# The Impact of Active Managers on the Pricing of Underlying Assets in ETFs

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**Abstract**

We investigate the impact of active managers on the information efficiency of the underlying assets in passive ETF portfolios. Specifically, we explore how the increasing popularity of ETFs prompts active mutual fund managers to execute informed trades that generate alpha. Using trade-level data, we test whether trades by skilled active managers more accurately predict future abnormal stock returns as ETF ownership in these stocks rises. By leveraging the annual reclassification of stocks from the Russell 1000 to the Russell 2000 as an exogenous variation, we find that high-performing mutual funds can mitigate the pricing inefficiency typically associated with ETFs.

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## I. Introduction

The U.S. Exchange Traded Funds ("ETF") market at the end of first quarter 2024 had \$8.8 trillion in assets under management with \$4.7 trillion in U.S. equity.[1] During 2023, ETFs accounted for roughly 30% of daily trading in U.S. common stocks. The growth of ETFs over the past 20 years is easily documented and, according to Morningstar, the number of active funds converting to ETFs has been increasing. The uniqueness of ETFs lies in their design: unlike other index-based composites such as index mutual funds, ETFs use the Authorized Participant (AP) market structure to provide intraday liquidity and real-time pricing. While this mechanism reduces trading costs and facilitates easier short selling, the effect of ETF ownership on the pricing efficiency of securities held by the ETF is controversial.

The Investment Company Institute ("ICI") argues that ETFs have a minimal effect on the pricing efficiencies of underlying securities. The 2023 ICI Factbook states (p.56) "Most ETF secondary market trades represent investors exchanging shares of ETFs among themselves. Unlike primary market activity, these trades do not affect the ETF's underlying securities." Supporting this view, theoretical models developed by Cong and Xu (2016) show that ETFs make factor investing more convenient by attracting more liquidity traders to trading ETFs instead of underlying securities, leading to higher information efficiency in the underlying assets. Glosten et al. (2021) empirically find that ETF ownership is correlated with a short-term factor information increase in the underlying assets. In contrast, Israeli et al. (2017) find that increased ETF ownership drives lower firm-specific information for the underlying securities due to the ETF arbitrage mechanism. Shim (2022) theorizes that this arbitrage mechanism mistranslates factor information to constituent securities in the ETFs. Empirically, Ben-David et al. (2018) find that the popularity of ETFs induces more non-fundamental trading of the underlying stocks by attracting "a new breed of short-horizon investors" with liquidity demand that increases the volatility of the securities in the ETF. Grigoris et al. (2024) model the volatility of ETFs as disagreement about factors

[1]Data Source: Morningstar direct, April 2024

and find evidence consistent with their model. Holden and Nam (2024) argue theoretically and empirically that ETFs drain liquidity from liquid securities and add liquidity to illiquid securities.

In this paper, we examine the empirical asset pricing implication of ETFs on their underlying assets. If ETF ownership improves the pricing efficiencies of the underlying assets, then after ETF ownership in a stock increases, fewer informed traders will be incentivized to trade the underlying assets, which potentially explains why ETFs are replacing the market shares of stock pickers such as active mutual fund managers. On the contrary, if ETF ownership causes underlying securities to be inefficiently priced, does the market respond? The literature has not yet examined the trades of potentially informed investors. This paper directly addresses the question by empirically analyzing the trading behavior of active mutual fund managers. If ETFs diminish information efficiency in these stocks, then informed traders should be poised to capitalize on the opportunities created by ETF ownership.

Mutual funds are not normally thought of as arbitrageurs, either in the industry or by financial economists. However, Ingersoll (1987) observes that any two sets of portfolio weights are linked by an arbitrage portfolio if assets under management do not change. When mutual funds respond to an unanticipated shock that does not affect their total assets under management but requires their weights to change, the purchases of assets are financed by the selling of the assets. The vector of portfolio weight changes is an arbitrage portfolio where the weights sum to zero. The unanticipated shock we use is the yearly reclassification of stocks in the Russell 1000 and Russell 2000. Several papers (Chang et al., 2015; Appel et al., 2016) show that a significantly larger amount of passive money tracks the top Russell 2000 stocks than the bottom Russell 1000 stocks. Moreover, more ETFs follow the Russell 2000 than the Russell 1000. We specifically examine mutual funds, trades of stocks that are reclassified from the Russell 1000 to Russell 2000 (or the reverse).

It is worth noting that it is plausible, even likely, that hedge funds and institutional funds also engage in ETF arbitrage; however, data do not exist on their portfolios. Form

13F data are not useful for this purpose since they are aggregated at the family level over positions that typically reflect the decisions of many portfolio managers, including short selling. The arbitrage portfolios are unlikely to be revealed by these filings. To test the impact of ETFs on pricing of underlying assets, we examine active mutual funds because of the availability of quarterly data on portfolio weights of individual funds.

Active mutual funds face hurdles to arbitrage trades. Some active asset managers argue that ETFs make their jobs more difficult. For example, a 2017 report by Bank of America argued that ETFs distort the market by increasing the volatility and trading costs of underlying stocks in the ETFs.[2] The BOA report argues that the popularity of ETFs increases the arbitrage costs of active managers by draining the liquidity in the underlying stocks, and/or by introducing excessive volatility and co-movements into the underlying stocks. Ben-David et al. (2018) use data from 2000 through 2007 and find that ETFs create volatility and that this volatility is a barrier to arbitrage. However, no study has directly addressed this question by looking at how active managers respond to exogenous changes in ETF ownership. This paper fills this void by examining the trades of active mutual funds over the period 2012 through 2020, which is the period of the fastest growth of ETFs.

Our baseline analysis examines the changes in passive ETF ownership resulting from the Russell reclassification on mutual funds' trades. We use the Appel et al. (2024) instrumental variable (IV) approach to control for endogenous variables. Our tests show that when ETF ownership increases, the trades of active mutual funds (measured by both mutual fund holding change between quarters and the trade-level data from Ancerno) better predict the four-factor excess returns of the traded stocks in the next quarter. Specifically, if ETF ownership due to index reassignment increases by one standard deviation, then the trades of active mutual fund managers perform 6% better over the quarter following the trade. This finding indicates that when the fraction of a stock's capitalization held by passive ETFs increases, active mutual fund managers can better predict the future excess return of the

[2] https://www.fnlondon.com/articles/bank-of-america-says-etfs-rise-is-distorting-the-stock-market-20170706

stock and trade on it.

Mutual funds whose trades are motivated by the mispricing may also bring more information to bear. It should not surprise anyone that a mispricing from one source generates analysis by the mutual fund to identify other sources of mispricing. First, to disentangle the information brought by mutual funds from the trading that is related to daily ETF price deviation from NAV, we construct a measure at the stock level that accounts for part of the daily flow-induced mispricing (see Agarwal et al., 2018). Our baseline results don't change, ETFs interacted with the trades of mutual fund managers positively predict the future stock alpha. Additionally, the mutual fund trades within the quarter reduces the differences between NAV and ETF price. The second step, we show that when passive ETF ownership of stocks increases, only the trades of skilled managers become more predictive of the stocks' future performance, while the trades of unskilled managers do not. Then we show that the improved predictability of the active managers' trades is more than would be expected by ETF-induced risk premiums suggested by previous literature. These studies argue that ETFs introduce volatility to the underlying securities and investors demand a risk premium for the stocks held by ETFs. However, these studies find that this effect usually reverts over the next 40 days. In contrast, we show that increases in ETF ownership predict the excess return of a stock three months after the trades. This is consistent with active managers collecting information and performing more informed trades after passive ETF ownership goes up. Using a separate database, Ancerno, we confirm these findings to the extent Ancerno allows it at the trade level.

Next, we examine the elements that could limit active managers' ability to earn an excess return. Our analysis looks at the effect of volatility and two liquidity measures on the impact of manager trades. We find that FHT and volatility reduce the future alpha of the stock, but the trades of the mutual fund when ETF ownership increases still predicts the alpha of the stocks. The limits of arbitrage do not prevent active mutual funds from earning the alpha from this effect.

Finally, we determine whether the actions of active managers change the pricing efficiency of the stocks they trade. Using three measures of pricing inefficiency, that is, the absolute variance ratio, the BGZ Rho measure (Bris et al., 2007) and the HM measure (Hou and Moskowitz, 2005). Our results confirm that the deteriorated pricing efficiency in stocks when ETF a increases is ameliorated by the trades of managers. This is true with the first two efficiency measures, with no results at the HM measure. In contrast, the pricing efficiencies of those stocks not traded by active managers deteriorate when ETF ownership increases. This is a common finding in the finance literature when passive ownership increases.(Höfler et al., 2023) We replicate the Ben-David et al. (2018) test, who sort ETF ownership and allocate stocks to different portfolios, and we find no excess alpha associated with ETF ownership.

These findings provide evidence consistent with the hypothesis that active managers are more actively collecting information about stocks with higher passive ETF ownership and at least partially correct the mispricing generated by such ownership. This complements the evidence of Sammon and Shim (2023) who find that active mutual fund trades predict future alpha.

This study relates to several strands of the literature. First, this paper directly addresses the question of whether ETF causes mispricing. We confirm the finding of Ben-David et al. (2018) and we examine whether mutual funds respond to the inefficiencies created by ETF ownership. We find that mutual fund trades partly offset the ETF mispricing and motivate more informed trades. Our findings directly address the ongoing debate in the literature and among policy makers regarding how ETFs affect the pricing efficiency of underlying securities.

Secondly this paper contributes to the literature on mutual fund performance measurement. While this literature is over fifty years old, recent papers have focused on the impact of mutual fund trades. Pástor et al. (2017) brought trading to the forefront of mutual fund performance and many papers have followed. Recently Sammon and Shim (2023) show that the separation of trades into passive trades, caused by flow into and out of a fund, and active trades is informative. They demonstrate that the active component of trades predict the future alpha of the stock. Our paper complements this evidence by considering trades in response to ETF holding which is a previously unrecognized dimension of manager skill. Our findings suggest an important role for active managers in financial equilibrium.

## II. Hypotheses

### *A. Does ETF Ownership Enhance or Diminish Price Efficiency?*

The primary question this paper addresses is whether ETF ownership of a stock leads to inefficiencies. Ben-David et al. (2018) argue that the lower cost of trading ETFs enables increased liquidity trading. The flow-induced pricing pressure from new liquidity trading influences the prices of the underlying securities through the mechanism of the authorized participant, leading to higher volatility and security mispricing. The channel is that a liquidity shock to the ETF is transmitted to the underlying portfolio. The key prediction of this theory is that the change in prices is temporary since fundamental information did not change. Note that this theory requires that the ETF draws new liquidity traders into the market rather than just shifting liquidity traders from the underlying securities to the ETF. If the ETF merely shifts traders, there should be no effect on the prices of the securities in the portfolio.

The mispricing may not be as short term as Ben-David et al. (2018) find. Israeli et al. (2017) show that ETFs result in higher trading costs (bid-ask spreads and market liquidity), an increase in stock return synchronicity, a decline in future earnings response coefficients, and a decline in the number of analysts covering the firm. The combination of these factors probably results in less informative security prices for the underlying firms over a longer period than the literature has found from pricing pressure. However, short term or not, if the ETF ownership creates mispricing, we hypothesize that active funds will exploit this opportunity by trading. Moreover, in addition to simply correcting mispricing caused by

ETF volatility, we hypothesize that ETFs create an opportunity to focus limited resources on the fundamental values of the securities. The higher the ETF ownership, the more that active funds add fundamental information to the pricing of the securities.

The competing theory is that fundamental information has changed the value of the underlying securities, and the ETF is a less expensive channel for incorporating information into their prices. This results in a positive relationship between ETF ownership and volatility, but increased volatility results from a faster impounding of information into the prices of securities in the portfolio. We label this the "information" hypothesis. A more substantive theory of the information hypothesis is offered by Grigoris et al. (2024), who develop a theory where factor disagreement drives investors to take correlated bets on the systematic component of returns. This will result in an impact on ETFs that follows the volatility of the factors. For either information theory, the impact of volatility is permanent and, importantly for our paper, ETF ownership does not create an opportunity for active funds.

We adopt the following equation to test between these hypotheses: we use an active mutual fund manager $i$'s trades of stock $j$ in quarter $t$ to predict the stock $j$'s excess return in quarter $t+1$[3], and test the passive ETF ownership's effect on this predictability. The passive ETF ownership of stock $j$ in quarter $t$ is the estimated passive ETF ownership from the first stage with Russell 2000 as an instrumental variable under the Russell 2000/1000. Control variables include the index (non-ETF) ownership of stock $j$ in quarter $t$, other stock characteristics variables, fund characteristics variables, and fund fixed effects. The standard errors are clustered at the fund $*$ year level.

