ETF Rebalancing, Hedge Fund Trades, and Capital Market

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Abstract: We study the interaction between ETF rebalancing and hedge fund "front-running" trades and its implications for the capital market. First, we document that ETF rebalancing has a strong negative relation with future stock returns. Second, we observe that hedge funds gradually increase (decrease) their net arbitrage positions before ETF rebalancing. Strikingly, the "front-running" stocks bought by hedge funds significantly outperform stocks not subject to hedge funds front-running by 0.86% (with a *t*-statistic of 3.86) before the month of ETF rebalancing. Our findings raise the question of the potential cost of ETFs rebalancing due to their embedded transparency and predictability, which creates anticipatory arbitrage trading by hedge funds.

EFM classification: 530, 570, 350, 370

Key words: ETF Rebalancing, Hedge Funds, Arbitrage Trades, Stock Returns

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Introduction

"For years during the longest bull market in history, Wall Street banks and hedge funds made big profits by anticipating the moves of stock index mutual funds and exchange traded funds, often held by ordinary Americans. But the March cancellation of scheduled rebalancing by major index providers hit some trader conducting arbitrage trades around them with large losses."

Forbes, "Following the money trail", March 27, 2020

The dramatic change in the exchange trade fund (ETF) market over the past decade has been accompanied by exponential growth in rebalancing activities. In 2020 alone, the rebalancing trades of passive ETFs comprised more than \$1.4 trillion.[1] The gigantic volume can be largely attributed to the rise in nontraditional ETFs characterized by frequent portfolio rebalancing. Recent studies have highlighted both the positive and negative consequences of ETFs on the capital market.[2] Our study contributes a new perspective to this important discussion by focusing on the interaction between ETF rebalancing and arbitrageur trading.

By design, passive ETFs must closely track an underlying index and rebalance their portfolios semi-annually, quarterly, or even monthly following any changes in the index. To minimize tracking errors, ETFs perform their rebalancing trades in bulk.[3] The transparency of ETFs and the predictability of their rebalancing events can attract systematic "front-running" trades by professional arbitragers (i.e., hedge funds [HFs]). The ETF–HF interaction could result in expected and unexpected consequences for the stock market; for example, front-running trades by HFs may drive price pressure on underlying securities prior to ETF rebalancing and may force ETFs to "buy-high and sell-low", thus incurring high costs on ETF investors. The importance of understanding such interaction was under the media's spotlight when S&P Dow Jones decided to postpone its

[1] We calculate aggregate dollar value of rebalancing trades in 2020 in the sample of passive domestic equity US ETFs. We measure rebalancing trades as the difference between total dollar trade and flows.
[2] For example, prior studies document that: 1) ETFs are associated with high volatility (Ben-David, Franzoni, and Moussawi, 2018), return comovement (Da and Shive, 2018), and liquidity risk (Agarwal, Hanouna, Moussawi, and Stahel, 2018) and impose non-fundamental demand shock (Brown, Davies, and Ringgenberg, 2021); 2) ETFs improve liquidity (Saglam, Tuzun, and Wermers, 2019), increase informational efficiency (Glosten, Nallareddy, and Zou, 2020), and benefit real investments (Antoniou, Li, Liu, Subrahmanyam, and Sun, 2020). Earlier studies, such as Wurgler (2010), raise important question of the economic consequences of index-linked investing.
[3] Li (2021) find that ETFs tracking passive indices rebalance at the market close to reduce tracking error with the underlying indices, as indices rebalance at the closing price. Chinco and Fos (2021) show that ETF trading volume mainly comes from rebalancing activity prior to market close.

index rebalancing on March 13, 2020. Forbes reported that "hedge funds that had positioned themselves to expect the rebalances were forced to quickly unwind positions amid increasing volatility, resulting in (huge) losses." [4] Understanding ETF rebalancing interactions with arbitrageurs could have significant implications for systematic risk.

We start by examining how ETF rebalancing affects underlying securities. We find that ETF rebalancing trades have significant and positive relation with contemporaneous stock returns and negative relation with future stock returns. The results remain significant after controlling for ETF flow–induced trades and ETF ownership. Interestingly, stocks with low ETF rebalancing consistently outperform those with high rebalancing by 0.38% per month. Overall, our first-step analyses confirm that ETF rebalancing activities play an important role in explaining future stock return patterns in addition to the previously documented nonfundamental demand shock imposed by ETF flows.[5]

To investigate the economic nature of ETF rebalancing and its implications, we hand-collect a comprehensive sample of ETFs with monthly holdings through Morningstar Direct. We exclude exotic ETFs, such as leveraged and active ETFs. As some types of ETFs might experience more frequent rebalancing due to the nature of their underlying index, we classify our sample into three categories—rules-based, broad-market, and sector ETFs—depending on the indices ETFs follow. Rules-based indices often rebalance to make sure they include stocks that satisfy particular rules or strategies, such as momentum or value. [6] Given the significant size of rules-based ETFs in recent years and their high turnover, we expect their rebalancing activities to have a strong impact on

