Exchange Traded Funds and Stock Returns*

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Abstract: We examine the implications of the growing popularity of ETFs on the stock markets. We document a strong negative relation between ETF trades and future stock returns. Long-short trading strategy which buys stocks with low ETF trading and sells stocks with high ETF trading yield significant return of 0.57% per month with *t*-statistics of 3.33. We find that non-flow induced trading may play an important role in stocks return reversal. We uncover the strongest return reversal patterns in stocks with high factor ETF trading. The reversal effect is strongest among the most illiquid stocks (bottom 20%) and is weaker and short-lived among the most liquid stocks (top 20%).

JEL classification: G10, G12, G14, G23

Key words: Exchange-Traded Funds (ETFs), Market Efficiency, Institutional Trading

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1. Introduction

The market of ETFs has grown exponentially over the last two decades. The number of ETFs more than doubled between 2010 and 2020 from 923 to 2,204 with total net asset value increasing from $992 billion to $5.4 trillion. Net share issuance comprised $323 billion in 2019 and $501 billion in 2020, demonstrating steady inflow into the ETF industry.[1] In contrast, cumulative net flows of mutual funds have been decreasing on a yearly basis and mutual funds experienced a net outflow of $1.7 trillion in 2019 and $486 billion in 2020. The dynamic of money flows in the market suggests that part of the outflows from mutual funds shift towards ETFs. Such a rapid increase in popularity of ETFs created uncertainty about their impacts on capital markets.

The main objective of this study is to examine the implications of the growing demand for ETFs and how their increased trading activities affect the stock market. Specifically, we investigate whether stocks highly traded by ETFs underperform. We measure ETF trading activities as the quarterly or monthly change in ETF stock holdings scaled by stocks shares outstanding.[2] We find that ETF trades have significant and negative relation with future stock returns. Our results are qualitatively similar, even after controlling for tradings by index and active mutual funds. Our findings may suggest that ETFs induce high trading pressure on underlying securities, which is negatively related to future stock returns. We further decompose ETF trades into flow- and non-flow induced trades (non-FIT) and find that even with the control for flow-induced ETF (FIT) trading activity, non-FIT has significant negative relation with the future stock returns. We also observe strong and significant negative relation in stocks highly traded by factor ETFs. This could be related to style chasing of factor ETF investors. Factor ETFs concentrate their portfolios on specific set of stocks satisfying some factor criteria. Higher non-flow induced trading by such ETFs

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[1] Investment Company Institute Factbook, 2021. https://www.ici.org/system/files/2021-05/2021_factbook.pdf

[2] Few studies document strong positive contemporaneous relation between institutional trading and stock returns (Nofsinger and Sias (1999), Wermers (1999), Sias, Starks, and Titman (2006), Cai and Zheng (2004), Boyer and Zheng (2002)). Cai and Zheng (2004) document negative relation between lagged institutional trading and stock returns consistent with price-pressure hypothesis and following price reversals. Campbell, Ramadorai, and Schwartz (2009) confirm relation on a daily frequency. Dasgupta, Prat, and Verardo (2011) corroborate negative relation between returns and persistent institutional trading, where stocks persistently sold over three to five quarters outperform persistently bought stocks.

corresponds to stronger overpricing of stocks in their basket, resulting in the future stock returns reversal.

We start our analysis by using Fama-MacBeth regression model to test the relation between ETF trades and future stock returns. The coefficient on ETF trade is significantly negative for next week and month returns. By contrast, we do not observe significant effect of index and active mutual funds trades. To explore the mechanism behind our results, we further divide ETF trades into FIT and non-FIT and find that even with the control for FIT, non-FIT significantly contributes to the negative relation between ETF trading and future stock returns. The coefficient on non-FIT is significantly negative and persistent over subsequent month, which can imply that ETF trading that is not induced by flows, but rather by rebalancing activities of ETFs, also plays ab important role in explaining future stock return patterns.

Next, we divide sample of stocks based on their Amihud illiquidity ratio, we would expect to see more pronounced results in the more illiquid stocks and the effect to be weaker in larger liquid stocks. As expected, we find that the effect is weaker and short-lived among most liquid (top 20%) stocks, but the reversal effect is strongest among the most illiquid stocks (bottom 20%) and is still present among medium liquidity stocks (the rest 60%). Further, we examine two subsample periods, before and after financial crisis of 2008. The results are more pronounced in the second period, which is explained by the growth of the number of ETFs and their trade magnitude after financial crisis.

To explore further, we disentangle the effect of ETF trades on stock returns by dividing the sample of ETFs into three major groups: broad-market, factor and sector ETFs. First, broad-market ETFs replicate broad market indices and rarely rebalance their portfolios. In their structure and behavior, they are similar to index mutual funds, therefore, we find that coefficient on broad market ETFs and index funds are close in terms of magnitude and significance. Second, factor ETFs trade according to one of the factors (e.g. momentum, value, size). Such ETFs have experienced substantial growth compared to other types of ETFs and rebalance their portfolios frequently and aim to generate higher returns relative to the market-cap-weighted indexes[3]. Increasing popularity in factor ETFs can be attributed to the competition for investors' attention in the ETF space. Our analyses show that the significant negative relation between ETF trading and future stock returns is attributed mainly to trades by factor ETFs. This confirms our previous results on non-FIT, as we expect factor ETFs to have higher non-FIT due to their nature, they rebalance their portfolios often according to their factor strategy. Third, we classify ETF as sector ETF if it has more than 30% of its holdings concentrated in one of the 12 Fama-French industry groups. For sector ETFs, we do not observe a significant effect of trading on stock returns as the magnitudes of their trading activities are smaller. Such ETFs are mostly used by other active institutional investors in their portfolios to hedge industry risk coming from their long positions in individual stocks (Huang, O'Hara, and Zhong (2021)).

At last, we discover whether trading by factor ETFs potentially affects factor price fluctuations. We study Fama-French value and size factor returns. By constructing factor level ETF trading we document that one standard deviation increase in trading activities of factor ETFs are associated with 0.59% push up in contemporaneous monthly size factor returns, followed by 0.35% decrease in next month returns. The relation holds on the weekly horizon. This finding suggests that factor ETFs became an important force that can temporarily affect factor returns.

This study contributes to three strands of literature. First, it explores the role of ETFs in the capital markets adding to the growing body of literature on increasing popularity of ETFs and their effect on market efficiency.[4] One key contribution of our research is that non-flow induced trading

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[3] For example, one of the largest ETF providers, Vanguard, in the Principal Investment Strategy section of their US Momentum Factor ETF prospectus states: *"The Fund invests primarily in U.S. common stocks with the potential to generate higher returns relative to the broad U.S. equity market by investing in stocks with strong recent performance as determined by the advisor."* During the 2020-21 year, the Vanguard U.S. Momentum Factor ETF's portfolio turnover rate was 115% of the average value of its portfolio. In comparison, Vanguard Russell 2000 ETF's investment objective is "to track the performance of a benchmark index that measures the investment return of small-capitalization stocks in the United States". Another example is Vanguard Energy ETF, whose investment strategy is "to track the performance of a benchmark index that measures the investment return of energy stocks" and has the turnover of 8%.

[4] Bhattacharya and O'Hara (2018) theoretically show that ETFs increase short-term fragility of the market. Empirically, Ben-David, Franzoni, and Moussawi (2018) document an increase in price volatility of stocks with higher ETF ownership, Da and Shive (2018) show that ETF arbitrage activity increases return comovement, and

by ETFs (non-FIT) may play an important role in explaining future stock returns. Existing studies focus on the effect of ETF flows on the ETF fund level performance (Brown, Davies, Ringgenberg, 2021) or correlation with the market returns (Dannhauser and Pontiff, 2019). Instead, our research focuses on the stock-level effects of ETF trading, motivated by both flow- and non-flow induced trading. Moreover, we disentangle the impact on stock market by different types of ETFs: broad-market, sector and factor ETFs.

Second, we contribute to the studies on active versus passive investments and stock returns. Theoretically Liu and Wang (2018) develop a model where they show if index investing increased due to cost of participation in non-index market, then the price informativeness of non-index market decreases, while if its due to the low profitability of the non-index market, then it increases price discovery. Bond and Garcia (2018) argue that cheaper indexing implies increase in index investment which results in a decrease of aggregate price efficiency. Wermers and Yao (2010) study passive and active funds trading and find significant price reversals during subsequent quarter for passive fund trading, in contrast to return continuations for active mutual fund trades. Our paper comes timely to open a new perspective on the debate of active versus passive investments. As ETFs have taken passive arena by storm, we show the possible impact of increased ETF tradings on the future stock returns. We contribute by considering different categories of ETFs, where the main objective deviates from tracking passive index. Factor ETFs have an element of activeness compared to broad-market ETFs as they rebalance their portfolios towards specific factor strategy. We open a new perspective on the passive versus active debate by showing that ETFs differ in their impact on the stock market depending on whether they passively track an index or implement more active strategy.

Third, we add to the growing literature on so called smart-beta ETFs. Cao, Hsu, Xiao, and Zhan show that the introduction of smart beta ETFs changed dynamics of money flows on the institutional investors arena. They argue that mutual funds have to switch from traditional factors

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Agarwal, Hanouna, Moussawi, and Stahel (2018) provide evidence of increased commonality in liquidity of underlying stocks.

to “multi-factor adjusted” strategies to compete with ETFs. However, Huang, Song, and Xiang (2020) document that high performance of the “smart beta indexes” that ETFs follow only exists in backtests and performance significantly deteriorates once ETFs are launched. We contribute to this debate by showing how factor ETFs trading affects stock returns and how their impact is different from other types of ETFs. Moreover, we add by showing that factor ETFs may be one of the contributing factors to temporary fluctuations in size factor returns.

This paper is organized as follows. The next section investigates institutional details of ETFs and their difference with active mutual funds and index funds. Section 3 describes data construction and summary statistics. Section 4 discusses methodologies and presents main results. In section 5 we disentangle ETFs effect on stock returns across different types of ETFs. We divide the effect of ETF trade on buy and sell trades, and study different time periods in section 6. We conclude in Section 7.

2. Background and institutional details

In the recent two decades we observe large shift in US investment assets from active to passive funds. ETFs are responsible for the most part of that trend. Panel A of Figure 1 shows aggregate assets under management of ETFs, active mutual funds, and index mutual funds during the sample period from 2000 to 2019. Even though there is an increase in AUM among all three types of funds, the growth of ETFs appears to be more dramatic when compared to index funds, which are considered to be the closest alternative to ETFs. Despite active funds being larger in aggregate AUM than passive funds, they have grown significantly less than ETFs. Panel B shows that allocation of assets to ETFs among the three types of funds has reached 26% by 2019.

[Insert Figure 1 here]

Such a rapid increase in popularity of ETFs can be attributed to their unique structure that provides investors with cheaper and more liquid alternative to mutual funds. Further, the disruptive force of ETFs comes with the rise of specialized factor and sector ETFs that are used by investors as building blocks in their portfolios. Sector ETFs are used by institutional investors to hedge industry risk exposure (Huang, O'Hara and Zhong, (2021)). The rise of factor investing and demand for factor tilted funds resulted in the increase of the number of factor ETFs, where index constituents are rebalanced according to a specific factor strategy (e.g. momentum, value, and size).

Figure 2 provides the evolution of different ETF types between 2000 and 2019. Panel A of Figure 2 shows the proportional distribution of total ETF assets among these categories. The proportion of factor ETFs achieved 37% compared to 36% of broad market ETFs. This trend is characterized by the rise of the number of factor ETFs. Panel B of Figure 2 illustrates the number of ETFs in each category. Compared to broad market ETFs that are large, factor ETFs are smaller, but the number of factor ETFs has grown from 21 in 2000 to 287 in 2019.

To understand the increasing popularity in ETFs compared to other mutual funds, we look at the differences and advantages provided by ETFs to their investors. Index mutual funds are considered to be the closest alternative to ETFs[5], however, we do not observe the same magnitude of growth in index funds. Ben-David, Franzoni, and Moussawi (2018) note that ETFs gained market share at the expense of traditional indexing products. There are several reasons why investors prefer ETFs over index mutual funds as passive investment vehicle. First, low prices or fees that ETFs charge attract price-conscious investors that are looking for cheapest possible way of getting an exposure to certain asset class (Ben-David, Franzoni, Kim, and Moussawi (2021), Potebra and Shoven (2002)). Second, ETFs provide tax advantages compared to index mutual funds. ETFs use "in kind" mechanism to reduce or eliminate their distributions of realized capital gain by transferring out the securities with the highest unrealized gains as part of the redemption process (Poterba and Shoven (2002), Moussawi, Shen, and Velthuis (2020)).

[5] Up to 2008 only those ETFs that tracked specified indexes were approved by the Securities and Exchange Commission (SEC), they are also called index-based ETFs and aim to replicate performance of the index they track or its multiple or its inverse. In 2008 SEC approved several fund sponsors to offer actively managed ETFs, with a requirement of full transparency. According to Investment Company Institute (ICI) 2020 Factbook, there were 1,708 index-based ETFs with $4.2 trillion total net assets and 320 actively managed ETFs with $99 billion net assets registered with SEC as of end of 2019. Active ETFs comprise only 2% of total assets managed by ETF industry

After financial crisis of 2008, investors directed funds into safer and more liquid alternatives to mutual funds, which resulted in rising numbers of rules-based ETFs that follow so called "quasi-active" strategies, allowing them to become more passive substitutes of active mutual funds. ETFs with higher costs and lower diversification, such as sector and factor ETFs, appeal to investors that are ready to pay higher fees in order to get exposure to desired theme. In this case, ETF providers have an incentive to design new products to satisfy investor demand for higher returns. Moreover, institutional and individual investors seek to diversify their portfolios using ETFs as building blocks (Easley, Michayluk, O'Hara, and Putnins (2018)). Advantages of ETFs such as greater liquidity, lower transaction fees and tax efficiency provide new tool for implementing investment strategies.

3. Data and summary statistics

We compile a large dataset of fund data from several sources, including CRSP, Compustat, Thomson Reuters Mutual Funds Holding Database, and Morningstar Direct.

3.1 Summary statistics

Exchange traded funds. We extract ETFs from CRSP securities database using Lipper objective codes. We include securities with shares code 73 that exclusively identifies ETFs, and exclude the funds with et_flag "N" that defines ETNs.[6] During the sample period of 2000-2019, our sample includes 993 unique ETFs.