[3]Stock $j$'s excess return in quarter $t+1$ is estimated in the following way: we start by estimating the monthly excess return in each month of quarter $t+1$, and then the three monthly excess returns are accumulated at the quarterly level. For each monthly excess return, we use the 12 months before the current month as the estimation period for betas. This is to account for the possible shifting beta due to ETF ownership and other reasons.

$$
\begin{aligned}
StockAlpha_{j,t+1} = {} & \beta_1 Trade_{i,j,t} * ETF\_\widehat{Ownership}_{j,t} + \beta_2 Trade_{i,j,t} + \beta_3 ETF\_Ow\hat{n}ership_{j,t} \\
& + \sum_{n=1}^{N=3} \theta_n [ln(MktCap)]^n + \beta_4 ln(Float_{j,t}) + \beta_5 band_{j,t} + \beta_6 R2000_{j,t-1} \\
& + \beta_7 (band_{j,t} * R2000_{j,t-1}) + \beta_8 ETFM_{j,t} + \beta_9 StockChar_{j,t} \\
& + \beta_{10} FundChar_{i,t} + FE + \epsilon_t
\end{aligned} \tag{1}
$$

### ***B. Two Channels***

To review, there are two possible channels that can drive up the performance of active managers' trades after the ETF ownership of the traded stocks increases: the *information* channel and the *flow-induced* channel. The flow-induced channel is described above, where stocks with higher ETF ownership display higher volatility, all else being equal; this creates mispricing. We hypothesize that the flow-induced channel creates profitable opportunities for active managers. We define the information channel, by contrast, as the action of active funds that use the ETF holding as an opportunity to add information to the price.

If active managers are adding research to stocks affected by ETF price pressure, then the more skilled an active manager, the better the predictability of the trade. Skilled managers should be better at collecting information and executing informed trades than their peers. This contrasts to the flow-induced theory, which posits that the mispricing is temporary. If the mispricing is temporary, then the predictability should be the same across all active managers, regardless of their skills. Thus, we separate the managers into three subsamples based on their recent fund performance[4] as proxy for their current skills. Then we examine equation (1) for active managers in low-skill, mid-performance, and high-performance subsamples.

[4]We use the fund's gross returns to estimate the fund's current four-factor excess return as a measure of performance.

In our second analysis to determine whether the ETF is causing price-pressure temporary mispricing or inducing funds to add information to the trades, we examine whether the excess returns earned revert after a short period. Specifically, Ben-David et al. (2018) find that ETF flows induce a short-term risk premium for the underlying securities. A long-short strategy based on ETF ownership earns a monthly excess return of 38 basis points. However, this effect reverts after 40 days. If we find that active managers earn a risk-adjusted performance for longer periods, this is evidence that active managers are adding information to the mispricing caused by liquidity traders. Given that we monitor changes in mutual fund holdings quarterly, we examine whether the predictability of active managers' trades persists or reverts in the subsequent quarter.

We examine equation (1) results month by month as shown in equation (2) to test this hypothesis. Specifically, the $StockAlpha_{j,m_k\_in\_t+1}$ in $t+1$ is the excess return of stock $j$ in the $k$th month of quarter $t+1$, where $k = 1, 2, 3$. If the results indicate that the predictability of active managers' trade persists, then this is evidence that the price pressure induces funds to add information.

$$\begin{aligned}StockAlpha_{j,m_k\_in\_t+1} = {} & \beta_1 Trade_{i,j,t} * ETF\_\widehat{Ownership}_{j,t} + \beta_2 Trade_{i,j,t} + \beta_3 ETF\_Ow\hat{n}ership_{j,t} \\ & + \sum_{n=1}^{N=3} \theta_n [ln(MktCap)]^n + \beta_4 ln(Float_{j,t}) + \beta_5 band_{j,t} + \beta_6 R2000_{j,t-1} \\ & + \beta_7 (band_{j,t} * R2000_{j,t-1}) + \beta_8 ETFM_{j,t} + \beta_9 StockChar_{j,t} \\ & + \beta_{10} FundChar_{i,t} + FE + \epsilon_t \end{aligned} \tag{2}$$

To account for the potential intra-quarter trading of mutual funds on these stocks, aimed at arbitraging short-term price deviations between the ETF basket NAV and stock prices, we construct a stock-quarter-level ETF mispricing measure following Agarwal et al. (2018). This measure captures the deviation between ETF prices and their underlying basket prices.

Specifically, the mispricing measure is computed as the sum of the daily differences between the ETF's end-of-day price and its end-of-day NAV (representing the ETF's discount or premium), aggregated over each quarter. Finally, we calculate a stock-level mispricing value by averaging this measure across ETFs, weighted by their ownership in the stock, to define the variable ETFM.

For each stock j in quarter t and portfolio k over days d:

$$ETFM_{j,t} = \sum_{k=1}^{K} \left[ \frac{1}{D} \sum_{d=1}^{D} (w_{j,k,d} * ETFDiscount\_or\_Premium_{k,d}) \right]$$

We are among the first studies in this literature to disentangle the effect of intra-quarter stock mispricing from the information channel. By controlling for ETFM at the stock level, if the results remain robust, it provides strong evidence that mutual fund trades perform better after an increase in ETF ownership because active managers capitalize on informational advantages rather than exploiting short-term price discrepancies between ETF NAV and market values.

### *C. Limits to Arbitrage*

The predictability of the flow-induced channel is dependent on the mutual funds overcoming the limits to arbitrage. Israeli et al. (2017) identify two limits created by ETF holdings: the liquidity of the stocks traded and the costs of information. Other studies have argued that volatility is also a barrier. According to Shleifer and Vishny (1997), high volatility makes mispricing opportunities less attractive for active managers, especially when fundamental risk is a substantial part of volatility. Gagnon and Karolyi (2010) show that price deviation between American Depositary Receipts (ADRs) and their respective home market share price is positively related to idiosyncratic volatility. When the volatility or/and trading costs of a stock are high, active managers might not find it profitable to trade on the inefficiencies. As a result, the trades of active managers who are forced to buy or sell securities because of the reclassification could incur higher transaction costs, resulting in worse future performance due to the increase in passive ETF ownership of the underlying stocks. Ben-David et al. (2018) show that ETF ownership increases the volatility of underlying securities in the ETFs. If the volatility, liquidity, or transaction costs are barriers to arbitrage, they will reduce or eliminate the impact of the trades of active managers.

To test the effect of liquidity and trading costs on the trades of active managers, we apply an interaction term of the trade with predicted ETF ownership and the Amihud ratio of the stock, for liquidity, and an interaction term with the Fong, Holden, and Trzcinka (FHT) measure, for trading cost (see Fong et al., 2017).

$$\begin{aligned} StockAlpha_{j,t+1} = {} & \beta_1 Trade_{i,j,t} * ETF\_Ow\hat{n}ership_{j,t} * Amihud_{j,t}(orFHT_{j,t}) \\ & + \beta_2 Trade_{i,j,t} * ETF\_Ow\hat{n}ership_{j,t} + \beta_3 Trade_{i,j,t} + \beta_4 ETF\_Ow\hat{n}ership_{j,t} \\ & + \beta_5 Amihud_{j,t}(orFHT_{j,t}) + \sum_{n=1}^{N=3} \theta_n [ln(MktCap)]^n + \beta_6 ln(Float_{j,t}) + \beta_7 band_{j,t} \\ & + \beta_8 R2000_{j,t-1} + \beta_9 (band_{j,t} * R2000_{j,t-1}) + \beta_{10} Char_{j,t} + FE + \epsilon_t \end{aligned} \tag{3}$$

where $\beta_1$ identifies how the liquidity of stock $j$ in quarter $t$ affects the trades of active managers, and whether those limits of arbitrage weaken the predictability of mutual fund trades.

To test the effect of volatility on the arbitraging of active managers, we apply an interaction term among the trade, predicted ETF ownership, and volatility of the stock returns in quarter $t$,

$$
\begin{aligned}
StockAlpha_{j,t+1} = {} & \beta_1 Trade_{i,j,t} * ETF\_Ow\hat{n}ership_{j,t} * Volatility_{j,t} \\
& + \beta_2 Trade_{i,j,t} * ETF\_Ow\hat{n}ership_{j,t} + \beta_3 Trade_{i,j,t} + \beta_4 ETF\_Ow\hat{n}ership_{j,t} \\
& + \beta_5 Volatility_{j,t} + \sum_{n=1}^{N=3} \theta_n [ln(MktCap)]^n + \beta_6 ln(Float_{j,t}) + \beta_7 band_{j,t} \\
& + \beta_8 R2000_{j,t-1} + \beta_9 (band_{j,t} * R2000_{j,t-1}) + \beta_{10} Char_{j,t} + FE + \epsilon_t
\end{aligned} \tag{4}
$$

where $\beta_1$ identifies how the volatility of stock $j$ in quarter $t$ affects the trades of active managers, and whether those limits of arbitrage weaken the predictability of mutual fund trades.

The limitation of this test is that the trades of stocks by active managers are not exogenous. The characteristics of the stocks traded by active managers can be very different from the characteristics of those not traded by active managers. However, it's difficult to capture the effect of ETFs on pricing efficiencies while active managers are trading on those stocks. Our test can provide suggestive evidence on the effect of the trades of active managers on stock pricing efficiencies after the increase in ETF ownership.

## III. Data and Empirical Design

### *A. Data*

We use data from the Center for Research in Security Prices (CRSP) and ETF Global to identify passive ETFs traded on major U.S. stock exchanges. [5] ETF Global data are primarily sourced directly from fund sponsors, custodians, distributors, and administrators, which provide historical data on ETF assets, constituents, and other characteristics. We first extract all the passive domestic equity ETFs from the ETF Global data with constituents

[5]ETF Global is an independent provider of Exchange-Traded-Fund Reference Data and Quantitative Research to the Investment, Academic and Governmental sectors worldwide.

information. Next, we screen all the constituent stocks that are traded on the major U.S. exchanges with CRSP information and merge this sample with CRSP stock information. The ETF Global dataset with constituent data starts from 2012[6]. This paper's sample period is from 2012 through 2020.

Our primary mutual fund trade-level data is from the mutual fund holdings data in the Thomson-Reuters Mutual Fund Ownership database. The final dataset contains around 4,500 domestic active equity mutual funds between January 2012 and December 2020. Mutual fund characteristics information is collected from the CRSP. A secondary source of trades is Ancerno, which provided data over the period 2012 through 2015. We observe daily level data on the trades of mutual funds. The Ancerno data have two limitations that make them secondary; Ancerno stopped releasing the data in 2015, and the traders are anonymized. Our hypothesis requires us to be able to observe characteristics of the mutual funds who are trading. Nevertheless, the Ancerno data is an important robustness check on our results since Ancerno reports the shares traded, the price the trades received, and the day of the trade. [7] The trades of active managers are computed with the net change of shares of stock $j$ held by manager $i$ between quarters $t$ and $t-1$. As a dependent variable in the main tests, the stocks' excess return is calculated with Carhart four-factor model with a 12-month rolling window.

For the main test, we use the Russell Index reassignment experiment. Specifically, we use the FTSE Russell Equity Data, which offers annual information on Russell Index constituents and weights. Other stock characteristics variables needed for the test are calculated from CRSP data. [8]

Table I reports the summary statistics.

[6]ETF Global LLC was founded in 2012.

[7]Ancerno also reports a time stamp, but this is not the exact time of the trade; it is the time the report was submitted to Ancerno. We call this daily data even though the trades take place at a higher frequency.

[8]Appel et al. (2019) show that using CRSP market cap doesn't affect the outcome of the experiment.

### B. Russell 1000/2000 Reassignment

The Russell 1000 consists of the 1000 largest U.S. stocks in terms of market capitalization in the Russell 3000 index, while the Russell 2000 index includes the remaining 2000 stocks, which are smaller in size. To adjust for the changes in stocks' market capitalization, the Russell 1000 and Russell 2000 indexes are reconstituted each year at the last trading day of June, with a proprietary measure of stocks, non-floating market capitalization applied by Russell as of the last trading day in May of that year. After the index reassignment, the stocks' portfolio weights in the indexes are calculated using June float-adjusted market capitalization.

After June of 2007, Russell adjusted its methodology and adapted a "banding policy" that requires stocks previously in the Russell 2000 to be moved to the Russell 1000 index during the annual reconstitution if their end-of-May Russell market capitalization ranking increased significantly over the past year. Specifically, three factors are used to determine a stock's reassignment: (1) the stock's market cap at the end of May of every year, (2) the stock's index assignment in the previous year, and (3) whether the stock's end-of-May market capitalization falls within a range of the cutoff market cap of Russell 1000 and Russell 2000.

This paper applies the method proposed by Appel et al. (2024), which accounts for the banding policy by controlling for whether the stock is within the banding policy's range for not moving, whether the stock was in the Russell 2000 in the past year, and an interaction term of the two. The stocks that move into the Russell 2000 have the largest market capitalization in the index, which means that mutual funds that follow the index will need to trade them. In contrast, the stocks who move into the Russell 1000 are usually the smallest in market capitalization and the mutual funds that follow the Russell 1000 typically will ignore them.