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[4] During pandemic of 2020, S&P Dow Jones Indices announced a historical postponement of quarterly rebalancing and claimed such action is "to protect investors" and avoid "undesirable 'buy-high and sell-low' scenario." See,e.g www.forbes.com/sites/nathanvardi/2020/03/27/hedge-funds-suffered-losses-as-index-rebalancing-trade-went-awry and www.etfstrategy.com/sp-dji-delays-quarterly-index-rebalance-amid-market-chaos-10339/

[5] Brown, Davies, and Ringgenberg (2021) show that ETF flows impose non-fundamental demand shock on underlying securities. Zou (2019) finds that ETF flows are negatively associated with subsequent firm operating performance, sales growth, and stock returns. Dannhauser and Pontiff (2019) show the positive correlations between aggregate ETF flows and market returns followed by significant reversal. Staer (2017) documents price pressure and reversal patterns in ETF flow-return relation. Ben-David, Franzoni, and Moussawi (2018) find that ETF flows predict price reversal of underlying stocks' within 40 days period.

[6] Rules-based ETFs perform their portfolio rebalancing on semi-annual, quarterly, or even monthly basis (Easley, Michayluk, O'Hara, and Putnins, 2021).

underlying stocks. Indeed, rules-based ETFs' turnover is, on average, 54% compared with 7% for broad-market ETFs during our sample period from 2005 to 2020.[7] We find that the negative relation between rebalancing and future returns is more pronounced for rules-based ETFs but remains statistically significant for broad-market ETFs.[8] The result is economically meaningful, as despite the lower number of inclusion or exclusion events for broad-market indices, the aggregate assets under management (hereafter, AUM) of broad-market indices is still the largest; hence, bulk trading during rebalancing events can lead to significant price movements.[9]

Our analyses of the interaction between ETF rebalancing and arbitrageur trading revealed several novel findings. First, we document that HFs gradually increase (decrease) their positions in stocks to be included (excluded) in (from) the ETF portfolio, which confirms popular reports by major financial media: professional arbitragers are making profits at the cost of ordinary ETF investors around ETF rebalancing events. Second, stocks that are subject to arbitrage trading by HFs significantly outperform stocks that are not front-run by HFs by 0.86% per month before the ETF rebalancing event. This finding implies that HFs' arbitrage trades may largely move stock prices before ETF rebalancing. As a result, ordinary ETF investors may suffer from the "buy-high and sell-low" effects more severely in the presence of HF arbitrageurs. Further, the outperformance remains significant at 0.75% during the ETF rebalancing month. Our analyses indicate that HFs may not necessarily close their arbitrage positions immediately after ETF rebalancing, and some may choose to ride on the wave and close their positions gradually.

Since ETFs and index mutual funds (IMFs) track indices, and their rebalancing events may be front-run by arbitrageurs, we assess stocks subject to rebalancing activities by both ETFs and IMFs. We may expect a larger volume of front-running trades in stocks that are part of the rebalancing portfolios of IMFs and ETFs, as these are stocks that might experience more significant

[7] See Table IA.2 in Appendix
[8] We do not find a significant relation between sector ETF rebalancing trades and stock returns, which might be due to the smaller total AUM of sector ETFs in line with lower frequency of reconstitution of sector indices.
[9] Chen, Noronha, and Singal (2004) show that there is a permanent increase in the price of firms added to S&P500 index but no permanent decline for excluded firms. Petajisto (2011) argue that price effect from addition and deletions to S&P500 and Russell 2000 indices reverses over the following two months.

price pressure, and arbitrage traders may want to benefit from expected price movements. Indeed, we document net arbitrage trades (NAT) by HFs in the stocks that are rebalanced in both ETFs and IMFs to be twice the size of the corresponding trade amount in stocks that are rebalanced in ETFs alone.

The difference between ETFs and IMFs lies in the fact that ETFs do not have the managerial discretion to execute rebalancing before or after the actual dates of index rebalancing, while IMFs can choose to avoid delegation costs and rebalance at a more convenient date.[10] Due to the flexibility of IMFs to decide when to rebalance, we may expect less decrease in returns following index reconstitution months in stocks subject to IMF rebalancing. We find that the stocks rebalanced by ETFs alone and front-run by HFs significantly underperform stocks with IMFs rebalancing by 1.05% with a *t*-statistic of 2.66 in the month following reconstitution events. This finding may be due to the flexibility of IMFs in strategically choosing rebalancing dates and spreading their trades to the following months, which in turn may reduce potential negative effects on future stock returns.