Data on fund returns and fund characteristics are from CRSP mutual funds database. We collect ETF holdings information from CRSP Mutual Funds Holdings Database and are able to extract holdings for 772 ETFs. We also extract ETF holdings from Thomson Reuters s12 file. To do so we first merge Thomson Reuters holdings data with the list of ETFs obtained from CRSP using MFLinks and we are able to extract holdings information for 506 ETFs. Zhu (2020)

[6] We restrict our sample to the following Lipper Objective Codes for broad-based U.S. equity: CA, EI, G, GI, MC, MR, SG, and SP. We also include sector funds that invest in U.S. companies with codes BM, CG, CS, FS, H, ID, NR, RE, TK, TL, S, and UT (Ben-David, Franzoni, and Moussawi (2018)).

documents that Thomson Reuters database fails to include a large fraction of newly-founded ETFs after 2008, while the data quality of CRSP Mutual Fund holdings database has been improving since 2007.[7] Therefore, we use portfolio holdings information from Thomson Reuters database up to 2008 and supplement the holdings data using CRSP Mutual Fund Database after 2008. In special cases where a fund family offers both ETF and open-end mutual fund share classes, we adjust holdings by using fractional total assets of ETF share class to extract proportional holdings of stocks attributed to ETF share class. Finally, we are able to get holdings information on 782 ETFs for the sample period from January 2000 to December 2019.

To pin down the impact and test whether the relationship holds using higher frequency data, we extract ETFs' *monthly* holdings data from Morningstar Direct database. Due to the limited data availability before 2005, we restrict our sample period from 2005 to 2020.

Table 1 presents descriptive statistics during the sample period. The table reports the number of ETFs per year, average number of holdings per ETF and average total net assets of ETFs by category, broad-market, factor or sector for CRSP and Morningstar data. Two samples are similar. The number of domestic equity ETFs in our sample steadily increases every year and reaches 753 by the end of 2019 in CRSP and 763 in Morningstar data. The average total net assets of the funds have increased almost four times in our sample period from 764 million US dollars in 2000 to 2.9 billion US dollars in 2019. In early 2000s most of the ETFs were tracking broad-market indices, with average TNA of 7.5 billion US dollars, while sector and factor ETFs were on average only 73 and 7 million US dollars in TNA respectively. By 2019 we see total growth in ETF TNA, however, average TNA of sector and factor ETFs remains small compared to broad market ETFs. At the same time, we observe that factor ETFs have outgrown sector ETFs and on average are twice larger with 2.77 billion of TNA in 2019 compared to 1.51 billion of sector funds.

[Insert Table 1 here]

[7] It is also noted by Schwarz and Potter (2016) that CRSP portfolios' positions are inaccurate prior to the fourth quarter of 2007.

Mutual Funds. We extract mutual funds using lipper objective codes and by further cleaning on fund names. Index funds are extracted using index fund flag identifiers in CRSP mutual funds database, we exclude funds with et_flag "F" and "N" that defines ETFs and ETNs. We further clean funds by name and exclude ETFs and international funds. The final sample includes 3930 active mutual funds and 489 index mutual funds for the sample period of January 2000 – December 2019.

3.2 ETF trades

Our goal is to examine the role of the exponential growth of ETFs in mispricing of underlying stocks. Unlike mutual funds, where managers are able to make decisions on distribution of flows, ETFs directly translate investor flows into trading of underlying securities.[8] Therefore, we choose trading to be our main variable in determining the impact of increasing ETF activities on stock returns. We measure ETF trading activities in the market as the net shares purchased (number of shares bought mines the number of shares sold by ETFs) during the last quarter divided by total shares outstanding at current quarter end. We calculate quarterly ETF trade for each stock in our sample. Specifically, ETF trade of the stock *i* during quarter *q* is calculated as follows:

$$ETF_{i,q} = \frac{\sum_{j=1}^{J}(shares_{i,j,q} - shares_{i,j,q-1})}{Shares\,Outstanding_{i,q}}, \tag{1}$$

where $shares_{i,j,q}$ is the number of the stock *i's* shares held by ETF *j*, which is extracted from the most recent quarterly report, and $Shares\ Outstanding_{i,,q}$ is the total shares outstanding of stock *i* at the end of the quarter. We construct trade variable for active mutual funds and index mutual funds in the similar fashion.

Figure 3 illustrates the net dollar amount of trading aggregated across ETFs, index and active mutual funds. Starting from 2010 ETFs experience substantial growth in trading activities compared to index and active mutual funds. In line with ETFs, index mutual funds have positive

[8] Danhauser and Pontiff (2019) study the differential response to fund flows of ETFs, active mutual funds, and index funds. They confirm that ETFs respond to flows by trading activity more often than active mutual funds or index funds.

net trading activities, which indicates that passive funds, on average, buy more stocks than sell. On the other hand, active mutual funds experience negative trading in the second decade of the sample period. Wermers and Yao (2010) document that passive funds and active mutual funds trade same stocks but in different directions. This indicates that active funds are on the other end of trades and supply liquidity to passive funds. Figure 3 shows that the magnitude of passive buying activities is larger than aggregate trading by active funds. As a result, we expect the price pressure induced by ETF trades to dominate the effect from trading by active funds.

[Insert Figure 3 here]

4. Main results

The goal of our paper is to examine how increasing popularity of ETFs may have influenced stock market. ETFs have a distinct mechanism in responding to investor flows compared to mutual funds. ETFs experience high flow-induced pressure, since all the flows must be translated into trading of underlying stock holdings, unlike mutual funds, where managers have higher discretion in allocation of flows (Dannhauser and Pontiff (2019)). This difference between ETFs and mutual funds brings an important question of how trading by ETFs affects future stock returns and whether the relation is distinct from the impact brought by index and active mutual funds trading. The idea is as follows. If ETFs bring information into prices via trading then we should observe an increase in prices when they buy heavily and no subsequent drift in returns. Alternatively, if ETF trades are forced by large amount of inflows, then we should observe significant negative relation between ETF trades and future stock returns.

4.1 ETF trade and future stock returns

In this section, we test the relation between ETF trading activities and future stock returns using regression methods. Because ETF trades are forced by large amount of inflows, we expect them to push stock prices away from fundamental values resulting in a negative relation with subsequent stock returns. To examine, for each quarter we estimate the following Fama-MacBeth regression of next quarter stock returns on trading by ETFs and controlling for index and active mutual funds trading and other stock characteristics:

$$Ret_{i,q+1} = b_0 + b_1\text{ETF}_{i,q} + b_2\text{IndexMF}_{i,q} + b_3\text{ActiveMF}_{i,q} + b_4\text{Controls}_{i,q} + e_{i,q}, \tag{2}$$

where dependent variable $Ret_{i,q+1}$ is cumulative return of stock *i* over the next quarter *q*+1. The explanatory variable $\text{ETF}_{i,q}$ is trading of stock *i* by all ETFs in quarter *q*, measured as the quarterly change in stock holdings by all ETFs divided by the stock's shares outstanding. $\text{IndexMF}_{i,q}$ and $\text{ActiveMF}_{i,q}$ are trading by index mutual funds and active mutual funds respectively, defined similarly to $\text{ETF}_{i,q}$. To avoid our results being contaminated by other potential channels, we include various control variables, $\text{Controls}_{i,q}$, known to impact stock prices. Control variables include the average monthly turnover over the previous quarter, lagged three-month return and lagged nine-month return preceding the beginning of the quarter, the firm size measured as the natural logarithm of market capitalization, book-to-market ratio, institutional ownership, idiosyncratic volatility, and the number of analysts covering the stock[9]. Appendix 1 provides details of how each variable is constructed and data source. We also conduct same regression on next month return ($Ret_{i,m+1}$) and cumulative return over the next three quarters ($Ret_{i,q+2}, Ret_{i,q+3}, Ret_{i,q+4}$). We estimate the above regression following the Fama-MacBeth (1973) procedure. The *t*-statistics are computed from standard errors that are adjusted for autocorrelation following Newey and West (1987).

Results of the regression analysis are reported in Table 2. The dependent variable is future one-month returns in column (1), future one quarter returns in columns (3), and quarters *q*+2, *q*+3, *q*+4 returns in column (4), (5), (6) respectively. The coefficient estimates show that ETF trading activities have a significant negative relation with future stock returns. In column (1), the estimated

[9] Banz (1981), Chan, Hamao, and Lakonishok (1991), and Fama and French (1992), among others, find that smaller sized firm will earn higher returns. Chan, Hamao, and Lakonishok (1991) and Fama and French (1992) find that firms with larger book-to-market ratio outperform. Ang, Hodrick, Xing, and Zhang (2006) document a negative relation between idiosyncratic volatility and subsequent stock returns. Nagel (2005) shows that stocks with low institutional ownership underperform. Amihud and Mendelson (1986), Amihud (2002) find the positive relation between illiquidity and expected return. Datar, Naik, Radcliffe (1998) use turnover rate as a proxy to illiquidity measure of Amihud. Chan and Hameed (2006) find that securities covered by more analysts incorporate greater market information and returns of portfolios with high analyst coverage outperform.

coefficient on ETF trade in the regression on next month returns is -1.096 with a *t*-statistic of -2.84. The coefficient of -1.912 (column (2)) remains statistically significant at 1% level for the next quarter with a *t*-statistic of -2.68, which means one standard deviation increase in ETF trading in quarter *q* is associated with 52 bps decrease in next quarter stocks returns. In columns (3), (4) and (5) we additionally control for the ETF trading in quarters preceding the returns quarter. For example, for returns in quarter *q*+2, we control for trading in quarter *q*+1. In column (3) the estimated coefficient on ETF trading in quarter *q* is -0.365 and becomes statistically insignificant with a *t*-statistics of -0.83. However, the estimated coefficients of ETF trading in quarter *q*+1 is -1.632 and significantly negative with a *t*-statistics of -2.51. In column (4) we have similar results, where only ETF trading in the quarter preceding returns quarter has a significant negative coefficient. These results indicate that negative relation between ETF trades and future stock returns holds up to one quarter and attenuates on longer horizons[10].

[Insert Table 2 here]

By contrast, the coefficient of active trade is insignificant and positive for stock returns during subsequent month, 0.041 with a *t*-statistic of 1.02, and subsequent quarter, 0.010 with a *t*-statistic of 0.14. This can have few explanations. First, it can indicate information incorporation into prices. The coefficient on $IndexMF_{i,q}$ is insignificant across all five specifications of future stock returns. There are few possible reasons for the difference between the impact of index funds trades and ETFs trades. First of all, the amount of buy trades is twice smaller for index funds than for ETFs, therefore, the impact brought by index funds is insignificant. However, the biggest advantage provided by ETFs to their investors is the choice in strategies. Unlike index funds, ETFs have experienced a growing popularity in "quasi-active" funds, which we refer to as factor and

[10] In Appendix 2 Table IA2.1 we run a regression of ETF trades on the contemporaneous weekly stock returns and on returns over the week following quarter-end. Results suggest that ETF trading temporarily results in the increase in stock prices following by the short-term reversal. One standard deviation increase in ETF trading is associated with 12 bps increase in contemporaneous weekly stock returns, following by price reversal in the following week, where one standard deviation increase in ETF trading is associated with 12 bps decrease in stock returns.

sector ETFs that follow specific factor strategy or industry. We will assess these sub-categories of ETFs and their impact on stock price efficiency in section 4.3.

4.2 Monthly ETF trades and future stock returns

In the previous sections we establish the negative relation between ETF trades and future stock returns and we find that it remains significant only for the next quarter returns and disappears on a longer horizons. We might observe such results due to the *quarterly* frequency of the holdings data that we use from Thomson Reuters mutual funds holdings database. To pin down the impact and test whether the relationship holds using higher frequency data, we extract ETFs' *monthly* holdings data from Morningstar Direct database. Due to the limited data availability before 2005, we restrict our sample period from 2005 to 2020.

To test the relation of monthly ETF trade and stock returns, we construct ETF trades of stock i during month m as follows:

$$ETF_{i,m} = \frac{\sum_{j=1}^{J}(shares_{i,j,m} - shares_{i,j,m-1})}{Shares\,Outstanding_{i,m}}, \tag{3}$$

where $shares_{i,j,m}$ is the number of the stock *i's* shares held by ETF j at the end of month m, and $Shares\ Outstanding_{i,,m}$ is the total shares outstanding of stock i at the end of the month.

We run the following Fama-MacBeth regression of the future-month stock returns on the monthly ETF trade:

$$Ret_{i,m+1} = b_0 + b_1 \mathrm{ETF}_{i,m} + b_2 \mathrm{Controls}_{i,m} + e_{i,m}, \tag{4}$$

where dependent variable $Ret_{i,m+1}$ is cumulative return of stock i in month $m+1$. The explanatory variable $\mathrm{ETF}_{\mathrm{i,m}}$ is trading of stock i by all ETFs in month m. To avoid our results being contaminated by other potential channels, we include various control variables, $\mathrm{Controls}_{\mathrm{i,m}}$, known to impact stock returns as used in the previous sections.

Results are reported in Table 3. First, we examine the relation between weekly stock returns and ETF trades. In Column (1) of Table 3, where the dependent variable is the stock returns in the last week of the month *m*, the estimated coefficient on the ETF trades is insignificant. In Columns (2) and (3), the dependent variables are returns in week $w+1$ and $w+2$ respectively, which are returns in the two weeks following month *m*. The estimated coefficient of ETF trades on returns in week $w+1$ is -0.851 with a *t*-statistics of -4.85. In other words, one standard deviation increase in the ETF trades in month *m* corresponds to 0.17% decrease in stock returns in the next week. The estimated coefficient for the $w+2$ return is statistically insignificant. This indicates, that the effect is short-lived and return reversal happens on a shorter weekly horizon, which could be determined by examining monthly holdings data.

[Insert Table 3 here]

Column (4) of Table 3 reports the regression results of ETF trading in month *m* on contemporaneous stock returns in the same month. The estimated coefficient of ETF trading is 2.188 with a *t*-statistics of 4.68, which means that one standard deviation increase in ETF trading corresponds to 0.43% increase in contemporaneous monthly stock returns. This confirms that the previously established negative relation between ETF trades and future stock returns is a result of price reversal due to the temporary boost in stock returns in current month. In Column (5) of Table 3, the dependent variable is stock returns in month $m+1$, and the estimated coefficient of the ETF trades in month *m* is -1.353 with a *t*-statistics of -4.02. This finding means that one standard deviation increase in ETF trading in month *m* is associated with 0.26% decrease in the next month returns. In Columns (6) and (7) the dependent variables are stock returns in months $m+2$ and $m+3$, respectively, where we additionally control for the previous-months ETF trades. The estimated coefficient on the ETF trading loses its significance after one month.

4.3 Exploring the channel: Non-flow induced ETF trading

In this section we explore the mechanism behind the return reversal in stocks with high ETF trading. Previous studies have documented that inflows into ETFs induce price pressure on stocks, which results in negative returns. One of the highlights of ETFs that distinguishes them from mutual funds is their passive nature. It is commonly assumed that due to the passiveness of ETFs, they directly translate flows into the trading, therefore, flows are considered to be one of the main drivers of price pressure on the underlying securities. Despite ETFs being considered as passive investment vehicles, the rise in demand for specific types of ETFs triggered launch of specialized ETFs, characterized by changing index constituent weights and active portfolio rebalancing (e.g. factor ETFs). Therefore, we aim to explore whether non-flow induced trading, triggered by the rebalancing activities of specialized ETFs, may play an important role in affecting stock returns.

