracking the S&P 500 surpassed the open interest in futures on the same index, suggesting that ETFs are becoming the security of choice to achieve exposure to the stock market (Amery, 2015).

The paper proceeds as follows. Section 2 provides institutional details on ETFs and develops the testable hypotheses, while Section 3 describes the data. Section 4 presents the main evidence of the effect of ETF ownership on stock volatility and noise. In Section 5, we provide evidence on the role of arbitrage in driving the main effect on volatility and noise. Section 6 addresses the question of whether ETFs attract a "new layer" of volatility to the stock market. Section 7 concludes.

[5] Earlier studies that examine the impact of derivatives on volatility focused on futures. The proposed economic channel in this literature is the same as the one that we test in this paper. In a cross-sectional analysis, Bessembinder and Seguin (1992) find that high trading volume in the futures market is associated with lower equity volatility. However, consistent with the idea that non-fundamental shocks in the futures market are passed down to the equity market, they find that unexpected futures trading volume is positively correlated with equity volatility. Chang, Cheng, and Pinegar (1999) document that the introduction of futures trading increased the volatility of stocks in the Nikkei index stocks. Roll, Schwartz, and Subrahmanyam (2007) find evidence of Granger causality between prices in the futures and equity markets: price shocks are transmitted from the futures market to the equity market and vice versa.

2 Institutional Details and Hypotheses Development

2.1 Mechanics of Arbitrage

Exchange traded funds (ETFs) are investment companies that typically focus on a single asset class, industry, or geographical area. Most ETFs track an index, very much like passive index mutual funds. Unlike index funds, ETFs are listed on an exchange and trade throughout the day. ETFs were first introduced in the late 1980s and became popular with the issuance in January 1993 of the SPDR (Standard & Poor's Depository Receipts, known as "Spider"), which is an ETF that tracks the S&P 500 (ticker: SPY). SPY is currently the largest ETF in the world, with about $181 billion of assets (December 2014). In 1995, another SPDR, the S&P MidCap 400 Index (ticker: MDY) was introduced, and the number of ETFs subsequently exploded to more than 1,600 by the end of 2012, spanning various asset classes and investment strategies.

To illustrate the growing importance of ETFs in the ownership of common stocks, we present descriptive statistics for the S&P 500 and Russell 3000 universes in Table 1. Due to the expansion of this asset class, ETF ownership of individual stocks has increased dramatically over the last decade. For S&P 500 stocks, the average fraction of a stock's capitalization held by ETFs has risen from 0.22% in 2000 to 3.90% in 2012. The table shows that the number of ETFs holding the average stock in the S&P500 universe grew from about 2 to about 49 during the same period. The average assets under management (AUM) for ETFs holding S&P 500 stocks was, in 2012, about $5bn. The statistics for the Russell 3000 universe paint a similar picture.

Unlike futures, ETFs do not involve a rollover of the expiring contract. Rollover can erode performance for investors with horizons spanning beyond the short maturity of a futures contract. According to BlackRock, the annualized rollover cost of a futures position in large cap stocks (S&P 500, Euro Stoxx 50, FTSE 100) ranges from 0.9% to 1.4%. The total expense ratio for an ETF on the same indexes can be as low as 0.05% (e.g., the Vanguard S&P 500 ETF, ticker: VOO). This lower cost can explain the fact that in December 2014 the assets in ETFs tracking the S&P 500 surpassed the open interest in futures contracts for the first time (see Amery, 2015).

In our analysis, we focus on ETFs that are listed on U.S. exchanges and whose baskets contain U.S. stocks. The discussion that follows applies strictly to these "plain vanilla" exchange traded products that do physical replication, that is, they hold the securities of the basket that they aim to track. We omit from our sample leveraged and inverse leveraged ETFs that use derivatives to deliver the performance of the index, which represent at most 2% of the assets in the sector according to BlackRock (December 2014). These more complex products are studied by Cheng and Madhavan (2009), among others. We also omit active ETFs that are still below 1% of AUM in the sector.

ETFs are traded in the secondary market by retail and institutional investors, in a similar fashion to closed-end funds. However, unlike closed-end funds, new ETF shares can be created and redeemed. Because the price of ETF shares is determined by the demand and supply in the secondary market, it can diverge from the value of the underlying securities (the NAV).[6] Some institutional investors (called "authorized participants," or APs) who are dealers that have signed an agreement with the ETF provider can trade bundles of ETF shares (called "creation units," typically 50,000 shares) with the ETF sponsor. An AP can create new ETF shares by transferring the securities underlying the ETF to the ETF sponsor. These transactions constitute the primary market for ETFs. Similarly, the AP can redeem ETF shares and receive the underlying securities in exchange. For some funds, ETF shares can be created and redeemed in cash.[7]

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

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[6] Unlike premia and discounts in closed-end funds (e.g., Lee, Shleifer, and Thaler, 1991; Pontiff, 1996), price divergence between the ETF and the NAV can be more easily arbitraged away thanks to the possibility of continuously creating and redeeming ETF shares. As a result, ETF premia/discounts are orders of magnitude smaller than for closed-end funds.

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

Creating/redeeming ETF shares has limited costs in most cases, especially for equity-focused funds. These costs include the fixed creation/redemption fee plus the costs of trading the underlying securities. Petajisto (2013) describes the fixed creation/redemption costs as ranging in absolute terms from $500 to $3,000 per creation/redemption transaction, irrespective of the number of units involved. This fee would amount to, at most, 2.9 bps for a single creation unit in SPY (that is, 50,000 shares worth about $10.2 million as of December 2014), or 0.6 bps for five creation units. During our sample period (2000–2012), share creation/redemption occurs on 9.2% of the trading days for the average ETF. However, a share creation event occurs on 72% of the trading days in our sample, across all ETFs. For the largest ETF, the S&P 500 SPDR, flows into and out of the fund occurred almost every day in 2012 (99.2% of the trading days).

ETF arbitrage also takes place continuously throughout the day as a result of the activity of hedge funds and high-frequency traders.[8] These investors do not need to engage in primary market trades. On the secondary market, they can buy the inexpensive asset and short sell the more expensive one between the ETF and the basket of underlying securities. They hold the positions until prices converge, at which point they close down the positions to realize the profit. ETF sponsors facilitate arbitrage activity by disseminating NAV values at a 15-second frequency throughout the trading day. They do so because the smooth functioning of arbitrage is what brings about the low tracking error of these instruments. As a result of the low trading costs and availability of information, arbitraging ETFs against the NAV has become a very popular trading strategy in recent years. According to some industry participants, statistical arbitrage accounts for 50% of the volume in the S&P 500 SPDR, which is the most traded security in the U.S. with $26 billion average daily volume (last 3 months of 2014).[9]

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

[9] http://ftalphaville.ft.com/blog/2009/07/30/64451/statistical–arbitrage–and–the–big–retail–etf–con/. Also see http://www.indexuniverse.com/publications/journalofindexes/joi–articles/4036–the–etf–index–pricing–relationship.html for a detailed example of ETF arbitrage. See http://ftalphaville.ft.com/2011/05/18/572086/how-profitable-is-etf-arbitrage/ and http://ftalphaville.ft.com/blog/2011/06/06/584876/manufacturing–arbitrage–with–etfs/ for the profitability of ETF arbitrage. ETF prices can also be arbitraged against other ETFs (Marshall, Nguyen, and Visaltanachoti, 2013) or against futures contracts (Richie, Daigler, and Gleason, 2008).

Both the creation/redemption activity by APs, which takes place at the daily frequency, and the intraday arbitrage by high-frequency traders have the potential to move the prices of the underlying securities. We will provide evidence that is consistent with the effects of ETF arbitrage playing out at both the daily and the intraday frequencies.

These institutional details, with some modifications, also apply to synthetic ETFs, which replicate the performance of the index using total return swaps and other derivatives, and for which creation and redemption are handled in cash. The secondary market arbitrage still involves transactions in the underlying securities. Thus, the potential for the propagation of demand shocks from the ETF market to the underlying securities via arbitrage is also present among synthetic ETFs. Similarly, the arbitrage process is an inherent characteristic of all types of ETFs, beyond the equity-based ones that are studied here. Hence, one should expect the effects that we describe in this paper to occur for all types of underlying assets.

2.2 ETFs vs. Stocks: Liquidity, Investor Types, and Trading Horizon

The main testable hypothesis of the paper, discussed in detail below, posits that ETFs are appealing to noise traders because they are more liquid than the underlying securities. In this subsection, we study how ETF liquidity contrasts to that of their portfolio constituents. Moreover, in order to provide a description of the users of ETFs, we compare the clienteles of ETFs and common stocks in terms of their trading horizon and institutional type.

The bid-ask spreads on ETFs are on average low, potentially due to a lack of information asymmetry. For a few representative ETFs, Madhavan and Sobczyk (2014) provide evidence that the bid-ask spread is lower than the average spread in the corresponding basket. These authors put forward a convincing argument for the higher liquidity of ETFs. Investors with stock-level private information are more likely to trade individual securities and market makers impose higher bid-ask spreads to overcome adverse selection. In contrast, investors who place uninformed directional bets or trade for hedging purposes are more likely to trade entire baskets, such as ETFs. As a result, ETF spreads are less likely to contain an adverse selection premium.

We carry out a similar analysis in our sample covering all U.S.-equity-based ETFs listed on U.S. exchanges (660 different products; see Section 3 for details on sample construction). In

Table 2, Panel A, we present systematic evidence on the difference in liquidity between ETFs and the underlying portfolios along three dimensions: the percentage bid-ask spread, the Amihud (2002) measure of price impact, and daily turnover. For all the ETFs in our sample, we compute the average of each liquidity measure across all the stocks in the basket in a given quarter. Then, to replicate the strategy of an investor that allocates funds to all ETFs according to their market capitalization, we take the value-weighted mean of these measures across all ETFs in a given quarter. The table reports the time-series average of these means in the 52 quarters of the sample (2000:Q1-2012:Q4), along with the results of tests for the statistical significance of their difference. Along all three dimensions, the average ETF is significantly more liquid than its basket stocks. The bid-ask spread is lower by about 20 bps. Price impact, as measured by the Amihud ratio, is also significantly lower for ETFs. Finally, ETFs' turnover is higher by about 8.3%.

A corollary of the conjecture that ETFs are more liquid than the underlying baskets is that ETF investors should display higher turnover. This prediction stems, for example, from Amihud and Mendelson's (1986) clientele effect, whereby short-horizon investors choose to trade in more liquid securities. The bottom of Table 2, Panel A supports this conjecture. We compare ETFs to their underlying baskets in terms of two measures of the investor churn ratio. The first measure comes from Cella, Ellul, and Giannetti (2013), who compute an institutional-investor-level churn ratio as the sum of quarterly absolute changes in dollar holdings over average assets under management, using institutional holdings in the 13-F filings. This measure is then averaged across institutions at the stock level using the fraction of a company held by each institution as weight. The second measure differs only in that the investor-level churn ratio is computed as the minimum between the absolute value of buys and sells, divided by prior quarter holdings.[11] In Table 2, Panel A, we note that the average ETF has a significantly higher investor churn ratio than its underling basket by about 6.7% per quarter, for the first measure, and 2.9%, for the second measure. These differences are economically significant as the average churn ratio for the basket of stocks is 24% and 12.5%, respectively, for the two measures. The evidence confirms that ETFs, rather than stocks, are the preferred habitat of investors with a short trading horizon.

[11] Buys (sells) are the sum of the dollar value of the quarterly positive (negative) changes in stock holdings for a given institutional portfolio, as reported in the SEC 13-F form. Values are computed using beginning-of-quarter prices.

Next, we compare classes of ownership for all ETFs in our sample and all common stocks in CRSP. Panel B of Table 2 uses Thomson-Reuters' classification of institutional owners filing the 13-F form. We provide variable definitions in Appendix Table A1 and the detailed definition of various investor classes in Appendix Table A2. The panel reports shares held by each group as a fraction of total shares outstanding. The first striking fact is that the institutional ownership of ETFs is by far smaller (at 47.4% on average) than the institutional ownership of stocks (at 62.1% on average) throughout the entire sample period.[12] One can roughly infer retail ownership as the complement to one of institutional ownership.[13] Based on Stambaugh's (2014) argument that noise traders are mostly present among retail investors, this evidence suggests a higher density of uninformed investors among ETF clients.

In analyzing Table 2, Panel B, two additional patterns emerge. First, investment companies, which are mostly comprised of mutual funds, have minimal investments (1.7%) in ETFs, compared to stocks (16.3%). Mutual funds only use ETFs to temporarily park their cash and avoid accumulating tracking error with respect to their benchmark. Second, research firms, which include broker-dealers, have greater ETF ownership (5.8%) than ownership of stocks (0.6%). This class of owners, along with hedge funds, corresponds to ETF arbitrageurs and market makers (including APs). In sum, Panel B of Table 2 paints a picture in which ETFs are mostly traded by retail investors, who are more likely to act as noise traders. Arbitrageurs are also overrepresented by virtue of the peculiar arbitrage mechanism that keeps ETF prices in line with the NAV.

From Panel A of Table 2, we learn that ETF investors have a significantly shorter investment horizon than investors in the underlying baskets. A related question is whether *all* investor classes turn over their ETF portfolio more often than they turn over their stock portfolio. Panel C of Table 2 addresses this issue by computing separately the quarterly churn ratio of the ETF and stock portfolios, for each institution filing a 13-F form, using Cella, Ellul, and Giannetti's (2013) churn ratio as defined above. The churn ratio is then averaged within each investor class.

[12] It is worth noting that part of the direct institutional ownership in stocks is through ETFs.

[13] This way of computing retail ownership is an approximation due to two elements. First, small institutions managing less than $100 million and professional investors managing solely their own proprietary accounts are not required to file a 13-F form. Second, reported shares include shares that are short-sold. Because we compute ownership as a fraction of shares outstanding, total institutional ownership for a firm could exceed one. This issue is especially relevant for ETFs, as short interest for some ETFs can be very large (even exceeding the total shares outstanding). However, expressing ownership as a fraction of the shares outstanding plus shares short sold would give an even higher estimate of retail ownership: 1 – Institutional Shares / (Shares Outstanding + Shares Sold Short) > 1 – Institutional Shares / Shares Outstanding.

The striking evidence is that all groups of institutions trade their ETF portfolios faster than their stock portfolios, except for Venture Capital, which nevertheless holds a negligible fraction of ETFs (Panel B).

The institutional class with the fastest turnover in ETFs is hedge funds (85.9% quarterly). Besides being arbitrageurs in the ETF market, hedge funds use ETFs to take directional bets on specific market segments or asset classes. Also, ETFs are part of statistical arbitrage strategies to hedge market or industry risk when taking positions in mispriced securities. In the next subsection, we argue that the arbitrage trades employing ETFs have the potential to propagate mispricing to the underlying securities.

2.3 Hypotheses Development

Our empirical analysis draws inspiration from the literature on the destabilizing impact of institutional flows (e.g., Coval and Stafford, 2007; Lou, 2012; Vayanos and Woolley, 2013). The ETF market that we study differs from the typical framework of this prior work by the fact that investors can trade ETF shares in the secondary market continuously throughout the day. This high-frequency arbitrage activity can transfer the price pressure from the ETF market to the prices of the underlying securities. As a result, the demand for ETF shares translates into demand for the underlying securities, similarly to the effect of mutual fund flows. What makes ETFs special, relative to standard mutual funds, is that ETFs allow investors to access the market continuously and at a low trading cost. Hence, ETFs attract potentially more noise trading than standard mutual funds do.

The main testable hypothesis of the paper is that ETFs are a catalyst for noise traders and that noise propagates to the underlying securities via arbitrage. According to this hypothesis, stocks with higher ETF ownership should display higher non-fundamental volatility, everything else being equal.

To illustrate the arbitrage channel for noise propagation, we imagine a situation in which the ETF price and the net asset value (NAV) of its portfolio are aligned at the level of the fundamental value, as in Figure 1a. Then, a noise trading shock, i.e., one that is unrelated to fundamentals, hits the ETF market. Arbitrageurs absorb the liquidity demand by shorting the ETF.