Our paper contributes to three strands of the literature. First, we add a new layer of research regarding ETF impacts on the capital market. Previous research documents that high ETF ownership is associated with high stock volatility (Ben-David, Franzoni, and Moussawi, 2018), and ETF arbitrage activity contributes to return comovement (Da and Shive, 2018). Few studies are dedicated to exploring the impact of ETFs on liquidity, where stocks with higher ETF ownership exhibit greater commonality in liquidity, reducing investor's ability to diversify liquidity risk (Agarwal, Hanouna, Moussawi, and Stahel, 2018), while another study shows that ETFs improve liquidity of the underlying securities (Saglam, Tuzun, and Wermers, 2019). Glosten, Nallareddy, and Zou (2020) and Antoniou, Li, Liu, Subrahmanyam, and Sun (2020) argue that ETFs help in

[10]Blume and Edelen (2003) show that less than half of index funds follow an exact-replications strategy in order to reduce delegation costs. The strategy of trading according to the index reconstitution at the announcement rather than at the actual change generates 19.2 bps additional return per year but results in substantial tracking errors. Therefore, some index mutual funds choose to forgo tracking error and trade before the index change for additional returns.

the timely incorporation of information into stock prices and improve market efficiency by providing liquidity. Several studies have explored the impact of ETF flows and documented the nonfundamental demand shock imposed by ETF flows on underlying securities (Brown, Davies, and Ringgenberg, 2021; Dannhauser and Pontiff, 2019; Zou, 2019). We contribute to this debate by examining the role of arbitrage traders in ETF rebalancing events and their impact on stock returns and capital markets. We show that ETF rebalancing may attract HF front-running trades that exacerbate the price impact on underlying securities, implying further costs for ETF investors.

Second, our research sheds new light on the central discussion of the equilibrium of passive and active investing. Pedersen (2018) challenges Sharpe's (1991) zero-sum game equality, in which the underlying assumption is that passive investors hold their portfolios throughout the whole period without changing them.[11] Pedersen (2018) discusses the dissonance of Sharpe's (1991) assumption with the real world, where passive investors have to rebalance their portfolios following index reconstitutions, share repurchases, and initial public offerings (IPOs), which implies costs on passive investors and lets active managers collect positive returns. In the same fashion, Berk and van Binsbergen (2015) highlight that the existing discussion ignores the transaction costs associated with passive investing. Passive ETFs track an underlying index directly and rebalance their portfolios in bulk following changes in the underlying index, which in turn imposes high transaction costs. Li (2021) uses transaction-level data and highlights significant transaction costs associated with ETF rebalancing trades. Our paper introduces a different perspective and highlights the embedded "buy-high and sell-low" costs of rebalancing brought about by arbitrage traders, which may affect the balance between active and passive investing.

Third, our study corresponds and communicates with recent discussions on the asset pricing implications of index-linked trading. Wurgler (2010) suggests that index-linked trading may have significant negative consequences and distort stock prices. In a recent study, Jiang, Vayanos, and Zheng (2020) empirically show that inflows into index-linked investing affects prices of large

[11] Garleanu and Pedersen (2018) provide theoretical framework, where markets can be inefficient enough so that informed managers would outperform after fees.

stocks significantly more. Davies (2022) documents that variation in stock returns may be attributed to index-linked trading, and the price impact is not equal across stocks, with riskier stocks experiencing more severe price impacts. Specifically, the volume of index-linked trading has more pronounced effects on smaller firms. Our study extends previous research by providing an ETF rebalancing perspective. When studying the impact of ETF rebalancing trades on stock prices across different size groups, we find that ETF rebalancing trades have a disproportionately large impact on small stocks and have an economically and statistically significant negative relation with future returns. Such results lend support to Davies' (2022) price-impact theory.

This paper is organized as follows. Section 2 discusses the institutional details of ETFs. Section 3 describes the data construction and summary statistics. Section 4 lays out the methodologies and presents the main results. Section 5 presents further tests and subsample analyses.

1. Background and institutional details

In the last two decades, we have observed a large shift in US investment assets from active to passive funds, particularly ETFs. Such a rapid increase in the popularity of ETFs can be attributed to their unique structure, which provides investors with relatively cheap and liquid alternatives to mutual funds (MFs). In this paper, we focus on passive ETFs, that is, ETFs that closely track underlying indices.[12] The growth in the number of ETFs can mainly be attributed to the growth in rules-based ETFs, which became popular investment tools after the financial crisis of 2008, when investors started looking for alternatives to MFs.