To do so, we construct the non-flow induced ETF trading by taking the difference between actual ETF trades and flow-induced trades. We first construct the stock-level flow-induced ETF trading following methodology in Lou (2012). For each stock i in month m:

$$FIT_{i,m} = \frac{\sum_{j=1}^{J} shares_{i,j,m-1} Flow_{j,m}}{Shares\,Outstanding_{i,m}}, \tag{5}$$

$$\text{where } Flow_{j,m} = \frac{TNA_{j,m} - TNA_{j,m-1}(1+Ret_{j,m})}{TNA_{j,m-1}}$$

where $shares_{i,j,m}$ is the number of the stock i*'s* shares held by ETF j in month m, and *Shares Outstanding*$_{i,,m}$ is the total shares outstanding of stock i at the end of the month. The monthly holdings data is extracted from Morningstar. The measure of FIT assumes that ETFs do not change their portfolios and direct all the flows into the stocks that were held in the previous month, which means they are passive in their nature. In contrast, ETF trading calculates the actual changes in the shares held by ETFs in the current month. The difference between these two measures shows whether trading that is non-flow driven plays an important role in the underperformance of the underlying stocks in the following month. We calculate the difference on the stock-level and call it Non-Flow induced trading:

$$NonFIT_{i,m} = ETF_{i,m} - FIT_{i,m}, \tag{6}$$

where $ETF_{,i,m}$ is ETF trading of stock i by all ETFs in month m . To formally explore, we run the following Fama-MacBeth regression:

$$Ret_{i,m+1} = b_0 + b_1 \text{NonFIT}_{i,m} + b_2 \text{FIT}_{i,m} + b_3 \text{Controls}_{i,m} + e_{i,m}, \tag{7}$$

where $Ret_{i,m+1}$ is the next month stock returns. We also conduct same regression on weekly returns.

Table 4 reports the results of the regression of stock returns on non-flow induced ETF trades with the control for flow-induced ETF trades. In Column (1) the dependent variable is contemporaneous month returns. The estimated coefficients on both non-FIT and FIT are positive and statistically and economically significant, which indicates that both flow and non-flow induced trading by ETFs push stock prices up. One standard deviation increase in non-FIT (FIT) is associated with 0.28% (0.45%) increase in contemporaneous stock returns. In Columns (3) and (4), the dependent variables are returns in week $w+1$ and $w+2$ respectively, which are returns in the two weeks following month *m*. The estimated coefficient of *NonFIT* on returns in week $w+1$ is -0.927 with a *t*-statistics of -4.92, while the coefficient on returns in week $w+2$ is -0.542 with a *t*-statistics of -3.22. Significant results are confirmed when looking at monthly stock returns. In Column (5) the dependent variable is stock returns in month $m+1$, and the estimated coefficient of the ETF trades in month *m* is -1.630 with a *t*-statistics of 4.13.

Looking at the FIT results, it is evident that flow-induced trades of ETFs are associated with the significant push up in contemporaneous returns, which is in line with previous studies on ETF flows. However, the reversal seems to be very short-lived and observed only in the first week after the month end, in Column (3) the estimated coefficient of ETF FIT is -0.975 with a *t*-statistics of -1.67.

This findings implicate that flow-induced trading is not the only mechanism through which ETFs contribute to the stock return reversal, non-flow induced trading may also play an important role. Such results add to the existing literature on ETFs trading activity nature and show that ETF trades happen not only due to the flows, but they may also include an active component to them, which in turn, affects stock returns.

[Insert Table 4 here]

4.4 Subsample analysis: stocks illiquidity

Previously we have established the negative relation between ETFs trades and future stock returns. This does not preclude the possibility of more extensive impact in certain types of stocks, such as illiquid stocks. In this section we examine whether previously documented relation is driven by the stocks with higher illiquidity[11]. To do so, we divide stocks based on the 20th and 80th percentile Amihud illiquidity ratio into three groups: illiquid stocks (top 20%), medium liquidity stocks, and liquid stocks (bottom 20%). We run the baseline regression specified in equation (4) for three groups of stocks.

Results of the regression are presented in Table 5. In Panel A, we run the Fama-MacBeth regression of stock returns on ETF trades. Columns (1)-(3) show that ETF trading is associated with the increase in the contemporaneous monthly stock returns across all three subsamples. In columns (4)-(6) the estimated coefficients of next week stock returns on the ETF trade is significantly negative both for illiquid and liquid stocks, where one standard deviation increase in ETF trade is associated with 0.63% decrease in returns for illiquid stocks and 0.22% decrease in future stock returns for liquid stocks. In columns (7)-(9), the dependent variable is next month stock

[11] We conduct the same analysis by dividing sample of stocks based on their size, B/M ratio and on their previous 12 months returns to account for size, value and momentum. Results are presented in Internet Appendix 3 Tables IA2.2, IA2.3 and IA2.4. The estimated coefficients of ETF trade are significant across all size samples (Table IA2.2), however, we observe a weaker effect in large stocks, which confirms the liquidity results, as large stocks tend to be more liquid. The results remain statistically significant for high and low B/M stocks in Table IA2.3. However, the coefficient for loser stocks, those with the lowest past 12 months returns, in Table IA2.4 are statistically less significant than for the sample of winner stocks. This is as expected since ETFs load on winner stocks, which experience high buying pressure and reverse in the future.

returns, where only ETF trade for illiquid and medium liquid stocks has a negative significant coefficient. In Panel B, we further divide trade variable into flow-induced and non-flow induced trades. We find that non-FIT has a negative significant relation with monthly and weekly stock returns for illiquid stocks. The effect is weaker and short-lived among most liquid stocks. We do not observe the same results for FIT. Overall, we find that the negative relation between ETF trades and future stock returns is strongest among the most illiquid stocks and is still present among medium liquidity stocks.

[Insert Table 5 here]

4.5 Betting against ETF trades

In this section, we examine stock return predictability using portfolio sorting to establish the empirical implication of the findings for the investors. At the end of each month, we rank stocks into quintiles based on their ETF trading activity, where stocks with the lowest ETF trading are assigned to portfolio 1 and stocks with the highest ETF trading are assigned to portfolio 5. We then compute the equal-weighted returns of each portfolio over the next month.[12] As we are interested in testing the previously established negative relation between future stock returns and ETF trading, we expect portfolio of stocks with the lowest ETF trading to outperform portfolio of stocks with highest ETF trading. Therefore, we also calculate the return to a long-short portfolio, which is formed by buying the quintile with the lowest ETF trading and short selling the quintile with the highest ETF trading. We also calculate returns to the long-short strategy based on non-FIT, where the long portfolio includes stocks with the lowest non-FIT and short portfolio includes stocks with the highest non-FIT.

[Insert Table 6 here]

Results are reported in Table 6. In Panel A, at the end of each month, all stocks are sorted into quintiles based on their ETF trades, in Panel B stocks are sorted based on ETFs non-FIT.

[12] In section 4.4 we have found that the negative relation between ETF trades and future stock returns is more pronounced among illiquid stocks, which tend to be smaller in size, therefore, we use the equal-weighted strategy.

Panels A.1 and B.1 present portfolios raw returns, Panels A.2 and B.2 contain DGTW adjusted returns, and Panels A.3 and B.3 reports returns adjusted for DGTW and Amihud illiquidity measures.[13] In column (1) of Panel A.1, the long-short portfolio of stocks sorted on ETF trading generates the monthly return of 0.4 % per month with a *t*-statistics of 2.26 for the sample period 2005-2020, and the spread is even larger after 2010 with the monthly return of 0.57% and a *t*-statistic of 3.33 (Column(5)). The strategy generates significant returns even when we adjust for DGTW portfolio returns and Amihud illiquidity. We also test the returns to the long-short portfolios for different types of ETFs. We divide the sample of ETFs into broad-market, factor and sector ETFs. We find that the long-short strategy generates most significant returns for the sample of factor ETFs. The return spread between long and short portfolios is 0.27% for the whole sample period (Column (2)) and 0.41% for the second half of the sample period (Column (6)).

In Panel B of Table 6 we generate similar trading strategy based on stock-level ETF non-FIT trading. We find that the strategy that buys stocks with the lowest non-FIT and short sells the stocks with the highest non-FIT yields significant returns of 0.38% for the whole sample period (Column (1) of Panel B.1) and 0.47% after 2010 (Column (5) of Panel B.1). Results remain significant after we adjust for DGTW and Amihud illiquidity portfolio returns.

5. Different types of ETFs

In this section, we examine how the impact of ETF trading on future stock returns may vary across different types of ETFs. Specifically, we are interested in the difference between broad-market ETFs and other specialized ETFs (factor, sector, and other ETFs).

5.5 Fama-MacBeth regression

Despite ETFs being considered as passive investment vehicles, the rise in demand for specific types of ETFs triggered launch of specialized ETFs, including sector and factor ETFs. This

[13] Similar to DGTW portfolios, we form 3x3x3x3 portfolios based on stock size, value, momentum and Amihud illiquidity ratio.

trend is largely responsible for the growing importance of ETFs in the market. Factor and sector ETFs are considered to be less passive as their portfolios are tilted to follow specific factor strategy or particular industry (Easley, Michayluk, O'Hara, and Putnins (2018)). Therefore, it is important to distinguish between different categories of ETFs when we consider the impact on stock market efficiency. In panel A of Figure 2 we document the rapid increase in proportion of factor ETFs compared to board-market ETFs. In Panel B we observe that factor ETFs dominate the growth in number of funds. Unlike broad-market index ETFs, when factor ETFs experience inflow-driven buying pressure, they increase holdings in their factor tilted portfolios, which puts a higher pressure on the particular set of stocks. This will temporarily lead to further overpricing of stock belonging to the long leg of particular factor (e.g., growth stocks for growth ETFs, value stock for value ETFs), followed by the strong reversal in returns of those stocks. Therefore, we expect to observe a significant negative relation between factor ETF trades and future stock returns. This may not be the case for sector ETFs, because the magnitude in sector ETF trades is smaller than that of factor ETFs.

We classify ETFs into three types of funds: broad-market based ETFs, sector ETFs and factor ETFs. Specifically, we classify ETFs that track broad market indices, including S&P 500, S&P 1500, Russell 1000, Russell 3000, and NYSE/NASDAQ Composite Index, as broad market ETFs (Easley, Michayluk, O'Hara, and Putnins (2018), Antoniou, Li, Liu, Subrahmanyam, and Sun (2018)). We identify sector ETFs as those with at least 30% of their holdings in the dominant industry according to Fama-French 12 industry classification (Huang, O'Hara, and Zhong (2021)). Finally, factor ETFs are those that adjust their holdings to reflect specific factor exposure, such as momentum or value (Easley, Michayluk, O'Hara, and Putnins (2018)).[14]

Figure 5 demonstrates aggregate dollar trades across the three types of ETFs. As expected, broad market ETFs have the highest net trades due to their size. Interestingly, factor ETFs have two times larger net trades than sector funds. This confirms the active in form and active in function

[14] Detailed description of ETF classification into categories with examples can be found in Internet Appendix 1

definition given by Easley, Michayluk, O'Hara, and Putnins (2018), where factor funds can be described as active in form and have higher trades compared to sector funds that do not have high trading activities, but used by other institutional investors as part of industry risk hedging strategy in their portfolios.[15]

[Insert Figure 5 here]

We run the following Fama-MacBeth regression of ETF trades on future stock returns:

$$Ret_{i,q:q+1} = b_0 + b_{1\mathrm{F}}\mathrm{FactorETF}_{i,q} + b_{1\mathrm{S}}\mathrm{SectorETF}_{i,q} + b_{1\mathrm{M}}\mathrm{MktETF}_{i,q} + b_{1\mathrm{O}}\mathrm{OtherETF}_{i,q} + b_2\mathrm{IndexMF}_{i,q} + b_3\mathrm{ActiveMF}_{i,q} + b_4\mathrm{Controls}_{i,q} + e_{i,q}, \tag{8}$$

where the explanatory variables $\mathrm{FactorETF}_{i,q}$, $\mathrm{SectorETF}_{i,q}$, $\mathrm{MktETF}_{i,q}$, and $\mathrm{OtherETF}_{i,q}$ correspond to trading of stock *i* by factor, sector, broad market and other ETFs in quarter *q* respectively. $\mathrm{IndexMF}_{i,q}$ and $\mathrm{ActiveMF}_{i,q}$ are trading by index mutual funds and active mutual funds. We also conduct same regression on next month returns ($Ret_{i,m+1}$) and cumulative returns over the next three quarters ($Ret_{i,q+2}, Ret_{i,q+3}, Ret_{i,q+4}$).

Panel A of Table 7 reports the results. As expected, factor ETF trades generate significant negative coefficients over subsequent periods. In columns (1) the dependent variable is the next month returns. The estimated coefficient of Factor ETF trading is -1.230 with a *t*-statistic of -2.68 controlling for mutual fund trades. The negative relation is continuous throughout the next quarter. In column (2) we run the regression in equation (3) on next quarter stock returns, where the estimated coefficient of FactorETF is -1.803 with a *t*-statistic of -2.12. This means that one standard deviation increase in trading by factor ETFs is associated with 41 bps decrease in next quarter stock returns. Factor ETFs are the only category of ETFs that exhibit significant negative effect on future stock prices. This corroborates our argument that factor funds are an important driver of increased demand for ETFs, hence, their trading activities induce price pressure on stocks in their portfolios.

[15] As factor ETFs follow investment strategy targeting specific factor, they are expected to rebalance their portfolios on a monthly, quarterly or yearly basis depending on the portfolio. Therefore, we expect factor ETFs to have higher trading activities compared to sector and broad-market ETFs.

It is important to note that broad market ETF trades exhibit the same behavior as index ETF trades and we do not observe a negative impact on stock returns. This indicates that large passive funds following broad market indices may not contribute to short term mispricing of stocks.

[Insert Table 7 here]

We repeat the analysis using monthly holdings from Morningstar Direct. First, we divide the sample of ETFs into broad market, factor, sector and other ETFs. Specifically, we classify ETFs that track broad market indices, including S&P 500, S&P 1500, Russell 1000, Russell 3000, and NYSE/NASDAQ Composite Index, as broad market ETFs. We use "Strategic beta" classification of Morningstar to identify factor ETFs. Sector ETFs are identified using Morningstar group "sector equity" classification. We construct the trade variable for each category of ETFs using the same approach as in equation (3). Further, we run the Fama-MacBeth regression specified in equation (8) using monthly ETF trades. The results are reported in Panel B of Table 7. In Columns (1) the estimated coefficient of factor ETF trades on contemporaneous monthly stock returns is 3.018 with a *t*-statistic of 3.34. We do not observe significant push up in stock returns in other ETFs. The significant return reversal is only present in factor ETF trades. In Column (2), where the dependent variable is next week stock returns, the estimated coefficient of factor ETF trades is -0.938 with a *t*-statistic of -3.07. The relation remains significant for the next month returns in column (5) with a coefficient of -1.473 and a *t*-statistic of -2.39. The estimated coefficients on all types of ETF trades are statistically insignificant.