Generally, Russell releases the "menu" of stocks that will be assigned to the Russell 1000 and Russell 2000 indices by the end of May each year. Then, by the end of June, Russell announces the weights of these stocks in the index. Hence, we analyze the trades of mutual fund managers afterward using mutual fund holdings data and Ancerno trade-level data. Specifically, we compare mutual fund holdings between the end of June and the end of September to infer the trades[9], or we directly analyze trades recorded in Ancerno between June and September. Next, we assess whether these active managers' trades in the third quarter of the year better predict stock alpha in the fourth quarter, after adjusting for ETF ownership by the end of June each year. A timeline is illustrated in Figure 1.

## IV. Passive ETF Ownership and the Trades of Active Managers

### *A. Manager Trades on Stocks Switching to Russell 1000 and 2000*

We start by looking at the daily trades of mutual funds on stocks with a recent change in ETF ownership. Specifically, we look at their trades on stocks that were reassigned from the Russell 1000 to Russell 2000, or from the Russell 2000 to Russell 1000. Chang et al. (2015), Appel et al. (2016) show that a significantly larger amount of passive money tracks the top Russell 2000 stocks than the bottom Russell 1000 stocks, due to the weighting scheme of the Russell indices. Moreover, more ETFs follow the Russell 2000 than the Russell 1000. Stocks that switched to the Russell 2000 from the bottom of the Russell 1000 will likely experience an increase in ETF ownership due to the reassignment rule, while those from the Russell 2000 to Russell 1000 will likely experience a decrease in ETF ownership.

As shown in Table II, we find that the trades of mutual funds become more informative for those who were reassigned to the top of the Russell 2000, and less informative for those were reassigned to the Russell 1000. A long-short strategy of replicating the trades of mutual funds on switchers to the Russell 2000 will generate a net alpha of 130 basis points per quarter, while the same strategy of replicating trades of funds on switchers to the Russell 1000 will generate a net alpha of -64 basis points. These results are consistent with the idea that mutual fund trades become more informative when ETF ownership in a stock rises.

[9]For mutual funds that report holdings by the end of July, we examine their holding changes between July and October and their predictability between November and the following January. Similarly, if a mutual fund reports by the end of August, we examine their holding changes between August and November.

Data on daily mutual fund trades are from Ancerno (2012-2015). As mentioned previously, while the Ancerno data show the actual trades, the identity of the trader is anonymized, and we cannot identify which mutual funds are trading. Moreover, Ancerno represents only about 10% of the volume on any given day. While the data support our hypothesis that trading is based on ETF ownership, we turn to the changes in holdings to build more powerful tests using actual ETF ownership and mutual fund characteristics.

### B. OLS Regressions

To assess whether ETF ownership generates price inefficiencies, we test whether active fund managers can generate better performance from trading stocks with higher ETF ownership. ETF ownership of stock $j$ in quarter $t$ is defined as the sum of the dollar value of holdings by all ETFs holding the stock, divided by the stock's capitalization at the end of the quarter:

$$ETFOwnership_{j,t} = \frac{\sum_{k=1}^{K} HoldingValue_{k,j,t}}{MktCap_{j,t}},$$

where $K$ is the set of ETFs that hold stock $j$; $w_{k,j,t}$ is the value of the holdings of stock $j$ by ETF $k$ at the end of quarter $t$. The trades of mutual funds in this regression are defined by the change in quarterly holdings reported by mutual funds:

$$Trade_{i,j,t} = \frac{Shares_{i,j,t} - Shares_{i,j,t-1} * (1 + Flow_{i,t-1})}{Shares_{i,j,t-1} * (1 + Flow_{i,t-1})},$$

where $Shares_{i,j,t}$ represents the number of shares in stock $j$ held by fund $i$ at the end of quarter $t$, and $Flow_{i,t-1}$ represents the net flows to fund $i$ in quarter $t$.

The profits of an active manager's trades are measured by how well the trade of a stock predicts the stock's four-factor excess return in the next quarter. The effect of passive ETF ownership on the profit of active managers' trades is measured with the interaction term of the trade and total passive ETF ownership in the stock. ETF ownership can be correlated with other passive ownership, as they very often track similar indices; hence we control for other index ownership in the same period. To further account for possible omitted variables, we follow three approaches. First, we control for stock size and liquidity, which is measured by the inverse of the stock price, the Amihud (2002) illiquidity measure of price impact. Second, we include other factors that can affect the predictability of mutual fund manager trades, such as fund characteristics. Finally, we cluster standard errors at fund and year level.

We start by reporting the results of OLS regressions of how ETF ownership affects the predictability of mutual fund trades. Mispricing caused by ETFs comes mainly from two sources: the possible flow-induced pricing pressure, i.e., the flow-induced channel, and the information channel. According to our hypotheses, active managers' trades of a stock should better predict the stock's future risk-adjusted performance when the passive ETF ownership of the stock increases.

Table III is consistent with this intuition. Controlling for the characteristics of the fund and the stock, and ETF-induced stock mispricing due to discount premium within the quarter, a one-standard-deviation increase in the passive ETF ownership of stock $j$ increases the performance of the trades by active managers by roughly 10 basis points. These active trades anticipate the future alpha of the stock at least one quarter after the stock is added to the ETF. If the September holding was the result of a trade before September, then the active trade predicts the future alpha of the stock longer than a quarter.

Table III rejects the hypothesis that ETFs allow faster changes in fundamental values. If ETFs, as correlated composite assets with lower transaction costs, lead to higher price variability because of faster changes in fundamental information, there should be no opportunities for mutual fund trades to predict future alpha. The ETF would have caused the fundamentals to change as soon as the stock was added to the ETF.

Table III is also inconsistent with the claim by those who argue that the popularity of ETFs weakens the ability of active managers to generate alpha for their clients. The ETFs add to the predictability of the mutual fund trade.

In columns (2) and (3) of Table III, we analyze the results for the subsample of stocks that recently were reassigned to Russell 2000 (1000), and we find that the improvement in the predictability of mutual fund trades is mainly driven by the trades of managers on the stocks that were recently reassigned to the top of Russell 2000, with higher ETF ownership. This finding is evidence that ETF ownership generates price inefficiency, given the fact that Russell 2000 membership generates more ETF ownership than the Russell 1000.

It is worth noting that the interaction between the trade and index ownership has the opposite sign of the interaction between the trade and the ETF ownership. This is remarkable given the high correlation between ETF ownership and index ownership. It is stronger evidence that ETFs, and not just passive ownership, are causing mispricing. The trades of stocks held by index funds generate a negative alpha roughly equivalent to the transaction costs of making the trade.

However, the OLS regressions can be problematic if the controls and fixed effects fail to capture characteristics that determine ETF ownership and the predictability of active managers' trades at the same time. As a result, we next examine the models under a more robust instrumental variables (IV) identification.

### *C. Identification with a Quasi-Natural Experiment*

Following the method of Chang et al. (2015) and the improvement of Appel et al. (2024), who implement their tests with an IV framework, we test our models with the quasi-natural experiment of Russell 1000/2000 re-assignment.

We thus carry out the two-stage least squares estimation as in Table IV with Russell 2000 as the instrumental variable for passive ETF ownership. The controls include factors that affect the assignment of stocks, stock characteristics variables, and mutual fund characteristics variables. Fund fixed effects are included in the regression, and standard errors are double- clustered at fund by year levels. We standardize the passive ownership variables. The models are run with different specifications of the ranking variable: first-, second-, and third-degree polynomials.

The models are run at the quarterly frequency because trades of mutual funds are only observed on a quarterly basis. The data sample is from 2012 through 2020, and the trades happen during the first quarter after the index reassignment.

Table IV presents the results of the IV estimations. The effect of passive ETF ownership on the trades of active managers is positive and significant across all the polynomial orders. The larger the passive ETF ownership in stock $j$ is, the better the trades of active managers executed on stock $j$ predict the future excess return of the stock in the next quarter, $t+1$. The coefficient indicates that for a one-standard-deviation increase in passive ETF ownership, the trade can better predict the future excess return of a stock by 6% per quarter on average.[10]

The positive IV estimates from Table IV suggest that the endogeneity of ETF ownership with omitted variables induces a positive omitted variable bias in the OLS estimates in Table III. We model ETF ownership as equal to the predicted value from a first-stage regression ("IV") plus omitted variables. The OLS estimates with ETF ownership show a positive and significant relationship while the IV is negative and significant. This means that the omitted variables that explain ETF ownership not predicted by the first stage are positive enough to overcome the negative relationship with the IV. However, the interaction term does not change much, suggesting that while the omitted variables are strong enough to change the sign of ownership, they do *not change the impact of the mutual fund trades*. This shows the empirical power of the mutual fund trades, which are clearly predictive.

As in Table III, Table IV shows that the effect of interacting mutual fund trades with ETF ownership is not a passive fund effect, but an ETF effect. When we interact the trade with index ownership in the same regression, we get a negative and significant coefficient, again roughly equivalent to the transaction cost of making the trade. The trade has less predictability as index ownership increases but more predictability when ETF ownership increases (the IV increases). This is consistent with the hypothesis that the ETF liquidity

[10]In our internet appendix, we show that our results hold for different polyomial orders.

traders are creating the mispricing.

It is worth noting that ETFM is a negative coefficient in the regression, suggesting that mutual fund trades are more than just correcting for flow-induced ETF mispricing. In Appendix Table A2, we confirm that mutual fund trading during quarter t reduces the mispricing between the ETF NAV and the basket value. This finding suggests that mutual funds trade not only to exploit short-term mispricing driven by ETF flows, but also but also through the information channel highlighted in this paper.

We next separate the buys and the sells. It is clear that the buys show stronger statistically significant predictive ability. It is the buying actions of mutual funds that are driving our results. Sell trades within the mutual funds are likely because these are larger stocks that move out of the Russell 2000 to the bottom of the Russell 1000.

### *D. Trade-Level Data*

Keep in mind that mutual fund holdings are only a proxy for trading, since they are reported on a quarterly basis. Many studies, such as Chakrabarty et al. (2017) and Puckett and Yan (2011) using the Ancerno database, have found that intra-quarter trading is profitable. As a result, we look at the trade-level data from Ancerno for the mutual funds from 2012 through 2015. The results of Table V are basically the same as Table IV, even though the data on the trades are from two completely unrelated sources. Table V shows that the daily trades of mutual funds positively predict the future alphas of the stocks for those stocks with an increase in instrumented ETF ownership. The trade of mutual funds in Ancerno of a stock held by an ETF (instrumented) has a positive and significant coefficient in predicting the future alpha of the stock.

To better focus the analysis, we divide our sample into three categories based on the number of trades of a stock on a given day. Our findings reveal that, although trades by managers on frequently traded stocks show good performance, trades by managers on stocks with low trading volumes yield the best performance. The results are consistent with managers exploiting information opportunity not just a proxy for investor interest.

The finding in Table IV that index ownership is negative is repeated in Table V. The coefficients of the interaction term of actual trading with index fund ownership is negative and significant in the "low number of trades" and "high number of trades" columns. It is not significant overall. This is again consistent with the hypothesis that ETF ownership creates opportunities but passive ownership does not.

Taken together, Tables IV and V provide strong evidence that mutual fund managers' trades predict future alpha when ETF ownership goes up. The tables show the same effect even though the data are from completely different sources. Specifically, after an increase in ETF ownership of a stock, mutual funds can achieve better performance, either because the stock's high demand allows managers to provide liquidity, or because the reduced number of traders leaves some information unincorporated into the stock's price. Fund managers can then trade on this information and profit. This supports the idea that some managers exploit an informational advantage when ETF ownership increases.

## V. Information Channel vs Flow-induced Channel

The finding that the trades of active managers perform better after the ETF ownership may be due to increased risk premium. Shim (2022) and Ben-David et al. (2018) find that there is a risk premium from holding stocks that are in ETFs due to the arbitrage mechanism of ETFs. Active managers could be buying the underlying stocks in ETFs and earn a positive risk premium due to ETF flows.

Specifically, Ben-David et al. (2018) find that an increase in ETF ownership drives up the stock return temporarily and the return reverts in 40 days on average. A long-short strategy based on ETF ownership that rebalances every month earns a monthly four-factor excess return of 36 basis points. As a result, the trades of the active managers might perform better due to the fact that higher passive ETF ownership generates risk premiums. Meanwhile, active managers are buying the stocks in the index because they predict the

ETF flows, or to follow a benchmark, or simply being closet-indexers. However, if that is the case, the predictability of the trades of active managers due to the increased ETF ownership should disappear or even reverse after a short time.

We examine the information content of the trades two ways. First, we consider the skill of the mutual fund manager. Based on the last year's active fund performance, measured by the fund's gross four-factor alphas[11], we sort the active managers into three subsamples. If the effects we find from Table IV are driven by increased informed trading of active managers after passive ownership goes up, then the more skilled a manager is, where skill is measured by alpha, the more improvement we will find in her trades.