Because they are risk averse, arbitrageurs require compensation for the (negative) inventory in the ETF that they are taking on. Hence, the ETF price has to rise (Figure 1b). At the same time, to hedge their short ETF position, arbitrageurs take a long position in the securities in the ETF basket. Again, to compensate the arbitrageurs for the risk that they take, the prices of the basket securities have to rise, as in Figure 1c. Eventually, when other sources of liquidity materialize, prices revert to fundamentals (Figure 1d).[14]

To make a concrete example of this channel, consider hedge funds' trading practices in ETFs. This group of institutions has the highest turnover (see Table 2, Panel C) and, therefore, has a high likelihood of being the marginal investor in the ETF market. Some hedge funds that specialize in high-frequency strategies carry out arbitrage trades of ETFs against the underlying baskets. These trades conform to the mechanism described in Figure 1. In addition, hedge funds can impound mispricing indirectly through their use of ETFs in statistical arbitrage. Suppose hedge funds short-sell an overpriced stock and hedge the industry risk by going long in the corresponding sector ETF. This trade puts upward pressure on the ETF price (as in Figure 1b). Then, cross-market arbitrageurs transfer the price pressure to the securities in the ETF basket (as in Figure 1c). This argument suggests that ETFs can propagate mispricing to the underlying securities not only because they are traded directly by uninformed investors, but also because they are traded indirectly through their participation in long-short strategies that involve other mispriced securities.

We note that the sequence of events in Figure 1 generates predictions that partly overlap with those from an alternative scenario positing gradual price discovery after a *fundamental* shock, as opposed to noise trading. If price discovery occurs first in the ETF market, ETF prices adjust immediately to the new information, while the underlying securities' prices remain temporarily fixed ("stale pricing"). We illustrate this scenario in Figure 2. The initial equilibrium (Figure 2a) is perturbed by a shock to the fundamental value of the ETF components (Figure 2b). The ETF price moves first because of price discovery (Figure 2c), and the prices of the underlying securities move with a delay because of stale pricing (Figure 2d). In this alternative situation, ETFs improve price discovery and the arbitrage activity facilitates the adjustment of prices to fundamentals. As

[14] The maintained assumption is that arbitrageurs have limited risk-bearing capacity. A similar effect arises in models with risk averse market makers, such as Grossman and Miller (1988) and Greenwood (2005).

a result, there could be a positive link between ETF ownership and "good" volatility (i.e., fundamental volatility). To disentangle the two scenarios, it is not sufficient to show that stocks with higher ETF ownership display higher volatility. We also need to show that ETFs are associated with increased mean reversion in prices, which follows from the propagation of noise (as per Figure 1).

The testable hypothesis spelled out above actually posits an *increase* in noise trading in the underlying securities because of ETF ownership. If the same amount of noise traders merely shifted from trading a given stock to trading the ETFs holding that security, the noise in the stock's price would not increase. To observe an increase in noise, one also needs the additional assumption that noise traders prefer ETFs to stocks as their habitat. Under this assumption, the creation of ETFs entails a migration of noise traders from stocks with low ETF ownership to stocks with high ETF ownership. Noise traders, especially those that affect price volatility at high frequency, are likely to be short-horizon investors. Table 2, Panel A reveals that ETFs are more liquid than the underlying securities and, as a result, they attract investors with higher turnover. Therefore, Table 2 provides background evidence that supports the main hypothesis.

Rather than simply redistributing existing noise from securities with low ETF ownership to those with high ownership, this new asset class can cause a *new layer* of noise to materialize in the stock market. The effect could follow from the enhanced trading opportunities that come with ETFs. For example, relative to standard mutual funds (including index funds), ETFs allow intraday trading and shorting at a low cost in a wide variety of market segments.[15] Hence, noise traders can gain access to previously unavailable opportunities to express their views. The possibility that ETFs attract a new layer of noise qualifies as a second testable hypothesis of the paper.

To test this conjecture, we shall look for a significant positive relation between the average stock volatility in the market and the average ETF ownership of stocks, in the time series. To

[15] As an example, the Vanguard 500 Index Fund is a passive mutual fund tracking the S&P 500 with AUM equal to $198.7 billion as of January 2015. It has the same portfolio as the Vanguard S&P 500 ETF, which has AUM of $28.12 billion for the same date. The index mutual fund has total expense ratio of 0.17% for Investor Shares (minimum investment of $3,000) and 0.05% for Admiral Shares (minimum investment of $10,000). The ETF's expense ratio is 0.05% (with no minimum investment). As per the index fund prospectus, Vanguard discourages frequent trading in its funds, with the exception of ETFs. Therefore, the company reserves the right to reject any purchase request of index fund shares without notice and regardless of size. Moreover, Vanguard prohibits investors' purchases into the index fund for 60 days after an investor has redeemed out of that fund. Given the higher costs and restrictions of index funds, it seems reasonable to conclude that noise traders with short investment horizons will prefer ETFs to index funds.

measure the effect of interest more closely, we will need to control for other contemporaneous developments in the market. Admittedly, the time-series tests can never completely rule out omitted factors, so that the evidence in favor of this second testable hypothesis will remain suggestive.

3 Data

We use Center for Research in Security Prices (CRSP), Compustat, Bloomberg, and OptionMetrics data to identify ETFs traded on the major U.S. exchanges and to extract returns, prices, and shares outstanding. We first draw information from CRSP for all securities that have a historical share code of 73, which exclusively defines ETFs in this data set. We then screen all U.S.-traded securities in the Compustat XpressFeed and OptionMetrics data, identifying ETFs using the security-type variables, and merge this sample with the CRSP ETF sample.[16] Our initial sample consists of 1,673 ETFs between 1993 and 2012.

Because very few ETFs traded during the 1990s, we restrict the sample to the 2000–2012 period. We further restrict our sample to ETFs that invest primarily in U.S. domestic equity stocks, because they are not plagued with stale pricing issues (global equity or bond ETFs) or other issues affecting the ease of replication (short bias, volatility, and futures-based ETFs, commodities, etc.). Therefore, we exclude leveraged ETFs, short equity ETFs, and all ETFs that invest in international or non-equity securities, or in futures and physical commodities. We also eliminate active and long/short ETFs as well as dedicated short bias funds and focus on plain vanilla U.S. domestic long equity ETFs. To do so, we use both the CRSP Style Codes and Lipper prospectus objective codes in the CRSP Mutual Fund Database and restrict our sample to the fund objectives that span broad-based U.S. Diversified Equity funds and U.S. sector ETFs that invest in equities (e.g., U.S. companies investing in oil and natural resources vs. those investing in oil or commodity futures).[17] We end up with 660 distinct equity ETF securities.

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

[17] The Lipper Asset Code is not sufficient to accurately filter for U.S. domestic equity funds, because the Equity Funds code comprises a wide array of U.S. and global funds that implement various direct investment or alternative/inverse strategies. Instead, we use the Lipper Objective Code classifications that are assigned by Lipper to a specific population of equity funds and that are based on how the fund invests by looking at the actual holdings of the fund to

We obtain quarterly holdings information using the Thomson-Reuters Mutual Fund holdings database. ETFs are subject to Investment Company Act reporting requirements, and similar to mutual funds, they have to disclose their portfolio holdings at the end of each fiscal quarter.[18] We use these data to align ETF ownership every month using the most recently reported holdings. Then, for every stock, we sum the total ownership by various ETFs to construct our ETF ownership measure. We also use the Thomson-Reuters Mutual Fund holdings database to compute the ownership by mutual funds other than ETFs, that is, index funds and active funds. To do that, we use the index fund flag in the CRSP Mutual Fund Database, and merge it with Thomson-Reuters holdings data using WRDS MFLinks. Similar to how ETF ownership is calculated, we compute monthly index and active fund ownership by using the most recently reported holdings.

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

As a dependent variable of our main tests, we compute daily stock volatility at the monthly frequency as the standard deviation of daily returns within a month. For the tests that are reported in the appendix, we compute volatility at a daily frequency using second-by-second data from the Trade and Quote database (TAQ). For each stock, we compute a return in each second during the

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determine market cap and style versus a benchmark. We restrict our sample to the following Lipper Objective Codes: Broad Based U.S. Equity: S&P 500 Index Objective Funds, Mid-Cap Funds, Small-Cap Funds, Micro-Cap Funds, Capital Appreciation Funds, Growth Funds, Growth and Income Funds, and Equity Income Funds (CA, EI, G, GI, MC, MR, SG, and SP respectively). We also include Sector Funds that invest in U.S. companies: Basic Materials, Consumer Goods, Consumer Services, Financial Services, Health/Biotechnology, Industrials, Natural Resources, Real Estate, Science and Technology, Telecommunications, Specialty/Miscellaneous Funds, and Utilities (BM, CG, CS, FS, H, ID, NR, RE, TK, TL, S, and UT, respectively).

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

day using the last trade price at the end of each second during market hours (between 9:30 am and 4:00 pm). Then, we compute the standard deviation of those second-by-second returns as the intraday volatility measure.[19]

We extract stock lending fees from the Markit Securities Finance (formerly Data Explorers) database.[20] We use the variable that reports the average lending fee over the prior seven days. Table 3 reports summary statistics for the variables that we use in the analysis. Panel A presents summary statistics for the monthly-stock-level sample of our main regressions; Panel B reports the correlations for the same variables. Panel C presents summary statistics for the variables that are used in the return regressions at the daily frequency. Panel D presents statistics for the stock-day-level sample. We further describe these variables in later sections and provide definitions in Appendix Table A1.

4 The Effect of ETF Ownership on Volatility

4.1 ETF Ownership and Volatility: OLS Regressions

We start by asking whether ETF ownership leads to an increase in the volatility of the underlying securities. In our first set of tests, we exploit variation in ETF ownership across stocks and over time in a simple OLS framework.

ETF ownership of stock *i* in month *t* is defined as the sum of the dollar value of holdings by all ETFs investing in the stock, divided by the stock's capitalization at the end of the month:

$$ETF\ ownership_{i,t} = \frac{\sum_{j=1}^{J} w_{i,j,t} AUM_{j,t}}{Mkt\ Cap_{i,t}}, \tag{1}$$

where *J* is the set of ETFs holding stock *i*; $w_{i,j,t}$ is the weight of the stock in the portfolio of ETF *j*, which is extracted from the most recent quarterly report; and $AUM_{j,t}$ is the assets under management of ETF *j* at the end of the month.

[19] We also compute intraday volatility using intraday returns based on National Best Bid and Offer (NBBO) midpoints; the results are similar.

[20] The database contains about 85% of the over-the-counter (OTC) security-lending market, with historical data going back to 2002. In constructing the aggregate security loan fee, Markit extracts the agreed fees from contract-level information and computes a fee value that is the volume-weighted average of each contract-level security loan fee.

Based on Equation (1), variation in ETF ownership comes from three sources. First, stocks are typically part of multiple indices (e.g., a stock might be part of the S&P 500, the S&P 500 Value, the Russell 3000, and a sector index). Second, there is variation in ETFs' assets under management over time and across products. Third, there is variation in weighting schemes. For example, the S&P 500 and the Russell 2000 are capitalization-weighted, but the Dow Jones is price-weighted; also, our sample contains 17 products that explicitly mention equal-weighting in their names.

The three sources of variation in ETF ownership present different degrees of exogeneity with respect to the dependent variable of interest, stock volatility. The portfolio weights follow the weighting scheme of the index mechanically. Hence, they are the most exogenous component in Equation (1). One caveat is that, if the weights do not grow at the same rate as the market capitalization at the denominator (e.g., for equal-weighted indexes), there could be a spurious link between ETF ownership and volatility resulting from the correlation between stock size and volatility. To avoid this issue, we include market capitalization (in logarithm) as a control in our regressions. Instead, ETF's AUM as well as the number of ETFs covering a stock are admittedly less exogenous. For example, investors' demand for existing or new ETFs may relate to how popular a given sector or asset class is at a given point in time. This popularity also affects the amount of trading intensity and the volatility of the underlying securities. This argument can generate a positive relation between ETF ownership and volatility that confounds the causal effect that we are trying to identify. On the other hand, the number of ETFs tracking a given stock depends on the number of indexes in which a stock appears. If more established, less volatile firms are more likely to be members of an index, then there can be a negative bias in the relation between ETF ownership and volatility.

In our tests, we take several steps to guard against potentially omitted variables. First, we include stock and month fixed effects. In addition, we control for stock size and liquidity as observable characteristics that relate to volatility. Also, we include standard predictors of returns, such as book-to-market, past-twelve-month returns, and gross profitability, which could also relate to volatility. Yet, we cannot entirely avoid the concern that ETF ownership is an endogenous variable within this framework. For this reason, in the next subsection, we provide additional analysis that derives exogenous variation of ETF ownership from the annual reconstitution of the Russell indexes.

With this caveat in mind, we start by reporting the results of OLS regressions of daily volatility in a given month on ETF ownership at the end of the prior month. In Table 4, we present separate regressions for S&P 500 stocks and for the broader sample of Russell 3000 stocks. The goal is to assess how the effect of interest varies with firm size. Besides the log of market capitalization, we include the following controls: the inverse of the stock price, the Amihud (2002) illiquidity measure of price impact, the bid-ask spread, the book-to-market ratio, the past-twelve-month return, and the gross profitability (gross income scaled by total assets, as in Novy-Marx, 2013). All the controls date from the end of the prior month. We also include stock and month fixed effects in all regressions. Standard errors are double-clustered at the stock and month level.

The results of the analysis are presented in Table 4. To ease interpretation, we standardize volatility and ETF ownership by subtracting the sample mean and dividing by the sample standard deviation. From Columns (1) of Table 4, we infer that the relationship between ETF ownership and volatility is positive and strongly statistically significant. The economic magnitude is also large, as a one-standard-deviation move in ownership is associated with 13.2% of a standard deviation change in daily volatility. This result is consistent with the hypothesis that ETFs impound noise in the underlying securities' prices.

Next, we test whether ETF ownership captures a different effect from the ownership of other institutional investors. Among these, open-end mutual funds are the most similar to ETFs because they also receive daily flows. ETFs are, however, different from other open-end funds in that they allow intraday trading. In Column (2) of Table 4, we include lagged ownership by active and index mutual funds, measured in the same way as ETF ownership (and standardized). The coefficients on both mutual fund ownership variables are positive and significant. However, the point estimates of both mutual fund ownership variables are significantly smaller in magnitude than the slope on ETF ownership, which remains intact. Thus, it appears that ETF ownership has an independent and stronger tie to volatility, which, according to the main hypothesis, depends on the fact that ETFs attract high-turnover investors.

In Column (3) of Table 4, we include three lags of the dependent variable to address the concern that the persistence in volatility could introduce reverse causality. The coefficient on ETF ownership remains large and significant at 7.3% of a standard deviation.

Extending the universe to smaller stocks (Columns (4) to (6)), the relationship between ETF ownership on volatility is weaker, amounting to about 3.3% to 5.2% of a standard deviation. Moreover, the slope is no longer statistically distinguishable from the coefficients for other mutual funds (Columns (5) and (6)).

The lower sensitivity of volatility to ETF ownership in a sample that is dominated by small stocks is consistent with the main hypothesis. The arbitrage activity that occurs at high frequency throughout the day does not require the creation or redemption of ETF shares. Hence, arbitrageurs can choose to concentrate on the larger stocks in the ETF baskets when constructing the replicating portfolio, in order to minimize transaction costs. Such behavior, called 'optimized replication' or 'representative sampling,' can explain why smaller stocks inherit less of the noise coming from the ETF market.

Given that ETF trading and the arbitrage activity involving the underlying securities occur intraday, one should expect the effect that we identify to also be visible at higher frequencies. In Appendix Table A3, we replicate the analysis of Table 4 using intraday volatility as the dependent variable, computed from second-by-second returns within a day. ETF ownership is updated daily using the daily market capitalization of the stock and daily ETF flows. The results from these daily stock-level regressions confirm the sign and significance from the monthly sample. The economic magnitude is also in the same ballpark (the variables of interest are standardized): one standard deviation increase in ETF ownership is associated with an increase of 10.6% in intraday volatility for S&P 500 stocks and with an increase of 2.4% in intraday volatility for Russell 3000 stocks. We give more emphasis to the results using daily volatility (Table 4) to stress the fact that we are not merely identifying a microstructure effect that washes out at lower frequencies.

4.2 Identification Using a Quasi-Natural Experiment

An identification based on cross-sectional and time-series variation in ETF ownership, which underlies the OLS results in Table 4, can raise doubts if the stock-level controls fail to capture characteristics that co-determine ETF ownership and volatility. For this reason, in this subsection we corroborate our main results with a more robust identification approach.

Appel, Gormley and Keim (2015) devise an identification strategy that exploits the exogenous variation in membership to the Russell 1000 and the Russell 2000 indexes. We follow closely their instrumental variable (IV) approach.[21]

The Russell 1000 index is comprised of the top 1000 stocks by market capitalization, while the Russell 2000 includes the next 2000 stocks. Russell Inc. reconstitutes the indexes on the last Friday of June, every year, based only on end-of-May stock capitalization; hence, no discretion is involved in index assignment.[22] Index composition remains constant for the rest of the year. For stocks in a close neighborhood of the cutoff, changes in index membership are random events, once controlling for the assignment variable, i.e. market capitalization, as they result from random variation in stock prices at the end of May.