5.6 Factor ETFs: Long and short

In the previous specification we document significant negative relation between factor ETF trades and future stock returns, evident of short-term mispricing of underlying stocks. There are two types of factor ETFs, those that trade on the long leg of the factor and those that trade on the short leg. Specifically, ETFs that invest in stocks that are considered undervalued based on the certain risk factor, such as value stocks in the value factor, are assigned to the long factor ETF sample. On the contrary, ETFs that load on stocks considered as overvalued are assigned to the short factor sample. We anticipate the long and short leg factor ETFs to have opposite impacts on stock returns. As ETFs tilt their portfolios towards specific factors, they are forced to increase their positions in case of inflows, which in turn would exacerbate mispricing of stocks because trading does not bring any fundamental information into prices.

To test the difference between long and short leg factor ETF trades we conduct the following Fama-MacBeth regression:

$$\begin{aligned} Ret_{i,q:q+1} &= b_0 + b_{1\mathrm{LF}}\mathrm{LongFactorETF}_{i,q} + b_{1\mathrm{SF}}\mathrm{ShortFactorETF}_{i,q} + b_{1\mathrm{S}}\mathrm{SectorETF}_{i,q} \\ &+ b_{1\mathrm{M}}\mathrm{MktETF}_{i,q} + b_{1\mathrm{O}}\mathrm{OtherETF}_{i,q} + b_2\mathrm{IndexMF}_{i,q} + b_3\mathrm{ActiveMF}_{i,q} + b_4\mathrm{Controls}_{i,q} + e_{i,q}, \quad (9) \end{aligned}$$

where the explanatory variables $\mathrm{LongFactorETF}_{i,q,}$ and $\mathrm{ShortFactorETF}_{i,q,}$ correspond to trading of stock *i* by long and short leg factor ETFs respectively. The rest of the variables remain the same as in regression (3).

Results are reported in Table 8. In column (1), the estimated coefficient on LongFactorETF, -1.557 with a *t*-statistic of 2.80, is significantly negative at 1% level for the following month returns. The negative effect following long factor ETF trading continues over the subsequent quarter, as evident by the estimated coefficient of -2.061 with a *t*-statistics of -2.01 in column (2). Interestingly, the coefficients on short leg ETF trades are insignificant regardless whether to look ahead one month, quarter or year. This is not surprising, since the number of ETFs trading on the short leg of the risk factors is smaller than long factor ETFs, therefore, the magnitude of trading activities by long factor ETFs is much larger.

[Insert Table 8 here]

5.7 ETF factor trades and factor returns

Previously we have documented that factor ETF trades are the main contributor to the negative relation between ETF trades and stock returns. In this section we try to answer the question whether growth in factor ETFs and their trading activities potentially contribute to temporary fluctuations in factor price movements? In their study, Li (2021) documents that flow-induced demand by mutual funds in the size and value factors negatively predict factor returns due to the price pressure reversals. We find the large increase in the amount of factor ETFs compared to other types of ETFs, which can be attributed to investors chasing a cheaper and safer alternative to active mutual funds after financial crisis of 2008. Therefore, the shift in demand from mutual funds to ETFs may contribute to the factor price fluctuations.

We consider two main factors: value and size. To do so, we measure factor ETF trading in the size and value factor portfolios. Following methodology in Huang, Song, Xiang (2019), we aggregate stock-level factor ETF trade on the size and value factor level as follows:

$$Factor_{k,m} = \sum_{j \in N_L^k} w_{i,m-1}^k ETFtrade_{i,m} - \sum_{j \in N_S^k} w_{i,m-1}^k ETFtrade_{i,m} \tag{10}$$

where N_L^k and N_S^k are the set of stocks consisting of the long-leg and short-leg of factor *k* at time *m*, respectively, and $w_{i,m-1}^k$ is the weight of stock *i* in factor *k*. Factors are constructed based on Fama-French methodology, where in each month, stocks are sorted into 2x3 portfolios based on market capitalization and book-to-market ratio breakpoints. After that, we run the following regression of factor returns in month *m* on factor level ETF trades:

$$Ret_{k,m} = b_0\, factorETF_{k,m} + b_1\, factorETF_{k,m-1} + b_2\, factorETF_{k,m-2} + Controls_{k,m} + e_{k,m} \tag{11}$$
$$\text{where factor } k \in \{\text{size, value}\}$$

where dependent variable $Ret_{k,m}$ is return of factor *k* in month *m.* We also run regression of factor returns in the last week *w* of month *m,* as well as returns in the first week *w*+1 following month *m.* The explanatory variables $factorETF_{k,m}$ is factor level trading by factor ETFs in month *m.* We also control for trading in the previous months *m*-1 and *m*-2, as well as up to 8 lags of corresponding factor returns.

Table 9 reports the results, Columns (1) - (3) present results of regression of the value factor returns and Columns (4) – (6) are estimated regression results of size factor returns. There is no significant reversal documented in value factor returns. However, for size factor, in Column (4), there is a positive relation between factor level ETF trading in month *m* and contemporaneous size factor returns in month *m*, followed by a significant reversal. One standard deviation in factor ETF trading is associated with 0.59% increase in contemporaneous factor returns, followed by 0.35% decrease in returns. In Column (5) the independent variable is size factor returns in the last week of month *m*, where estimated coefficients on factor ETF trading are insignificant. In Column (6) we explore whether the reversal in prices happens within the following week. We document that factor ETF trading results in significant price reversals in the first week of the following month, where one standard deviation in factor ETF trading is associated with 0.22% decrease in the next week returns. This findings might indicate that factor ETF trading create temporary price pressure on size factor.

[Insert Table 9 here]

6. Subsample analyses

In this section, we examine whether our finding is limited to a particular sample period.

Panel A of Figure 1 shows the exponential growth of ETFs after financial crisis. We would expect to see that the relation between ETF trading activities and future stock returns may be more pronounced in recent years, as the increasing investments into ETFs trigger higher trading of underlying securities of these funds. To explore, we estimate the baseline regression specified in equation (2) in the two subsample periods: before financial crisis (2000-2007), during (2008-2009) and after (2010-2019).

The results are presented in Table 10. The dependent variable in Columns (1)-(3) is next month returns and in Columns (4)-(6) is next quarter returns. The estimated coefficients of next month returns on the ETF trades are insignificant for the sample period before 2010. In contrast, after 2010, the estimated coefficient of ETF trades is -0.926 and significant at 1% level with a a *t*-statistics of -2.83. In column (6), the relation remains negative and significant with estimated coefficient of -1.109 and *t*-statistics of -1.76. This findings could be explained by the unprecedented growth in the ETFs that occurred after financial crisis, when investors started to look for cheaper and less risky alternatives to mutual funds. the second subsample. We observe a large shift in flows from active funds to passive funds accompanied by the overall investment market growth.

[Insert Table 10 here]

7. Conclusion

The study examines the relation between trading activities of ETFs and future stock returns. Specifically, we aim at discovering whether growing popularity of ETFs erodes efficiency of stock prices. Our paper finds that ETFs induce trading pressure on underlying securities, which results in a negative relation between ETF trades and future stock returns. One key contribution of our research is that we decompose ETF trades into flow-induced and non-flow induced trades. We find that non-flow induced trading by ETFs (non-FIT) may play an important role in explaining future stock returns. We show that the effect is weaker and short-lived among most liquid (top 20%) stocks, but, as expected, the reversal effect is strongest among the most illiquid stocks (bottom 20%) and is still present among medium liquidity stocks (the rest 60%). We also find that significant relation mainly comes from specialized ETFs, driven by factor ETFs growth, that perform rebalancing activities to their portfolios. On top of that, we document more pronounced negative relation after financial crisis of 2008, which can be explained by the sudden growth in the number of ETFs in that period. Overall, our study contributes to the growing literature on ETFs and passive investments. Our results suggest that trading by ETFs contributes to short term mispricing of stocks in the underlying portfolio decreasing overall market efficiency.

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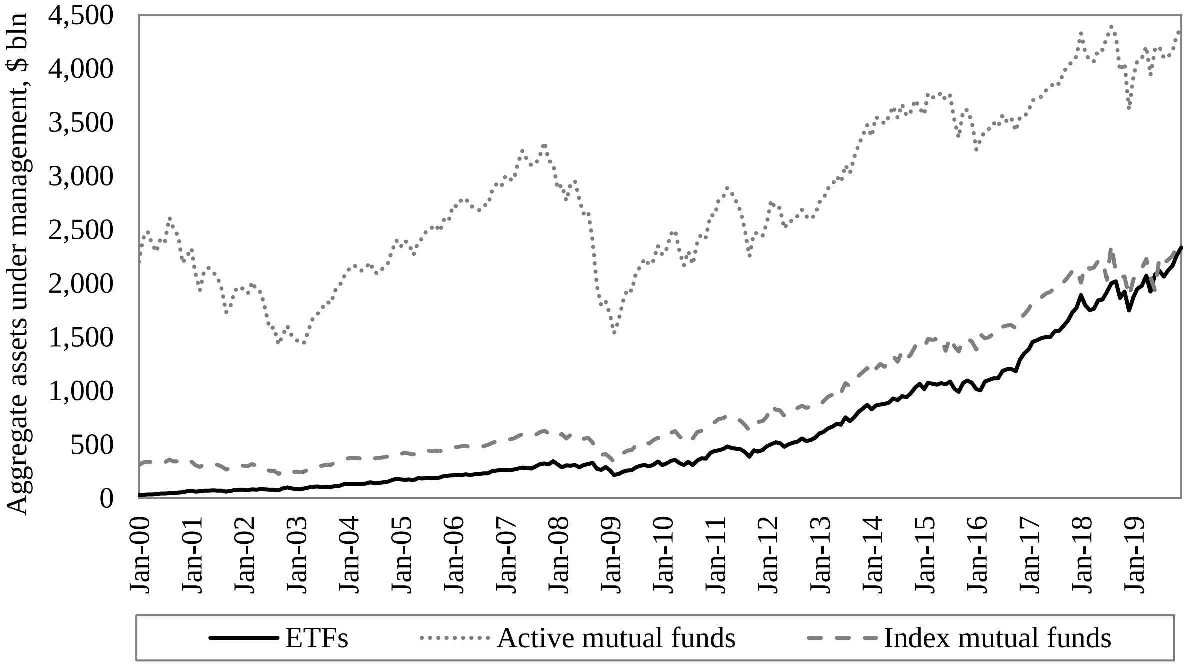
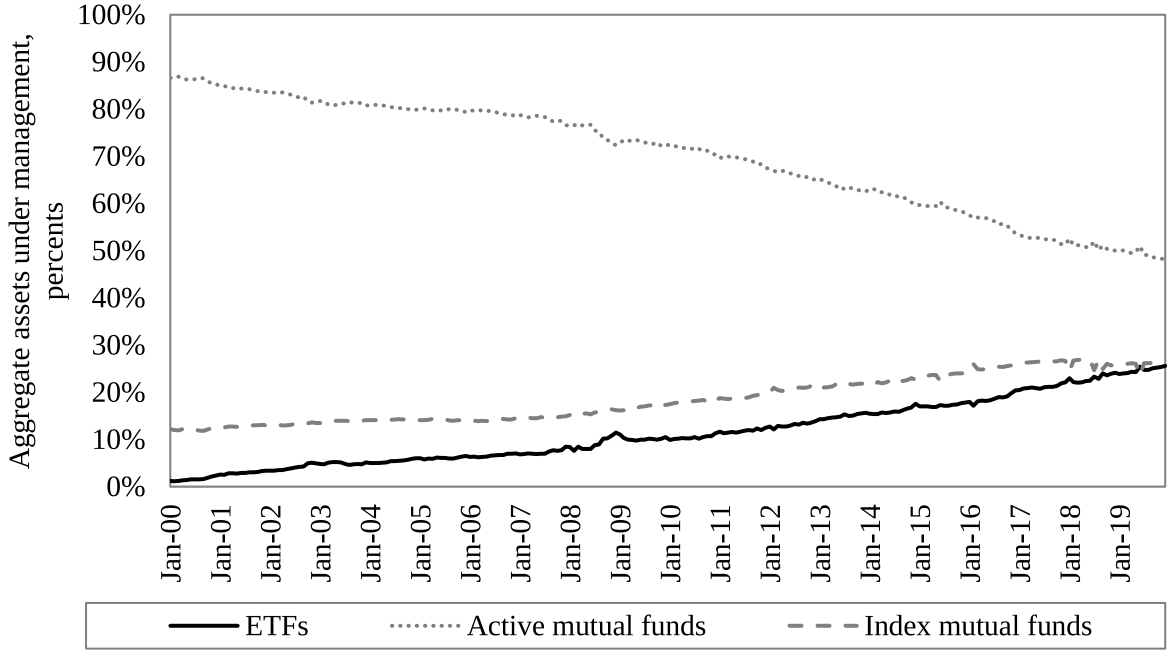
Appendix 1: Variable Definitions

Variable	Description	Source
ETF (or index, active) trade	The net shares purchased by ETFs (or index, active mutual funds) measured as the number of shares bought minus the number of shares sold during the last quarter, divided by total shares outstanding at current quarter-end	Thomson-Reuters, CRSP Mutual Fund, CRSP securities
ETF (or index, active) buy	The net shares purchased by ETFs (or index, active mutual funds) measured as the number of shares bought during the last quarter, divided by total shares outstanding at current quarter end	Thomson-Reuters, CRSP Mutual Fund, CRSP securities
ETF (or index, active) sell	The net shares sold by ETFs (or index, active mutual funds) measured as the number of shares sold during the last quarter, divided by total shares outstanding at current quarter end	Thomson-Reuters, CRSP Mutual Fund, CRSP securities
Institutional ownership	The sum of shares held by institutions from 13F filings in the last quarter-end divided by shares outstanding.	Thomson-Reuters 13f
log(SIZE)	Firm size measured as the log of market capitalization.	CRSP
Turnover	Average monthly turnover over the previous quarter measured as share volume divided by total shares outstanding.	CRSP
Idiosyncratic volatility	The standard deviation of the residuals from a regression of daily stock returns on the Fama and French (1993) factors. We require at least 21 daily returns to compute IVOL	CRSP
#analysts	Number of analysts covering the firm	I/B/E/S
log(B/M)	Log of book-to-market ratio where the book value is measured as of the preceding fiscal year, and market value is measured as of the end of that calendar year. We define book equity, *B*, as the Compustat book value of stockholders' equity (SEQ), plus balance-sheet deferred taxes (TXDITC) minus the book value of preferred stock. Depending on availability, we use the redemption (PSTKRV), liquidation (PSTKL), or par value (PSTK) to estimate the value of preferred stock. We exclude negative *B/M* firms.	CRSP, Compustat
$Ret_{i,m-3:m}$	Cumulative returns in the previous quarter	CRSP
$Ret_{i,m-12:m-3}$	Cumulative return over nine-months preceding the beginning of the last quarter	CRSP