Table VI column (3) shows that the mutual fund trade by the top performers better predicts the future excess return of a stock by a statistically significant 5.6% per quarter, for a one-standard-deviation increase in the passive ETF ownership. For the bottom performers, their predictability of future performance is negatively affected by ETF ownership, which indicates that the bottom performers are not taking advantage of the inefficiencies that come with ETF ownership. This evidence is consistent with the hypothesis that the improved predictability of the trades by active managers is driven by increased informed trading of the skilled managers. If all mutual trades were simply to take advantage of the flow-induced channel, then they all would be significant, but we find that the only statistically significant interaction coefficient is for the high-performing mutual funds.

It is worth noting that the expense ratio of the low performers is negatively related to the future alpha of the stock while positively related for the mid performers. This is consistent with the Berk and Green (2004) predictions. The bottom third of performers will reward managers who do well with higher expenses. These managers get higher alphas. But there are limits. Berk and Green (2004) hypothesizes that managers charge fees equal to their value added is consistent with what we find here. The mid-performing funds likely have good managers who are highly compensated; but they can clearly be overpaid and expenses

[11]In Appendix Table 3, we use last year's active fund DGTW adjusted performance, and the results remain the same.

can be too high.

We examine the predictability of the mutual fund trades month by month in the quarter after the trade, $t+1$. As shown in Table VII, the trades of active managers after the passive ETF ownership remain strong until month 3 of quarter $t+1$. This provides evidence that the predictability of the trades by active managers after the passive ETF ownership goes up is not driven by the liquidity mispricing risk premium, but instead by information developed by the active managers. Otherwise, the risk premium found by previous studies should disappear after one or two months.

## VI. Limits of Arbitrage

In this section, we continue to test whether there are factors that curb the ability of active managers to take advantage of the opportunities driven by increased passive ETF ownership.

Table VIII tests whether the liquidity, transactions cost, or volatility of a stock limits an active manager's ability to arbitrage on the inefficiencies. Using Amihud Ratio as a measure of liquidity (price impact), FHT as a measure trading cost, and the volatility of the stock, we test how limits to arbitrage affect the predictability of trades executed by active managers after ETF ownership goes up. In Panel B of Table IX we show a univariate test that the subsample of stocks that are traded by mutual funds have higher liquidity and lower volatility. This shows some evidence that mutual funds might have trouble exploiting information and making profits out of high ETF ownership stocks with low liquidity and high volatility. However, when we interact each of these variables with the ETF ownership estimated from the first stage and with the trades of active managers, we find that Amihud ratio doesn't impact the effect identified in Table IV, while volatility and FHT clearly has a negative effect.

As shown in Table VIII, the results suggest that the limits to arbitrage do not influence the effect of passive ETF ownership on the predictability of active managers' trades. The coefficient of ETF ownership does not change with any of the measures proxying for limits to arbitrage. As in Tables IV and V, the ETF ownership has a significantly different sign than index ownership. These results are not surprising given that Tables IV and V show the predictability of mutual fund trades. If the limits to arbitrage were effective, then the trades should have no predictive power.

The results in Table VIII shows some signs of limits to arbitrage for managers. This indicates that when liquidity is drained from the market or when the market is volatile, mutual fund managers might not be able to trade on the inefficiencies in the pricing of stocks with high ETF ownership. This is consistent with the argument of O'Hara and Ye (2011).

## VII. Does the trading of active skilled mutual fund managers eliminate mispricing?

To review, the results in Table IV and Table V are consistent with the argument that ETFs generate inefficiencies in the underlying stocks and that mutual fund trades capitalize on these inefficiencies. But do the trades eliminate the inefficiencies?

If the trades of active managers are information based, the inefficiencies introduced by passive ETF ownership should be at least partially arbitraged by the managers and the ETF-induced inefficiencies should be lower than those of similar stocks that are not traded by active managers. We apply three sets of pricing efficiency measures to examine the effect of mutual funds trades on the underlying stocks in ETFs. First, following Lo and MacKinlay (1988) and O'Hara and Ye (2011), we use the variance ratio and absolute value of the variance ratio as measures of pricing efficiency. The variance ratio is defined as below,

$$abs(VR_{i,t}) = |\frac{Var(r_{5,j,t})}{5Var(r_{1,j,t}) - 1}|$$

where $Var(r_{5,j,t}$ is the variance of 5-day returns of stock j in quarter t, and $Var(r_{1,j,t}Var(r_{1,j,t}$ is the variance of one-day returns of stock j in quarter t. If the prices follow a random walk, then the absolute variance ratio should be equal to zero.

Given that authorized participants engage in daily ETF arbitrage, we expect they will increase the autocorrelation of returns. If ETFs cause stock prices to deviate from a random walk, we expect ETF ownership to increase the abs(VAR). If trades offset the impact of ETF ownership, trades interacted with ETFs should have a negative coefficient with abs(VAR). The liquidity trading hypothesis makes an even stronger prediction about the effects of ETF ownership on VAR. If ETFs impound a mean-reverting process into price, this will make the returns negatively autocorrelated. The numerator of VAR will fall relative to the denominator. ETF ownership should have a negative effect on VAR, so ETF ownership interacted with mutual fund trades should have a positive effect on VAR.

Secondly, we use Bris et al. (2007) rho measure to account for the pricing efficiency in a cross-sectional framework. The rho measure is the cross-autocorrelations between market returns lagged 1 week and individual stock returns. For each quarter t stock j, we calculate $\rho^{+}_{j,t} = corr(r_{j,w}, r^{+}_{m,w-1})$ and $\rho^{-}_{j,t} = corr(r_{j,w}, r^{-}_{m,w-1})$ for all stocks using weekly returns within the quarter. The rho measure is then calculated as:

$$\rho^{Diff}_{j,t} = \rho^{-}_{j,t} - \rho^{+}_{j,t}$$

The larger this rho difference measure is, the larger the price delay is for stock j in quarter t.

Third, we use the price delay measure from Hou and Moskowitz (2005). We run a regression of each stock j's weekly returns on contemporaneous and four weeks of lagged returns on the market portfolio.

$$r_{j,t} = \alpha_{j,t} + \beta_j R_{m,t} + \sum_{n=1}^{4} \delta_j^{(-n)} R_{m,t-n} + \epsilon_{j,t}$$

where $r_{j,t}$ is the stock j's weekly returns and $R_{m,t}$ is the market return. Then the HM measure is calculated as

$$D1 = 1 - \frac{R^2_{\delta_j(-n)=0,\forall n\in[1,4]}}{R^2}$$

This measure is simply one minus the ratio of the $R^2$ from the regression restricting $\delta_j(-n) = 0, \forall n \in [1, 4]$ over the $R^2$ from the regression with no restrictions. The larger this number, the more return variation is captured by lagged returns, and hence the less efficient is the pricing.

With the three sets of pricing efficiency measures, we estimate the cross-sectional regression:

$$\begin{aligned} Y_{j,t+1} = {} & \beta_1 ETF\_Own\hat{e}rship_{j,t} + \sum_{n=1}^{N=3} \theta_n [ln(MktCap)]^n + \beta_2 ln(Float_{j,t}) + \beta_3 band_{j,t} \\ & + \beta_4 R2000_{j,t-1} + \beta_5 (band_{j,t} * R2000_{j,t-1}) + \beta_6 Char_{j,t} + FE + \epsilon_t \end{aligned} \tag{5}$$

where $Y = Abs\_Variance\_Ratio$ and $Variance\_Ratio$, $BGZ\rho$ or $HM$.

Table IX, Panel A shows the estimation of the above equation at the stock/quarter level. The interaction coefficients have the correct signs. The coefficients in the equation with abs(VAR) and BGZ $\rho$ are respectively statistically significant at the 10% level, while the coefficient with VAR is statistically significant at the 5% level. However, ETF ownership is not significant, which suggests that the mutual fund trade variable, together with the trades of other informed traders, may have eliminated its effect.

In all cases, the ETF ownership variable has a different sign than the index ownership, offering (marginal) evidence that ETF ownership is causing the mispricing. Taken as a whole, the evidence shows that mutual fund trades at least partially mitigate the mispricing caused by ETF ownership.

The fourth way to assess whether the trades of active funds result in more efficient pricing is to replicate the tests of Ben-David et al. (2018), who follow the standard approach in asset pricing to determine whether a characteristic correlates with a premium in returns.

We form monthly portfolios of available stocks based on the ETF ownership in the previous month. We allocate stocks to five quintiles and equally weight the portfolios, obtaining a time series of portfolio returns ranging from February 2012 through December 2020 (107 months).[12]

Table X shows the results. In Panel A, the raw excess (of the market) returns is significantly positive for each quintile at the 5% level except for the highest ownership, which is significantly positive at the 10% level. Interestingly, the highest ownership quintile also has the lowest average excess returns. The highest average return is for the portfolio with the lowest ETF ownership. In Panel B of our Table X, we use the Fama-French (2015) five-factor model to adjust the risk of the return on the highest quintile minus the lowest. The alpha is not significant regardless of how many factors we use. These findings suggest that active managers are exploiting the opportunities created by ETFs and causing the prices to be more efficient.

Table XI shows that the increased efficiency is likely a result of mutual fund trades. We examine the future alpha of all stocks as a function of whether the stock was traded by a mutual fund in the previous quarter. Table XI shows that ETFs have no predictive power for stocks traded by mutual funds. In contrast, for those *not* traded by mutual funds, ETF ownership predicts the future alpha. Of course, mutual funds are not the only arbitrageurs. Hedge funds, institutional funds, and no doubt some individual traders are fully capable of exploiting the opportunities created by ETFs. Trades from these entities are likely to be correlated with mutual fund trades, so nobody should conclude from Table XI that mutual funds alone eliminate the predictability of ETFs. But the evidence is clear that ETF ownership is associated with future alpha only when there are no active mutual fund trades. Table XI supports the view in the industry and among academics that if informed traders are limited in trading the high ETF ownership stocks, the underlying assets' pricing efficiency remains low.

[12]Ben-David et al. (2018) report results from February 2000 through December 2015.

## VIII. Concluding Remarks

We find evidence that skilled, active mutual fund managers respond to an increase in ETF ownership caused by the reclassification from the Russell 1000 to the Russell 2000 by creating arbitrage portfolios that earn an excess return of about 6% on the stocks traded. This suggests that the popularity of ETFs is driving up volatility of stocks in the market and mispricing stocks. The belief that ETF volatility prevents mutual funds from investing is not supported by our data. At best we can argue that unskilled active managers do not find opportunities when ETF ownership changes. We find no evidence that limits to arbitrage, namely price impact (measured by the Amihud ratio/FHT ratio) or volatility, affect this type of mutual fund arbitrage. The impact of the trades by mutual funds is related to past alpha of the fund, suggesting that not all arbitrage portfolios and mutual fund trades earn excess return. Moreover, skilled managers appear to take advantage of the arbitrage opportunities imposed by ETFs and likely add more information to the price than simply correcting mispricing caused by ETFs.

We show that the trading by active funds at least partially mitigates the mispricing caused by ETF volatility. Variance ratios and BGZ measure showing mispricing are brought more in line with market efficiency, and the risk premium for bearing non-diversifiable ETF volatility risk found by previous studies has largely disappeared.

This study does not imply that all mispricing caused by ETFs is corrected by arbitrage. Our sample is confined to stocks that were reclassified during the 2012-2020 period. The evidence in the literature is for a much broader list of stocks being affected by ETFs. Similarly, our paper only partially addresses the much-examined question of whether managers have "skill", which is usually defined as being able to persistently earn positive alphas. Our evidence is limited to the one-time shift in ownership created by the Russell reclassification. However, some mutual funds clearly do understand mispricing and definitely create arbitrage portfolios to capitalize on the mispricing. This dimension of "skill" has been largely ignored in the literature. Finally, the reaction of active mutual funds to increases in ETF ownership supports the findings by a series of papers that ETFs are, in fact, causing the mispricing.