Chang, Hong, and Liskovich (2015) show that, although the amount of passive assets benchmarked to the Russell 1000 is 2 to 3.5 times larger than those tracking the Russell 2000, the weights of the top stocks in the Russell 2000 are about 10 times larger than those for the bottom stocks in the Russell 1000. Consequently, a significantly larger amount of passive money tracks the top Russell 2000 stocks.

Figure 3 provides evidence that is consistent with the latter claim in the context of ETFs. The figure plots average ETF ownership as a function of market capitalization rankings for the Russell 3000 universe, in bins of 10 stocks, for 500 stocks to the right and left of the cutoff (the 1000th position). We note that around the cutoff position, there is a discontinuity in ownership. Stocks immediately after the cutoff appear to display higher ownership than stocks immediately to the left.

Spurred by this evidence, we focus on stocks that move between the two indexes, and we use the event of a switch as an instrument for ETF ownership. Then, we regress our outcome variable, daily stock volatility, on instrumented ETF ownership. To identify the effect of interest, we rely on Appel, Gormley and Keim's (2015) insight that variation in ETF ownership around the

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[21] Other papers that exploit the Russell reconstitution are Chang, Hong, and Liskovich (2015); Cao, Gustafson and Velthuis (2014); Crane, Michenaud and Weston (2014); Fich, Harford and Tran (2014); Lu (2014); and Mullins (2014).

[22] When the last Friday falls on the 29th or 30th day of the month, the two indexes are reconstituted on the preceding Friday. For more details, on the index formation process see Appel, Gormley, and Keim (2015), and Russell Investments (2013).

cutoff is exogenous, once we control for the ranking variable (i.e., market capitalization).[26] Unlike these authors, we also need to control for lagged volatility, because it affects the probability of switching index and it is correlated with our dependent variable. Below, we provide further details.

The additional identifying assumption that needs to be satisfied is the exclusion restriction, that is, the requirement that the event affects the outcome variable only through the treatment variable. In our context, this translates into the condition that a switch in index membership only affects volatility through ETF ownership. Later in this section, we discuss reasons why this assumption may fail and conclude that this concern does not appear to be relevant in our context.

While Appel, Gormley and Keim (2015) are constrained to use annual data by the availability of their governance measures, we cast our analysis at the monthly frequency because every month we have a different observation on the dependent variable (i.e. daily volatility). We note that the exogenous variation in ETF ownership only comes from the June-switch. However, this exogenous component of ETF ownership is contained in all the monthly observations of this variable through May of the next year. Therefore, the twelve monthly observations of ETF ownership provide relevant explanatory power for the different observations of the dependent variable. Using one observation per year would entail a loss of power.

The first index reconstitution in our sample occurs in May 2000. Mullins (2014) and Appel, Gormley and Keim (2015) report that the classification method of stocks to the Russell indices was modified after the reconstitution of June 2006. Until the June 2006 reconstitution, the cutoff for reclassification was simply the 1000th position in terms of market capitalization. Thus, we include end-of-month data between June 2000 and May 2007. As in Appel, Gormley, and Keim (2015), we consider several bandwidths: 100, 200, 300, 400, and 500 stocks on each side of the cutoff. Another difference in our implementation is that we consider switches in both directions, i.e. to the Russell 1000 from the Russell 2000 and to the Russell 2000 from the Russell 1000, while these authors only consider moves to the Russell 2000. The drop in ETF ownership that comes from switching to the Russell 1000 is informative in our context.

[26] Indeed, Russells inc. uses a proprietary methodology to compute market capitalization (see Mullins, 2014). This fact implies that we cannot perfectly control for the ranking variable if we use the market capitalization from CRSP. However, Appel, Gormley, and Keim (2015) show that the procedure is robust to substituting the CRSP measure with the Russell proprietary measure of market capitalization, for the years between 2002 and 2006, when it is made available.

The validity of the Russell experiment becomes questionable after 2006, as market capitalization is no longer strictly related to the index switch. Specifically, starting with the 2007 reconstitution, Russell Inc. adopted a banding rule whereby stocks only switch from their current index if they move beyond a 5% range around the market capitalization percentile of the 1000th stock. As expected, switches are more frequent before the introduction of the banding rule (Appendix Table 4, Panel A). In Appendix Table 4, we show however that our results survive also in the longer sample period.

We carry out a two-stage least squares estimation. In each stage, we run our regressions on two separate groups of stocks: those that in May, before index reconstitution, are in the Russell 1000 and those that are in the Russell 2000. The sample composition remains constant for all the months between June, the first end-of-month after index reconstitution, and May of the next year. The first stage consists of a regression of ETF ownership on an indicator variable for whether the stock switches index membership in June. For the Russell 1000 sample, the indicator variable flags stocks that switch to the Russell 2000. Vice versa, for the Russell 2000 sample, the dummy captures a switch to the Russell 1000. In regression form, the first stage is:

$$ETF\ Ownership_{it} = \alpha + \beta * I(Switched\ to\ other\ index\ )_{it} + Controls + Fixed\ effects + \varepsilon_{it} \qquad (2)$$

In the second stage, for the same two separate groups of stocks, we regress volatility on the fitted value of ETF ownership from the first stage. In regression form:

$$Volatility_{it} = \alpha + \beta * ETF\ \widehat{Ownership}_{it} + Controls + Fixed\ effects + \varepsilon_{it} \qquad (3)$$

Besides the control for market capitalization, i.e. the assignment variable, we include the same set of controls as in the OLS regressions. While time fixed effects are part of the regression, we do not include stock fixed effects because identification in this experiment is inherently cross sectional, that is, it results from comparing switchers to non-switchers in a given time period. Standard errors are double-clustered at the stock and month level. We standardize the ownership variables and volatility in the relevant samples to ease interpretation. Finally, following Appel, Gormley and Keim (2015), we include different polynomials of the ranking variable: first (Panels A and B of Table 5), second (Panel C of Table 5), and third degree (Panel D of Table 5). Here, we report only the estimates on the main variable, to save space. The full results are in the Internet Appendix.[28]

Table 5, Panel A shows the first stage regressions. We separately consider stocks that belong to the Russell 1000 before index reconstitution (Columns (1)-(5)) and stocks belonging to the Russell 2000 before index reconstitution (Columns (6)-(10)). The instrument is an indicator for whether the stock switches to the other index. The dependent variable (ETF ownership) is measured in each month following the index reconstitution. To illustrate the setting, consider Column (1). The sample includes stocks that are in the Russell 1000 index in May (prior to the reconstitution). We use the end-of-May cutoff to determine the stocks that are included in the sample (±100 stocks around the cutoff). The stocks remain in the sample in all months between June (after reconstitution) and May of next year, unless they drop out of the sample for exogenous events (e.g. a merger). The indicator variable flags the stocks that switch to the Russell 2000 after reconstitution.

The results of this test show that switching index has strong impact on ETF ownership. The slope on the switch indicator in Column (1) suggests that ETF ownership in the twelve months after reconstitution increases for the stocks switching to the Russell 2000 by about 24.4% of a standard deviation. Across Columns (1) through (5), the average effect is larger at about 41%.

Column (6) focuses on stocks that start out in the Russell 2000 in May prior to reconstitution, with the same bandwidth (±100 stocks around the cutoff). For the stocks that switch to the Russell 1000 after reconstitution, ETF ownership decreases by about 14.5% of a standard deviation. Across Columns (6) through (10), the average estimate is about -35%, which is of similar magnitude to the effect of switching to the Russell 2000. The strong statistical significance of the first stage regressions reassures us about the validity of the instrument.

Table 5, Panel B, reports the second stage estimates of the effect of ETF ownership on volatility in the next month. Analogous to the layout in Panel A, the instruments are indicators for a switch to either index, and the sample is restricted to members of either index before reconstitution. In this panel, only the first power of market capitalization is included among the controls. The effect of ETF ownership on volatility is significant across all samples and

[28] The Internet Appendix is at http://www.people.usi.ch/franzonf/ETFs_Internet_Appendix.pdf or http://fisher.osu.edu/fin/faculty/Ben-David/articles/ETFs_Internet_Appendix.pdf.

bandwidths. The magnitudes in Table 5, Panel B, are considerably larger than the OLS estimates in Table 4. The coefficients range between 16.8% and 80.3%, averaging at about 32% of a standard deviation.

At first sight, the results in Tables 4 and 5 may appear contradictory. On the one hand, in Table 4, we find stronger effects among the large S&P 500 stocks than among the broader universe of Russell 3000 companies. On the other hand, the effects in Table 5 are more economically significant than the ones in Table 4, although Table 5 focuses on relatively small stocks. Recognizing that the two tables use different estimation techniques, applied to different samples, explains this apparent inconsistency. First, the larger IV estimates from Table 5 may be revealing that the endogeneity of ETF ownership induces a negative bias in the OLS estimates in Table 4. A negative bias can occur, e.g., if higher ETF ownership signals companies that belong to multiple indexes, which have less volatile stocks because they are more established companies. Second, Table 4 reports estimates for the average effects across all the stocks in the index Russell 3000. In Table 5, instead, we examine the effect in a neighborhood around the cutoff between the Russell 1000 and Russell 2000. Specifically, the IV estimates measure the local average treatment effect (LATE), where the weights in the average are the ex-ante probability that a unit receives treatment (see, e.g., Lee and Lemieux, 2010). In other words, the IV estimates over-weight stocks that are highly likely to switch indexes. These stocks can experience a drastic change from not being included in arbitrageurs' strategies to having top weights in these strategies, and vice versa. Arguably, we should expect that changes in ETF ownership have a bigger effect on these stocks. Given these considerations, we are inclined to conclude that the IV estimates represent an upper bound, while the OLS coefficients are the lower bound, for the effect of ETF ownership on volatility.

A sign of a well-specified experiment is the fact that the estimates are stable when different degrees of the polynomials of the ranking variable are included (Lee and Lemieux, 2010). In Panel B of Table 5, we control for a linear specification of the ranking variable. Panels C and D replicates the instrumental variable estimation with a quadratic and cubic polynomials, respectively (the first stages are adjusted accordingly). Reassuringly, the estimates are in the same ballpark as in Panel B.

Finally, we come back to assessing the validity of the exclusion restriction in our context. The exclusion restriction is not satisfied if there is a correlated omitted variable, which varies with index switches and affects volatility. ETF ownership could merely be a proxy for this omitted factor. For example, a violation occurs if, after appearing among the top stocks in the Russell 2000, a firm becomes more visible to investors. It is then possible that prices react more quickly to fundamental information and returns become more volatile, as shown by Andrei and Hasler (2015). In this case, price efficiency increases. Appel, Gormley, and Keim (2015) find that analyst coverage is largely unaffected after the inclusion in the Russell 2000. Similarly, Crane, Michenaud, and Weston (2014) show that a switch to the Russell 2000 does not lead to increased media coverage. These results are important for our study as they suggest that the increase in volatility associated with the increase in ETF ownership is not likely to be caused by an increase in information production following switching. Moreover, in the next subsection, we show that price efficiency decreases with ETF ownership. Therefore, the evidence seems to rule out this specific case of violation of the exclusion restriction.

More generally, we obtain further corroboration of the validity of the exclusion restriction by combining the cross-sectional identification from the index switching experiment with time-series variation in ETF ownership. In particular, if the IV exercise is truly measuring the causal effect of ETF ownership, we should observe a stronger impact of index switching on volatility at times when aggregate ETF ownership is larger. The underlying logic is that a larger presence of ETFs in the market should leave a bigger footprint on stocks that switch indexes. Following this argument, we regress stock-level volatility on the interaction between the index-switching indicator and the (equally-weighted) average of ETF ownership across Russell 2000 stocks. If the exclusion restriction is satisfied, we expect that switching to the Russell 2000 (Russell 1000) has a more positive (negative) effect on volatility at times when ETF ownership is overall larger.[29] The regressions include additional interactions to control for aggregate ownership by other mutual funds (passive and active) and for a time trend, given that ETF ownership increases over time. The uninteracted variables are also present, as well as the usual stock-level controls, and month fixed effects. Standard errors are double-clustered by stock and month. The estimates in Panel E of Table 5 are broadly consistent with the causal interpretation for the effect of ETF ownership. In Columns

[29] We remind the reader that we expect a switch to the Russell 2000 (Russell 1000) to increase (decrease) volatility because that switch increases (decreases) ETF ownership, based on the evidence in Panel A of Table 5.

(1)-(5), the addition to the Russell 2000 has a larger impact on volatility at times of higher average ETF ownership. In two cases, the effect is statistically significant. In all five specifications focusing on the switch to the Russell 1000 (Columns (6)-(10)), the decrease in volatility is significantly larger in months when ETF ownership is higher. Although they are not a direct test of the exclusion restriction, these results are reassuring on its validity.

Given the outcome of the IV estimation in Table 5, we feel more confident in imputing a causal interpretation to the positive relation between ETF ownership and stock level volatility. This evidence is consistent with the main testable hypothesis. We next study whether the observed increase in volatility corresponds to an increase in noise in stock prices.

4.3 Identifying the Impact on Non-Fundamental Volatility

4.3.1 Variance Ratios

The finding that higher ETF ownership is associated with increased volatility is not necessarily evidence in favor of the hypothesis that ETFs increase the noise in the prices of the underlying securities. For example, Amihud and Mendelson (1987) provide a simple model in which the volatility of trading prices is positively related to the speed at which prices adjust to fundamentals. In addition, Andrei and Hasler (2015) prove theoretically and empirically that investor attention increases the sensitivity of prices to fundamentals and, therefore, volatility. If ETF arbitrage makes prices adjust more promptly to fundamentals, or if stocks in ETFs are exposed to higher investor attention, it could be the case that the *fundamental* volatility of the underlying securities goes up. This increase in volatility differs from the prediction of the hypothesis that is tested in this paper, which instead focuses on *non-fundamental* volatility, or noise as defined by Black (1986).

O'Hara and Ye (2011) use variance ratios to measure price efficiency. At time t, stock i's variance ratio is defined as:

$$VR_{i,t} = \left| \frac{Var\left(r_{k,i,t}\right)}{k \cdot Var\left(r_{1,i,t}\right)} - 1 \right|, \tag{2}$$

where the numerator is the variance of k-period returns in the estimation window corresponding to time t, and the denominator is k times the variance of the single-period log returns in the same window t (also see Lo and MacKinlay, 1988).[30] As argued by these authors, in an efficient market, the ratio of variances should be closer to one as prices follow a random walk, and the quantity in Equation (2) approaches zero. This simple device provides a non-parametric test of the impact of ETFs on non-fundamental volatility. If ETFs add noise to prices, *VR* should increase with ETF ownership.

In our application, we construct the variance ratio using two different horizons. The motivation is that ETF arbitrage can affect stock prices at two different frequencies. As discussed in Section 2, arbitrageurs can affect volatility intraday, through the activity of hedge funds and high-frequency traders. We are testing this channel by constructing variance ratios from intraday returns. Moreover, Authorized Participants (APs) can impact stock prices at the daily frequency through their daily creation and redemption of ETF shares. To find evidence of this channel, we construct the variance ratio using daily returns.

First, to construct intraday variance ratios, we measure single-period returns from transaction prices at five-second intervals and choose $k = 3$, so that multi-period returns are measured over 15-second intervals. To estimate both variances, we use all the returns within a day. Then, we average the daily estimates over the month to obtain monthly observations. The choice of 15-second time-intervals follows from the observation that ETF sponsors disseminate information about the portfolio NAV at 15-second intervals to facilitate high-frequency arbitrage. This frequency is therefore relevant to capture the intraday effect of arbitrageurs on the underlying stock prices. Second, to capture the lower frequency impact of APs, we also compute the ratio of the five-day return variance to five times the one-day return variance. To have sufficient observations to estimate these variances, we use all the returns within a quarter.

Table 6 reports estimates from regressions of the standardized values of the stock-level variance ratio on standardized ETF ownership in the prior period. For the 15-second frequency variance ratio (VR 15), the sample is monthly, while for the 5-day frequency (VR 5), it is quarterly. We include the same set of controls as in the previous tables.