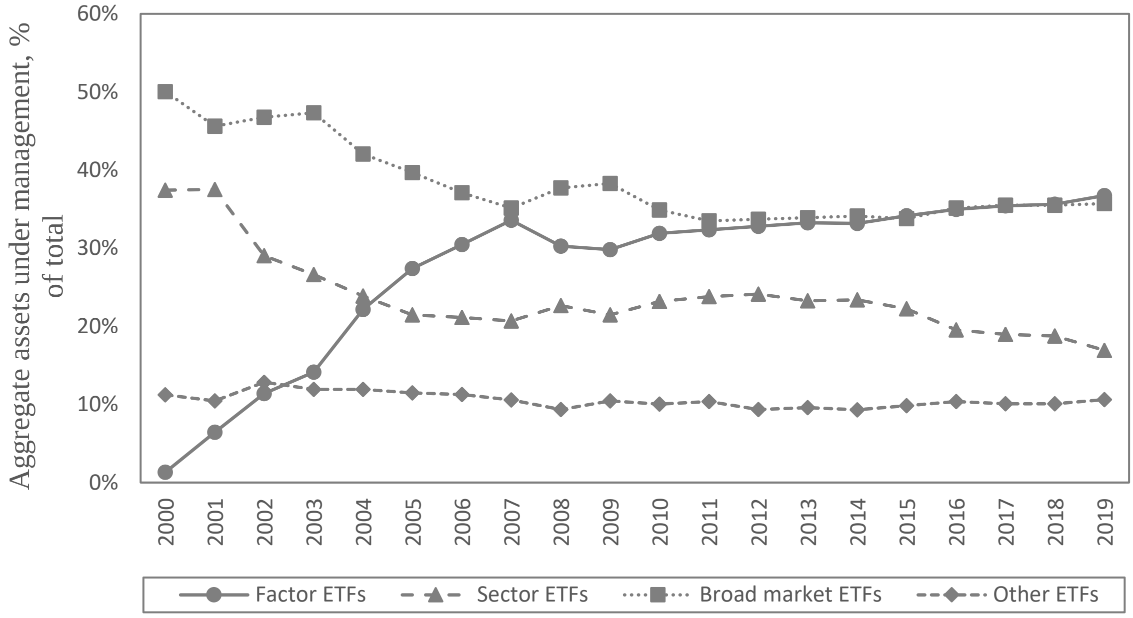
Panel A: US equity funds (AUM, $ billions)



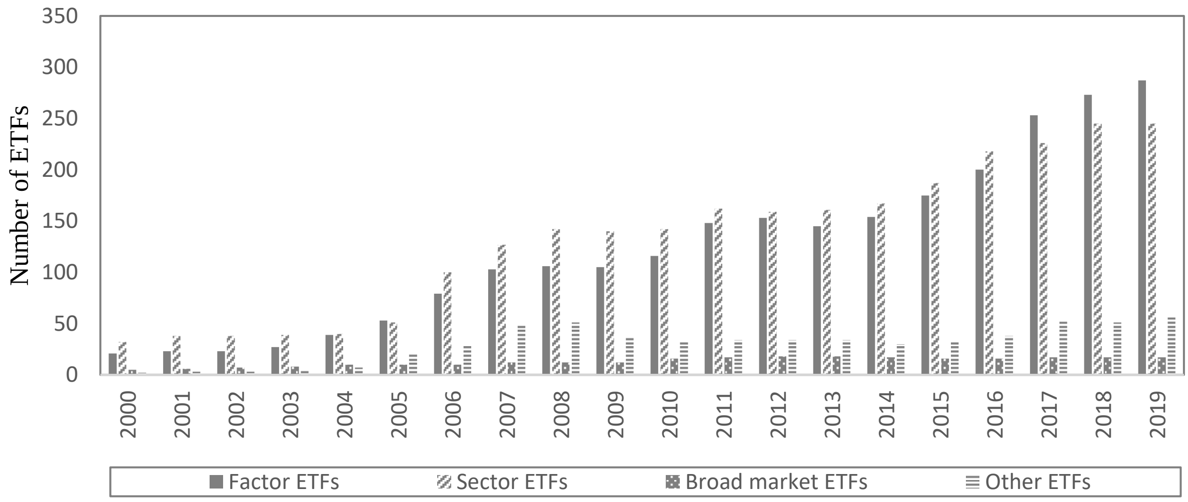
Panel B: US equity funds (AUM, %)

Figure 1: Aggregate assets under management (AUM) of US domestic ETFs, active mutual funds, index mutual funds

This figure shows assets under management of U.S.-domiciled ETFs, actively- and passively-managed mutual funds during the sample period of January 2000 and December 2019. AUM is aggregated for each type of funds. Panel A shows AUM by type of funds measured in billions of US dollars. Panel B shows proportional allocation of assets, measured in percentage.



Panel A: US equity ETFs (AUM, %)



Panel B: US equity ETFs (number of funds)

Figure 2: Proportional allocation of Aggregate assets under management (AUM) of US domestic ETFs by type

This figure shows proportional allocation of assets under management, measured in percentage, of U.S.-domiciled ETFs during the sample period of 2000 and 2019. The sample of funds is divided into factor, industry, broad market and other funds. We classify funds that track broad market indices, including S&P 500, S&P 1500, Russell 1000, Russell 3000, and NYSE/NASDAQ Composite Index as broad market funds. Sector funds are those that have at least 30% of their holdings in the dominant industry according to Fama-French 12 industry classification. Factor funds are those that follow specific factor in their investment strategy. AUM is aggregated for each type of funds. Panel A shows AUM by type of funds measured in billions of US dollars. Panel B shows number of ETFs by category each year.

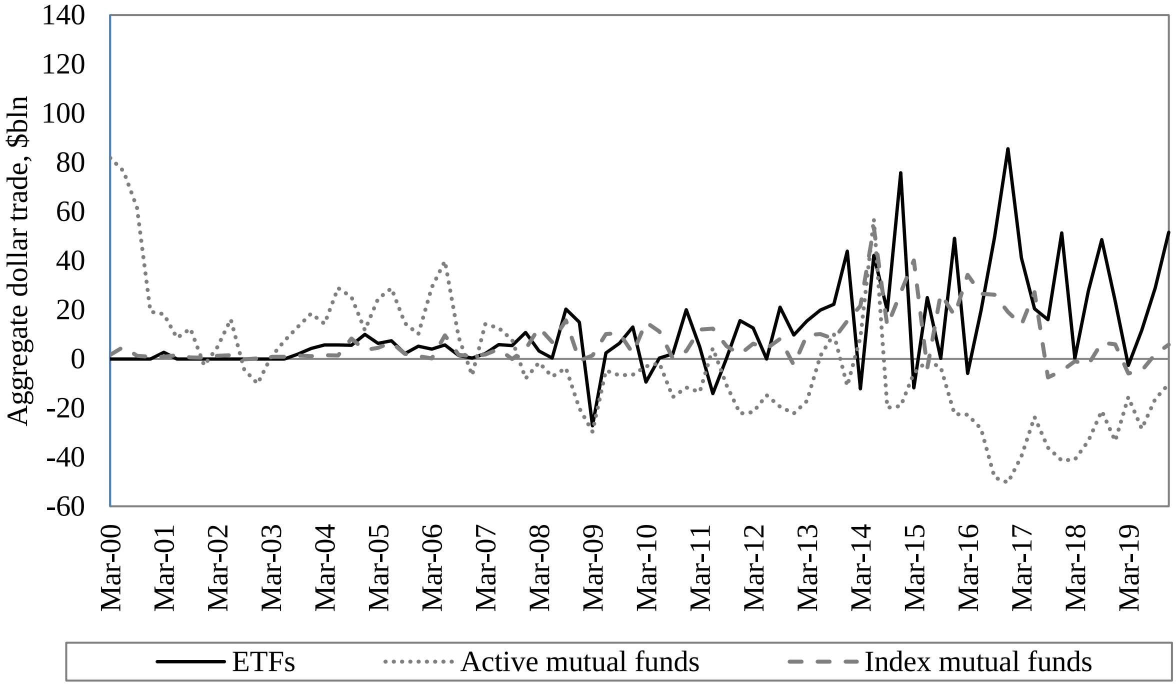


Figure 3: Aggregate dollar trade of US domestic ETFs, active mutual funds, and index mutual funds

This figure shows the aggregate dollar value of trading by U.S.-domiciled ETFs, actively- and passively-managed mutual funds for the sample period of January 2000 and December 2019. Trade value is measured as the quarterly change in fund holdings and aggregated across each fund type.

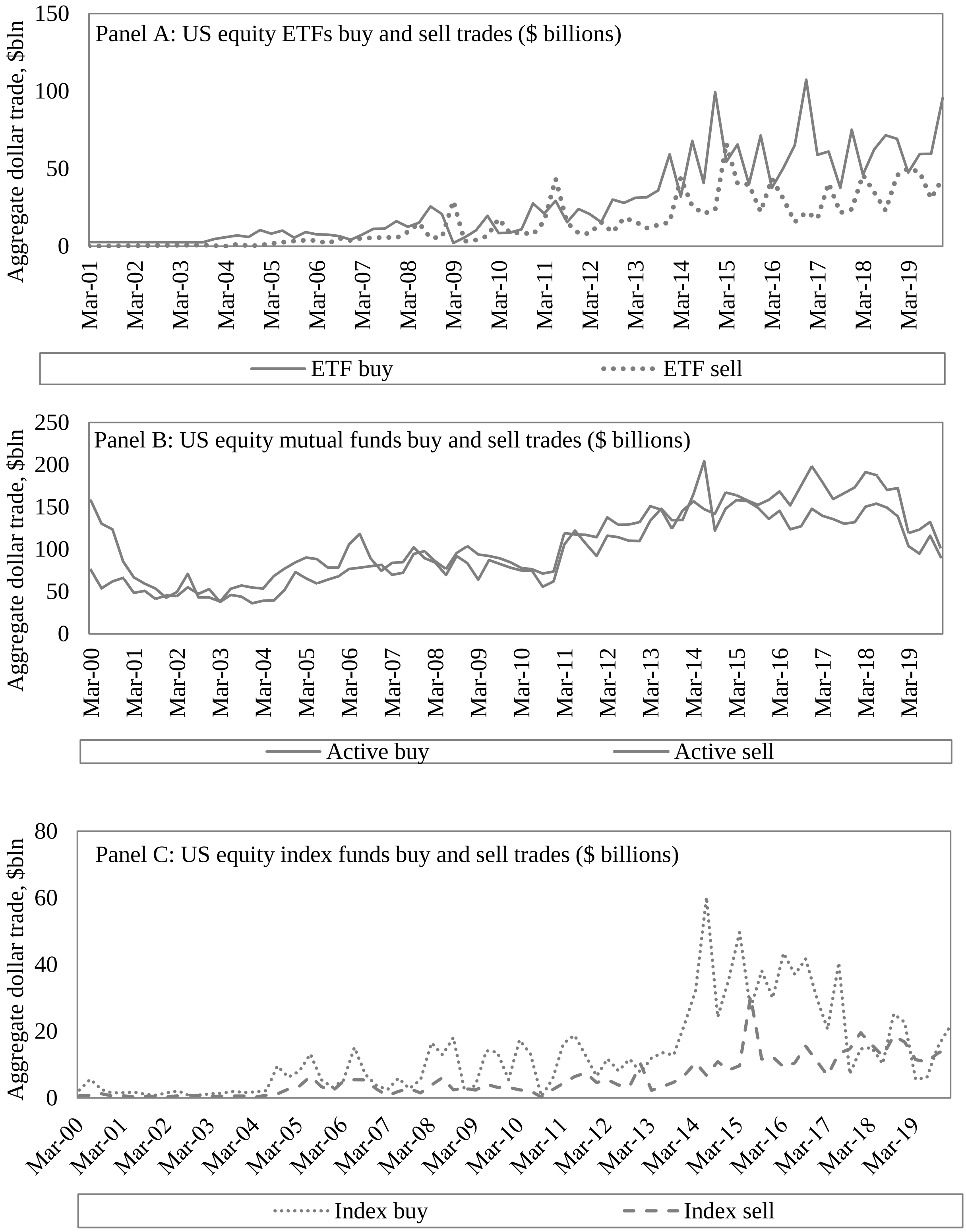


Figure 4: Aggregate dollar buy and sell trades of US domestic ETFs, active mutual funds, and index mutual funds

These figures show the aggregate dollar value of buy and sell trades by US domestic active mutual funds and ETFs for the sample period of January 2000 and December 2019. Buy (sell) trades are measured as the quarterly positive (negative) change in fund holdings and aggregated across each fund type.

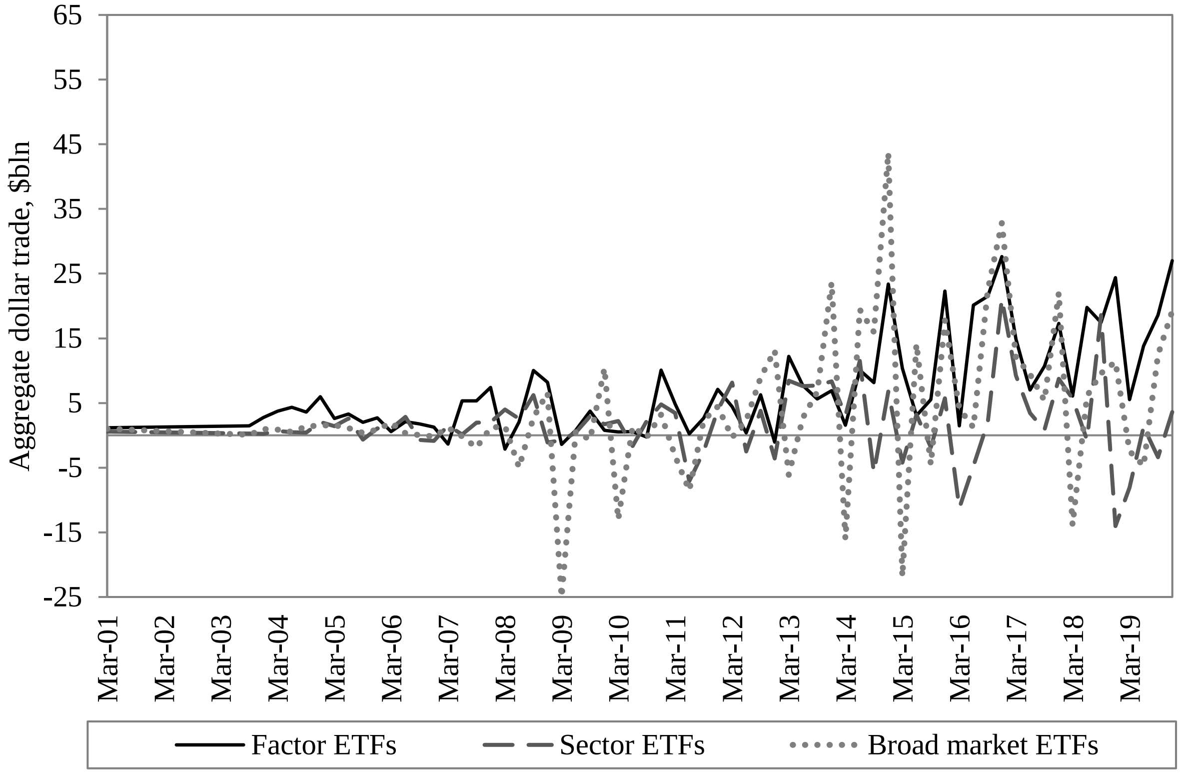


Figure 5: Aggregate dollar trade of US domestic ETFs by type

This figure shows the aggregate dollar value of trading by US domestic ETFs for the sample period of January 2000 and December 2019. ETFs sample is divided into factor, industry and broad market ETFs. We classify ETFs that track broad market indices, including S&P 500, S&P 1500, Russel 1000, Russel 3000, and NYSE/NASDAQ Composite Index as broad market ETFs. Sector ETFs are those that have at least 30% of their holdings in the dominant industry according to Fama-French 12 industry classification. Factor ETFs are those that follow specific factor in their investment strategy. Trade value is measured as the quarterly change in fund holdings and aggregated across each ETF type.