The trading of ETFs in the underlying securities consists of two parts. First, ETFs trade in response to inflows or outflows. ETFs have a distinct mechanism in responding to investor flows compared to MFs. Unlike MFs, where managers have discretion in the allocation of flows, ETFs experience high flow-induced pressure because all flows must be translated into trading underlying

[12] We use the term ETFs for passive ETFs throughout the paper. The majority of ETFs are index-linked passive ETFs with $5.1 trillion in total net asset in 2020 compared to $174 billion for actively managed ETFs.

stock holdings (Dannhauser and Pontiff, 2019). Inflows and outflows originate in the primary market of ETFs, where ETF shares are created or redeemed due to the flows. Second, ETF trades might be driven by the rebalancing of the underlying indices they follow. This type of rebalancing event creates trading in underlying stocks independent of the trades due to money flows. There are two reasons ETFs need to perform rebalancing: 1) inclusion or exclusion of a stock in or from the underlying index (including IPOs, M&As, and delistings) and 2) weight rebalancing in the case of equal-weighted ETFs. With the increased number of ETFs, especially ETFs that follow a rules-based index that rebalances frequently (semi-annually, quarterly, or monthly), the impact of ETF rebalancing trades must be studied carefully, as they may potentially generate additional price pressure on underlying securities, deteriorating future stock returns even further. [13]

Unlike IMFs, ETFs do not have the ability to rebalance their portfolios before index reconstitution or postpone rebalancing to avoid the front-running costs imposed by arbitrageurs. This creates a unique setting in which rebalancing trades by ETFs impose additional pressure on underlying stock returns. Additionally, the transparency of the indices ETFs follow creates a perfect setting for strategic traders, such as HFs, to benefit from the price pressure created from rebalancing trades, which may exacerbate the negative impacts on stock returns.

In this paper, we classify ETFs into three types: broad-market, rules-based, and sector ETFs. Broad-market ETFs follow broad-market indices based on portfolios of US stocks, with weights proportional to their market capitalization. Examples of broad-market ETFs include Vanguard Total Stock Market Index Fund, iShares Russell 3000 ETF, and Schwab US Broad Market ETF. Additions and deletions to the broad-market indices are announced in advance and are not very frequent events. Sector ETFs concentrate on stocks from a specific industry and follow an industry-concentrated index. Similar to board-market indices, such types of indices do not experience reconstitution on a frequent basis; events of additions and deletions are relatively rare events.

[13] In the similar spirit, Nagel (2005) suggests that style trading (e.g. momentum, value) contributes to the changes in trading volume. He shows on the example of mutual funds' style trading that propensity to sell is related to the changes in stock characteristics. Hrdlicka (2022) shows that changes in stock's risk exposures are an important source of trading volume.

Examples of sector ETFs are iShares US Technology ETF, Focus Morningstar Health Care Index ETF, First Trust Natural Gas ETF, and VanEck Vectors Energy Income ETF.

Rules-based ETFs focus on a specific rules-based index. The underlying indices of rules-based ETFs follow a specific rule or strategy that requires more frequent (e.g., monthly or quarterly) portfolio rebalancing so that constituent stocks satisfy the conditions, for example, Vanguard US Momentum Factor ETF and JPMorgan US Value Factor ETF. Rules-based ETFs follow very transparent rules-based indices, which makes index reconstitutions predictable events, especially by sophisticated investors, such as HFs.

Panel A of Figure 1 provides the evolution of different ETF types between 2005 and 2020 and shows the proportional distribution of total ETF assets among them. The proportion of broad-market ETFs is the largest among the three types of ETFs. However, since 2005, rules-based ETFs have been exponentially increasing and reached 30% of total ETF AUM in 2020 compared to 33% of broad-market ETFs. This trend is characterized by the rise in the number of rules-based ETFs. In our sample, by the end of 2020, the number of rules-based domestic equity ETFs reached 311. The number of sector ETFs has also been increasing; however, in terms of aggregate AUM, they remain small compared to other types of ETFs.

[Insert Figure 1 here]

2. Data and summary statistics

2.1 ETF holdings

We obtain ETF holdings data from Morningstar Direct. Our choice of Morningstar over the CRSP and Refinitiv (formerly known as Thomson Reuters) databases to obtain holdings information was for the following reasons. First, we can obtain ETF holdings data with a monthly frequency from Morningstar, while CRSP and Refinitiv only provide quarterly-level data. Monthly frequency data allow us to estimate the timing of trades more precisely. This is important in our study, as it will diminish the noise present in quarterly trades and allow us to observe the actual change in holdings within the quarter. In the case of rules-based ETFs, rebalancing happens on a quarterly or monthly frequency; therefore, using quarterly data will not capture the total effect of ETF rebalancing trades on stock returns. Second, monthly holdings data contain a larger number of trades that are missing in quarterly data (e.g., Elton, Gruber, Blake, Krasny, and Ozelge, 2010).