Panel A shows OLS regressions. The results point unambiguously to a positive and significant relation between ETF ownership and variance ratios. At both frequencies, the evidence

[30] Strictly speaking, only the first element in the absolute value in Equation (2) is a variance ratio. We label the whole expression as a "variance ratio" for convenience.

suggests that the prices of stocks with higher ETF ownership are farther away from a random walk and therefore contain more noise. The effect is twice as large at the intraday frequency as it is at the five-day frequency (11% of a standard deviation of VR 15 for a one-standard-deviation change in ETF ownership, for S&P 500 stocks). It is, however, statistically and economically significant for the 5-day frequency as well. Consistent with the pattern in Table 4, the effect is reduced, but still significant in the intraday setting, when the universe is extended to smaller stocks (Russell 3000).

Given the concerns about the potential endogeneity of ETF ownership in the OLS regressions, we implement the IV estimation based on the Russell indexes reconstitution, using the variance ratio as dependent variable in the second-stage regressions. (The first stage is identical to Table 5, Panel A). As before, we restrict the sample to the months following the reconstitutions between 2000 and 2006. Panel B of Table 6 reports the results for VR 15, from the monthly sample, while Panel C has the results for VR 5, from the quarterly sample. In all specifications, the IV confirms the positive slope on ETF ownership. Statistical significance is present in the majority of cases. Finally, the larger magnitude of the IV slopes than the OLS slopes mirrors the previous evidence regarding the effect on total volatility and can be explained in the same way. The results from the IV give us more confidence on the causal interpretation of the positive link between ETF ownership and noise in stock prices.

4.3.2 Price Reversals

An alternative way to test whether ETFs add noise to the underlying securities is to look for direct evidence of the sequence of events predicted by the conjectured channel for noise propagation (summarized in Figure 1). Following a demand shock in the ETF market, the prices of the underlying securities should move in the same direction as the initial shock. Then, because the fundamentals have not changed, prices should revert to the initial level. Finding evidence of mean reversion in prices would also contribute to ruling out the alternative story that ETFs merely improve price discovery (as in Figure 2), which could also explain the increase in volatility.

For this analysis, we focus on the daily frequency because the demand shocks in the ETF market can be clearly identified by measuring daily flows in ETFs. As explained above, ETF flows (redemptions and creations) are the result of APs' arbitrage activity, which responds to ETF prices' deviations from the NAV. Stock-level flows are defined as the weighted average of the daily flows in the ETFs that own the stock. The weights are the fraction of ownership in the stock by each ETF. Dollar daily ETF flows are then expressed as a fraction of prior-day stock capitalization.

On the day when flows occur, we expect a price move in the same direction as the flows, irrespective of whether the motive for trade is fundamental or non-fundamental (i.e., noise trading). To the extent that at least part of the originating shock is non-fundamental, a reversal should occur in the next days. To capture this behavior, we regress returns at different horizons (five, ten, and twenty days) on stock-level flows, using overlapping daily observations. We include the usual stock-level controls and time fixed effects, in addition to order imbalance, as the dollar value of buy minus sell trades from TAQ, divided by market capitalization. Order imbalance is a natural control in this context because daily flows in ETFs could merely be a proxy for aggregate demand in the underlying securities, which induces negative autocorrelation in returns (Chordia and Subrahmanyam, 2004). The standard errors are clustered at the day level and we correct for the autocorrelation of residuals induced by overlapping observations for multiday returns using the Newey and West (1987) estimate of variance.

In Table 7, returns are in percent, while net flows are standardized. From Column (1), we note that, on the same day, ETF flows and returns move in the same direction. The contemporaneous price move is 16.7 bps for a one-standard-deviation change in net flows for S&P 500 stocks. The high significance is not surprising, as flows and returns are measured on the same day (hence, this is not a predictive regression). In addition, we note that the magnitude of the change in prices exceeds the half-spread, which is about 8.5 bps for the sample of large stocks. This magnitude rules out the possibility that flows cause a simple bid-ask bounce.

More relevant to identifying the transmission of noise, ETF flows predict a reversal of the underlying stocks' prices in the next twenty days (Columns (2)-(4)). The evidence is consistent with the conjecture that the demand shocks in the ETF market add a mean-reverting component to stock prices. From Column (4), we can infer that almost half of the initial price impact is reversed (1.00167*0.00072/0.00167 = 0.43). Extending the horizon farther out to 40 days does not increase the magnitude of reversals (not reported). As in the prior tables, the absolute effects are smaller in the extended universe of Russell 3000 stocks.

There may be an alternative explanation for our findings in Table 7. APs may create ETF units (and generate positive ETF flows) to lend to clients wishing to short the ETF. If these shorts are informed, ETF prices as well as those of basket securities will subsequently fall. To rule out this alternative, in Appendix Table A5, we repeat the test, controlling for lending fees, which proxy for the tightness of the share lending market. Since this variable is available only for a subset of securities, including it shrinks the sample. Reassuringly, the results in the S&P 500 sample are mostly unaffected.

In sum, the evidence in this subsection suggests that the positive link between ETF ownership and volatility, which we report in Tables 4 and 5, is consistent with an increase in noise in stock prices. Specifically, ETFs appear to add a mean-reverting component to stock prices both intraday and at the daily frequency. The finding of a 43% reversal of the initial price impact of ETF flows suggests that, at the daily frequency, at least half of the impact of ETFs on return volatility is due to noise propagation.

5 Exploring the Arbitrage Channel

Having established a causal link between ETF ownership and noise in the prices of the underlying securities, we next look for evidence that noise propagates through the arbitrage channel. To this end, we first define a proxy for arbitrage activity. The difference between the ETF price and the net asset value of the underlying basket (NAV), labeled ETF mispricing, is a signal for the profitability of ETF arbitrage. Hence, we expect a stock's involvement in arbitrage trades to be a positive function of the mispricing of the ETFs that hold the stock. Using this proxy, we study whether arbitrage activity has an incremental impact on volatility and noise for a given level of ETF ownership.[31]

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[31] It could actually be the case that ETF mispricing signals a *lack of* arbitrage activity. That is, more mispricing is present when arbitrageurs refrain from entering the market. This could be an issue for our tests if the reason why arbitrageurs abstain from their trades is volatility in the underlying securities, which is the dependent variable in our tests. In such a case, the endogeneity of mispricing could bring a positive spurious correlation with volatility. To address this concern, we control for the lagged value of the dependent variable, so that we study the impact of mispricing on innovations in volatility. This contributes to attenuate the endogeneity concern because arbitrage trades are not likely to condition on innovations in volatility in the next period. Further, in the tests in which we interact mispricing with measures of the limits of arbitrage, this potential endogeneity would lead to the opposite sign of the coefficient relative to what we find. See the discussion below.

Then, we conjecture that the proxy for expected arbitrage activity should have a weaker effect on stock prices for stocks that are harder to arbitrage. In other words, we seek evidence that limits to arbitrage play a role in attenuating the propagation of noise to the underlying securities. This evidence would indirectly testify to the importance of the arbitrage channel.

We use two proxies for limits of arbitrage: the stock-level bid-ask spread and share-lending fees. First, because ETF arbitrage involves a roundtrip transaction in the stock, a large stock-level bid-ask spread reduces the profitability of arbitrage trades and therefore the incidence of arbitrage trading in a given stock. Second, when the arbitrage transaction involves shorting the stock (i.e., the NAV is above the ETF price), higher stock-lending fees discourage arbitrageurs. In addition, a high share-lending fee can reflect a shortage of shares for lending, meaning that some arbitrageurs may simply not be able to carry out the trade (Cohen, Diether, and Malloy, 2007).

Given the high-frequency fluctuations in arbitrage activity, we carry out our tests at the daily frequency, which allows us to measure the variables of interest in a more timely way. Thus, the dependent variables for these tests are intraday volatility, which is estimated from second-by-second returns within a day, and the daily variance ratio resulting from the comparison of fifteen-second returns to three times five-second returns within a day (VR 15, see Section 4). The main explanatory variable is the stock-level measure of absolute ETF mispricing in the prior day. This variable is calculated by summing the absolute dollar mispricing (i.e., the difference between the ETF price and NAV, as a fraction of the ETF price, multiplied by the dollar holdings in the stock) across all ETFs holding stock i, and expressing this quantity as a fraction of a stock's capitalization:

$$Abs\left(mispricing_{i,t}\right) = \frac{\sum_{j=1}^{J} w_{i,j,t} * AUM_{j,t} * \left|mispricing_{j,t}\right|}{Mkt\ Cap_{i,t}}. \tag{5}$$

This variable interacts the effect of the ETF mispricing, which is a signal for the attractiveness of the stock for arbitrage trades, with the ownership of each ETF in the stock's capital base, which measures the relative importance of each ETF for the given stock. We take the absolute value of mispricing because arbitrage activity is triggered by both positive and negative discrepancies between ETF prices and the NAV. It is therefore important to avoid netting out these deviations across ETFs. For a second set of tests, in which we condition on the direction of the arbitrage trades, we refer to net mispricing, which differs from the definition in Equation (3) for the omission of the absolute value.

In Panel A of Table 8, the dependent variable is intraday volatility. The sample consists of S&P 500 stocks, where, according to our prior results, most of the effect of ETFs occurs. In Column (1), we test whether absolute mispricing at the close of day $t - 1$, which is a proxy for arbitrage activity on day t, has an incremental effect on volatility for a given level of ETF ownership. Besides the usual controls, we include the mispricing on day $t - 2$ and the lagged dependent variable. The goal is to capture the effect of the innovation in mispricing on the innovation in volatility, given that mispricing on day $t - 1$ could itself depend on volatility (i.e., ETFs holding stocks that are more volatile are more likely to be mispriced, as discussed in footnote 31). We also include the return on the stock on day $t - 1$ to capture variation in mispricing that is exogenous to movements in the stock price itself. That is, we identify variation in mispricing resulting from movements in the ETF price or in the prices of the other stocks in the basket, but not in the stock's own price. We note that the effect of absolute mispricing is positive and significant, amounting to about 2.3% of a standard deviation of the dependent variable for a one-standard-deviation change in mispricing (both variables are standardized). Further, the effect of ETF ownership drops in magnitude relative to the specification without mispricing (compare with Appendix Table A3). This evidence supports the view that arbitrage activity, as proxied by mispricing, is the transmission channel for the effect of ETF ownership on volatility.

Next, we report specifications that include interactions of absolute mispricing with the proxies for arbitrage costs. For each measure of limits of arbitrage, we define a dummy variable for stocks that are in the top of half of the distribution of the variable in the prior period.[32] We leave out stock fixed effects, because we wish to achieve identification from the cross-sectional variation in the proxies. (Including stock fixed effects has no material impact on the results.) From Table 8, Panel A, Column (2), we infer that the effect of arbitrage on volatility, as proxied by absolute mispricing, is significantly weaker for stocks with a high bid-ask spread. This evidence suggests that limits of arbitrage are playing a role in the transmission of noise to the underlying securities.

[32] Information on share-lending fees is sparse, especially in the initial part of the sample. Therefore, we use the average fee in the month.

Next, we break up the sample by the sign of net mispricing. A priori, we do not expect the sign of mispricing to matter for the interaction with the bid-ask spread, because the arbitrage trade involves a roundtrip transaction in the underlying stock in any case. The results in Columns (3) and (4) confirm this conjecture.

In Column (5), Panel A, Table 8, share-lending fees have a marginally significant impact in attenuating the effect of arbitrage on volatility. More importantly, we now expect this effect to differ based on the sign of net mispricing. Only when mispricing is negative (i.e., the ETF price is below the NAV) does the arbitrage trade involve a short sale of the underlying stocks. The estimates in Columns (6) and (7) square nicely with this prediction and provide strong evidence for the role of arbitrage activity in generating the effect of interest.

It is worth noting that the sign of the interactions with the proxies for arbitrage costs tends to rule out concerns about the endogeneity of mispricing (see footnote 31). Indeed, if mispricing was capturing the fact that arbitrageurs abstain from trading because volatility discourages them, we would expect this effect to be even stronger for illiquid stocks or for stocks that are hard to locate, given that these characteristics correlate positively with volatility. That is, the sign on the interactions with arbitrage costs should be positive. Instead, contrary to this view, the interactions have negative and significant coefficients.

Panel B of Table 8 replicates the analysis using the variance ratio from intraday returns as dependent variable. Mostly, the results mirror the evidence in Panel A. Hence, the evidence further supports the role of arbitrage in transmitting the noise to the prices of the securities in the ETF baskets.

For completeness, in Appendix Table A6, we report the analysis for the Russell 3000 universe. As expected, in this sample, the effects are weaker or non-existent. These results confirm our prior belief that arbitrageurs tend to focus on the larger stocks in the ETF baskets when doing optimized replication. Therefore, the effect of interest is located mostly among large stocks.

6 Are ETFs Attracting a "New Layer" of Noise?

In the previous sections, we show a positive link between ETF ownership and stock volatility. The identification provided by the quasi-natural experiment allows us to attach a causal interpretation to these estimates. We also find that ETF ownership increases the mean-reverting component of stock prices. These results are consistent with the argument that stocks with higher ETF ownership are more attractive to noise traders. Therefore, the evidence supports the first testable hypothesis in Section 2.

The second testable hypothesis is that the noise hitting ETF-owned stocks represents a *new layer* of demand, which would not be present in the market if ETFs did not exist. The argument is that ETFs provide previously unavailable trading opportunities, at low cost and high frequency, which cause new traders and/or new trading strategies to materialize. For example, ETFs might make the hedging of industry risk in statistical arbitrage strategies that involve mispriced securities significantly cheaper, so that the volume of these trades might increase. In this sense, the introduction of ETFs is analogous to a decrease in trading costs that enables traders to operate at higher frequency.[33]

The alternative view to this hypothesis is that ETFs merely provide a convenient conduit for existing investors who wish to trade the underlying securities. According to this view, noise is reshuffled from stocks with low ETF ownership to stocks with high ETF ownership. We label this argument the "reshuffling hypothesis." To stay with the previous example, the same statistical arbitrageurs that currently employ ETFs for hedging purposes were previously constructing a hedging portfolio using stocks in the same industry as the mispriced security.

As argued in Section 2, the evidence in Table 2 suggests that ETFs attract high-turnover investors. However, it does not rule out the reshuffling hypothesis, that is, the possibility that these investors would directly trade in stocks had the ETFs not been in existence. Therefore, we need to produce evidence that allows us to more convincingly separate the new-layer hypothesis from the reshuffling hypothesis. This evidence can only come from comparing the time-series evolutions of ETF ownership and volatility. The ultimate prediction of the new-layer hypothesis is that the growth in the ETF market attracts more noise trading to the stock market. Hence, we should observe higher volatility at times of higher ETF stock ownership. The reshuffling hypothesis, instead, predicts that aggregate volatility should not change because of ETFs.

[33] Of course, a similar argument applies to futures and other derivatives. ETFs, however, allow a higher degree of specialization in terms of the segments of the market they cover.

In Panel A of Table 9, we report the estimates from a regression of average daily volatility on lagged average ETF ownership across all stocks in CRSP. The frequency is monthly and volatility is computed using the daily returns in a month. We include lagged volatility to set up the regression as a test for Granger causality. To mitigate the concern that ETF ownership proxies for omitted factors relating to institutional ownership, we include lagged average ownership by index and active funds. Importantly, we add a time trend as a catchall control for developments in aggregate conditions (e.g., a protracted reduction in trading costs). We find that ETF ownership significantly predicts volatility, with a positive sign. The economic magnitude is between that in Table 4 and that in Table 5. In Column (2), we replicate the analysis in first differences. The results are robust to this modification, and the magnitude is even larger.

This evidence supports the hypothesis that ETF ownership adds a new layer of volatility to the stock market. The caveat is that the time-series identification does not allow us to rule out the possibility that time-varying omitted factors could be driving our results. However, we believe that including controls for the ownership of other mutual funds, as well as a time trend, attenuates this concern.

We note that this analysis does not imply that volatility has increased over the sample period as a result of the positive trend in ETF ownership (see Table 1). Indeed, the positive association between ETF average ownership and volatility in Table 9 does not hold without the inclusion of the time trend. Therefore, our results point to a significant relation between *de-trended* ETF ownership and aggregate volatility. For this reason, our findings are not in contradiction with Brandt, Brav, Graham, and Kumar (2010) who show a decrease in aggregate stock volatility after 2003.