Table 1: Summary Statistics of ETFs

This table presents descriptive statistics of ETFs for the sample period of 2000-2019. Number of ETFs represents the number of US domestic equity ETFs in our sample each year. Number of holdings is the average number of stocks in portfolios of ETFs each year. Average total net assets are presented in billions of dollars and represents the average yearly TNA for three categories of ETFs: broad-market, factor and sector. Statistics are presented for data extracted from CRSP and Morningstar Direct (MS). Sample period for Morningstar data starts from 2002.

					Total net assets ($ bln)					
	Number of ETFs		**Number of holdings**		**Broad-market ETFs**		**Factor ETFs**		**Sector ETFs**	
Year	CRSP	MS	CRSP	MS	CRSP	MS	CRSP	MS	CRSP	MS
2000	60	-	591	-	7.51	-	0.07	-	0.73	-
2001	72	-	577	-	5.70	-	0.23	-	0.74	-
2002	73	44	605	533	6.53	7.33	0.45	0.37	0.64	0.17
2003	79	49	584	638	7.90	10.07	0.64	0.54	0.73	0.27
2004	98	61	606	794	7.10	9.25	0.94	0.94	0.91	0.42
2005	137	90	549	568	8.23	10.35	1.17	1.18	0.92	0.28
2006	226	168	530	466	9.54	10.50	1.09	0.98	0.68	0.18
2007	337	219	332	425	11.43	12.00	1.06	1.05	0.51	0.19
2008	366	243	353	406	12.59	12.8	0.92	0.86	0.50	0.25
2009	351	259	329	413	11.76	11.84	0.85	0.75	0.44	0.27
2010	380	269	373	475	12.33	14.5	1.05	0.86	0.58	0.33
2011	439	332	364	427	12.46	18.01	1.12	1.01	0.70	0.36
2012	440	341	383	435	14.23	21.01	1.2	1.18	0.83	0.41
2013	442	336	402	439	18.78	27.25	1.71	1.53	1.13	0.61
2014	464	346	394	410	24.82	34.33	2.04	1.88	1.35	0.81
2015	517	410	393	418	29.78	38.87	2.14	1.98	1.35	0.87
2016	586	542	358	378	33.80	43.88	2.13	1.83	1.12	0.68
2017	665	629	342	372	46.07	59.54	2.53	2.00	1.32	0.74
2018	715	690	353	386	55.16	70.88	2.54	2.11	1.52	0.8
2019	753	763	354	377	61.86	78.94	2.77	2.44	1.51	0.79

Table 2: Institutional trades and future stock returns

This table reports the results of Fama-MacBeth regressions of next month and next four quarters returns on quarterly trading of ETFs, active and index equity mutual funds. The sample period is from January 2000 to December 2019. $Ret_{i,m+1}$ is next month returns, $Ret_{i,q+1}$, $Ret_{i,q+2}$, $Ret_{i,q+3}$, $Ret_{i,q+4}$ are cumulative returns over the next quarters q+1, q+2, q+3, and q+4 respectively. $ETF_{i,q}$, $ETF_{i,q+1}$, $ETF_{i,q+2}$, and $ETF_{i,q+3}$ are quarterly trading of stocks by ETFs in quarters q, q+1, q+2, q+3 respectively, measured as the number of shares bought minus the number of shares sold during the last quarter, divided by total shares outstanding at current quarter-end. $IndexMF_{i,q}$ and $ActiveMF_{i,q}$ are quarterly trading of stocks by index and active mutual funds, constructed similarly. Control variables include lagged three-months return ($Ret_{i,q-1}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,q-4:q-1}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbf{Ret_{i,m+1}}$	$\mathbf{Ret_{i,q+1}}$	$\mathbf{Ret_{i,q+2}}$	$\mathbf{Ret_{i,q+3}}$	$\mathbf{Ret_{i,q+4}}$
	(1)	(2)	(3)	(4)	(5)
$ETF_{i,q}$	**-1.096*** **	**-1.912*** **	-0.365	-0.469	-0.203
	(-2.84)	**(-2.68)**	(-0.83)	(-0.78)	(-0.48)
$ETF_{i,q+1}$			**-1.632** **	-0.068	-0.147
			(-2.51)	(-0.15)	(-0.30)
$ETF_{i,q+2}$				**-1.395** **	0.266
				(-2.07)	(0.48)
$ETF_{i,q+3}$					-1.248
					(-1.58)
$IndexMF_{i,q}$	1.125	1.431	-0.376	2.847	-0.949
	(0.84)	(0.56)	(-0.21)	(1.41)	(-0.38)
$ActiveMF_{i,q}$	0.041	0.010	0.040	-0.045	0.020
	(1.02)	(0.14)	(0.61)	(-0.56)	(0.23)
$Ret_{i,q-1:q}$	-0.023***	-0.007	0.011	0.001	-0.025**
	(-2.90)	(-0.64)	(1.07)	(0.11)	(-2.43)
$Ret_{i,q-4:q-1}$	-0.007	-0.007	-0.009	-0.015**	-0.010*
	(-1.21)	(-0.70)	(-1.16)	(-2.18)	(-1.77)
$log(SIZE)_{i,q}$	-0.001	-0.006***	-0.004**	-0.004*	-0.003
	(-1.26)	(-2.67)	(-2.29)	(-1.86)	(-1.24)
$turnover_{i,q}$	-0.004	-0.037***	-0.035***	-0.021**	-0.030***
	(-0.40)	(-3.29)	(-3.33)	(-2.05)	(-3.20)
$log(B/M)_{i,q}$	0.003**	0.004	0.002	0.002	0.003
	(1.99)	(1.44)	(0.80)	(0.56)	(1.17)
$inst\_own_{i,q}$	-0.005	0.014	0.021***	0.016**	0.011*
	(-1.07)	(1.37)	(2.69)	(2.35)	(1.67)
$\#analysts_{i,q}$	0.000**	0.001**	0.001*	0.000	0.000
	(2.32)	(2.30)	(1.89)	(1.35)	(0.97)
$idvol_{i,q}$	-0.074	-0.362	-0.124	0.032	0.431
	(-0.68)	(-1.37)	(-0.51)	(0.13)	(1.50)
$Adj\ R^2$	0.061	0.060	0.058	0.058	0.058

Table 3: ETF trades and future stock returns

This table reports the results of Fama-MacBeth regressions of weekly and monthly returns on monthly trading of ETFs. The sample period is from January 2005 to December 2020. $Ret_{i,w}$, $Ret_{i,w+1}$, $Ret_{i,w+2}$ are contemporaneous and next two weeks returns, $Ret_{i,m}$, $Ret_{i,m+1}$, $Ret_{i,m+2}$ are contemporaneous and next months' returns. $ETF_{i,m}$, $ETF_{i,m+1}$, $ETF_{i,m+2}$, are monthly trading of stocks by ETFs in months m, $m+1$, $m+2$ respectively, measured as the number of shares bought minus the number of shares sold during the last month, divided by total shares outstanding at current month-end. Control variables include lagged three-months return ($Ret_{i,m-2:m}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,m-12:m-3}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbf{Ret_{i,w}}$	$\mathbf{Ret_{i,w+1}}$	$\mathbf{Ret_{i,w+2}}$	$\mathbf{Ret_{i,m}}$	$\mathbf{Ret_{i,m+1}}$	$\mathbf{Ret_{i,m+2}}$	$\mathbf{Ret_{i,m+3}}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ETF_{i,m}$	-0.151	**-0.851*** **	-0.231	**2.188*** **	**-1.353*** **	-0.238	0.590
	(-0.63)	**(-4.85)**	(-1.01)	**(4.68)**	**(-4.02)**	(-0.47)	(1.57)
$ETF_{i,m+1}$						-1.369**	-0.621
						(-2.64)	(-0.74)
$ETF_{i,m+2}$							-1.013*
							(-1.80)
Controls $_{i,m}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.057	0.044	0.039	0.090	0.041	0.041	0.039

Table 4: Non-Flow Induced ETF trades and future stock returns

This table reports the results of Fama-MacBeth regressions of weekly and monthly returns on monthly non-flow induced trading of ETFs. The sample period is from January 2005 to December 2020. $Ret_{i,w}$, $Ret_{i,w+1}$, $Ret_{i,w+2}$ are contemporaneous and next two weeks returns, $Ret_{i,m}$, $Ret_{i,m+1}$, $Ret_{i,m+2}$ are contemporaneous and next months' returns. $NonFIT_{i,m}$ is monthly non-flow induced trading of stocks by ETFs in month *m*, measured as the difference between monthly ETF trades and flow-induced trades (FIT). We control for $FIT_{i,m}$, which is stock-level monthly flow-induced trades. Other control variables include lagged three-months return ($Ret_{i,m-2:m}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,m-12:m-3}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	$Ret_{i,m}$	$Ret_{i,w}$	$Ret_{i,w+1}$	$Ret_{i,w+2}$	$Ret_{i,m+1}$	$Ret_{i,m+2}$
	(1)	(2)	(3)	(4)	(5)	(6)
$NonFIT_{i,m}$	**1.571*** **	0.356	**-0.927*** **	**-0.542*** **	**-1.630*** **	-0.471
	(3.42)	(1.59)	**(-4.92)**	**(-3.22)**	**(-4.13)**	(-1.55)
$FIT_{i,m}$	5.772***	-0.707	-0.975*	-0.581	-2.398**	-1.026
	(5.10)	(-1.13)	(-1.67)	(-0.97)	(-2.42)	(-1.03)
$Controls_{i,m}$	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.092	0.060	0.045	0.041	0.043	0.037

Table 5: Subsample analysis: stocks illiquidity

This table reports the results of Fama-MacBeth regressions of next month and next week returns on monthly trading of ETFs, nonfit and FIT. The sample period is from January 2005 to December 2020. Stocks in the sample are divided into three subsamples based on their illiquidity. We use Amihud illiquidity ratio 20th and 80th percentiles as breakpoints. Panel A reports results for ETF trading activity, Panel B reports results for regression on ETF non-FIT and FIT. $Ret_{i,w+1}$ is next week returns, $Ret_{i,m}$, $Ret_{i,m+1}$ are contemporaneous and next months' returns. $ETF_{i,m}$, is monthly trading of stocks by ETFs in months m, measured as the number of shares bought minus the number of shares sold during the last month, divided by total shares outstanding at current month-end. Control variables include lagged three-months return ($Ret_{i,m-2:m}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,m-12:m-3}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. $*$,$**$, $***$ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: ETF trade

	$Ret_{i,m}$			$Ret_{i,w+1}$			$Ret_{i,m+1}$		
	Illiquid	**Medium**	**Liquid**	**Illiquid**	**Medium**	**Liquid**	**Illiquid**	**Medium**	**Liquid**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ETF_{i,m}$	**3.989***	**1.496*****	1.525***	**-3.201*****	**-0.579****	-1.110***	**-6.988*****	**-1.083*****	-0.411
	(1.81)	**(2.82)**	(2.77)	**(-3.21)**	**(-2.04)**	(-4.60)	**(-2.87)**	**(-2.98)**	(-1.08)
$Controls_{i,m}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.159	0.092	0.122	0.034	0.05	0.106	0.035	0.046	0.096

Panel B: ETF non-FIT and FIT

	$Ret_{i,m}$			$Ret_{i,w+1}$			$Ret_{i,m+1}$		
	Illiquid	**Medium**	**Liquid**	**Illiquid**	**Medium**	**Liquid**	**Illiquid**	**Medium**	**Liquid**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$NonFIT_{i,m}$	0.716	1.325	0.985*	**-3.001*****	**-0.857*****	-1.017***	**-6.446****	**-1.498*****	-0.576
	(0.30)	(1.47)	(1.71)	**(-3.07)**	**(-2.95)**	(-3.80)	**(-2.47)**	**(-2.81)**	(-1.49)
$FIT_{i,m}$	8.302	4.416***	10.044***	-3.680	-0.668	-1.836**	-18.181	-1.992**	-0.634
	(0.82)	(3.67)	(5.47)	(-0.97)	(-0.99)	(-2.22)	(-1.06)	(-2.11)	(-0.42)
$Controls_{i,m}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.164	0.093	0.133	0.035	0.052	0.112	0.039	0.048	0.102

Table 6: Betting against ETFs trading strategy

This table reports the equal-weighted monthly returns for Long, Short, and Long-Short portfolios sorted on ETF trading activity. In Panel A, at the end of each month, all stocks are sorted into quintiles based on their ETF trades, in Panel B stocks are sorted based on ETFs nonFIT. Panels A.1 and B.1 present portfolios raw returns, Panels A.2 and B.2 contain DGTW adjusted returns, and Panels A.3 and B.3 include DGTW + Illiquidity adjusted returns for portfolios sorted based on monthly ETF trading or nonfit respectively using Morningstar data and 1 month holding period. Columns (2) and (5) report results for factor ETFs, (3) and (6) for sector ETFs, and (4) and (8) for broad market ETFs. The long (short) portfolio contains stocks with the lowest (highest) ETF trading or nonFIT activities. Long-Short portfolio is formed by taking a long position in the stocks with the lowest ETF trading (nonFIT) activities and taking a short position in the stocks with the highest ETF trading (nonFIT) activities. Results are presented for the whole sample period (2005-2020) and for second half of the sample (2010-2020).