Due to the limited data availability before 2005, our sample covers the period from 2005 to 2020. We identify a sample of ETFs using the "US category group" in Morningstar by including only domestic equity ETFs. We restrict our sample to passive ETFs that physically own securities of the index they aim to track. We exclude active, leveraged, inverse, and hedged ETFs, as well as commodities and fixed-income ETFs, from the sample. To ensure the accuracy of our holdings data, we exclude ETFs where the ratio between total net assets (TNA) and dollar amount of holdings differ by more than a factor of 2 (0.5 < *TNA/Dollar holdings* < 2). For special cases in which a fund family reports ETF as a share class (e.g., Vanguard), we adjust holdings using proportional TNA to impute holdings in a stock attributable to ETF share class. The final sample of ETFs with available holding information consists of 1,071 ETFs.[14]

2.3 ETF rebalancing trades

Our goal is to examine the impact of ETF rebalancing trades on underlying stocks. First, we measure the total value of ETF trades. We define ETF trades of a particular stock *i* as the changes in shares held by all ETFs (i.e., number of shares bought minus the number of shares sold by all ETFs) from month *m*-1 to month *m* divided by total shares outstanding at the end of month *m*. Specifically, the ETF trade of stock *i* in month *m* is calculated as follows:

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

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

[14] Table IA.1 in the internet appendix shows that the number of domestic equity ETFs reaches 909 by the end of 2020. The aggregate value of AUM across all rules-based ETFs has almost reached the level of AUM of broad-market ETFs by the end of 2020.

To define ETF rebalancing trades, we decompose ETF trades into two components: flow-induced ETF trades (FIT) and rebalancing-induced ETF trades (RIT). We first construct stock-level FIT. Unlike MFs, where managers are able to make decisions on the timing of the distribution of flows, ETFs directly translate investor flows into the trading of underlying securities.[15] We define the FIT for each stock *i* in month *m* as follows:

$$FIT_{i,m} = \frac{\sum_{j=1}^{J} shares_{i,j,m-1} Flow_{j,m}}{Shares\,Outstanding_{i,m}}, \tag{2}$$

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

Where $TNA_{j,m}$ is total net assets of ETF *j* in month *m* and $Ret_{j,m}$ is returns of ETF *j* in month *m*.

Finally, ETF rebalancing trades occur in the case of the rebalancing of underlying indices, where ETFs must follow to reduce tracking errors. We define the difference between the actual trades and the flow-induced trades as RIT:

$$RIT_{i,m} = Trade_{i,m} - FIT_{i,m}, \tag{3}$$

where $Trade_{,i,m}$ is the ETF trading of stock *i* by all ETFs in month *m*.

2.4 Hedge fund trades

We obtain HF quarter-end holdings from the Thomson Reuters 13F equity portfolio holdings database. This database does not separately identify HFs; therefore, to extract the list of HF firms, we follow the methodology of Agarwal, Fos, and Jiang (2013), where they manually identify an institution as HF if it satisfies the following criteria: 1) it matches the name of a fund from the Union Hedge Fund Database,[16] 2) it is one of the top HFs listed by industry publications, 3) on the firm's website description, HF management is listed as the main business area, 4) it is listed as a

[15] 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. We omit the partial scaling factor used by Lou (2012) as it is very close to 1 for ETFs as documented in Danhauser and Pontiff (2019).

[16] Agarwal, Fos, and Jiang (2013) compile the Union Hedge Fund Database that merges four commercial databases: Eureka, Hedge Fund Research, Morningstar, and Lipper TASS.

HF firm in Factiva, and 5) if the filer name in 13F is one of the leading personnel in a HF.[17] As a result, we obtain the final sample of 1,854 unique HF firms from 13F filing institutions.

To measure HFs' anticipatory trading, we use the NAT of stocks proposed by Chen, Da, and Huang (2019), where they define NAT as the difference between abnormal HF holdings (AHF) and abnormal short interest (ASI). We obtain short interest data from the Compustat short interest file, which reports short interest for stocks listed on the NYSE, AMEX, and NASDAQ.[18] AHF is defined as the difference between the current quarter hedge fund holdings of stock *i* and the average HF holdings of stock *i* in the past four quarters. Similarly, the ASI is measured as the difference between the current quarter short interest of stock *i* and the average short interest of stock *i* in the past four quarters. Both measures are standardized by shares outstanding.

$$AHF_{i,q} = HF_{i,q} - averageHF_{i,q-1:q-4} \tag{4}$$

$$ASI_{i,q} = SI_{i,q} - averageSI_{i,q-1:q-4} \tag{5}$$

$$NAT_{i,q} = AHF_{i,q} - ASI_{i,q} \tag{6}$$

NAT combines HF holdings as the proxy for the long side of arbitrage trades with short interest as the proxy for the short side, which provides a complete view of arbitrage trading that includes long and short positions.

2.5 Stock returns and financial variables

We extract information on stock characteristics from CRSP and Compustat. As a dependent variable in our main regressions, we use monthly stock returns obtained from CRSP. To avoid our results being contaminated by other potential channels, we include various control variables known to impact stock prices. Control variables include turnover, previous one-month and one-year stock returns, 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. We

[17] Agarwal, Jiang, Tang, and Yang (2013); Agarwal, Ruenzi, and Weigert (2017)
[18] After September 2007, short interested data is reported twice each month. We use the last available report of the month.

compute the short interest ratio as monthly short interest divided by the total shares outstanding at the end of the month. Appendix 1 includes an explanation of each variable's construction and data source.