While this analysis does not support the extreme version of the reshuffling hypothesis for the market-wide effect of ETF ownership on volatility, it is still interesting to ask whether some stocks experience a decrease in volatility at the expense of others as ETF ownership increases. In other words, we ask whether some partial reshuffling of noise trading is taking place. To this purpose, we test whether, as aggregate ETF ownership increases, volatility declines for some groups of stocks and rises for others. We sort the universe of stocks into five quintiles by ETF ownership. The average ETF ownership in the bottom quintile is 0.70% of a stock's capitalization, while in the top quintile it is about 4%. For each quintile, at the monthly frequency, we regress the average volatility for that group of stocks on the (lagged) average ETF ownership across the entire market and include controls. The explanatory variables are the same across quintiles, because the goal is to test whether the same aggregate developments are related to different changes in the volatility of different groups of stocks. From Panel B of Table 9, we note that all groups of stocks experience a significant increase in volatility as aggregate ETF ownership increases. This evidence does not support a partial reshuffling of noise across stocks. Quite relevantly, the effect of interest is strongest in the quintile with top ETF ownership, which strengthens the case for a causal interpretation of the time-series association between ETF ownership and volatility. Finally, running the same regressions in first differences strongly confirms our results (Table 9, Panel C).

To conclude, while the time-series setting of this analysis prevents us from drawing unambiguous causal inference, the evidence in this section is consistent with the view that ETFs attract a new layer of demand shocks to the market as opposed to causing a reshuffling of existing demand across stocks.

7 Conclusion

With $2.8 trillion of assets under management globally (December 2014), 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, ETFs and other exchange traded products accounted for about 40% of all trading volume in U.S. markets. This explosive growth has attracted the attention of regulators. In particular, the Securities and Exchange Commission (SEC) has begun to review the potential role of ETFs in inflating the volatility of the underlying securities.[34]

The success of ETFs is justified by the fact that these investment vehicles provide an unprecedented source of diversification at low cost and high liquidity. However, the evidence in

[34] Regulators have investigated the potential illiquidity of ETFs, which manifested during the Flash Crash of May 6, 2010, when 65% of the cancelled trades were ETF trades. Also relevant is 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 lent out). Concerns have been expressed that a run on ETFs might endanger the stability of the financial system (Ramaswamy, 2011). With regard to the SEC ETF-related concerns, see "SEC Reviewing Effects of ETFs on Volatility" by Andrew Ackerman, *Wall Street Journal*, October 19, 2011, and "Volatility, Thy Name is E.T.F." by Andrew Ross Sorkin, *New York Times*, October 10, 2011. With regard to the SEC focus on short-term volatility, see the SEC Concept release No. 34-61358.

this paper seems to point to an unintended effect of this relatively new asset class, which can stoke regulators' concerns.

We present results showing that the stocks in ETFs' baskets display higher volatility than otherwise similar securities. Through a quasi-natural experiment based on the reconstitution of the Russell indexes, we are able to attach a causal interpretation to this finding. The presence of ETFs also causes the underlying securities' prices to diverge from random walks, both intraday and daily. These effects are significantly related to proxies for the intensity of arbitrage activity between the ETFs and their baskets.

This evidence paints a picture in which noise trading in the ETF market is passed down to the prices of the underlying securities by the transmission chain of arbitrage trades. Moreover, because of their ease of trade and cost effectiveness, ETFs attract higher turnover investors than the average stock in their baskets. Consequently, noise in stock prices increases with ETF ownership.

In addition, we find that aggregate volatility varies significantly over time with aggregate ETF ownership in the stock market, controlling for ownership by other mutual funds and for a time trend. With the caveat that the time-series identification of this effect does not allow for a conclusive causal inference, the evidence suggests that ETFs bring a new layer of noise to the market, as opposed to just causing a migration of existing noise traders across securities. We explain this finding with the new trading opportunities, at low cost and high frequency, made possible by ETFs.

A new theoretical framework seems necessary to gauge the tradeoff between the decreased transaction costs and the improved access to diversification that ETFs bring about and the deterioration in price efficiency revealed by our empirical analysis. The general equilibrium and welfare implications of this important wave of financial innovation therefore remain unclear.

To conclude, the effects that we describe resonate with the literature showing that flows into institutional portfolios impound noise into asset prices (e.g., Coval and Stafford, 2007; Lou, 2012). Along with this prior evidence, our results suggest that the recent rise in institutional stock ownership is not by itself a guarantee that stock prices are more efficient. Noise traders can still cause mispricing through their allocations to institutional portfolios.

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Table 1. ETF Ownership Statistics

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

	S&P 500				Russell 3000			
Year	#ETFs	Average ETF AUM ($m)	Average stock weight in ETF (%)	Average ownership of ETF in firm (%)	#ETFs	Average ETF AUM ($m)	Average stock weight in ETF (%)	Average ownership of ETF in firm (%)
2000	2.45	5577.69	0.64	0.22	2.41	5138.81	0.53	0.25
2001	13.45	2173.41	0.42	0.48	8.91	1062.08	0.16	0.36
2002	15.47	2798.87	0.45	0.90	10.18	1185.39	0.14	0.83
2003	15.95	3542.45	0.45	1.05	10.42	1465.49	0.14	0.95
2004	21.40	3451.84	0.47	1.22	14.30	1702.26	0.14	1.26
2005	24.75	3758.30	0.49	1.51	15.73	2040.02	0.16	1.55
2006	25.80	4337.34	0.51	1.67	16.81	2447.86	0.18	1.84
2007	36.04	4082.81	0.64	2.00	22.60	2439.07	0.24	2.21
2008	50.61	2980.85	0.69	2.76	30.26	1789.18	0.28	2.87
2009	53.19	2733.88	0.67	3.27	31.30	1710.54	0.26	3.53
2010	52.08	3260.33	0.68	3.30	30.08	2311.04	0.27	3.74
2011	52.77	3977.15	0.67	3.61	28.87	2937.45	0.27	3.81
2012	49.25	5033.17	0.67	3.90	27.24	3429.71	0.26	3.91
Average	30.69	3563.73	0.57	2.09	20.13	2064.87	0.21	2.37

Table 2. ETFs vs. Stocks: Liquidity, Institutional Ownership, Churn Ratio

The table reports statistics for ETF- and stock-level liquidity, investor turnover, and ownership. Panel A shows the security-level liquidity measures (bid-ask spread, Amihud (2002) ratio, and daily turnover) as well as the churn ratio measures of the investors in the securities (churn ratios 1 and 2). For all ETFs in our sample, we compute the average measure of liquidity or churn ratio across the stocks in the basket in a given quarter. Then, we value-weight the ETF-level and basket-level measures across all ETFs at the quarter level using ETF market capitalization (thus having 52 quarters in our sample). Churn ratio 1 is from Cella, Ellul, and Giannetti (2013), who compute an institutional-investor-level churn ratio as the sum of quarterly absolute changes in dollar holdings over average assets under management (the data are from SEC 13-F filings). This measure is then averaged across institutions at the stock level using the fraction of a company held by each institution as weight. Churn ratio 2 differs only in that the investor-level churn ratio is computed as the minimum between the absolute value of buys and sells, divided by prior quarter holdings. Panel B presents information about institutional ownership: averaged across all 52 quarters, in the first quarter of the sample, and in the last quarter of the sample. Ownership averages are presented for the ETFs in our sample and all the stocks in CRSP. Panel C presents the institutional classes' turnover (churn ratio 1) separately for the ETF portfolio and the stock portfolio. Variable descriptions are provided in Appendix Table A1. *t-statistics* for the test of the null hypothesis that the difference is equal to zero are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between 2000:Q1 and 2012:Q4.

Panel A: Liquidity and Investors' Churn Ratio Measures

Liquidity measures	Variable	Quarters	ETFs	Stocks	Difference	t-stat
Security-level	Bid-Ask Spread	52	0.003	0.005	-0.002***	(-3.518)
	Amihud ratio	52	0.002	0.008	-0.006***	(-9.702)
	Daily turnover	52	0.093	0.011	0.083***	(13.462)
Investor-level	Churn Ratio 1	52	0.307	0.240	0.067***	(10.195)
	Churn Ratio 2	52	0.154	0.125	0.029***	(7.493)

Panel B: Types of Institutional Ownership

	Ownership averaged across the sample			Ownership at 2000:Q1		Ownership at 2012:Q4	
Type of Institution	Quarters	ETFs	Stocks	ETFs	Stocks	ETFs	Stocks
All Institutions	52	0.474	0.621	0.280	0.511	0.492	0.651
Banks	52	0.131	0.137	0.052	0.114	0.202	0.116
Endowments	52	0.006	0.001	0.000	0.003	0.001	0.001
Hedge Funds	52	0.033	0.030	0.022	0.019	0.028	0.036
Insurance	52	0.014	0.033	0.007	0.034	0.011	0.026
Investment Advisors	52	0.198	0.211	0.125	0.166	0.167	0.231
Investment Companies	52	0.017	0.163	0.010	0.139	0.023	0.196
Pension Funds	52	0.009	0.035	0.001	0.031	0.008	0.026
Individual Investor (in 13F)	52	0.001	0.000	0.000	0.000	0.000	0.001
Research Firms	52	0.058	0.006	0.061	0.003	0.028	0.008
Corporations	52	0.003	0.001	0.000	0.001	0.017	0.003
Venture Capital	52	0.000	0.000	0.000	0.000	0.000	0.001
Private Equity	52	0.000	0.001	0.000	0.000	0.000	0.001
Sovereign Funds	19	0.000	0.000	0.000	0.000	0.000	0.001

Table 2. ETFs vs. Stocks: Liquidity, Institutional Ownership, Investor Horizon (Cont.)

Panel C: Institutional Turnover, by Type of Institution

Type of Institution	Observations	Turnover in ETFs	Turnover in Stocks	Difference	t-stat
All Institutions	52	0.671	0.247	0.424***	(31.363)
Banks	52	0.551	0.170	0.381***	(15.282)
Endowments	52	0.499	0.183	0.317***	(9.185)
Hedge Funds	52	0.859	0.662	0.197***	(17.064)
Insurance	52	0.549	0.205	0.344***	(17.129)
Investment Advisors	52	0.737	0.288	0.450***	(59.553)
Investment Companies	52	0.670	0.208	0.462***	(18.961)
Pension Funds	52	0.660	0.145	0.515***	(27.298)
Individual Investors (in 13F)	47	0.531	0.169	0.362***	(3.544)
Research Firm	52	0.661	0.456	0.205***	(25.997)
Corporations	40	0.300	0.257	0.043**	(2.288)
Venture Capital	47	0.158	0.226	-0.069***	(-4.865)
Private Equity	27	0.455	0.221	0.234***	(4.266)
Sovereign Funds	18	0.550	0.353	0.197	(1.422)

Table 3. Summary Statistics

The table presents summary statistics for the variables used in the study. Panels A shows summary statistics for the stock-month sample. Panel B reports correlations for the same sample, and Panel C shows summary statistics for the variables used in the return regressions (stock-day sample). Panel D shows summary statistics for the stock-day sample. Panels A, C, and D present separate statistics for the S&P 500 and the Russell 3000 universes. The samples range between January 2000 and December 2012.

Panel A: Monthly Sample

S&P 500

	N	Mean	Std Dev	Min	Median	Max
Daily stock volatility (%)	67,261	2.180	1.470	0.612	1.770	10.800
Log(abs(VR 5 days/(5*1 day)))	67,261	-1.810	0.900	-3.880	-1.590	-0.588
ETF ownership (%)	67,261	2.060	1.580	0.012	1.730	9.610
Index Fund ownership (%)	67,261	5.970	2.080	0.440	5.800	12.300
Active Fund ownership (%)	67,261	17.900	6.430	0.803	17.600	36.600
log(Mktcap ($m))	67,261	9.250	1.070	4.760	9.180	11.300
1/Price	67,261	0.040	0.037	0.006	0.030	0.578
Amihud	67,261	0.000	0.001	0.000	0.000	0.026
Bid-ask spread (%)	67,261	0.287	0.528	0.022	0.080	3.190
Book-to-Market	67,261	0.466	0.394	0.029	0.361	2.560
Past 12-month Return	67,261	0.090	0.378	-0.773	0.067	2.230
Gross Profitability	67,261	0.308	0.224	-0.242	0.271	1.080

Russell 3000

	N	Mean	Std Dev	Min	Median	Max
Daily stock volatility (%)	289,563	2.620	1.660	0.612	2.170	10.800
Log(abs(VR 5 days/(5*1 day)))	289,563	-1.740	0.906	-3.880	-1.530	-0.588
ETF ownership (%)	289,563	2.360	1.980	0.012	1.850	9.610
Index Fund ownership (%)	289,563	4.660	2.480	0.315	4.440	12.300
Active Fund ownership (%)	289,563	16.500	8.280	0.500	16.500	36.600
log(Mktcap ($m))	289,563	7.350	1.410	4.170	7.100	11.300
1/Price	289,563	0.061	0.060	0.006	0.044	0.578
Amihud	289,563	0.011	0.031	0.000	0.002	0.335
Bid-ask spread (%)	289,563	0.333	0.484	0.022	0.152	3.190
Book-to-Market	289,563	0.518	0.423	0.029	0.414	2.560
Past 12-month Return	289,563	0.144	0.479	-0.773	0.087	2.230
Gross Profitability	289,563	0.301	0.244	-0.242	0.268	1.080

Table 3. Summary Statistics (Cont.)

Panel B: Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Daily stock volatility (%)	(1)	1.00										
Log(abs(VR 5 days/(5*1 day)))	(2)	0.01	1.00									
ETF ownership (%)	(3)	0.00	-0.02	1.00								
Index Fund ownership (%)	(4)	-0.03	-0.06	0.34	1.00							
Active Fund ownership (%)	(5)	-0.04	-0.10	0.21	0.41	1.00						
log(Mktcap ($m))	(6)	-0.31	-0.07	-0.03	0.29	0.27	1.00					
1/Price	(7)	0.35	0.02	-0.05	-0.12	-0.23	-0.39	1.00				
Amihud	(8)	0.18	0.09	-0.19	-0.26	-0.35	-0.39	0.30	1.00			
Bid-ask spread (%)	(9)	0.23	0.06	-0.39	-0.26	-0.27	-0.25	0.28	0.49	1.00		
Book-to-Market	(10)	0.21	0.03	0.12	0.08	-0.15	-0.24	0.34	0.16	0.19	1.00	
Past 12-month Return	(11)	-0.11	-0.03	-0.05	-0.03	0.02	0.05	-0.17	-0.10	-0.12	-0.31	1.00
Gross Profitability	(12)	0.01	-0.03	-0.01	0.02	0.20	0.00	-0.05	-0.06	-0.03	-0.26	0.04

Panel C: Variables Used in Return Regressions (Daily Frequency)

S&P 500

	N	Mean	Std Dev	Min	Median	Max
Ret(t) (%)	1,123,157	0.062	2.114	-9.459	0.023	10.403
Ret(t+1,t+5) (%)	1,123,157	0.244	4.520	-19.922	0.244	21.330
Ret(t+1,t+10) (%)	1,123,157	0.465	6.146	-23.823	0.514	25.242
Ret(t+1,t+20) (%)	1,123,157	0.898	8.605	-31.350	1.071	33.629
net(ETF Flows) (%)	1,123,157	0.000	0.000	-0.001	0.000	0.001

Russell 3000

	N	Mean	Std Dev	Min	Median	Max
Ret(t) (%)	5,014,804	0.070	2.373	-9.459	0.000	10.405
Ret(t+1,t+5) (%)	5,014,804	0.228	5.054	-19.923	0.200	21.333
Ret(t+1,t+10) (%)	5,014,804	0.452	6.829	-23.825	0.456	25.245
Ret(t+1,t+20) (%)	5,014,804	0.873	9.626	-31.355	0.950	33.641
net(ETF Flows) (%)	5,014,804	0.000	0.000	-0.001	0.000	0.001

Table 3. Summary Statistics (Cont.)

Panel D: Daily Sample

	N	Mean	Std Dev	Min	Median	Max
ETF ownership (%)	1,029,618	2.320	1.360	0.030	2.190	9.770
Abs(mispricing) (bps)	1,024,398	0.256	0.287	0.028	0.161	2.390
Net(mispricing) (bps)	1,002,866	-0.049	0.237	-1.160	-0.004	0.466
Intraday volatility (%)	1,029,618	0.019	0.015	0.005	0.014	0.123
Variance Ratio (VR 15)	1,000,903	-2.040	1.040	-8.230	-1.820	-0.546
Share lending fee (%)	1,029,618	0.213	1.110	0.000	0.099	72.400

Russell 3000

	N	Mean	Std Dev	Min	Median	Max
ETF ownership (%)	4,554,404	2.660	1.780	0.030	2.320	9.770
Abs(mispricing) (%)	4,357,317	0.324	0.349	0.028	0.211	2.390
Net(mispricing) (%)	4,260,036	-0.108	0.334	-1.160	-0.023	0.466
Intraday volatility (%)	4,554,404	0.021	0.015	0.005	0.017	0.123
Variance Ratio (VR 15)	4,485,442	-2.680	1.290	-8.230	-2.440	-0.546
Share lending fee (%)	4,554,404	0.444	2.240	0.000	0.132	132.000

Table 4. ETF Ownership and Stock Volatility

The table reports estimates from OLS regressions of daily volatility on ETF ownership and controls. In Columns (1) to (3), the sample consists of S&P 500 stocks, and in Columns (4) to (6) the sample consists of Russell 3000 stocks. The frequency of the observations is monthly and volatility is computed using all daily returns within the month. The dependent variable as well as the ownership variables have been standardized by subtracting the mean and dividing by the standard deviation. Variable descriptions are provided in Appendix Table A1. Standard errors are double-clustered at the stock and month level. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between January 2000 and December 2012.