Figure 1: Timeline of Identification

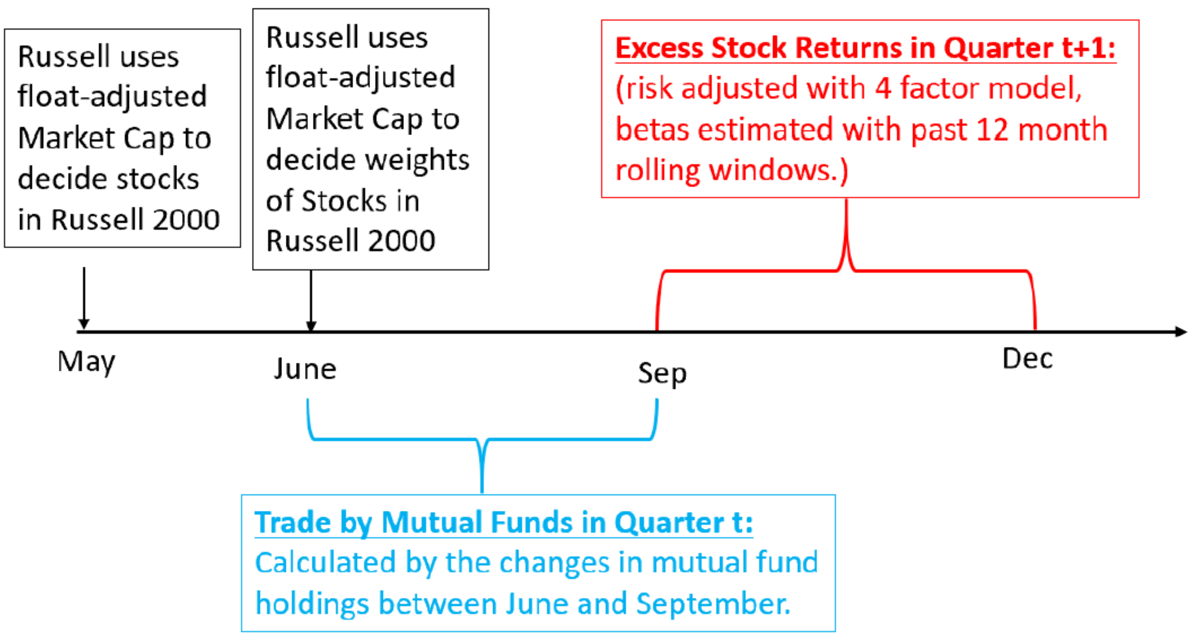

Table I: Summary Statistics

The data period is from 2012 through 2020. ETF Ownership is the standardized total ownership of ETF in stock $j$. The trade of mutual fund $i$ in stock $j$ is calculated based on the changes from quarterly holding reports by mutual funds, adjusted by fund flows. The log of float shares of stock $j$ in quarter $t$ is calculated based on the Russell Index weights.

| **Variable Name** | **N** | **Mean** | **SD** | **p5** | **p50** | **p95** |
|---|---|---|---|---|---|---|
| ETF Ownership$_{j,t}$($Standardized$) | 110,980 | 0.2630 | 1.7681 | -0.5015 | -0.2989 | 4.9027 |
| Index MF Ownership$_{j,t}$($Standardized$) | 132,605 | -0.2823 | 1.0746 | -1.7331 | -0.2479 | 1.5222 |
| Trade of Mutual Fund in Stocki,j,t | 3,206,160 | 0.0592 | 0.5566 | -1.0000 | 0.0092 | 1.0000 |
| Ln Float Shares$_{j,t}$ | 105,392 | 14.6222 | 1.7149 | 12.0553 | 14.5040 | 17.6837 |
| One Over Stock Price$_{j,t}$ | 130,366 | 0.0707 | 0.1793 | 0.0063 | 0.0326 | 0.2320 |
| Amihud Ratio$_{j,t}$ | 130,015 | 5.5016 | 107.6561 | 0.0157 | 0.4821 | 12.6388 |
| Mutual Fund Quarterly Return$_{i,t}$ | 108375 | 0.03377 | 0.09328 | -0.1296 | 0.03677 | 0.16779 |
| Mutual Fund Expense Ratio$_{i,t}$ | 89,503 | 0.01 | 0.00 | 0.00 | 0.01 | 0.02 |
| Ln Mutual Fund AUM$_{i,t}$ | 108,210 | 2312.00 | 9551.59 | 16.30 | 375.70 | 8573.30 |
| Fund Flow$_{i,t}$ | 108,186 | 0.0317 | 3.7655 | -0.1524 | -0.0182 | 0.1902 |
| Stock Alpha$_{j,t+1}NextQuarter$ | 128,176 | 0.0095 | 0.1116 | -0.1749 | 0.0038 | 0.2200 |
| R2000 | 105,629 | 0.5817 | 0.4933 | 0 | 1 | 1 |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | 105,629 | 0.4841 | 0.4998 | 0 | 0 | 1 |
| In Russell 2000 Last Year$_{j,t}$ | 105,629 | 0.5571 | 0.4967 | 0 | 1 | 1 |
| Volatility$_{j,t}$ | 127,908 | 0.0007 | 0.0050 | 0.0001 | 0.0003 | 0.0021 |
| FHT$_{j,t}$ | 127,908 | 0.0011 | 0.0029 | 0.0000 | 0.0004 | 0.0049 |
| Absolute Variance Ratio$_{j,t}$ | 115,603 | 0.2661 | 0.1872 | 0.0229 | 0.2348 | 0.6233 |
| Variance Ratio$_{j,t}$ | 115,603 | -0.1160 | 0.3029 | -0.5648 | -0.1473 | 0.4400 |

Table II: Trade Predicting Future Stock Returns

In this table, we examine daily-level trades by mutual fund managers in the Ancerno database. "Buy" is an equally weighted portfolio that longs all the buy trades of Ancerno managers on stocks that were recently reassigned to the Russell 2000 (or Russell 1000). "Sell" is an equally weighted portfolio that shorts all the sell trades of Ancerno managers. "Buy-Sell" is a long-short portfolio that longs the buys of stocks that were reassigned to Russell 2000 (or Russell 1000) by mutual fund managers in Ancerno and shorts the sells of stocks that were reassigned to Russell 2000 (or Russell 1000) by mutual fund managers in Ancerno in an equally weighted way. $StockAlpha_{j,t+1}$ is the four-factor alpha of a stock in the next quarter.

| $StockAlpha_{j,t+1}$ (2012-2015) | | | |
|---|---|---|---|
| Subsample | Buy | Sell | Buy- Sell (t-stats) |
| Switcher to Russell 2000 | 0.0277 | 0.0147 | 0.0130 (6.40)*** |
| (Num of Obs) | 16613 | 11064 | |
| Switcher to Russell 1000 | 0.0378 | 0.0442 | -0.0064 (-3.42)** |
| (Num of Obs) | 5703 | 4864 | |

Table III: OLS Results: Mutual Fund Trade after ETF Ownership Change

This is the OLS regression result of next quarter $t+1$ stock four-factor alpha regressed on ETF ownership and trade of mutual funds. The ETF Ownership in stock $j$ in quarter $t$ is standardized. The trade of mutual fund $i$ on stock $j$ in quarter $t$ is calculated with mutual fund holdings data in quarter $t$ and quarter $t-1$, adjusted by fund flows. Stock characteristics, mutual fund characteristics, and fund fixed effects are included, and standard errors are adjusted at the fund by year level. The switchers to R1000 stand for the subgroup of stocks that were reassigned to the Russell 1000. The switchers to R2000 stand for the subgroup of stocks reassigned to the Russell 2000 from the Russell 1000.

| | Full Sample | Switcher to R1000 | Switcher to R2000 |
|---|---|---|---|
| | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ |
| ETF Ownership$_{j,t} * TradeofMutualFundinStock_{i,j,t}$ | 0.001 | 0.002 | 0.003 |
| | (3.27)*** | (0.64) | (2.06)** |
| ETF Ownership$_{j,t}(Standardized)$ | 0.002 | 0.032 | 0.007 |
| | (15.67)*** | (14.62)*** | (5.88)*** |
| Index MF Ownership$_{j,t} * TradeofMutualFundinStock_{i,j,t}$ | -0.002 | -0.002 | -0.013 |
| | (-6.82)*** | (-1.31) | (-7.29)*** |
| Index MF Ownership$_{j,t}(Standardized)$ | -0.002 | -0.002 | 0.001 |
| | (-15.65)*** | (-1.41) | (0.49) |
| Trade of Mutual Fund in Stock$_{i,j,t}$ | 0.007 | 0.002 | 0.013 |
| | (28.80)*** | (1.05) | (6.36)*** |
| Ln Float Shares$_{j,t}$ | 0.001 | -0.004 | -0.018 |
| | (7.04)*** | (-2.09)** | (-10.69)*** |
| ETFM$_{j,t}$ | -0.002 | -0.003 | -0.011 |
| | (-4.14)*** | (-0.86) | (-2.92)*** |
| One Over Stock Price$_{j,t}$ | -0.178 | -0.235 | -0.253 |
| | (-27.99)*** | (-5.48)*** | (-13.74)*** |
| Amihud Ratio$_{j,t}$ | 0.000 | 0.000 | -0.000 |
| | (1.70)* | (0.99) | (-2.07)** |
| Mutual Fund Quarterly Return$_{i,t}$ | 0.025 | -0.019 | -0.054 |
| | (12.26)*** | (-1.54) | (-3.05)*** |
| Mutual Fund Expense Ratio$_{i,t}$ | 1.536 | 4.511 | -1.987 |
| | (10.73)*** | (5.44)*** | (-1.37) |
| Fund Flow$_{i,t}$ | 0.008 | 0.024 | 0.027 |
| | (7.59)*** | (3.57)*** | (3.00)*** |
| Ln Mutual Fund AUM$_{i,t}$ | -0.003 | -0.010 | 0.000 |
| | (-11.02)*** | (-7.47)*** | (0.07) |
| Fund Fixed Effect | Y | Y | Y |
| Cluster: Fund *Year | Y | Y | Y |
| N | 1651407 | 25126 | 19992 |
| adj. R-sq | 0.022 | 0.054 | 0.118 |

## Table IV: IV ETF Ownership and Mutual Fund Arbitrage

This is the IV2SLS result of stock alpha in quarter $t+1$ regressed on ETF ownership and trade of mutual funds in quarter $t$. The standardized ETF Ownership of stock $j$ in quarter $t$ is instrumented with the Russell 2000 dummy (with Russell band decision, floating shares, market cap of stock $j$, and Russell 2000 dummy in the previous years as controls). All the other variables are the same as Table III. Buy only is the subsample of buy trades of mutual funds, while sell only is the subsample of sell trades of mutual funds.

Panel A: First Stage

| | ETF Ownership_j,t | ETF Ownership_j,t | ETF Ownership_j,t | ETF Ownership_j,t | ETF Ownership_j,t | ETF Ownership_j,t |
|---|---|---|---|---|---|---|
| R2000 | 0.036 | 0.028 | 0.032 | 0.017 | 0.035 | 0.035 |
| | (7.27)*** | (4.96)*** | (5.03)*** | (2.39)** | (4.74)*** | (4.16)*** |
| R2000* Trade of Mutual Fund in Stock_i,j,t | 0.012 | 0.010 | 0.025 | 0.029 | 0.011 | 0.008 |
| | (3.43)*** | (2.58)*** | (3.87)*** | (4.23)*** | (1.48) | (0.96) |
| Index Ownership_j,t* Trade of Mutual Fund in Stock_i,j,t | -0.014 | -0.013 | -0.025 | -0.022 | 0.004 | 0.001 |
| | (-6.38)*** | (-5.33)*** | (-5.06)*** | (-3.91)*** | (0.76) | (0.12) |
| Passive Index Ownership_j,t (Standardized) | 0.247 | 0.264 | 0.248 | 0.265 | 0.254 | 0.269 |
| | (79.06)*** | (81.45)*** | (59.92)*** | (60.34)*** | (61.00)*** | (59.08)*** |
| Trade of Mutual Fund in Stock_i,j,t | -0.007 | -0.007 | -0.017 | -0.012 | 0.016 | -0.002 |
| | (-2.49)** | (-2.31)** | (-2.92)*** | (-1.96)* | (2.70)*** | (-0.26) |
| Ln Market Cap in May_j,t | -57.128 | -44.717 | -56.255 | -43.025 | -60.296 | -49.389 |
| | (-11.49)*** | (-8.49)*** | (-8.91)*** | (-6.48)*** | (-8.64)*** | (-6.73)*** |
| Ln Market Cap in May$\hat{2}$_j,t | 2.595 | 2.030 | 2.556 | 1.952 | 2.735 | 2.241 |
| | (11.52)*** | (8.51)*** | (8.92)*** | (6.48)*** | (8.64)*** | (6.73)*** |
| Ln Market Cap in May$\hat{3}$_j,t | -0.039 | -0.031 | -0.038 | -0.029 | -0.041 | -0.034 |
| | (-11.51)*** | (-8.48)*** | (-8.90)*** | (-6.44)*** | (-8.61)*** | (-6.69)*** |
| Ln Float Shares_j,t | -0.553 | -0.530 | -0.550 | -0.525 | -0.541 | -0.518 |
| | (-34.49)*** | (-30.56)*** | (-28.92)*** | (-25.70)*** | (-25.60)*** | (-22.85)*** |
| Dummy: Market Cap in May within Russell Band_j,t | -0.067 | -0.066 | -0.071 | -0.070 | -0.058 | -0.057 |
| | (-17.08)*** | (-15.22)*** | (-14.84)*** | (-13.62)*** | (-11.42)*** | (-10.50)*** |
| In Russell 2000 Last Year_j,t | 0.021 | 0.030 | 0.026 | 0.034 | 0.012 | 0.023 |
| | (5.60)*** | (7.74)*** | (5.75)*** | (7.23)*** | (1.93)* | (3.77)*** |
| Dummy: Market Cap within Russell Band_j,t* In Russell Last Year_j,t | -0.063 | -0.070 | -0.068 | -0.071 | -0.052 | -0.065 |
| | (-11.77)*** | (-11.98)*** | (-10.11)*** | (-9.89)*** | (-6.39)*** | (-7.23)*** |
| ETFM_j,t | -0.212 | -0.317 | -0.210 | -0.315 | -0.210 | -0.316 |
| | (-12.14)*** | (-18.75)*** | (-10.52)*** | (-16.28)*** | (-11.25)*** | (-17.22)*** |
| Mutual Fund Quarterly Return_i,t | | -1.506 | | -1.566 | | -1.492 |
| | | (-24.47)*** | | (-26.38)*** | | (-20.53)*** |
| Mutual Fund Expense Ratio_i,t | | 16.753 | | 18.058 | | 17.044 |
| | | (4.58)*** | | (4.63)*** | | (3.68)*** |
| Fund Flow_i,t | | 0.101 | | 0.119 | | 0.098 |
| | | (3.35)*** | | (3.41)*** | | (2.73)*** |
| Ln Mutual Fund AUM_i,t | | -0.026 | | -0.021 | | -0.031 |
| | | (-4.25)*** | | (-3.01)*** | | (-4.33)*** |
| Fund Fixed Effect | Y | Y | Y | Y | Y | Y |
| Cluster: Fund *Year | Y | Y | Y | Y | Y | Y |
| N | 672213 | 563877 | 391452 | 327133 | 280496 | 236548 |