3. ETF rebalancing trades

We examine the effect of increasing trading volume of ETFs on the stock market. In particular, we assess how ETF rebalancing trades may impact the future returns of the underlying securities. The idea is as follows. If ETFs bring information into prices via trading, we should observe an increase in prices when they buy heavily, and there is no subsequent drift in returns. Alternatively, if ETF trades push stock prices away from fundamental values, we should observe a significant negative relation between ETF trades and subsequent stock returns. We focus our analysis on ETF rebalancing trades to bring a new perspective on the role of ETFs in capital markets.

Previous studies have documented that inflows into ETFs induce price pressure on stocks, which results in negative returns (e.g., Brown, Davies, and Ringgenberg, 2019). It is commonly assumed that due to the passive nature of ETFs, they directly translate flows into trading; therefore, flows are considered to be one of the main drivers of price pressure on underlying securities. However, as the underlying indices may change index constituents or their weights, ETFs should trade accordingly to follow indices closely. Therefore, it is important to consider the effect of ETF rebalancing activities on top of the documented impacts of ETF flows.[19] We are among the first to examine the impact of ETF rebalancing–induced trades on stock returns, which have been largely overlooked by prior studies.[20]

[19]Brown, Davies, and Ringgenberg (2021) show that ETF flows impose non-fundamental demand shock on underlying securities. Zou (2019) finds that ETF flows are negatively associated with subsequent firm operating performance, sales growth, and stock returns. Dannhauser and Pontiff (2019) show the positive correlations between aggregate ETF flows and market returns followed by significant reversal. Ben-David, Franzoni, and Moussawi (2018) and Staer (2017) document price pressure and reversal patterns in ETF flow-return relation.
[20] Li (2021) focuses on the transaction costs incurred from ETF rebalancing trades, while our study examines the direct impact on stock returns as well as its interaction with arbitrageurs

3.1 Rebalancing ETF trades and future stock returns

We test the relation between ETF rebalancing trades and future returns of the underlying stocks using regression methods. We run the following Fama–MacBeth regression of the future-month stock returns on the monthly ETF rebalancing trades:

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

where the dependent variable $Ret_{i,m+1}$ is return of stock *i* in month *m*+1. The explanatory variable $\mathrm{RIT}_{i,m}$ is the rebalancing-induced trading of stock *i* by all ETFs in month *m*. Previous studies have documented a negative relation between ETF flows and stock returns; therefore, in our analysis, we control for ETF flow–induced trades $\mathrm{FIT}_{i,m}$. To avoid our results being contaminated by other potential channels, we include various control variables, $\mathrm{Controls}_{i,m}$, known to impact stock returns, as used in the previous sections. The control variables include turnover, previous one-month and one-year returns, 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.[21] Appendix 1 provides details of how each variable is constructed and its data source. We also conduct Fama–MacBeth regressions on stock returns in contemporaneous month *m* and the future months *m*+2 and *m*+3. The *t*-statistics are computed from standard errors adjusted for autocorrelation, following Newey and West (1987).

The results are reported in Table 1. In Column (1), the dependent variable is the contemporaneous month returns of the underlying securities. The estimated coefficients on both RIT and FIT are positive and statistically and economically significant, which indicates that both flow- and rebalancing-induced trading by ETFs push stock prices up. One standard deviation

[21] Banz (1981), Chan, Hamao, and Lakonishok (1991), and Fama and French (1992), among others, find that smaller sized firms 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) and Amihud (2002) find the positive relation between illiquidity and expected return. Datar, Naik, and 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.

increase in RIT (FIT) is associated with a 0.28% (0.47%) increase in contemporaneous stock returns. In Column (2), the dependent variable is stock returns in month m+1, and the estimated coefficient of the ETF RIT in month m is -1.611, with a t-statistic of -4.00. In Columns (3) and (4), the dependent variables are returns in months m+2 and m+3, respectively. Estimated coefficients on RIT are insignificant; hence, the reversal is short-lived. The reversal may rule out the possibility of negative returns signaling a deterioration in stock fundamental value; instead, the effects may be likely to reflect temporary price pressure of ETF rebalancing trades.

In the case of FIT, our results are consistent with previous studies. We find that the flow-induced trades of ETFs are associated with a significant push-up in contemporaneous returns, followed by short-term reversal. More importantly, these findings suggest that flow-induced trading is not the only mechanism through which ETF trades contribute to stock return reversal; rebalancing-induced trades may also play an important role in enhancing the previously documented deteriorating effect of ETF flows. Such results add to the existing literature on the nature of ETF trading activity by showing that ETF trades not only originate from the flows but may be driven by the changes in the underlying indices they follow, which, in turn, affect stock returns.