Dependent variable:	Daily stock volatility					
Sample:	S&P 500			Russell 3000		
	(1)	(2)	(3)	(4)	(5)	(6)
ETF ownership	0.132***	0.127***	0.073***	0.052***	0.042***	0.033***
	(4.828)	(4.700)	(4.488)	(4.606)	(3.784)	(4.661)
log(Mktcap (t-1))	0.048	0.038	-0.035*	-0.096***	-0.116***	-0.104***
	(1.271)	(1.010)	(-1.691)	(-3.799)	(-4.550)	(-5.630)
1/Price (t-1)	1.574**	1.502**	0.073	0.814***	0.905***	0.172
	(2.446)	(2.343)	(0.209)	(2.954)	(3.291)	(0.918)
Amihud (t-1)	-9.242	-3.037	-8.665	0.195	0.305	-0.127
	(-0.604)	(-0.206)	(-1.238)	(0.704)	(1.087)	(-0.690)
Bid-ask spread (t-1)	-7.346**	-7.215**	-4.544***	-8.894***	-8.168***	-5.513***
	(-2.085)	(-2.041)	(-2.826)	(-2.989)	(-2.723)	(-3.337)
Book-to-Market (t-1)	0.531***	0.530***	0.190***	0.332***	0.325***	0.158***
	(9.162)	(9.172)	(7.110)	(9.539)	(9.381)	(8.032)
Past 12-month Return (t-1)	0.025	0.016	0.055***	0.056***	0.061***	0.050***
	(0.668)	(0.430)	(2.714)	(2.791)	(3.051)	(4.294)
Gross Profitability (t-1)	0.454***	0.493***	0.189***	0.032	0.042	0.041
	(4.143)	(4.400)	(4.213)	(0.607)	(0.788)	(1.484)
Index Fund Ownership		0.028**	0.008		0.021***	0.010***
		(2.287)	(1.503)		(3.537)	(2.982)
Active Fund Ownership		0.062***	0.030***		0.060***	0.037***
		(3.884)	(4.227)		(6.509)	(6.994)
Volatility (t-1)			0.295***			0.217***
			(17.911)			(17.608)
Volatility (t-2)			0.170***			0.155***
			(9.312)			(18.587)
Volatility (t-3)			0.197***			0.186***
			(11.930)			(21.707)
Stock fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	67,261	67,261	65,866	289,563	289,563	275,962
Adjusted R^2	0.645	0.647	0.743	0.593	0.595	0.664

Table 5. Quasi-Natural Experiment Based on the Russell Index Reconstitution

The table reports estimates from a quasi-natural experiment relying on the reconstitution of the Russell 1000 and Russell 2000 indexes. The frequency of the data is monthly at the stock level. In Panel A, the dependent variable is ETF ownership. The explanatory variables are: a dummy for inclusion in the Russell 2000, for stocks in the Russell 1000 before index reconstitution (Columns (1)-(5)), and a dummy for inclusion in the Russell 1000, for stocks in the Russell 2000 before index reconstitution (Columns (6)-(10)). Stocks are ranked in terms of market capitalization in May of each year. Different ranges of this rank around the cutoff are used for inclusion in the sample: 100 stocks on each side (Columns (1) and (6)), 200 stocks on each side (Columns (2) and (7)), 300 stocks on each side (Columns (3) and (8)), 400 stocks on each side (Columns (4) and (9)), and 500 stocks on each side (Columns (5) and (10)). The same stocks enter the sample from June after index reconstitution to May of the next year, except if delistings occur. The controls in all panels include logged market capitalization, lagged inverse share price ratio, lagged Amihud ratio, lagged average bid-ask spread, lagged book-to-market ratio, lagged past 12 months' returns, lagged gross profitability (as in Novy-Marx 2013), lagged volatility, index fund ownership, and active fund ownership. In Panels B, C, and D, the dependent variable is daily stock volatility (computed using all daily returns within a month). The main explanatory variable is instrumented ETF ownership. The instruments are either a dummy for inclusion in the Russell 2000 for stocks in the Russell 1000 before reconstitution (Columns (1)-(5)) or a dummy for inclusion in the Russell 1000 for stocks in the Russell 2000 before reconstitution (Columns (7)-(10)). The same bandwidths around the cutoff are used to restrict the sample as in Panel A. The regressions in Panel B, as well as in Panel A, include a linear specification of the ranking variable (not reported). Panels C and D replicate the analysis in Panel B, including instead a quadratic and a cubic specifications of the ranking variable (not reported). The first stages are modified accordingly and are reported in the Internet Appendix. For the two-stage estimation whose results are reported in Panels B, C, and D, ETF ownership, as well as ownership by index and active funds, is standardized by subtracting the mean and dividing by the standard deviation in the estimation sample. In Panel E, the dependent variable is daily volatility. The main explanatory variable is an interaction between the dummy variables for index inclusion and average ETF ownership in the sample of Russell 2000 stocks. Other explanatory variables include interactions between the index inclusion dummies and ownership by index and active funds, a time trend. The dependent variable as well as the ownership variables have been standardized by subtracting the mean and dividing by the standard deviation. Panel E includes also controls for average ETF ownership as well as average index funds ownership and mutual fund ownership in the Russell 2000 sample. Variable descriptions are provided in Appendix Table A1. Standard errors are double-clustered at the stock and month level. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between June 2000 and May 2007.

Panel A: First-Stage Regressions, First Degree Polynomial

Dependent variable:	ETF ownership									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Switching index	0.244***	0.345***	0.451***	0.518***	0.490***	-0.145***	-0.404***	-0.415***	-0.383***	-0.396***
	(6.397)	(7.100)	(7.644)	(8.825)	(8.991)	(-2.842)	(-8.461)	(-9.822)	(-8.115)	(-8.528)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,885	10,152	16,162	22,403	28,742	6,528	12,798	18,360	23,744	29,186
Adjusted R^2	0.375	0.390	0.378	0.346	0.336	0.410	0.421	0.455	0.471	0.461

Table 5. Quasi-Natural Experiment Based on the Russell Index Reconstitution (Cont.)

Panel B: Second-Stage Regressions, First Degree Polynomial

Dependent variable:	Daily stock volatility									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF ownership (instrumented)	0.498**	0.362**	0.263***	0.171**	0.240***	0.803**	0.258***	0.202***	0.220***	0.168***
	(2.206)	(2.603)	(3.229)	(2.617)	(3.632)	(2.232)	(3.660)	(3.357)	(3.569)	(3.517)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,885	10,152	16,162	22,403	28,742	6,528	12,798	18,360	23,744	29,186

Panel C: Second-Stage Regressions, Second Degree Polynomial

Dependent variable:	Daily stock volatility									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF ownership (instrumented)	1.355	0.349**	0.395***	0.333***	0.289***	0.388***	0.259***	0.287***	0.310***	0.338***
	(0.793)	(2.341)	(3.022)	(3.267)	(3.225)	(2.687)	(3.636)	(3.649)	(3.574)	(3.645)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,885	10,152	16,162	22,403	28,742	6,528	12,798	18,360	23,744	29,186

Panel D: Second-Stage Regressions, Third Degree Polynomial

Dependent variable:	Daily stock volatility									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF ownership (instrumented)	-2.206	0.370	0.426***	0.431***	0.369***	0.247*	0.223**	0.245***	0.265***	0.273***
	(-1.227)	(1.441)	(2.931)	(2.994)	(2.639)	(1.782)	(2.545)	(3.569)	(3.430)	(3.454)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cubic polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,885	10,152	16,162	22,403	28,742	6,528	12,798	18,360	23,744	29,186

Table 5. Quasi-Natural Experiment Based on the Russell Index Reconstitution (Cont.)

Panel E: Interaction with Average ETF Ownership

Dependent variable:	Daily stock volatility									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF ownership × Switch	0.294**	0.284**	0.137	0.051	0.029	-0.262	-0.398***	-0.483***	-0.536***	-0.625***
	(2.040)	(2.118)	(1.049)	(0.432)	(0.228)	(-1.590)	(-3.592)	(-3.848)	(-3.469)	(-3.321)
Index funds ownership × Switch	-0.082***	-0.052***	-0.028**	-0.026**	-0.023**	0.069***	0.014	-0.005	-0.011	-0.016
	(-5.246)	(-3.993)	(-2.425)	(-2.443)	(-2.025)	(3.409)	(0.906)	(-0.377)	(-0.867)	(-0.975)
Active funds ownership × Switch	0.280***	0.052	0.021	0.025	0.018	-0.146**	0.005	0.077	0.093	0.155*
	(3.983)	(0.916)	(0.365)	(0.445)	(0.332)	(-2.103)	(0.086)	(1.053)	(1.369)	(1.859)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Aggregate ownership controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend, interacted with switch	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,887	10,157	16,173	22,420	28,769	6,532	12,808	18,372	23,761	29,204
Adjusted R^2	0.631	0.606	0.602	0.592	0.593	0.495	0.473	0.476	0.484	0.488

Table 6. ETF Ownership and Price Efficiency: Variance Ratios

The table reports estimates from OLS regressions of variance ratios on ETF ownership and controls (Panel A), as well as IV regressions (Panel B and C). In Panel A, Columns (1) and (2), the sample consists of S&P 500 stocks, and in Columns (3) and (4), the sample consists of Russell 3000 stocks. The frequency of the observations is monthly for VR 15 seconds and quarterly for VR 5 days. VR 15 seconds is the absolute value of the ratio of the variance of 15-second log returns on day *t* and 3 times the variance of 5-second log returns on day $t - 1$, using data from the TAQ database and averaging the numerator and denominator within a month. VR 5 days is the absolute value of the ratio of the variance of 5-day returns in a given quarter on and 5 times the variance of one-day returns in the same quarter. Panels B and C show IV regressions for 15-seconds variance ratio (Panel B) and for 5-days variance ratio (Panel C) based on the Russell 1000/Russell 2000 inclusion experiment. The dependent variable as well as the ownership variables have been standardized by subtracting the mean and dividing by the standard deviation. The controls in all panels include logged market capitalization, lagged inverse share price ratio, lagged Amihud ratio, lagged average bid-ask spread, lagged book-to-market ratio, lagged past 12 months' returns, lagged gross profitability (as in Novy-Marx 2013), lagged volatility, index fund ownership, and active fund ownership. Variable descriptions are provided in Appendix Table A1. Standard errors are double-clustered at the stock and time level. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between January 2000 and December 2012 in Panel A, and June 2000 and May 2007 in Panels B and C.

Panel A: Variance Ratios (OLS)

Sample:	S&P 500		Russell 3000	
Dependent Variable:	VR 15 seconds	VR 5 days	VR 15 seconds	VR 5 days
	(1)	(2)	(3)	(4)
ETF ownership	0.109***	0.049*	0.061***	0.013
	(4.485)	(1.809)	(7.620)	(1.188)
Controls	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Observations	56,623	22,887	268,418	100,836
Adjusted R^2	0.473	0.032	0.488	0.041

Table 6. ETF Ownership and Price Efficiency: Variance Ratios (Cont.)

Panel B: Variance Ratios – 15 Seconds (IV)

Dependent variable:	VR 15 seconds									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF ownership (instrumented)	-0.074	0.316*	0.238**	0.152	0.283***	0.436	0.016	0.055	-0.007	-0.057
	(-0.258)	(1.686)	(2.076)	(1.597)	(2.666)	(1.382)	(0.193)	(0.812)	(-0.099)	(-1.064)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,809	10,008	15,947	22,114	28,387	6,469	12,673	18,175	23,493	28,863

Panel C: Variance Ratios – 5 Days (IV)

Dependent variable:	VR 5 days									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF ownership (instrumented)	0.248	0.232	0.241*	0.189*	0.190*	0.584	0.470**	0.490**	0.537**	0.515**
	(1.108)	(1.556)	(1.886)	(1.828)	(1.806)	(1.284)	(2.343)	(2.720)	(2.476)	(2.505)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,540	3,214	5,124	7,118	9,148	2,071	4,048	5,798	7,498	9,217

Table 7. Price Reversals

The table reports estimates from OLS regressions of one- and multi-day returns on ETF flows and controls. The specifications also include the *k*-period lagged dependent variable, where *k* is set to have the return-measurement horizon end in *t*-1. In Columns (1) to (4), the sample consists of S&P 500 stocks, and in Columns (5) to (8), the sample consists of Russell 3000 stocks. The frequency of the observations is daily. Returns are in percentages. Flows have been standardized by subtracting the mean and dividing by the standard deviation. The controls in all panels include logged market capitalization, lagged inverse share price ratio, lagged Amihud ratio, lagged average bid-ask spread, lagged book-to-market ratio, lagged past 12 months' returns, lagged gross profitability (as in Novy-Marx 2013), order imbalance, and lagged dependent variable. Variable descriptions are provided in Appendix Table A1. Standard errors are clustered at the day level and are computed using the Newey and West (1987) estimator. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between January 2000 and December 2012.

Sample:	S&P 500				Russell 3000			
Dependent variable:	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)
net(ETF Flows)	0.167***	-0.024	-0.054**	-0.072**	0.062***	-0.011	0.000	-0.032**
	(17.420)	(-1.328)	(-2.248)	(-2.278)	(13.176)	(-1.136)	(0.027)	(-2.104)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,120,058	1,120,058	1,120,058	1,120,058	4,988,503	4,988,503	4,988,503	4,988,503
Adjusted R^2	0.361	0.311	0.289	0.287	0.332	0.271	0.243	0.240

Table 8. Evidence on the Arbitrage Channel

The table reports estimates from OLS regressions of intraday volatility (Panel A) and intraday variance ratio (Panel B) on absolute stock-level mispricing in the prior period interacted with measures of arbitrage costs. The frequency is daily and the observations are at the stock level. The sample includes S&P 500 stocks. In Columns (2)-(4), arbitrage cost is captured by the bid-ask spread in the prior day, and in Columns (5)-(7), by the average share-lending fee in the month. For both measures of arbitrage costs, we construct dummy variables denoting whether the stock is in the top half of the distribution of that measure in the relevant period. In Columns (3) and (6), we restrict the sample to observations for which the stock-level mispricing is positive. In Columns (4) and (7), we restrict the sample to observations for which the stock-level mispricing is negative. The controls in all panels include logged market capitalization, lagged inverse share price ratio, lagged Amihud ratio, lagged average bid-ask spread, lagged book-to-market ratio, lagged past 12 months' returns, lagged gross profitability (as in Novy-Marx 2013), lagged returns, lagged dependent variable, and the absolute mispricing in period *t* - 2. Variable descriptions are provided in Appendix Table A1. Standard errors are double-clustered at the stock and day level. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between January 2000 and December 2012.

Panel A: Intraday Volatility

Dependent variable:	Intraday stock volatility						
	All	All	Misp > 0	Misp < 0	All	Misp > 0	Misp < 0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abs(Mispricing) (t-1)	0.023***	0.043***	0.076***	0.035***	0.020***	0.048***	0.018***
	(6.897)	(8.025)	(10.300)	(6.988)	(4.642)	(7.530)	(4.302)
× I(High bid-ask spread)		-0.053***	-0.055***	-0.043***			
		(-6.554)	(-4.257)	(-6.392)			
× I(High lending fee)					-0.009*	0.003	-0.010**
					(-1.956)	(0.444)	(-2.548)
High bid-ask spread		0.042***	0.038***	0.045***			
		(7.186)	(6.318)	(7.130)			
High lending fee					-0.005	-0.003	-0.005
					(-1.565)	(-0.957)	(-1.433)
ETF ownership (t-1)	0.022***	0.022***	-0.004	0.031***	0.021***	-0.006	0.031***
	(3.611)	(4.217)	(-0.692)	(5.531)	(4.042)	(-1.227)	(5.417)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	No	No	No	No	No	No
Observations	1,022,548	1,022,548	509,240	513,308	1,022,548	509,240	513,308
Adjusted R^2	0.549	0.500	0.505	0.498	0.499	0.504	0.497

Table 8. Evidence on the Arbitrage Channel (Cont.)