Panel B: Second Stage

| | All trades | | Buy Only | | Sell Only | |
|---|---|---|---|---|---|---|
| | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ |
| $\widehat{ETFOwnership}_{j,t}$* Trade of Mutual Fund in Stock$_{i,j,t}$ | 0.097 | 0.092 | 0.234 | 0.339 | 0.083 | 0.046 |
| | (3.59)*** | (2.62)*** | (4.69)*** | (3.34)*** | (1.28) | (0.78) |
| $\widehat{ETFOwnership}_{j,t}$(Standardized) | -0.751 | -0.935 | -0.772 | -1.182 | -0.792 | -0.749 |
| | (-7.25)*** | (-4.95)*** | (-6.40)*** | (-3.78)*** | (-4.52)*** | (-4.06)*** |
| Index MF Ownership$_{j,t} * TradeofMutualFundinStock_{i,j,t}$ | -0.031 | -0.032 | -0.073 | -0.101 | -0.010 | -0.005 |
| | (-4.73)*** | (-3.58)*** | (-5.64)*** | (-3.66)*** | (-0.62) | (-0.35) |
| Index MF Ownership$_{j,t}(Standardized)$ | 0.183 | 0.243 | 0.190 | 0.308 | 0.199 | 0.198 |
| | (7.01)*** | (4.79)*** | (6.29)*** | (3.71)*** | (4.45)*** | (3.95)*** |
| Trade of Mutual Fund in Stock$_{i,j,t}$ | -0.013 | -0.014 | -0.037 | -0.054 | 0.019 | 0.009 |
| | (-2.52)** | (-1.95)* | (-3.82)*** | (-2.83)*** | (1.61) | (0.84) |
| Ln Market Cap in May$_{j,t}$ | -30.483 | -29.491 | -25.892 | -32.599 | -37.637 | -25.511 |
| | (-4.64)*** | (-3.16)*** | (-3.84)*** | (-2.50)** | (-3.23)*** | (-2.49)** |
| Ln Market Cap in May$^2_{j,t}$ | 1.384 | 1.337 | 1.176 | 1.478 | 1.705 | 1.156 |
| | (4.65)*** | (3.17)*** | (3.84)*** | (2.50)** | (3.23)*** | (2.49)** |
| Ln Market Cap in May$^3_{j,t}$ | -0.021 | -0.020 | -0.018 | -0.022 | -0.026 | -0.017 |
| | (-4.65)*** | (-3.16)*** | (-3.84)*** | (-2.50)** | (-3.22)*** | (-2.48)** |
| Ln Float Shares$_{j,t}$ | -0.370 | -0.449 | -0.340 | -0.518 | -0.398 | -0.347 |
| | (-6.48)*** | (-4.46)*** | (-5.72)*** | (-3.48)*** | (-4.11)*** | (-3.56)*** |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | -0.057 | -0.067 | -0.057 | -0.080 | -0.054 | -0.048 |
| | (-6.96)*** | (-4.70)*** | (-6.00)*** | (-3.58)*** | (-4.49)*** | (-3.91)*** |
| In Russell 2000 Last Year$_{j,t}$ | 0.042 | 0.055 | 0.043 | 0.063 | 0.038 | 0.047 |
| | (12.03)*** | (8.54)*** | (10.46)*** | (6.00)*** | (7.06)*** | (7.34)*** |
| Dummy: Market Cap within Russell Band$_{j,t} * InRussellLastYear_{j,t}$ | -0.035 | -0.054 | -0.034 | -0.064 | -0.034 | -0.040 |
| | (-6.32)*** | (-4.87)*** | (-5.57)*** | (-3.75)*** | (-4.19)*** | (-4.14)*** |
| ETFM$_{j,t}$ | -0.170 | -0.305 | -0.161 | -0.350 | -0.183 | -0.250 |
| | (-6.26)*** | (-4.79)*** | (-5.69)*** | (-3.74)*** | (-4.31)*** | (-4.00)*** |
| Mutual Fund Quarterly Return$_{i,t}$ | | -1.385 | | -1.636 | | -1.117 |
| | | (-4.60)*** | | (-3.59)*** | | (-3.81)*** |
| Mutual Fund Expense Ratio$_{i,t}$ | | 17.802 | | 20.331 | | 16.003 |
| | | (4.08)*** | | (3.44)*** | | (3.47)*** |
| Fund Flow$_{i,t}$ | | 0.103 | | 0.127 | | 0.085 |
| | | (2.99)*** | | (2.56)** | | (2.55)** |
| Ln Mutual Fund AUM$_{i,t}$ | | -0.029 | | -0.028 | | -0.028 |
| | | (-3.91)*** | | (-2.90)*** | | (-3.53)*** |
| Fund Fixed Effect | Y | Y | Y | Y | Y | Y |
| Cluster: Fund *Year | Y | Y | Y | Y | Y | Y |
| N | 672213 | 563877 | 391452 | 327133 | 280496 | 236548 |

Table V: Ancerno Trade: Net Mutual Fund Industry Trade of Stock $j$ after Instrumented ETF Ownership Change in Stock $j$

The net trade of mutual funds in stock $j$ at quarter $t$ represents the net trade of all the mutual funds within the Ancerno dataset, 1 stands for a net buy, 0 stands for no trade, and -1 stands for a net sell. In this table, we use the instrumented ETF Ownership and the net trade from Ancerno in quarter $t$ to predict the stock four-factor alpha in quarter $t+1$.

| | **Full Sample** | Low Num of Trades | Mid Num of Trades | High Num of Trades |
|---|---|---|---|---|
| | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ |
| $ETF\widehat{Ownership}_{j,t}$* Net Trade of Ancerno Mutual Funds in Stock$_{j,t}$ | 0.003 | 0.072 | 0.005 | 0.006 |
| | (3.68)*** | (3.43)*** | (3.01)*** | (7.09)*** |
| $ETF\widehat{Ownership}_{j,t}$ (Standardized) | -0.095 | 0.492 | -0.019 | 0.087 |
| | (-17.31)*** | (9.39)*** | (-4.25)*** | (8.24)*** |
| Index MF Ownership$_{j,t} * TradeofMutualFundinStock_i, j, t$ | -0.001 | -0.050 | -0.004 | -0.005 |
| | (-3.12)*** | (-4.06)*** | (-3.82)*** | (-8.07)*** |
| Index MF Ownership$_{j,t}(Standardized)$ | 0.032 | -0.191 | 0.001 | -0.039 |
| | (14.24)*** | (-9.67)*** | (0.67) | (-9.77)*** |
| Net Trade of Ancerno Mutual Funds in Stock$_{j,t}$ | 0.000 | -0.036 | -0.002 | -0.000 |
| | (0.39) | (-3.82)*** | (-1.55) | (-0.27) |
| Ln Market Cap in May$_{j,t}$ | -0.073 | 0.209 | -0.028 | 0.047 |
| | (-22.93)*** | (8.40)*** | (-9.26)*** | (7.40)*** |
| Ln Float Shares$_{j,t}$ | 0.069 | -0.252 | 0.033 | -0.036 |
| | (23.30)*** | (-8.38)*** | (9.71)*** | (-7.39)*** |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | 0.026 | -0.008 | -0.001 | -0.029 |
| | (15.65)*** | (-0.81) | (-0.86) | (-13.93)*** |
| In Russell 2000 Last Year$_{j,t}$ | 0.013 | -0.096 | 0.025 | 0.027 |
| | (14.16)*** | (-6.22)*** | (11.94)*** | (13.45)*** |
| Dummy: Market Cap within Russell Band$_{j,t} * InRussellLastYear_{j,t}$ | 0.022 | -0.133 | -0.002 | -0.022 |
| | (16.09)*** | (-14.16)*** | (-1.16) | (-5.57)*** |
| ETFM$_{j,t}$ | 0.013 | -0.055 | 0.005 | -0.015 |
| | (14.97)*** | (-7.88)*** | (5.15)*** | (-7.58)*** |
| N | 836214 | 232324 | 282120 | 321770 |

Table VI: Mutual Fund Manager Skills and ETF Ownership

The sample is sub-categorized by mutual fund past performance. We look at the trades of mutual funds with low past performance, mid past performance, and high past performance. Russell 2000 is used as instrumental variable for standardized ETF ownership. All the measures are the same as Table III and Table IV.

| | Fund Average Performance in the last 6 months | | |
|---|---|---|---|
| | Low Performance | Mid Performance | High Performance |
| | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ |
| $\widehat{ETFOwnership}_{j,t}$* Trade of Mutual Fund in Stock$_{i,j,t}$ | -0.021 | 0.027 | 0.056 |
| | (-0.97) | (0.99) | (3.39)*** |
| $\widehat{ETFOwnership}_{j,t}$ (Standardized) | 0.339 | -0.589 | -0.232 |
| | (5.62)*** | (-4.18)*** | (-8.29)*** |
| Index MF Ownership$_{j,t} * TradeofMutualFundinStock_{i,j,t}$ | 0.007 | -0.016 | -0.021 |
| | (1.32) | (-2.60)*** | (-5.12)*** |
| Index MF Ownership$_{j,t}(Standardized)$ | -0.097 | 0.113 | 0.037 |
| | (-5.78)*** | (3.85)*** | (5.91)*** |
| Trade of Mutual Fund in Stock$_{i,j,t}$ | 0.008 | -0.002 | -0.009 |
| | (3.17)*** | (-0.33) | (-1.98)** |
| Ln Market Cap in May$_{j,t}$ | 20.478 | -22.872 | -35.463 |
| | (5.07)*** | (-2.28)** | (-6.54)*** |
| Ln Market Cap in May$^2_{j,t}$ | -0.927 | 1.022 | 1.584 |
| | (-5.09)*** | (2.26)** | (6.50)*** |
| Ln Market Cap in May$^3_{j,t}$ | 0.014 | -0.015 | -0.024 |
| | (5.09)*** | (-2.24)** | (-6.46)*** |
| Ln Float Shares$_{j,t}$ | 0.179 | -0.202 | -0.070 |
| | (8.31)*** | (-3.09)*** | (-3.92)*** |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | 0.034 | -0.046 | 0.002 |
| | (6.40)*** | (-3.01)*** | (0.49) |
| In Russell 2000 Last Year$_{j,t}$ | 0.022 | 0.039 | 0.036 |
| | (9.21)*** | (7.76)*** | (13.27)*** |
| Dummy: Market Cap within Russell Band$_{j,t} * InRussellLastYear_{j,t}$ | 0.002 | -0.029 | -0.015 |
| | (0.72) | (-3.70)*** | (-4.73)*** |
| ETFM$_{j,t}$ | 0.118 | -0.153 | -0.064 |
| | (4.57)*** | (-4.16)*** | (-7.27)*** |
| Mutual Fund Quarterly Return$_{i,t}$ | 0.486 | -1.159 | -0.306 |
| | (5.11)*** | (-3.96)*** | (-6.79)*** |
| Mutual Fund Expense Ratio$_{i,t}$ | -7.191 | 16.563 | -0.521 |
| | (-2.31)** | (2.06)** | (-0.12) |
| Fund Flow$_{i,t}$ | -0.031 | 0.089 | -0.000 |
| | (-0.97) | (1.66)* | (-0.00) |
| Ln Mutual Fund AUM$_{i,t}$ | 0.006 | -0.064 | -0.027 |
| | (1.34) | (-3.20)*** | (-3.03)*** |
| Fund Fixed Effect | Y | Y | Y |
| Cluster: Fund *Year | Y | Y | Y |
| N | 196119 | 168014 | 115538 |

Table VII: Month by Month Results: IV ETF Ownership and Mutual Fund Arbitrage

This table shows instrumental variable results, which are similar to those in Table IV. Instead of using instrumented ETF ownership to predict the alpha of the stock in the next quarter, we look into quarter $t+1$ month by month, with the first column representing the IV results for predicting the first month within quarter $t+1$ and the third column representing the IV results for predicting the last month within quarter $t+1$.