Panel A: Trade

Panel A.1: Raw returns

	2005-2020				**2010-2020**			
	All	**Factor**	**Sector**	**Mkt**	**All**	**Factor**	**Sector**	**Mkt**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long	1.242	1.104	0.998	1.109	1.453	1.360	1.206	1.442
	(2.68)	(2.36)	(2.17)	(2.48)	(2.66)	(2.52)	(2.3)	(2.79)
Short	0.836	0.834	0.884	0.967	0.881	0.950	1.207	0.990
	(1.71)	(1.75)	(1.83)	(2.15)	(1.58)	(1.8)	(2.09)	(1.94)
Long-Short	**0.406****	**0.271***	0.114	0.142	**0.572*****	**0.410****	-0.001	**0.452****
	(2.26)	**(1.66)**	(0.66)	(0.87)	**(3.33)**	**(2.47)**	(-0.01)	**(2.50)**

Panel A.2: DGTW adjusted returns

	2005-2020				**2010-2020**			
	All	**Factor**	**Sector**	**Mkt**	**All**	**Factor**	**Sector**	**Mkt**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long	0.302	0.120	0.026	0.202	0.252	0.112	-0.007	0.165
	(2.91)	(1.69)	(0.24)	(1.59)	(2.65)	(1.54)	(-0.07)	(1.32)
Short	-0.109	-0.042	-0.064	-0.056	-0.259	-0.132	-0.029	-0.219
	(-1.36)	(-0.49)	(-0.62)	(-0.74)	(-3.44)	(-1.81)	(-0.26)	(-2.76)
Long-Short	**0.411*****	0.162	0.090	**0.258****	**0.511*****	**0.245****	0.023	**0.384*****
	(3.06)	(1.40)	(0.61)	**(1.97)**	**(4.18)**	**(2.43)**	(0.15)	**(2.76)**

Panel A.3: DGTW + Illiquidity adjusted returns

	2005-2020				**2010-2020**			
	All	**Factor**	**Sector**	**Mkt**	**All**	**Factor**	**Sector**	**Mkt**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long	0.238	0.090	0.039	0.130	0.190	0.084	-0.009	0.093
	(2.71)	(1.28)	(0.35)	(1.33)	(2.06)	(1.17)	(-0.08)	(0.83)
Short	-0.134	-0.056	-0.103	-0.108	-0.262	-0.126	-0.075	-0.305
	(-1.61)	(-0.63)	(-0.93)	(-1.36)	(-2.91)	(-1.43)	(-0.61)	(-3.56)
Long-Short	**0.372*****	0.146	0.141	**0.238****	**0.452*****	**0.210****	0.067	**0.398*****
	(3.08)	(1.21)	(0.92)	**(2.20)**	**(3.66)**	**(1.84)**	(0.42)	**(3.11)**

Panel B: nonFIT

Panel B.1: Raw returns

	2005-2020				2010-2020			
	All	**Factor**	**Sector**	**Mkt**	**All**	**Factor**	**Sector**	**Mkt**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long	1.124**	1.109**	1.066**	1.103**	1.353**	1.311**	1.291**	1.375**
	(2.48)	(2.48)	(2.35)	(2.42)	(2.57)	(2.52)	(2.46)	(2.52)
Short	0.744	0.793	0.786	0.927**	0.885	0.969*	1.099*	0.978*
	(1.49)	(1.60)	(1.60)	(1.98)	(1.54)	(1.77)	(1.89)	(1.80)
Long-Short	**0.379*** **	**0.316** **	**0.280***	0.176	**0.468*** **	**0.343** **	0.192	**0.397** **
	(2.84)	**(2.04)**	**(1.79)**	(1.25)	**(3.02)**	**(2.16)**	(1.06)	**(2.37)**

Panel B.2: DGTW adjusted returns

	2005-2020				2010-2020			
	All	**Factor**	**Sector**	**Mkt**	**All**	**Factor**	**Sector**	**Mkt**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long	0.204***	0.149**	0.082	0.217**	0.147**	0.100	0.041	0.113
	(2.80)	(2.20)	(0.82)	(2.15)	(2.03)	(1.48)	(0.43)	(1.20)
Short	-0.182**	-0.052	-0.147	-0.071	-0.278***	-0.121	-0.156	-0.189**
	(-2.28)	(-0.58)	(-1.49)	(-1.00)	(-3.65)	(-1.47)	(-1.46)	(-2.40)
Long-Short	**0.386*** **	0.201	**0.229***	**0.287*** **	**0.425*** **	**0.221** **	0.197	**0.301*** **
	(3.51)	(1.63)	**(1.90)**	**(2.80)**	**(4.09)**	**(2.03)**	(1.49)	**(2.73)**

Panel B.3: DGTW + Illiquidity adjusted returns

	2005-2020				2010-2020			
	All	**Factor**	**Sector**	**Mkt**	**All**	**Factor**	**Sector**	**Mkt**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Long	0.156**	0.136**	0.080	0.143*	0.102	0.085	0.036	0.063
	(2.25)	(1.99)	(0.75)	(1.71)	(1.37)	(1.22)	(0.34)	(0.65)
Short	-0.199**	-0.059	-0.168	-0.114	-0.291***	-0.119	-0.183	-0.227***
	(-2.39)	(-0.66)	(-1.57)	(-1.60)	(-3.16)	(-1.26)	(-1.58)	(-2.62)
Long-Short	**0.355*** **	0.195	**0.248***	**0.258*** **	**0.393*** **	**0.204***	0.220	**0.290*** **
	(3.43)	(1.63)	**(1.90)**	**(2.94)**	**(3.48)**	**(1.71)**	(1.57)	**(2.66)**

Table 7: ETF trades and future stock returns: ETFs classified by investment type

This table reports the results of Fama-MacBeth regressions of ETF trades and stock returns. Panel A reports results for next month and next four quarters returns on quarterly trading of different types of ETFs, active and index equity mutual funds. Panel B presents regression results of weekly and monthly stock returns on monthly trading of ETFs. The sample period is from January 2000 to December 2019 for quarterly results and 2005-2020 for monthly results. $Ret_{i,w}$, $Ret_{i,w+1}$ are contemporaneous and next week returns, $Ret_{i,m}$, $Ret_{i,m+1}$, $Ret_{i,m+2}$ are contemporaneous and next months' returns, $Ret_{i,q+1}$, $Ret_{i,q+2}$, $Ret_{i,q+3}$, $Ret_{i,q+4}$ are cumulative returns over the next quarters q+1, q+2, q+3, and q+4 respectively. Trading activity is measured as the number of shares bought minus the number of shares sold during the last quarter, divided by total shares outstanding at current quarter-end. ETF sample is divided into 4 categories. Broad market ETFs are those that track broad market indices, including S&P 500, S&P 1500, Russel 1000, Russel 3000, and NYSE/NASDAQ Composite Index. In Panel A, Sector ETFs include ETFs with more than 30% of holdings in one of the 12 industries defined by Fama and French; in Panel B Sector ETFs include ETFs with "Sector Equity" Morningstar Category. In Panel A, Factor ETFs include ETFs that trade according to one of the pricing factors; in Panel B Factor ETFs are defined by Morningstar Strategic Beta group. The rest of the ETFs included in others sample. $ETF_{i,q+1}$, $ETF_{i,q+2}$, and $ETF_{i,q+3}$ are quarterly trading of stocks by ETFs in quarters q, q+1, q+2, q+3 respectively. $IndexMF_{i,q}$ and $ActiveMF_{i,q}$ are quarterly trading of stocks by index and active mutual funds, constructed similarly. Control variables include lagged three-months return ($Ret_{i,q-1}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,q-4:q-1}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. *,**, *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Quarterly ETF trades

	$\mathbf{Ret_{i,m+1}}$	$\mathbf{Ret_{i,q+1}}$	$\mathbf{Ret_{i,q+2}}$	$\mathbf{Ret_{i,q+3}}$	$\mathbf{Ret_{i,q+4}}$
	(1)	(2)	(3)	(4)	(5)
FactorETF $_{i,q}$	**-1.230*****	**-1.803****	0.256	0.094	0.070
	(-2.68)	**(-2.12)**	(0.30)	(0.09)	(0.12)
SectorETF $_{i,q}$	-1.841*	0.968	-5.193	6.933	-0.789
	(-1.77)	(0.24)	(-0.86)	(0.82)	(-1.10)
MktETF $_{i,q}$	10.630*	2.712	15.501	-12.168	0.226
	(1.81)	(0.24)	(0.91)	(-0.80)	(0.02)
OtherETF $_{i,q}$	-1.003	-0.158	-9.084	-0.728	1.874
	(-0.46)	(-0.03)	(-1.08)	(-0.23)	(0.38)
ETF $_{i,q+1}$			**-1.554****	-0.380	0.451
			(-2.57)	(-0.60)	(0.59)
ETF $_{i,q+2}$				**-1.352****	-0.043
				(-2.22)	(-0.08)
ETF $_{i,q+3}$					-0.841
					(-1.20)
IndexMF $_{i,q}$	0.713	1.402	-1.028	3.564	-0.842
	(0.42)	(0.51)	(-0.50)	(1.43)	(-0.28)
ActiveMF $_{i,q}$	0.035	0.007	0.057	-0.070	0.012
	(0.84)	(0.09)	(0.80)	(-0.83)	(0.14)
Controls $_{i,q}$	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.061	0.056	0.054	0.053	0.053

Panel B: Monthly ETF trades

	Ret$_{i,w}$	**Ret$_{i,w+1}$**	**Ret$_{i,w+2}$**	**Ret$_{i,m}$**	**Ret$_{i,m+1}$**	**Ret$_{i,m+2}$**	**Ret$_{i,m+3}$**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FactorETF $_{i,m}$	-0.155	**-0.938*** **	-0.450	**3.018*** **	**-1.473** **	-1.510	-0.314
	(-0.45)	**(-3.07)**	(-1.27)	**(3.34)**	**(-2.39)**	(-1.62)	(-0.42)
SectorETF $_{i,m}$	1.253	-2.173	-1.298	6.336	0.317	-4.498	-2.523
	(0.89)	(-0.83)	(-0.82)	(1.25)	(0.07)	(-0.94)	(-0.73)
MktETF $_{i,m}$	-3.769	-0.376	-2.650**	-1.072	-3.294	0.298	0.832
	(-1.46)	(-0.28)	(-2.08)	(-0.19)	(-1.65)	(0.08)	(0.11)
OtherETF $_{i,m}$	-0.423	-0.565	0.315	1.977	-0.152	1.089	1.855
	(-0.77)	(-0.88)	(0.48)	(1.61)	(-0.14)	(0.75)	(1.32)
ETF $_{i,m+1}$						-1.266**	-0.639
						(-2.34)	(-0.92)
ETF $_{i,m+2}$							-1.046**
							(-2.07)
Controls $_{i,m}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.059	0.046	0.042	0.95	0.044	0.045	0.045

Table 8: Long/Short-type Factor ETF trades and future stock returns

This table reports the results of Fama-MacBeth regressions of next month and next four quarters returns on quarterly trading of different types of ETFs, active and index equity mutual funds. The sample period is from January 2000 to December 2019 $Ret_{i,m+1}$ is next month returns, $Ret_{i,q+1}$, $Ret_{i,q+2}$, $Ret_{i,q+3}$, $Ret_{i,q+4}$ are cumulative returns over the next quarters q+1, q+2, q+3, and q+4 respectively. Trading activity is measured as the number of shares bought minus the number of shares sold during the last quarter, divided by total shares outstanding at current quarter-end. ETF sample is divided into 4 categories. Broad market ETFs are those that track broad market indices, including S&P 500, S&P 1500, Russel 1000, Russel 3000, and NYSE/NASDAQ Composite Index. Sector ETFs include ETFs with more than 30% of holdings in one of the 12 industries defined by Fama and French. Factor ETFs are divided into long and short categories, where long (short) factor ETFs are those that invest in the long (short) leg of the corresponding factor. The rest of the ETFs included in others sample. $ETF_{i,q+1}$, $ETF_{i,q+2}$, and $ETF_{i,q+3}$ are quarterly trading of stocks by ETFs in quarters q, q+1, q+2, q+3 respectively. Control variables include lagged three-months return ($Ret_{i,q-1}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,q-4:q-1}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbf{Ret_{i,m+1}}$	$\mathbf{Ret_{i,q+1}}$	$\mathbf{Ret_{i,q+2}}$	$\mathbf{Ret_{i,q+3}}$	$\mathbf{Ret_{i,q+4}}$
	(1)	(2)	(3)	(4)	(5)
LongETF $_{i,q}$	**-1.557*** **	**-2.061** **	-0.236	-0.255	0.165
	(-2.80)	**(-2.01)**	(-0.25)	(-0.20)	(0.21)
ShortETF $_{i,q}$	0.698	-2.393	3.389*	-0.525	-0.791
	(0.63)	(-0.52)	(1.86)	(-0.29)	(-0.48)
SectorETF $_{i,q}$	-1.975*	-0.380	-5.121	6.606	-1.059
	(-1.75)	(-0.13)	(-0.86)	(0.81)	(-1.40)
MktETF $_{i,q}$	10.241*	1.419	13.920	-12.849	-0.371
	(1.77)	(0.13)	(0.82)	(-0.84)	(-0.04)
OtherETF $_{i,q}$	-1.544	-2.502	-9.772	-1.274	1.603
	(-0.65)	(-0.57)	(-1.18)	(-0.39)	(0.32)
ETF $_{i,q+1}$			**-1.539** **	-0.434	0.448
			(-2.56)	(-0.69)	(0.59)
ETF $_{i,q+2}$				**-1.286** **	-0.082
				(-2.11)	(-0.15)
ETF $_{i,q+3}$					-0.831
					(-1.17)
IndexMF $_{i,q}$	0.588	1.925	-1.142	3.657	-0.359
	(0.35)	(0.70)	(-0.55)	(1.48)	(-0.12)
ActiveMF $_{i,q}$	0.035	0.010	0.051	-0.067	0.010
	(0.86)	(0.14)	(0.71)	(-0.78)	(0.12)
Controls $_{i,q}$	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.062	0.057	0.054	0.053	0.053

Table 9: ETF factor trades and factor returns

This table reports the results of panel regressions of factor returns in month *m* , last week *w* of the current month *m*, and first week *w*+1 following month *m* on contemporaneous and lagged factor trades. Columns (1) - (3) present results of regression of the value factor returns and Columns (4) – (6) are estimated regression of size factor returns. $FactorETF_{i,m}$, $FactorETF_{i,m-1}$, $FactorETF_{i,m-2}$ are monthly trading of stocks by factor ETFs in months *m*, *m*-1, *m*-2 respectively, measured as the number of shares bought minus the number of shares sold during the last month, divided by total shares outstanding at current month-end. We control for the 8 lags of the respective factor returns, in columns (1) and (4) controls include monthly factor returns (*t*=*m*), in columns (2), (3), (5), and (6) controls include weekly factor returns (*t*=*w*). The sample period is from January 2002 to December 2020.