[Insert Table 1 here]

In recent study, Glosten, Nallaredy, and Zou (2020) find that ETF trades have significant positive relation with contemporaneous stock returns, which is consistent with our results.[22] They decompose ETF activity into the addition and deletion of a stock into the ETF effect and ETF activity attributed to the creation and redemption process (flow-induced trade in our case) and find that both of these components have a positive relation with contemporaneous stock returns. However, our study is unique, as it provides a full picture of ETF rebalancing activities. First, we focus on higher-frequency monthly holdings data from Morningstar, which allows us to clearly

[22] Table IA.2 in Internet appendix reports results of the regression of aggregate ETF trades on stock returns. We find that in aggregate, one standard deviation increase in ETF trading corresponds to 0.44% increase in contemporaneous monthly stock returns and 0.27% decrease in the next month returns.

identify ETF rebalancing months and calculate trades more precisely. Our measure of ETF RIT includes not only additions and deletions but all the ETF trading that is attributed to its rebalancing activities, including rebalancing of a stock's weight in an equal-weighted portfolio. Further, we look into the impact on stock returns in the months following the rebalancing event, which helps identify the full effect of ETF trades on underlying securities.

3.2 Different types of ETFs

In this section, we examine how the impact of ETF rebalancing trades on future stock returns may vary across different types of ETFs. Specifically, we are interested in the differences between broad-market, rules-based, and sector ETFs.

Despite ETFs being considered passive investment vehicles, their growth in the last decade has been accompanied by the rise of rules-based ETFs. Rules-based ETFs are considered less passive, as their portfolios are tilted to follow a specific rules-based index or factor strategy (Easley, Michayluk, O'Hara, and Putnins, 2021). As rules-based ETFs follow an investment strategy targeting a specific rule, they are expected to rebalance their portfolios on a monthly, quarterly, or yearly basis, depending on the portfolio. Therefore, we expect rules-based ETFs to have higher rebalancing activities compared to sector and broad-market ETFs. Panel B of Figure 1 shows rolling three-year aggregate dollar rebalancing trades across the three types of ETFs. Despite broad-market ETFs being the largest ETF type in terms of AUM, rules-based ETFs have the largest amount of aggregate rebalancing trades compared to both broad-market and sector ETFs. This is explained by the nature of the underlying index these ETFs follow.[23] By comparison, sector funds do not have high trading activities, but they are used by other institutional investors as part of the industry risk hedging strategy in their portfolios.

Compared to active MFs that follow a proprietary active strategy, rules-based ETFs follow a specific rules-based index, which makes it easier for arbitrage traders to predict which stocks will

[23] Rules-based funds can be described as active in form. Easley, Michayluk, O'Hara, and Putnins (2021) propose to distinguish between active in form and active in function ETFs, where active in form ETFs characterised by higher portfolio turnover, and active in function ETFs are used by other institutional investors in their investment strategies.

be included or excluded during the next portfolio rebalancing event. Therefore, arbitrage traders are motivated to exploit an opportunity and buy stocks to be included in the portfolio prior to the ETF rebalancing date to profit from the temporary increase in prices. Such behavior of arbitrageurs may contribute to even higher price pressure on contemporaneous stock prices, followed by stock return reversals. Therefore, we expect to observe a significant negative relation between rules-based 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 rules-based ETFs. Therefore, it is important to distinguish between different categories of ETFs when considering their impact on stock market efficiency.

We classify ETFs into three types of funds: broad-market ETFs, rules-based ETFs, and sector 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, 2021; Antoniou, Li, Liu, Subrahmanyam, and Sun, 2018). We identify broad-market ETFs by screening fund names. Further, we identify rules-based ETFs using the "Strategic Beta" identifier in Morningstar. Morningstar tags investment products using the Strategic Beta identifier if the underlying index of a product employs a rule or follows a specific list of factors to improve their return profile. Therefore, we define rules-based ETFs if their "Strategic beta" is set to "Yes." Finally, sector ETFs concentrate their portfolios on specific industries. We identify sector ETFs using the Morningstar "sector equity" classification. We screen for fund names and delete any international funds or ETNs.

To test empirically, we run the Fama–MacBeth regression of future stock returns on rules-based, sector, and broad-market ETF RIT and FIT. We expect RIT to have significant results for rules-based ETFs, as they rebalance their portfolios more often compared to other ETFs and experience the highest volume of rebalancing-induced trades. Table 2 reports the results. Rules-based ETF RIT has a significant reversal; however, there are no significant results for FIT. The estimated coefficient for rules-based RIT in Column (1) is 3.06, with a *t*-statistic of 4. This indicates that during rebalancing events, stock prices move in the direction of ETF rebalancing–induced trading activity. However, stocks with the highest trading experience short-term reversal, with a coefficient of -2.140 and a *t*-statistic of -2.54 in the next month.