| | First month,$Q_{t+1}$ | Second month,$Q_{t+1}$ | Third month,$Q_{t+1}$ |
|---|---|---|---|
| $ETF\widehat{Ownership}_{j,t} * TradeofMutualFundinStock_{i,j,t}$ | 0.049 | 0.045 | 0.036 |
| | (3.57)*** | (3.26)*** | (3.36)*** |
| $ETF\widehat{Ownership}_{j,t}(Standardized)$ | -0.381 | -0.388 | -0.296 |
| | (-7.24)*** | (-7.19)*** | (-7.17)*** |
| Index MF Ownership$_{j,t} * TradeofMutualFundinStock_{i,j,t}$ | -0.016 | -0.015 | -0.012 |
| | (-4.81)*** | (-4.44)*** | (-4.47)*** |
| Index MF Ownership$_{j,t}(Standardized)$ | 0.092 | 0.094 | 0.072 |
| | (6.99)*** | (6.97)*** | (6.99)*** |
| Trade of Mutual Fund in Stock$_{i,j,t}$ | -0.007 | -0.007 | -0.005 |
| | (-2.68)*** | (-2.55)** | (-2.58)*** |
| Ln Market Cap in May$_{j,t}$ | -17.943 | -16.182 | -11.631 |
| | (-5.38)*** | (-4.75)*** | (-4.46)*** |
| Ln Market Cap in May$^2_{j,t}$ | 0.814 | 0.736 | 0.528 |
| | (5.39)*** | (4.77)*** | (4.48)*** |
| Ln Market Cap in May$^3_{j,t}$ | -0.012 | -0.011 | -0.008 |
| | (-5.39)*** | (-4.78)*** | (-4.48)*** |
| Ln Float Shares$_{j,t}$ | -0.193 | -0.198 | -0.144 |
| | (-6.66)*** | (-6.65)*** | (-6.33)*** |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | -0.027 | -0.029 | -0.021 |
| | (-6.39)*** | (-6.87)*** | (-6.53)*** |
| In Russell 2000 Last Year$_{j,t}$ | 0.020 | 0.017 | 0.012 |
| | (11.17)*** | (9.63)*** | (8.33)*** |
| Dummy: Market Cap within Russell Band$_{j,t} * InRussellLastYear_{j,t}$ | -0.016 | -0.014 | -0.011 |
| | (-5.86)*** | (-4.92)*** | (-5.03)*** |
| ETFM$_{j,t}$ | -0.082 | -0.085 | -0.071 |
| | (-5.98)*** | (-6.08)*** | (-6.58)*** |
| Fund Fixed Effect | Y | Y | Y |
| Cluster: Fund *Year | Y | Y | Y |
| N | 672213 | 672213 | 672213 |

Table VIII: ETF Ownership, Mutual Fund Trade and Liquidity

This table shows the IV regression results, with the trade and instrumented ETF ownership variable interacted with the Amihud ratio of stock $j$, the FHT of stock $j$, and the volatility of stock $j$ in quarter $t$ respectively.

| | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ |
|---|---|---|---|
| $\widehat{ETFOwnership}_{j,t}$* Trade of Mutual Fund in Stock$_{i,j,t} * Amihud_{j,t}$ | 0.049<br>(0.77) | | |
| $\widehat{ETFOwnership}_{j,t}$* Trade of Mutual Fund in Stock$_{i,j,t} * FHT_{j,t}$ | | -29.713<br>(-4.86)*** | |
| $\widehat{ETFOwnership}_{j,t}$* Trade of Mutual Fund in Stock$_{i,j,t} * Volatility_{j,t}$ | | | -22.227<br>(-2.65)*** |
| $\widehat{ETFOwnership}_{j,t}$* Trade of Mutual Fund in Stock$_{i,j,t}$ | 0.059<br>(1.12) | 0.118<br>(4.91)*** | 0.127<br>(4.00)*** |
| $\widehat{ETFOwnership}_{j,t}$ (Standardized) | -0.728<br>(-5.82)*** | -0.641<br>(-7.96)*** | -0.790<br>(-6.49)*** |
| Index MF Ownership$_{j,t} * TradeofMutualFundinStock_{i,j,t}$ | -0.029<br>(-4.71)*** | -0.031<br>(-5.78)*** | -0.035<br>(-4.89)*** |
| Index MF Ownership$_{j,t}(Standardized)$ | 0.175<br>(5.76)*** | 0.157<br>(7.67)*** | 0.194<br>(6.31)*** |
| Trade of Mutual Fund in Stock$_{i,j,t}$ | -0.014<br>(-2.66)*** | -0.014<br>(-3.21)*** | -0.017<br>(-2.88)*** |
| Amihud Ratio$_{j,t}$ | -0.016<br>(-0.89) | | |
| FHT$_{j,t}$ | | -19.668<br>(-6.70)*** | |
| Volatility$_{j,t}$ | | | 40.287<br>(5.03)*** |
| Ln Market Cap in May$_{j,t}$ | -30.941<br>(-3.43)*** | -22.376<br>(-4.30)*** | -30.281<br>(-4.08)*** |
| Ln Market Cap in May$^2_{j,t}$ | 1.401<br>(3.44)*** | 1.015<br>(4.31)*** | 1.374<br>(4.09)*** |
| Ln Market Cap in May$^3_{j,t}$ | -0.021<br>(-3.44)*** | -0.015<br>(-4.30)*** | -0.021<br>(-4.09)*** |
| Ln Float Shares$_{j,t}$ | -0.371<br>(-5.11)*** | -0.315<br>(-7.04)*** | -0.396<br>(-5.90)*** |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | -0.054<br>(-6.02)*** | -0.050<br>(-7.68)*** | -0.062<br>(-6.34)*** |
| In Russell 2000 Last Year$_{j,t}$ | 0.041<br>(10.45)*** | 0.039<br>(13.16)*** | 0.037<br>(10.62)*** |
| Dummy: Market Cap within Russell Band$_{j,t} * InRussellLastYear_{j,t}$ | -0.035<br>(-6.24)*** | -0.033<br>(-7.31)*** | -0.036<br>(-6.12)*** |
| ETFM$_{j,t}$ | -0.165<br>(-5.44)*** | -0.145<br>(-6.80)*** | -0.180<br>(-5.80)*** |
| One Over Price$_{j,t}$ | -0.474<br>(-2.31)** | -0.062<br>(-1.59) | -0.450<br>(-11.03)*** |
| Fund Fixed Effect | Y | Y | Y |
| Cluster: Fund *Year | Y | Y | Y |
| N | 670550 | 670536 | 670536 |

## Table IX: Instrumented ETF Ownership and Variance Ratio

Panel A uses the instrumented ETF Ownership variable and the dummy representing whether a stock has been traded at all by any mutual fund within quarter $t$, to predict the future mispricing measures of stock $j$ in quarter $t+1$. Panel B compare the characteristic differences between the subsample of stocks that are traded by mutual funds and the subsample that are not traded by any funds.

Panel A: Pricing Efficiency Variable IV Results

| | Abs Variance Ratio j,t+1 | VAR j,t+1 | BGZ Rhoj,t+1 | HMj,t+1 |
|---|---|---|---|---|
| ETF Ownership j,t* Dummy: Traded by MF j,t | -0.067 | 0.134 | -0.103 | 0.094 |
| | (-1.71)* | (2.16)** | (-1.90)* | (1.30) |
| ETF Ownership j,t (Standardized) | -0.022 | -0.116 | -0.033 | 0.274 |
| | (-0.38) | (-1.28) | (-0.41) | (2.45)** |
| Index MF Ownership j,t* Dummy: Traded by MF j,t | 0.001 | -0.014 | -0.002 | -0.002 |
| | (0.11) | (-1.16) | (-0.18) | (-0.11) |
| Index MF Ownership j,t (Standardized) | 0.017 | 0.003 | -0.020 | 0.029 |
| | (2.99)*** | (0.31) | (-2.47)** | (2.64)*** |
| Dummy: Traded by MF j,t | -0.013 | 0.079 | -0.057 | 0.001 |
| | (-2.81)*** | (10.55)*** | (-8.80)*** | (0.07) |
| Ln Market Cap in May_j,t | -1.566 | -1.244 | 6.025 | 5.402 |
| | (-0.27) | (-0.16) | (0.76) | (0.56) |
| Ln Market Cap in May$\hat{2}$_j,t | 0.066 | 0.071 | -0.268 | -0.256 |
| | (0.25) | (0.20) | (-0.74) | (-0.58) |
| Ln Market Cap in May$\hat{3}$_j,t | -0.001 | -0.001 | 0.004 | 0.004 |
| | (-0.22) | (-0.24) | (0.73) | (0.62) |
| Ln Float Shares_j,t | -0.029 | -0.027 | 0.021 | -0.086 |
| | (-2.72)*** | (-1.57) | (1.41) | (-3.97)*** |
| Dummy: Market Cap in May within Russell Band_j,t | -0.004 | -0.003 | 0.031 | -0.004 |
| | (-0.72) | (-0.40) | (4.65)*** | (-0.44) |
| In Russell 2000 Last Year_j,t | -0.023 | -0.014 | -0.001 | 0.006 |
| | (-2.33)** | (-0.82) | (-0.08) | (0.31) |
| Dummy: Market Cap within Russell Band_j,t* In Russell Last Year_j,t | 0.016 | -0.003 | 0.005 | -0.034 |
| | (1.55) | (-0.14) | (0.26) | (-1.70)* |
| One Over Price_j,t | 0.040 | 0.113 | 0.230 | -0.059 |
| | (0.41) | (0.77) | (2.10)** | (-0.49) |
| Amihud_j, t | 0.000 | 0.000 | 0.000 | -0.000 |
| | (6.99)*** | (1.26) | (1.60) | (-3.45)*** |
| Volatility_j, t | 3.752 | 6.575 | 3.735 | -7.486 |
| | (3.09)*** | (2.54)** | (1.63) | (-1.55) |
| FHT_j, t | 2.553 | -1.566 | -1.064 | 6.464 |
| | (1.58) | (-0.60) | (-0.44) | (2.06)** |
| Alpha_j, t-1 | 0.009 | -0.059 | 0.063 | -0.024 |
| | (1.21) | (-2.49)** | (4.06)*** | (-1.19) |
| Stock Fixed Effect | Y | Y | Y | Y |
| Cluster: Firm *Year | Y | Y | Y | Y |
| N | 21109 | 21109 | 20893 | 20872 |

Table IX: Instrumented ETF Ownership and Absolute Variance Ratio

Charateristic differences between the subsample of stocks that are traded by mutual funds and the subsample of stocks that are not traded by any mutual fund in quarter $t$.

Panel B: Stocks Traded by MF vs. Stocks Not Traded by MF

| | Stocks Traded by MF in Quarter t | Stocks Not Traded by MF in Quarter t | Dif |
|---|---|---|---|
| Amihud j,t | 7.2027 | 20.5113 | -13.3086 |
| | | | (-10.64)*** |
| (Num of Obs) | 42,492 | 72,747 | |
| FHT j,t | 0.0013 | 0.0024 | -0.0011 |
| | | | (-43.80)*** |
| (Num of Obs) | 42,584 | 73,029 | |
| Volatility j,t | 0.0008 | 0.0017 | -0.0008 |
| | | | (-16.65)*** |
| (Num of Obs) | 42,584 | 73,029 | |

## Table X: Portfolio Based on ETF Ownership

Stocks are sorted into five baskets based on ETF ownership in the past month. Portfolios are updated each month.