	Value factor			Size factor		
	$HML_{i,m}$	$HML_{i,w}$	$HML_{i,w+1}$	$SMB_{i,m}$	$SMB_{i,w}$	$SMB_{i,w+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$FactorETF_{i,m}$	9.270	**8.607**	-1.975	**19.048**	2.033	**-7.098**
	(1.34)	**(2.40)**	(-0.47)	**(3.20)**	(0.75)	**(-2.27)**
$FactorETF_{i,m-1}$	-3.202	-0.616	-0.030	**-11.120**	-3.934	0.330
	(-0.44)	(-0.17)	(-0.01)	**(-1.83)**	(-1.52)	(0.11)
$FactorETF_{i,m-2}$	-2.039	-5.899	-5.144	-7.069	-2.640	-2.036
	(-0.28)	(-1.64)	(-1.3)	(-1.16)	(-1.04)	(-0.7)
$factor_{i,t}$			0.179			-0.021
			(2.2)			(-0.27)
$factor_{i,t-1}$	0.187	-0.245	0.084	-0.106	-0.150	0.037
	(2.65)	(-3.92)	(1.11)	(-1.44)	(-2.13)	(0.45)
$factor_{i,t-2}$	0.018	-0.056	0.096	0.071	0.069	0.056
	(0.25)	(-1.01)	(1.47)	(0.93)	(1.17)	(0.83)
$factor_{i,t-3}$	0.019	-0.205	-0.001	0.046	-0.166	-0.034
	(0.26)	(-3.63)	(-0.02)	(0.62)	(-2.53)	(-0.45)
$factor_{i,t-4}$	-0.033	0.123	0.150	-0.067	-0.072	0.014
	(-0.47)	(1.8)	(1.84)	(-0.95)	(-1.04)	(0.18)
$factor_{i,t-5}$	0.016	0.024	-0.018	0.041	-0.060	-0.030
	(0.22)	(0.36)	(-0.23)	(0.59)	(-0.88)	(-0.38)
$factor_{i,t-6}$	-0.164	-0.036	-0.049	-0.068	-0.002	-0.048
	(-2.35)	(-0.61)	(-0.71)	(-1)	(-0.07)	(-1.34)
$factor_{i,t-7}$	0.086	0.088	0.138	-0.004	-0.015	0.072
	(1.24)	(1.48)	(1.95)	(-0.07)	(-0.25)	(1.02)
R^2	0.081	0.165	0.096	0.087	0.079	0.058

Table 10: ETF trades and future stock returns across different time periods

This table reports the results of Fama-MacBeth regressions of next month and next quarter returns on quarterly trading of ETFs, active and index equity mutual funds. The sample period is divided into three subsamples: from January 2000 to December 2007, from January 2008 to December 2009, and from January 2010 to December 2019. $Ret_{i,m+1}$ is next month returns, $Ret_{i,q+1}$ is cumulative returns over the next quarter q+1. $ETF_{i,q}$ is quarterly trading of stocks by ETFs in quarter q, measured as the number of shares bought minus the number of shares sold during the last quarter, divided by total shares outstanding at current quarter-end. $IndexMF_{i,q}$ and $ActiveMF_{i,q}$ are quarterly trading of stocks by index and active mutual funds, constructed similarly. Control variables include lagged three-months return ($Ret_{i,q-1}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,q-4:q-1}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. $*$,$**$, $***$ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	$Ret_{i,m+1}$			**$Ret_{i,q+1}$**		
	2000-2007	**2008-2009**	**2010-2019**	**2000-2007**	**2008-2009**	**2010-2019**
	(1)	(2)	(3)	(4)	(5)	(6)
$ETF_{i,q}$	-1.051	-2.108	**-0.926*** **	-1.869	**-6.005***	**-1.109***
	(-1.31)	(-1.67)	**(-2.83)**	(-1.47)	**(-2.21)**	**(-1.76)**
$IndexMF_{i,q}$	-1.369	11.408	1.056	-0.965	18.727	-0.146
	(-0.81)	(1.83)	(1.00)	(-0.28)	(1.46)	(-0.06)
$ActiveMF_{i,q}$	0.031	-0.060	0.070	0.082	-0.196	-0.005
	(0.58)	(-0.30)	(1.29)	(0.70)	(-0.66)	(-0.05)
$Controls_{i,q}$	-0.175	0.010	-0.007	-0.695	0.125	-0.185
	(-0.82)	(0.03)	(-0.06)	(-1.39)	(0.12)	(-0.72)
Adj R^2	0.074	0.076	0.048	0.079	0.085	0.038

Internet Appendix

Appendix 1: ETF categories description

We divide the sample of ETFs into three categories: broad-market based ETFs, sector ETFs and factor ETFs.

1. **Broad-market ETFs.** We identify broad market ETFs as those that track broad market indices, S&P 500, S&P 1500, Russell 1000, Russell 3000, and NYSE/NASDAQ Composite Index, and if their name contains words such as "broad market", "composite index", "total market". The final sample includes 21 broad market ETFs.

   Examples of broad-market ETFs:
   - "Vanguard Total Stock Market Index Fund"
   - "iShares Russell 3000 ETF"
   - "Schwab US Broad Market ETF"

2. **Sector ETFs.** We identify sector ETFs following approach used by Huang, O'Hara, and Zhong (2021). We use ETFs holdings information and match holdings with the Fama-French 12 industry classification. Further, ETFs with at least 30% of their holdings in the dominant industry are classified as sector ETFs. We exclude sector ETFs with the names containing words such as "value", "growth, "momentum", "volatility", "dividend", "Russell" to make sure that the primary objective of the ETF is to track specific industry. The final sample includes 317 sector ETFs.

   Examples of sector ETFs:
   - "iShares US Technology ETF"
   - "Focus Morningstar Health Care Index ETF"
   - "VanEck Vectors Energy Income ETF"

   Examples of ETFs that are excluded from sector ETFs category:
   - "Invesco DWA Financial Momentum ETF"
   - "Invesco DWA Energy Momentum ETF"
   - "First Trust NASDAQ Technology Dividend Index Fund"

3. **Factor ETFs.** We categorise ETFs as factor if their main objective is to replicate factor strategy (Easley, Michayluk, O'Hara, and Putnins (2018)). We identify factor ETFs with the names containing "momentum", "value", "growth", "contrarian", "small cap", "large cap", "beta", "volatility" and any other factor characteristic. Our final sample contains 369 factor ETFs.

   Examples of factor ETFs:
   - "JPMorgan US Quality Factor ETF"
   - "WisdomTree US Multifactor Fund"
   - "Vanguard US Value Factor ETF"

Appendix 2: Additional results

Table IA2.1 Institutional trades and weekly stock returns

This table reports the results of Fama-MacBeth regressions of weekly stock returns on quarterly trading of ETFs, active and index equity mutual funds. The sample period is from January 2000 to December 2019. The dependent variable in columns (1) and (2) is cumulative returns of stocks over the week preceding quarter end *q* ($Ret_{i,w}$). The dependent variable in columns (3) and (4) is cumulative returns of stocks over the week following quarter end *q*. $ETF_{i,q}$ *is* quarterly trading of stocks by ETFs in quarter *q*, measured as the number of shares bought minus the number of shares sold during the last quarter, divided by total shares outstanding at current quarter-end. $IndexMF_{i,q}$ and $ActiveMF_{i,q}$ are quarterly trading of stocks by index and active mutual funds, constructed similarly. Control variables include lagged three-months return ($Ret_{i,q\text{-}1}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,q\text{-}4:q\text{-}1}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbf{Ret_{i,w}}$		$\mathbf{Ret_{i,w+1}}$	
	(1)	(2)	(3)	(4)
$ETF_{i,q}$	**0.442*** **	**0.415*** **	**-0.458*** **	**-0.483*** **
	(3.08)	**(2.77)**	**(-3.23)**	**(-3.58)**
$IndexMF_{i,q}$	-2.155*		0.312	
	(-1.79)		(0.52)	
$ActiveMF_{i,q}$	0.216***		0.058***	
	(12.62)		(3.13)	
$Controls_{i,q}$	Yes	Yes	Yes	Yes
$Adj\ R^2$	0.107	0.106	0.073	0.072

Table IA2.2: Subsample analysis: Small and large firms

This table reports the results of Fama-MacBeth regressions of next month and next four quarters returns on quarterly trading of ETFs, active and index equity mutual funds. The sample period is from January 2000 to December 2019. Stocks in the sample are divided into two subsamples based on their size. We use NYSE median as the breakpoint. $Ret_{i,m+1}$ is next month returns, $Ret_{i,q+1}$, $Ret_{i,q+2}$, are cumulative returns over the next quarters q+1 and q+2 respectively. $ETF_{i,q}$, $ETF_{i,q+1}$, are quarterly trading of stocks by ETFs in quarters q and q+1 respectively, measured as the number of shares bought minus the number of shares sold during the last quarter, divided by total shares outstanding at current quarter-end. $IndexMF_{i,q}$ and $ActiveMF_{i,q}$ are quarterly trading of stocks by index and active mutual funds, constructed similarly. Control variables include lagged three-months return ($Ret_{i,q-1}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,q-4:q-1}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbf{Ret_{i,m+1}}$		$\mathbf{Ret_{i,q+1}}$		$\mathbf{Ret_{i,q+2}}$	
	Small stocks	**Large stocks**	**Small stocks**	**Large stocks**	**Small stocks**	**Large stocks**
	(1)	(2)	(3)	(4)	(5)	(6)
$ETF_{i,q}$	**-0.957****	**-1.122***	**-2.526****	**-2.634****	0.220	0.259
	(-2.51)	**(-1.71)**	**(-2.24)**	**(-2.24)**	(0.40)	(0.20)
$ETF_{i,q+1}$					**-2.166****	**-1.445***
					(-2.35)	**(-1.71)**
$IndexMF_{i,q}$	2.647	-0.691	5.238	-0.137	0.254	-0.585
	(0.93)	(-0.55)	(1.25)	(-0.05)	(0.10)	(-0.21)
$ActiveMF_{i,q}$	0.004	0.122**	-0.048	0.118	-0.065	0.147
	(0.09)	(2.27)	(-0.52)	(1.48)	(-0.72)	(1.40)
$Controls_{i,q}$	Yes	Yes	Yes	Yes	Yes	Yes
$Adj\ R^2$	0.056	0.103	0.053	0.106	0.051	0.098

Table IA2.3: Subsample analysis: Value vs growth firms

This table reports the results of Fama-MacBeth regressions of next month and next four quarters returns on quarterly trading of ETFs, active and index equity mutual funds. The sample period is from January 2000 to December 2019. Stocks in the sample are divided into two subsamples based on their B/M ratio. We use median value as a breakpoint. $Ret_{i,m+1}$ is next month returns, $Ret_{i,q+1}$, $Ret_{i,q+2}$, are cumulative returns over the next quarters q+1 and q+2 respectively. $ETF_{i,q}$, $ETF_{i,q+1}$, are quarterly trading of stocks by ETFs in quarters q and q+1 respectively, measured as the number of shares bought minus the number of shares sold during the last quarter, divided by total shares outstanding at current quarter-end. $IndexMF_{i,q}$ and $ActiveMF_{i,q}$ are quarterly trading of stocks by index and active mutual funds, constructed similarly. Control variables include lagged three-months return ($Ret_{i,q-1}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,q-4:q-1}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	$\mathbf{Ret_{i,m+1}}$		$\mathbf{Ret_{i,q+1}}$		$\mathbf{Ret_{i,q+2}}$	
	Low	**High**	**Low**	**High**	**Low**	**High**
	(1)	(2)	(3)	(4)	(5)	(6)
$ETF_{i,q}$	**-0.639****	**-0.948****	**-1.179***	**-1.813****	-0.641	-0.030
	(-2.05)	**(-2.19)**	**(-1.73)**	**(-2.16)**	(-1.26)	(-0.04)
$ETF_{i,q+1}$					-0.828	**-2.047*****
					(-1.20)	**(-2.67)**
$IndexMF_{i,q}$	0.587	1.864	0.649	2.752	3.079	0.335
	(0.43)	(1.07)	(0.32)	(0.99)	(1.26)	(0.10)
$ActiveMF_{i,q}$	0.057	0.005	-0.013	-0.031	0.076	-0.065
	(1.29)	(0.07)	(-0.13)	(-0.26)	(1.02)	(-0.42)
$Controls_{i,q}$	Yes	Yes	Yes	Yes	Yes	Yes
$Adj\ R^2$	0.052	0.060	0.055	0.058	0.050	0.054

Table IA2.4: Subsample analysis: Winner vs loser stocks

This table reports the results of Fama-MacBeth regressions of next month and next four quarters returns on quarterly trading of ETFs, active and index equity mutual funds. The sample period is from January 2000 to December 2019. Stocks in the sample are divided into two subsamples based on their previous 12 months return. $Ret_{i,m+1}$ is next month returns, $Ret_{i,q+1}$, $Ret_{i,q+2}$, are cumulative returns over the next quarters q+1 and q+2 respectively. $ETF_{i,q}$, $ETF_{i,q+1}$, are quarterly trading of stocks by ETFs in quarters q and q+1 respectively, measured as the number of shares bought minus the number of shares sold during the last quarter, divided by total shares outstanding at current quarter-end. $IndexMF_{i,q}$ and $ActiveMF_{i,q}$ are quarterly trading of stocks by index and active mutual funds, constructed similarly. Control variables include lagged three-months return ($Ret_{i,q-1}$), lagged nine-months return preceding the beginning of the quarter ($Ret_{i,q-4:q-1}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and number of analysts. Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentile. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% level, respectively.

	$Ret_{i,m+1}$		**$Ret_{i,q+1}$**		**$Ret_{i,q+2}$**	
	Losers	**Winners**	**Losers**	**Winners**	**Losers**	**Winners**
	(1)	(2)	(3)	(4)	(5)	(6)
$ETF_{i,q}$	**-1.054****	**-0.947****	**-1.688***	**-2.045*****	-0.217	-0.777*
	(-2.35)	**(-2.43)**	**(-1.86)**	**(-2.76)**	(-0.29)	(-1.68)
$ETF_{i,q+1}$					-1.153	**-1.622****
					(-1.63)	**(-2.58)**
$IndexMF_{i,q}$	1.137	-0.676	3.606	-0.928	2.605	-0.579
	(0.52)	(-0.77)	(0.88)	(-0.37)	(0.62)	(-0.28)
$ActiveMF_{i,q}$	-0.011	0.131***	-0.197	0.218*	-0.081	0.155*
	(-0.18)	(3.22)	(-1.58)	(1.97)	(-0.68)	(1.80)
$Controls_{i,q}$	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.054	0.055	0.054	0.058	0.051	0.055