Panel B: Intraday Variance Ratio

Dependent variable:	Intraday variance ratio (VR 15)						
	All	All	Misp > 0	Misp < 0	All	Misp > 0	Misp < 0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abs(Mispricing) (t-1)	0.002	0.030***	0.055***	0.024***	0.007	0.026***	0.006
	(0.741)	(4.658)	(6.920)	(3.531)	(1.440)	(4.012)	(1.276)
× I(High bid-ask spread)		-0.056***	-0.062***	-0.046***			
		(-5.781)	(-4.739)	(-4.765)			
× I(High lending fee)					-0.011**	-0.001	-0.012**
					(-2.083)	(-0.125)	(-2.127)
High bid-ask spread		0.120***	0.119***	0.120***			
		(12.401)	(11.907)	(11.991)			
High lending fee					-0.009**	-0.006	-0.010**
					(-2.115)	(-1.341)	(-2.298)
ETF ownership (t-1)	0.037***	0.030***	0.016**	0.032***	0.027***	0.010	0.030***
	(4.864)	(4.401)	(2.123)	(4.599)	(3.825)	(1.297)	(4.161)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	No	No	No	No	No	No
Observations	983,625	983,625	490,321	493,304	983,625	490,321	493,304
Adjusted R^2	0.245	0.186	0.188	0.185	0.180	0.183	0.179

Table 9. Volatility and ETF Ownership in the Time-Series

Panel A reports estimates from a time-series regression at the monthly frequency of average daily volatility in a given month across the stocks in the CRSP universe on lagged average ETF ownership for the same universe. The controls include lagged average volatility, lagged average index and active fund ownership (IF and AF variables respectively), and a time trend. The same regression is performed in first differences, excluding the time trend. Panel B reports estimates from time-series regressions of average volatility in each quintile of ETF ownership on lagged average ETF ownership across all stocks in the CRSP universe. Panel C reports estimates from time-series regressions of the changes in the average volatility in each quintile of ETF ownership on lagged changes in the average ETF ownership across all stocks in the CRSP universe. The other ownership variables are also computed as averages across all stocks. The dependent as well as the ownership variables have been standardized by subtracting the mean and dividing by the standard deviation. Variable descriptions are provided in Appendix Table A1. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between January 2000 and December 2012.

Panel A: Regression of Volatility on ETF Ownership

Dependent Variable:	Volatility (t+1)	ΔVolatility (t+1)
	(1)	(2)
ETF ownership (t)	0.216***	
	(3.938)	
IF ownership (t)	-0.066	
	(-1.106)	
AF ownership (t)	0.082	
	(1.629)	
Volatility (t)	0.701***	
	(12.939)	
Trend	-0.001	
	(-0.483)	
ΔETF ownership (t)		0.344***
		(4.388)
ΔIF ownership (t)		-0.052
		(-0.632)
ΔAF ownership (t)		0.030
		(0.358)
ΔVolatility (t)		-0.150*
		(-1.934)
Observations	149	148
Adjusted R^2	0.721	0.151

Table 9. Volatility and ETF Ownership in the Time-Series (Cont.)

Panel B: Regression of Volatility and ETF Ownership, by Quintiles of ETF Ownership

Dependent Variable:	Volatility (t+1)				
Quintile of ETF ownership:	Smallest	2	3	4	Largest
ETF ownership (t)	0.189***	0.213***	0.206***	0.216***	0.247***
	(3.532)	(4.075)	(3.890)	(4.154)	(3.856)
Index mutual funds ownership (t)	-0.063	-0.068	-0.049	-0.049	-0.093
	(-1.062)	(-1.144)	(-0.823)	(-0.863)	(-1.381)
Active mutual funds ownership (t)	0.025	0.060	0.091*	0.089*	0.150**
	(0.497)	(1.193)	(1.799)	(1.823)	(2.560)
Volatility (t)	0.760***	0.688***	0.656***	0.638***	0.667***
	(15.050)	(12.508)	(11.261)	(10.779)	(11.548)
Trend	-0.000	-0.000	-0.001	-0.000	-0.002
	(-0.027)	(-0.238)	(-0.606)	(-0.183)	(-1.216)
Observations	149	149	149	149	149
Adjusted R^2	0.759	0.691	0.648	0.662	0.726

Panel C: Regression of Changes in Volatility and ETF Ownership, by Quintiles of ETF Ownership

Dependent Variable:	ΔVolatility (t+1)				
Quintile of ETF ownership:	Smallest	2	3	4	Largest
ΔETF ownership (t)	0.297***	0.289***	0.326***	0.312***	0.384***
	(3.886)	(3.654)	(4.161)	(4.189)	(4.482)
ΔIndex mutual funds ownership (t)	-0.049	-0.064	-0.040	-0.061	-0.030
	(-0.607)	(-0.777)	(-0.479)	(-0.764)	(-0.326)
ΔActive mutual funds ownership (t)	-0.016	0.009	0.053	0.044	0.051
	(-0.195)	(0.114)	(0.638)	(0.549)	(0.551)
ΔVolatility (t)	-0.098	-0.149*	-0.184**	-0.200**	-0.197**
	(-1.219)	(-1.859)	(-2.356)	(-2.596)	(-2.540)
Observations	148	148	148	148	148
Adjusted R^2	0.120	0.128	0.157	0.159	0.150

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

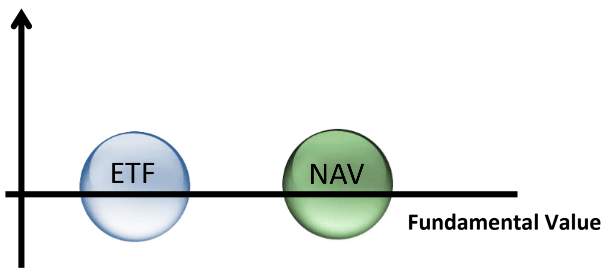


Figure 1a. Initial equilibrium

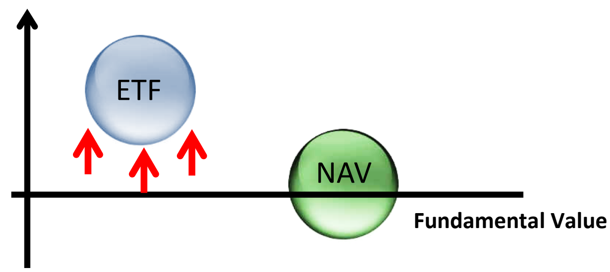


Figure 1b. Non-fundamental shock to ETF

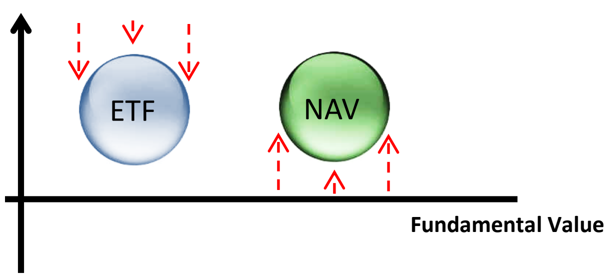


Figure 1c. Initial outcome of arbitrage: the non-fundamental shock is propagated to the NAV, and the ETF price starts reverting to the fundamental value.

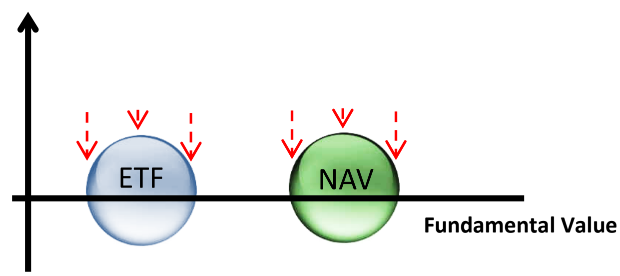


Figure 1d. Re-establishment of equilibrium: after some time, both the ETF price and the NAV revert to the fundamental value.

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

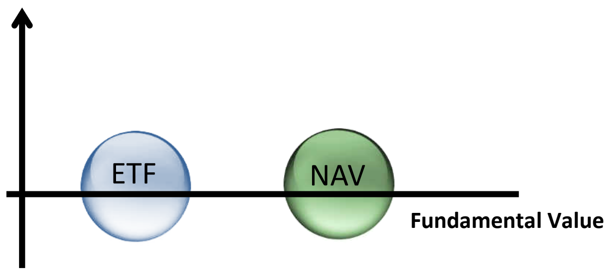


Figure 2a. Initial equilibrium

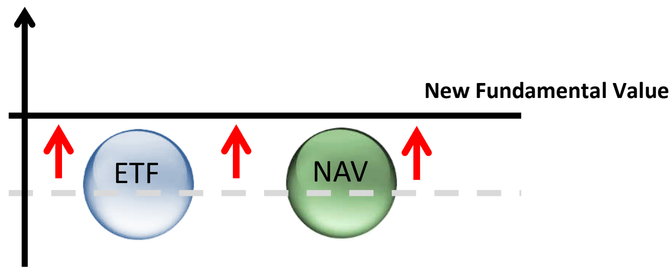


Figure 2b. Shock to fundamental value

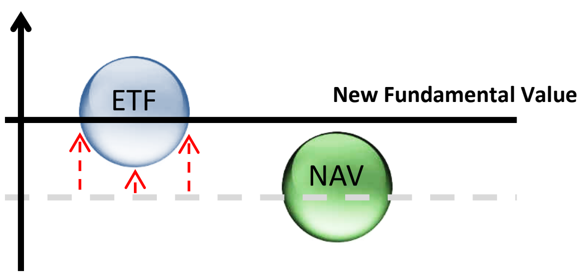


Figure 2c. Price discovery takes place in the ETF market. The ETF price moves to the new fundamental value.

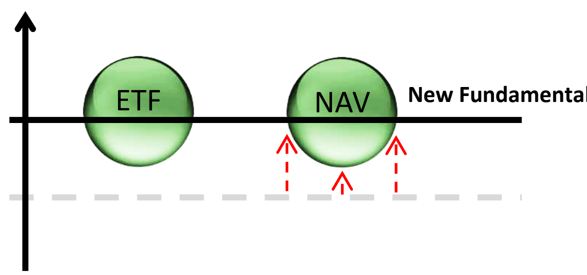
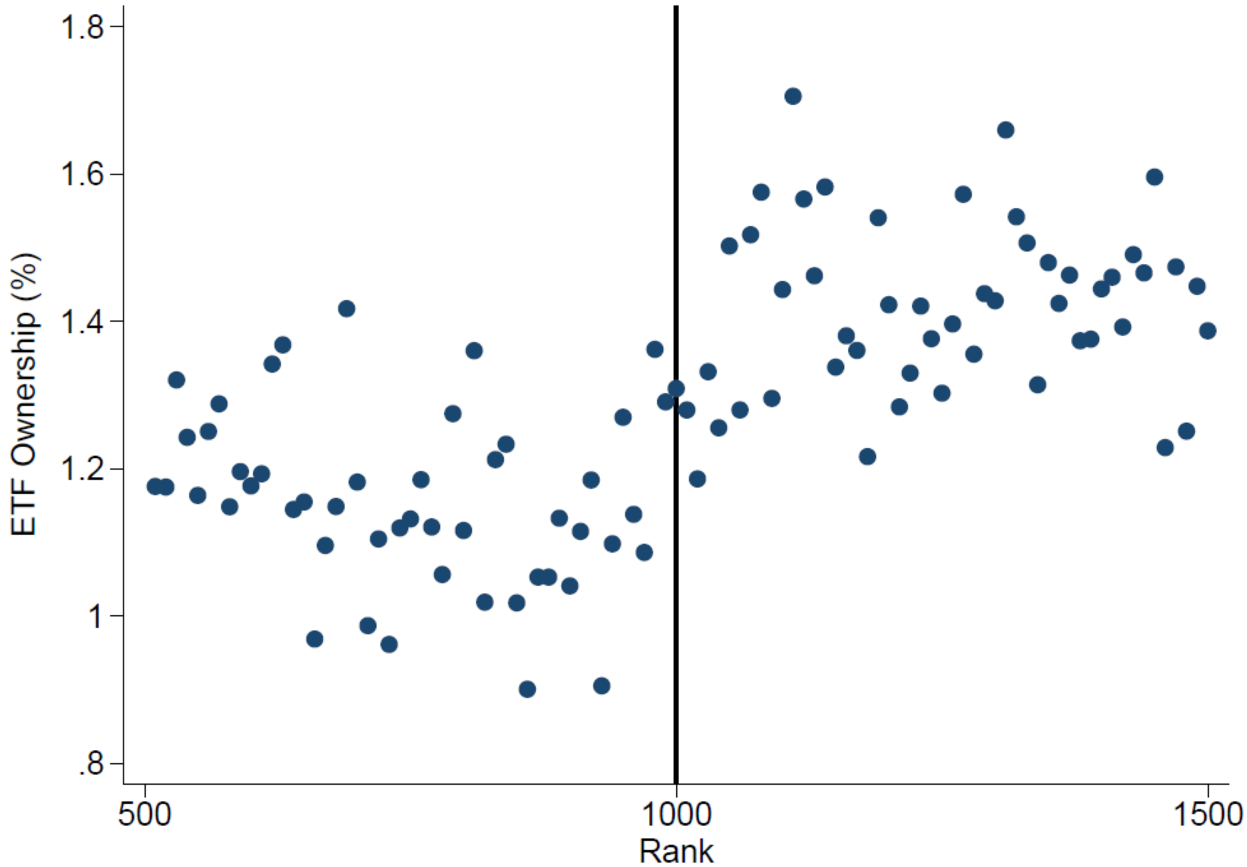


Figure 2d. After a delay, the NAV catches up with the new fundamental.

Figure 3: ETF Ownership around the Russell Cutoff



The figure reports average ETF ownership (in %) for stocks ranked by market capitalization and included in the Russell 3000. The average is computed first by ranking over time, then across the ranking in bins of 10 stocks. The vertical line denotes the 1000th rank. The sample ranges between January 2000 and May 2007.

Appendix Table A1. Variable Definitions

Variable	Description	Source
ETF ownership	The sum of the ownership of all ETFs holding the stock, using the most recent quarterly investment company reports for equity ETFs. The lagged quarterly portfolio weights are interacted with daily ETF AUM and daily stock capitalization, to compute daily ownership. The monthly variable is defined accordingly.	Thomson-Reuters, CRSP, Bloomberg
Index (or active) mutual fund ownership	The sum of the ownership by all index (or active) mutual funds holding the stock, using the most recent quarterly investment company reports.	Thomson-Reuters, CRSP Mutual Fund, and MFLinks
Daily volatility	Standard deviation of daily stock returns within a month.	CRSP
Intraday volatility	Standard deviation of second-by-second intraday returns.	TAQ
Variance ratio 15 seconds	The ratio of 15-second log return variance divided by 3 times the 5-second log return variance minus 1. The numerator and denominator are computed using returns within a day and averaged over a month. The dependent variable in the regressions is the logarithm of the absolute value of this difference.	TAQ
Variance ratio 5 days	The ratio of 5-day return variance divided by 5 times the 1-day return variance minus 1. The numerator and denominator are computed using daily and 5-day returns within a quarter. The dependent variable in the regressions is the logarithm of the absolute value of this difference.	CRSP
Net(ETF flows)	Stock-day-level measure. Weighted average of the percentage change in ETF shares outstanding across the ETFs holding the stock. The weight is ETF ownership of the stock.	Bloomberg, Compustat
Ret(t_1, t_2)	The total return of the stock between the close of t_1 and the close of t_2.	CRSP
Abs(mispricing)	Sum of absolute dollar mispricing across all the ETFs holding the stock divided by stock capitalization (Equation (3)). Dollar mispricing is the product of ETF mispricing (i.e., the difference between the ETF price and its NAV, as a fraction of the ETF price) times dollar holdings of an ETF in the stock.	Thomson-Reuters, CRSP, Bloomberg
Net(mispricing)	Similar construction to abs(mispricing). The only difference is that the ETF-level mispricing is not in absolute value.	Thomson-Reuters, CRSP, Bloomberg
Lending fees	Share-lending fee at the security level, 7-day average. Average within the month.	Markit
log(Mktcap)	The logged market capitalization of the stock (in $ millions) at the end of the month.	CRSP
1/Price	The inverse of the nominal share price at the end of the month.	CRSP
Amihud ratio	Absolute return scaled by dollar volume in $million, average within the month. Based on Amihud (2002).	CRSP
Bid-ask spread	The quoted spread divided by the bid-ask midpoint. End-of-month value.	CRSP
Book-to-Market	Book value of assets / Market value of assets.	CRSP, Compustat
Past 12-month Return	Cumulative returns in the previous 12 months.	CRSP
Gross Profitability	(Revenue – Cost of goods sold) / Total assets. Following Novy-Marx (2013)	Compustat
Churn ratio 1	This measure follows Cella, Ellul, and Giannetti (2013) in computing the investor-level churn ratio, which is then aggregated at the stock level using ownership weights.	CRSP, 13-F
Churn ratio 2	This measure uses an investor-level churn ratio that is computed as the minimum between the absolute value of buys and sells divided by prior quarter holdings. Buys and sells use prior quarter prices.	CRSP, 13-F