Panel A: Raw Excess Returns for the Quintile Portfolios

| | Quintiles Based on ETF Ownership | | | | |
|---|---|---|---|---|---|
| | Low | (2) | (3) | (4) | High |
| Raw Excess Returns | 0.0133 | 0.0126 | 0.0108 | 0.0127 | 0.0106 |
| | (2.33)** | (2.16)** | (2.05)** | (2.40)** | (1.94)* |
| Number of Months | 107 | 107 | 107 | 107 | 107 |

Panel B: High-Minus-Low Portfolio

| | Ret(High-Minus_low ETF Ownership) | | | | | | |
|---|---|---|---|---|---|---|---|
| Alpha | -0.003 | -0.004 | -0.002 | -0.002 | -0.002 | -0.002 | -0.003 |
| | (-0.90) | (-1.18) | (-0.53) | (-0.55) | (-0.79) | (-0.76) | (-0.87) |
| MKTRF | | 0.080 | 0.033 | 0.042 | 0.097 | 0.068 | 0.094 |
| | | (1.10) | (0.47) | (0.56) | (1.24) | (0.89) | (1.17) |
| HML | | | 0.346 | 0.350 | 0.479 | 0.472 | 0.402 |
| | | | (3.34)*** | (3.34)*** | (4.01)*** | (4.08)*** | (3.07)*** |
| SMB | | | | -0.045 | -0.001 | 0.169 | 0.180 |
| | | | | (-0.36) | (-0.01) | (1.23) | (1.32) |
| UMD | | | | | 0.218 | 0.237 | 0.248 |
| | | | | | (2.13)** | (2.38)** | (2.48)** |
| RMW | | | | | | 0.554 | 0.537 |
| | | | | | | (2.75)*** | (2.66)*** |
| CMA | | | | | | | 0.255 |
| | | | | | | | (1.14) |
| Number of Months | 107 | 107 | 107 | 107 | 107 | 107 | 107 |
| Adjusted R Squared | 0.000 | 0.002 | 0.090 | 0.082 | 0.112 | 0.166 | 0.169 |

Table XI: ETF Ownership and Stock Alpha Next Quarter

Here we use the instrumented ETF Ownership variable and the dummy representing whether a stock has been traded at all by any mutual fund within quarter $t$, to predict the future Absolute variance ratio of stock $j$ in quarter $t+1$.

| | Stock Alpha$_{j,t+1}$ | |
|---|---|---|
| | Stocks Traded by MF | Stocks Not Traded by MF |
| ETF Ownership$_{j,t}$$(Standardized)$ | -1.453 | 0.605 |
| | (-0.98) | (5.64)*** |
| Index Ownership$_{j,t}$$(Standardized)$ | 0.107 | -0.116 |
| | (0.86) | (-6.28)*** |
| Ln Market Cap in May$_{j,t}$ | -10.523 | -0.958 |
| | (-1.00) | (-1.29) |
| Ln Market Cap in May$^2_{j,t}$ | 0.444 | 0.057 |
| | (0.99) | (1.61) |
| Ln Market Cap in May$^3_{j,t}$ | -0.006 | -0.001 |
| | (-0.98) | (-1.87)* |
| Ln Float Shares$_{j,t}$ | -0.067 | 0.013 |
| | (-0.64) | (1.36) |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | 0.045 | -0.013 |
| | (0.90) | (-0.74) |
| In Russell 2000 Last Year$_{j,t}$ | 0.340 | -0.113 |
| | (0.94) | (-4.65)*** |
| Dummy: Market Cap within Russell Band$_{j,t}$ $* InRussellLastYear_{j,t}$ | -0.208 | 0.093 |
| | (-0.95) | (3.44)*** |

## Appendix A1: Definition of Variables

| **Variable Name** | **Description** | **Source** |
|---|---|---|
| ETF Ownership$_{j,t}$ | Standardized total ETF Ownership in a given stock j by in quarter t in numeric value (from 0-1) | ETF Global |
| Trade of Mutual Fund in $Stock_{i,j,t}$ | Trade by mutual fund i, on stock j, in quarter t, adjusted by fund flow. Trade of Mutual Fund in $Stock_{i,j,t}$=[Holding of Mutual Fund $i$ of Stock $j$ in Quarter $t$- Holding of Mutual Fund $i$ of Stock $j$ in Quarter $t-1$*(1+Fund Flow)]/ Holding of Mutual Fund $i$ of Stock $j$ in Quarter $t-1$*(1+Fund Flow) | Thomson Reuters |
| $LnFloatShares_{j,t}$ | Log of floating shares calculated based on Russell weights and sharesoutstanding | Russell Proprietary Dataset |
| One Over Stock Price$_{j,t}$ | One over stock price in quarter t | CRSP Stock |
| Amihud Ratio$_{j,t}$ | Absolute stock return to its dollar volume in quarter t | CRSP Stock |
| Mutual Fund Quarterly Return$_{i,t}$ | Mutual fund quarterly gross return | CRSP Mutual Fund |
| Mutual Fund Expense Ratio$_{i,t}$ | Mutual fund expense ratio (yearly) | CRSP Mutual Fund |
| Ln Mutual Fund AUM$_{i,t}$ | Log of mutual fund asset under management in quarter t | CRSP Mutual Fund |
| Fund Flow$_{i,t}$ | Fund flow of mutual fund I in quarter t | CRSP Mutual Fund |
| Stock Alpha$_{j,t+1}NextQuarter$ | Stock j alpha in quarter t+1 | CRSP Stock |
| R2000 | Whether a stock is in the newly assigned Russell 2000 | Russell Proprietary Dataset |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | Whether the stock has a market cap that falls within Russell banding policy | Russell Proprietary Dataset |
| In Russell 2000 Last Year$_{j,t}$ | Dummy for stock i in Russell 2000 last year | Russell Proprietary Dataset |
| Volatility$_{j,t}$ | Volatility of a stock's return in the most recent month | CRSP Stock |
| FHT$_{j,t}$ | FHT liquidity measure of a stock in the most recent month | CRSP Stock |

# Appendix A2: Active Mutual Fund Trades and ETF Mispricing

$ETFM_{j,t}$ is the stock level aggregated mispricing of ETF NAV's deviation from the basket value. All the other variables are the same as Table 4.

| | All trades | | Buy Only | | Sell Only | |
|---|---|---|---|---|---|---|
| | ETFM$_{j,t}$ | ETFM$_{j,t}$ | ETFM$_{j,t}$ | ETFM$_{j,t}$ | ETFM$_{j,t}$ | ETFM$_{j,t}$ |
| $\widehat{ETFOwnership}_{j,t}$* Trade of Mutual Fund in Stock$_{i,j,t}$ | -0.077 | -0.059 | -0.084 | -0.098 | -0.188 | -0.147 |
| | (-2.89)*** | (-2.33)** | (-1.63) | (-1.48) | (-3.02)*** | (-2.90)*** |
| $\widehat{ETFOwnership}_{j,t}$ (Standardized) | 0.680 | 0.596 | 0.658 | 0.617 | 0.580 | 0.445 |
| | (6.24)*** | (4.01)*** | (4.97)*** | (2.83)*** | (3.69)*** | (2.91)*** |
| Index MF Ownership$_{j,t}$ $* Trade of Mutual Fund in Stock_{i,j,t}$ | 0.028 | 0.023 | 0.037 | 0.037 | 0.045 | 0.039 |
| | (4.33)*** | (3.49)*** | (2.83)*** | (2.08)** | (3.01)*** | (3.20)*** |
| Index MF Ownership$_{j,t}$$(Standardized)$ | -0.141 | -0.118 | -0.135 | -0.122 | -0.122 | -0.083 |
| | (-5.37)*** | (-3.13)*** | (-4.24)*** | (-2.23)** | (-3.13)*** | (-2.11)** |
| Trade of Mutual Fund in Stock$_{i,j,t}$ | 0.017 | 0.015 | 0.024 | 0.027 | 0.017 | 0.021 |
| | (3.37)*** | (2.95)*** | (2.42)** | (2.14)** | (1.66)* | (2.32)** |
| Ln Market Cap in May$_{j,t}$ | 40.782 | 27.630 | 36.200 | 25.518 | 43.914 | 27.238 |
| | (5.82)*** | (3.74)*** | (4.91)*** | (2.83)*** | (4.02)*** | (3.09)*** |
| Ln Market Cap in May$^2_{j,t}$ | -1.841 | -1.243 | -1.634 | -1.147 | -1.979 | -1.224 |
| | (-5.81)*** | (-3.72)*** | (-4.89)*** | (-2.81)*** | (-4.01)*** | (-3.07)*** |
| Ln Market Cap in May$^3_{j,t}$ | 0.028 | 0.019 | 0.024 | 0.017 | 0.030 | 0.018 |
| | (5.79)*** | (3.70)*** | (4.87)*** | (2.80)*** | (3.99)*** | (3.05)*** |
| Ln Float Shares$_{j,t}$ | 0.368 | 0.291 | 0.336 | 0.280 | 0.350 | 0.242 |
| | (6.17)*** | (3.74)*** | (5.14)*** | (2.73)*** | (4.01)*** | (2.98)*** |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | 0.067 | 0.060 | 0.068 | 0.062 | 0.055 | 0.045 |
| | (7.44)*** | (5.05)*** | (6.40)*** | (3.80)*** | (4.81)*** | (4.09)*** |
| In Russell 2000 Last Year$_{j,t}$ | -0.006 | -0.009 | -0.014 | -0.018 | 0.007 | 0.003 |
| | (-1.85)* | (-1.97)** | (-3.21)*** | (-2.39)** | (1.49) | (0.56) |
| Dummy: Market Cap within Russell Band$_{j,t}$ $* InRussellLastYear_{j,t}$ | 0.023 | 0.023 | 0.028 | 0.029 | 0.012 | 0.008 |
| | (4.10)*** | (2.69)*** | (4.23)*** | (2.51)** | (1.65)* | (1.09) |
| Mutual Fund Quarterly Return$_{i,t}$ | | 0.322 | | 0.304 | | 0.207 |
| | | (1.50) | | (1.06) | | (0.92) |
| Mutual Fund Expense Ratio$_{i,t}$ | | -11.975 | | -13.253 | | -9.730 |
| | | (-3.47)*** | | (-3.11)*** | | (-2.51)** |
| Fund Flow$_{i,t}$ | | -0.059 | | -0.070 | | -0.049 |
| | | (-2.26)** | | (-2.05)** | | (-1.87)* |
| Ln Mutual Fund AUM$_{i,t}$ | | 0.014 | | 0.012 | | 0.014 |
| | | (2.46)** | | (1.76)* | | (2.14)** |
| Fund Fixed Effect | Y | Y | Y | Y | Y | Y |
| Cluster: Fund *Year | Y | Y | Y | Y | Y | Y |
| N | 674494 | 565780 | 392920 | 328359 | 281315 | 237227 |

## Appendix A3 : By Fund Past Risk Adjusted Performane (DGTW return) results

| | Fund Average DGTW-Adjusted Performance in the last 6 months | | |
|---|---|---|---|
| | Low Performance | Mid Performance | High Performance |
| | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ | Stock Alpha$_{j,t+1}$ |
| $ETF\widehat{Ownership}_{j,t}$* Trade of Mutual Fund in Stock$_{i,j,t}$ | 0.011 | 0.012 | 0.020 |
| | (1.20) | (1.67)* | (3.90)*** |
| $ETF\widehat{Ownership}_{j,t}$ (Standardized) | -0.176 | -0.120 | -0.087 |
| | (-12.41)*** | (-12.25)*** | (-7.90)*** |
| Index Ownership$_{j,t} * TradeofMutualFundinStock_{i,j,t}$ | -0.006 | -0.004 | -0.002 |
| | (-4.09)*** | (-2.73)*** | (-1.67)* |
| Passive Index Ownership$_{j,t}(Standardized)$ | 0.002 | -0.005 | -0.009 |
| | (1.15) | (-3.53)*** | (-5.22)*** |
| Trade of Mutual Fund in Stock$_{i,j,t}$ | 0.003 | 0.002 | 0.000 |
| | (1.10) | (0.97) | (0.17) |
| Ln Market Cap in May$_{j,t}$ | -4.912 | 4.741 | 11.929 |
| | (-2.11)** | (3.02)*** | (8.73)*** |
| Ln Market Cap in May$^2_{j,t}$ | 0.218 | -0.222 | -0.549 |
| | (2.06)** | (-3.12)*** | (-8.85)*** |
| Ln Market Cap in May$^3_{j,t}$ | -0.003 | 0.003 | 0.008 |
| | (-2.02)** | (3.21)*** | (8.94)*** |
| Ln Float Shares$_{j,t}$ | 0.001 | 0.024 | 0.057 |
| | (0.23) | (4.95)*** | (14.03)*** |
| Dummy: Market Cap in May within Russell Band$_{j,t}$ | 0.005 | 0.003 | 0.001 |
| | (2.51)** | (2.16)** | (1.15) |
| In Russell 2000 Last Year$_{j,t}$ | 0.028 | 0.036 | 0.035 |
| | (12.05)*** | (19.46)*** | (25.24)*** |
| Dummy: Market Cap within Russell Band$_{j,t} * InRussellLastYear_j,t$ | 0.003 | -0.008 | -0.007 |
| | (1.17) | (-4.02)*** | (-3.85)*** |
| Mutual Fund Quarterly Return$_{i,t}$ | -0.321 | -0.216 | -0.128 |
| | (-9.11)*** | (-8.50)*** | (-7.77)*** |
| Mutual Fund Expense Ratio$_{i,t}$ | -3.715 | -1.352 | -0.331 |
| | (-2.31)** | (-0.63) | (-0.31) |
| Ln Mutual Fund AUM$_{i,t}$ | 0.019 | -0.002 | 0.001 |
| | (1.73)* | (-0.19) | (0.18) |
| Fund Flow$_{i,t}$ | -0.008 | -0.005 | 0.000 |
| | (-2.19)** | (-1.86)* | (0.21) |
| ETF Mispricing$_{i,t}$ | -0.076 | -0.048 | -0.025 |
| | (-10.12)*** | (-10.38)*** | (-8.17)*** |
| Fund Fixed Effect | Y | Y | Y |
| Cluster: Fund *Year | Y | Y | Y |
| N | 118778 | 196080 | 160433 |

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