Appendix Table A2. Institution Type Definitions

Source: Thomson Reuters Owner Types - Global Equity Ownership Feed

Institution Type	Definition
Banks	These firms perform all of the functions of a retail bank. As a retail bank, a portfolio of investments are put together by an investment adviser and sold in units to investors by brokers. They may also handle Trust Accounts, which are outside companies or individuals that have a bank manage their money for their own pensions or for various other reasons. They invest the money their customers hold in their accounts in order to make interest payments and their own profits.
Endowments	Endowment Funds are permanent gifts, often to universities or colleges, which are re-invested to ensure continuing profit.
Hedge Funds	A hedge fund management firm who, through its hedge fund products, is permitted to use aggressive strategies that are unavailable to mutual funds, including selling short, leverage, program trading, swaps, arbitrage, and derivatives. Many times they are highly secretive because they use risky investment styles and also involve high net investors. Since they are restricted by law to less than 100 investors, the minimum investment is typically $1 million.
Insurance	Insurance Companies invest in a similar fashion as Investment Advisors. They re-invest the money they take in in order to make coverage payouts as well as their own profits.
Investment Advisors	This is the most common institution type found in the database. These are buy-side institutions who invest in stocks (equities) or bonds (fixed income). They have discretionary power over assets under management (AUM) and actually make buy/sell decisions.
Investment Companies	An investment vehicle operated by an investment company which raises money from shareholders and invests in a group of assets, in accordance with a stated set of objectives. Includes mutual funds.
Pension Funds	A qualified retirement plan set up by a corporation, labor union, government, or other organization for its employees. In order to be included in the TF database, the pension fund must manage a portion of its assets internally.
Individual Investors (in 13-F)	Individual investors that file the 13-F because they exercises investment discretion over the account of any other natural person or entity.
Research Firm	A firm that writes research intended for the buy-side community. The firm does not have an underwriting business or investment banking business. The firm does not have a proprietary trading operation. These firms typically charge for their individual research reports.
Corporations	Typically a business organization that is given many legal rights as an entity separate from its owners. For ownership purposes, these entities will typically be set up to represent its strategic investments.
Venture Capital	A firm that specializes in providing money to startup firms and small businesses with exceptional growth potential.
Private Equity	Firm that invests solely in private equity investments (i.e., privately held companies). They provide equity financing to small and middle market companies engaged in a variety of industries. They often focus on management buyouts, industry consolidations, recapitalization of existing business and other private equity opportunities.
Sovereign Funds	State-owned institutions, which invest public resources to reduce the unpredictability of government revenues, offset the boom-bust cycles' adverse effect on government spending and the national economy or foster savings for future generations. As such, SWFs aim to diversify and boost risk-adjusted returns by holding baskets of currencies, credit, and equities.

Appendix Table A3. ETF Ownership and Stock Intraday Volatility

The table reports estimates from OLS regressions of intraday volatility and variance ratio on ETF ownership and controls. In Columns (1) and (2), the sample consists of S&P 500 stocks, and in Columns (3) and (4) the sample consists of Russell 3000 stocks. The frequency of the observations is daily. Intraday stock volatility is computed using second-by-second data from the TAQ database. VR 15 seconds is the absolute value of the ratio of the variance of 15-second log returns on day *t* and 3 times the variance of 5-second log returns on day *t*, minus 1, using data from the TAQ database. Variable descriptions are provided in Appendix Table A1. Standard errors are double-clustered at the stock and month level. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between January 2000 and December 2012.

Sample:	S&P 500		Russell 3000	
Dependent variable:	Intraday volatility	VR 15 seconds	Intraday volatility	VR 15 seconds
	(1)	(2)	(3)	(4)
ETF ownership (t-1)	0.106***	0.078***	0.024***	0.024***
	(7.910)	(6.947)	(7.262)	(6.565)
log(Mktcap (t-1))	0.090***	0.024	-0.065***	0.068***
	(4.175)	(1.210)	(-9.136)	(9.083)
1/Price (t-1)	5.612***	1.988***	1.205***	0.649***
	(7.669)	(5.865)	(13.638)	(9.793)
Amihud (t-1)	-6.557	-75.413***	-0.700***	-2.350***
	(-0.289)	(-4.527)	(-4.791)	(-17.465)
Bid-ask spread (t-1)	5.594	2.363	20.765***	-6.297***
	(0.876)	(0.651)	(11.029)	(-3.938)
Book-to-Market (t-1)	0.111***	0.002	0.108***	0.033***
	(3.280)	(0.202)	(8.969)	(5.248)
Past 12-month Return (t-1)	0.007	-0.008	0.045***	0.019***
	(0.621)	(-0.959)	(12.471)	(7.139)
Gross Profitability (t-1)	-0.004	-0.081	-0.036*	-0.051***
	(-0.055)	(-1.340)	(-1.664)	(-2.582)
Ret (t-1)	-0.101**	0.027	-0.139***	0.026
	(-2.119)	(0.748)	(-7.355)	(1.538)
Lagged dep. variable	0.410***	0.140***	0.427***	0.101***
	(22.012)	(42.494)	(74.680)	(74.679)
Stock fixed effects	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes
Observations	1,032,361	994,461	4,566,163	4,519,920
Adjusted R^2	0.550	0.245	0.510	0.232

Appendix Table A4. Quasi-Natural Experiment, Additional Results, Entire Sample

The table reports estimates from a quasi-natural experiment relying on the reconstitution of the Russell 1000 and Russell 2000 indexes. The frequency of the data is monthly at the stock level. In Panel A, we report the number of companies moving across indexes at each yearly reconstitutions. In Panel B, the dependent variable is ETF ownership. The explanatory variables are: a dummy for inclusion in the Russell 2000, for stocks in the Russell 1000 before index reconstitution (Columns (1)-(5)), and a dummy for inclusion in the Russell 1000, for stocks in the Russell 2000 before index reconstitution (Columns (6)-(10)). Stocks are ranked in terms of market capitalization in May of each year. Different ranges of this rank around the cutoff are used for inclusion in the sample: 100 stocks on each side (Columns (1) and (6)), 200 stocks on each side (Columns (2) and (7)), 300 stocks on each side (Columns (3) and (8)), 400 stocks on each side (Columns (4) and (9)), and 500 stocks on each side (Columns (5) and (10)). The same stocks enter the sample from June after index reconstitution to May of the next year, except if delistings occur. The controls in all panels include logged market capitalization, lagged inverse share price ratio, lagged Amihud ratio, lagged average bid-ask spread, lagged book-to-market ratio, lagged past 12 months' returns, lagged gross profitability (as in Novy-Marx 2013), lagged volatility, index fund ownership, and active fund ownership. In Panels C, D, and E, the dependent variable is daily stock volatility (computed using all daily returns within a month). The main explanatory variable is instrumented ETF ownership. The instruments are either a dummy for inclusion in the Russell 2000 for stocks in the Russell 1000 before reconstitution (Columns (1)-(5)) or a dummy for inclusion in the Russell 1000 for stocks in the Russell 2000 before reconstitution (Columns (7)-(10)). The same bandwidths around the cutoff are used to restrict the sample as in Panel B. The regressions in Panel C, as well as in Panel B, include a linear specification of the ranking variable (not reported). Panels D and E replicate the analysis in Panel C, including instead a quadratic and a cubic specifications of the ranking variable (not reported). The first stages are modified accordingly and are reported in the Internet Appendix. For the two-stage estimation whose results are reported in Panels C, D, and E, ETF ownership, as well as ownership by index and active funds, is standardized by subtracting the mean and dividing by the standard deviation in the estimation sample. Variable descriptions are provided in Appendix Table A1. Standard errors are double-clustered at the stock and month level. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between June 2000 and December 2012.

Panel A: Number of Index Switchers

	Switch to…	
Year	Russell 2000	Russell 1000
2000	126	114
2001	106	148
2002	103	126
2003	79	82
2004	63	63
2005	80	82
2006	52	85
2007	9	17
2008	38	42
2009	37	39
2010	15	23
2011	22	35
2012	27	26

Appendix Table A4. Regression Discontinuity, Additional Results (Cont.)

Panel B: First-Stage Regressions, First Degree Polynomial, Entire Sample

Dependent variable:	ETF ownership									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Switching index	0.325***	0.460***	0.556***	0.612***	0.579***	-0.381***	-0.538***	-0.524***	-0.486***	-0.505***
	(7.266)	(9.460)	(10.710)	(11.694)	(11.489)	(-6.351)	(-10.591)	(-11.690)	(-10.496)	(-10.922)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,566	13,893	22,587	32,167	42,631	9,151	18,325	27,137	36,568	46,029
Adjusted R^2	0.515	0.540	0.542	0.531	0.529	0.670	0.645	0.660	0.666	0.662

Panel C: Second-Stage Regressions, First Degree Polynomial, Entire Sample

Dependent variable:	Daily stock volatility									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF ownership (instrumented)	0.497**	0.362***	0.337***	0.227***	0.308***	0.554***	0.326***	0.308***	0.336***	0.232***
	(2.601)	(2.933)	(4.186)	(3.229)	(4.314)	(3.732)	(4.295)	(4.525)	(4.902)	(4.130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,566	13,893	22,587	32,167	42,631	9,151	18,325	27,137	36,568	46,029

Panel D: Second-Stage Regressions, Second Degree Polynomial, Entire Sample

Dependent variable:	Daily stock volatility									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF ownership (instrumented)	0.438	0.354**	0.429***	0.419***	0.372***	0.390***	0.383***	0.448***	0.489***	0.493***
	(0.993)	(2.398)	(3.320)	(3.604)	(3.525)	(3.813)	(4.510)	(4.799)	(4.955)	(4.725)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,566	13,893	22,587	32,167	42,631	9,151	18,325	27,137	36,568	46,029

Appendix Table A4. Regression Discontinuity, Additional Results (Cont.)

Panel E: Second-Stage Regressions, Third Degree Polynomial, Entire Sample

Dependent variable:	Daily stock volatility									
Instrument:	Switch to the Russell 2000					Switch to the Russell 1000				
Bandwidth:	± 100	± 200	± 300	± 400	± 500	± 100	± 200	± 300	± 400	± 500
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ETF ownership (instrumented)	4.001	0.504*	0.413***	0.482***	0.410***	0.368***	0.419***	0.370***	0.452***	0.484***
	(0.709)	(1.815)	(2.921)	(3.456)	(2.846)	(3.270)	(3.958)	(4.199)	(4.589)	(4.832)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cubic polynomials of rank	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,566	13,893	22,587	32,167	42,631	9,151	18,325	27,137	36,568	46,029

Appendix Table A5. Price Reversals, Controlling for Lending Fees

The table reports estimates from OLS regressions of one- and multiday returns on ETF flows and controls. The specifications also include the k-period lagged dependent variable, where k is set to have the return-measurement horizon end in t-1. In Columns (1) to (4), the sample consists of S&P 500 stocks, and in Columns (5) to (8), the sample consists of Russell 3000 stocks. The frequency of the observations is daily. Returns are in percentages. Flows have been standardized by subtracting the mean and dividing by the standard deviation. The controls in all panels include logged market capitalization, lagged inverse share price ratio, lagged Amihud ratio, lagged average bid-ask spread, lagged book-to-market ratio, lagged past 12 months' returns, lagged gross profitability (as in Novy-Marx 2013), lending fees, and lagged dependent variable. Variable descriptions are provided in Appendix Table A1. Standard errors are clustered at the day level and are computed using the Newey and West (1987) estimator. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between January 2000 and December 2012.

Sample:	S&P 500				Russell 3000			
Dependent variable:	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)
net(ETF Flows)	0.252***	-0.038	-0.071**	-0.124***	0.082***	0.003	0.024	-0.019
	(18.746)	(-1.569)	(-2.188)	(-2.855)	(12.597)	(0.215)	(1.441)	(-0.869)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	562,061	562,061	562,061	562,061	2,589,658	2,589,658	2,589,658	2,589,658
Adjusted R^2	0.432	0.367	0.333	0.335	0.404	0.323	0.283	0.276

Appendix Table A6. Evidence on the Arbitrage Channel (Russell 3000 Sample)

The table reports estimates from OLS regressions of intraday volatility (Panel A) and intraday variance ratio (Panel B) on absolute stock-level mispricing in the prior period interacted with measures of arbitrage costs. The frequency is daily and the observations are at the stock level. The sample includes Russell 3000 stocks. In Columns (2)-(4), arbitrage cost is captured by the bid-ask spread in the prior day, and in Columns (5)-(7), by the average share-lending fee in the month. For both measures of arbitrage costs, we construct dummy variables denoting whether the stock is in the top half of the distribution of that measure in the relevant period. In Columns (3) and (6), we restrict the sample to observations for which the stock-level mispricing is positive. In Columns (4) and (7), we restrict the sample to observations for which the stock-level mispricing is negative. The controls in all panels include logged market capitalization, lagged inverse share price ratio, lagged Amihud ratio, lagged average bid-ask spread, lagged book-to-market ratio, lagged past 12 months' returns, lagged gross profitability (as in Novy-Marx 2013), lagged returns, lagged dependent variable, and the absolute mispricing in period t - 2. Variable descriptions are provided in Appendix Table A1. Standard errors are double-clustered at the stock and day level. *t-statistics* are presented in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The sample ranges between January 2000 and December 2012.

Panel A: Intraday Volatility

Dependent variable:	Intraday stock volatility						
	All	All	Misp > 0	Misp < 0	All	Misp > 0	Misp < 0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abs(Mispricing) (t-1)	0.006***	0.005***	0.017***	0.001	0.002	0.008***	-0.001
	(6.452)	(3.424)	(8.650)	(0.326)	(1.220)	(4.531)	(-0.573)
× I(High bid-ask spread)		-0.010***	-0.022***	-0.005			
		(-2.950)	(-6.015)	(-1.391)			
× I(High lending fee)					-0.001	0.001	-0.003
					(-0.635)	(0.376)	(-1.566)
High bid-ask spread		0.077***	0.077***	0.075***			
		(18.020)	(18.166)	(17.012)			
High lending fee					0.040***	0.041***	0.039***
					(16.488)	(16.471)	(15.455)
ETF ownership (t-1)	0.005*	0.004**	0.001	0.004**	0.002	-0.001	0.003
	(1.867)	(2.305)	(0.684)	(2.277)	(1.357)	(-0.433)	(1.635)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	No	No	No	No	No	No
Observations	4,333,078	4,333,078	2,050,177	2,282,901	4,333,078	2,050,177	2,282,901
Adjusted R^2	0.513	0.466	0.468	0.465	0.465	0.467	0.464

Appendix Table A5. Evidence on the Arbitrage Channel (Russell 3000 Sample) (Cont.)

Panel B: Intraday Variance Ratio

Dependent variable:	Intraday variance ratio (VR 15)						
	All	All	Misp > 0	Misp < 0	All	Misp > 0	Misp < 0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Abs(Mispricing) (t-1)	-0.000	-0.004*	0.009***	-0.009***	-0.002	0.005**	-0.005**
	(-0.018)	(-1.680)	(3.611)	(-3.787)	(-0.960)	(2.349)	(-2.264)
× I(High bid-ask spread)		0.018***	0.005	0.024***			
		(3.825)	(0.902)	(4.741)			
× I(High lending fee)					0.008***	0.012***	0.005
					(2.782)	(3.527)	(1.590)
High bid-ask spread		0.028***	0.027***	0.027***			
		(4.042)	(3.835)	(3.954)			
High lending fee					0.027***	0.028***	0.026***
					(7.773)	(7.722)	(7.385)
ETF ownership (t-1)	0.015***	0.013***	0.011***	0.012***	0.014***	0.011***	0.014***
	(4.920)	(4.331)	(3.560)	(3.904)	(4.733)	(3.565)	(4.653)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	No	No	No	No	No	No
Observations	4,282,464	4,282,464	2,028,151	2,254,313	4,282,464	2,028,151	2,254,313
Adjusted R^2	0.236	0.180	0.182	0.178	0.180	0.183	0.178