We also find significant reversal patterns for market RIT. In comparison to rules-based ETFs, market ETFs are value-weighted and experience rebalancing-induced trading; only a stock is included in or excluded from the index, which happens less often. However, due to the large amount of assets and flows into market ETFs, the volume of rebalancing trades in the case of such events generates significant force, which moves prices away from their initial level, resulting in short-term reversal.

In the case of sector ETFs, we find that only FIT has a significant relation with stock returns. Specifically, FIT has a significant positive relation with contemporaneous monthly returns, with a coefficient of 11.738 and a *t*-statistic of 2.08. However, we do not find a significant reversal in the next months. This can be explained by the persistence of ETF flows. Lou (2012) finds such patterns for MF flows, showing that there is no immediate reversal in MF flows due to their persistence. We observe the same effect in sector ETFs. There are no significant results for RIT because sector ETFs do not experience high rebalancing activities, as sector indices do not change very often.

[Insert Table 2 here]

Overall, we find that RIT may play a crucial role in determining the impact of ETFs on stock returns. More importantly, we identify that rules-based ETFs are the main driving force of RIT impact on stock return reversal. We assume that return reversal patterns are further exacerbated by the arbitrage activity of rational investors who front-run portfolio rebalancing associated with index additions or deletions for market ETFs or index rebalancing for rules-based ETFs. The previous literature supports our evidence. Petajisto (2011) studies additions and deletions to S&P500 and Russell 2000 indices and finds that price effects reverse within the next two months due to arbitrageurs activity.

3.3 The nature of ETF rebalancing trades

In this section, we explore the nature of ETF rebalancing trades and test whether they are indeed associated with index reconstitutions. Unlike flow-induced trades that can be attributed to the flows into and out of ETFs generated in the primary market, rebalancing-induced trades of ETFs are mostly the result of underlying index reconstitutions and portfolio weight adjustments for equal-weighted ETFs. Since all ETFs must closely follow an underlying index, whenever there is a change in the index composition, ETFs should follow by rebalancing their portfolios.

To empirically test, we use data on the index constituents for the S&P and Russell universes of indices. Compustat stopped providing data on S&P indices in 2020; therefore, our data cover the period from 2005–2019. Next, to investigate the relation between stock-level RIT and reconstitution events, we run the following regression:

$$RIT_{i,m} = b_0 + b_1 \text{Inclusion}_{i,m} + b_2 \text{Exclusion}_{i,m} + b_3 \text{Controls}_{i,m} + e_{i,m}, \qquad (8)$$

where the dependent variable is the RIT of stock i in month m. Inclusion (Exclusion) is a dummy variable equal to one if a stock was added (excluded) to (from) one of the indices in month m and zero otherwise. We also control for different stock characteristics.

The results are presented in Table 3. In Column (1), for the whole sample of ETFs, the estimated coefficient on the inclusion dummy is 0.378, with a t-statistic of 15.5, which indicates that when a stock is added to the index, its RIT by ETFs significantly increases. The coefficient on the exclusion dummy is significant at -0.194, with a t-statistic of -7.28. This indicates that the RIT for a stock decreases if it is excluded from the index. In Column (2), we use alternative explanatory variables—the number of indices the stock was included in (*N_Incl*) and excluded from (*N_Excl*). The estimated coefficients remain economically and statistically significant. We repeat the analysis for the rules-based ETFs in Columns (3) and (4), broad-market ETFs in Columns (5) and (6), and sector ETFs in Columns (7) and (8). The results remain significant across all types of ETFs.

The above findings suggest that the rebalancing-induced trading activities of ETFs can be attributed to changes in the underlying indices.

[Insert Table 3 here]

4 Who benefits from ETF rebalancing trades

The rebalancing trades of ETFs originate from changes to the underlying indices, which can happen due to 1) the inclusion or exclusion of a stock in or from the index (including IPOs, M&As, and delistings) and 2) weight rebalancing in the case of equal-weighted ETFs. Transparency of indices that passive ETFs follow attracts arbitrage traders who have an incentive to trade prior to ETF rebalancing events. In anticipation of the price fluctuations caused by rebalancing trades, arbitrageurs, specifically HFs, might choose to front-run and buy (short sell) stocks that are expected to be bought (sold) as part of ETF rebalancing events prior to ETFs. Such front-running activities by HFs can exacerbate the already existing price impacts of ETF RIT on stock returns and destabilize prices prior to the rebalancing date. This, in turn, may impose execution costs on ETFs and force them to "buy-high and sell-low."

Previous literature theoretically shows that strategic traders profit from front-running and selling the stock ahead of a distressed trader, which results in price overshooting (Brunnermeier and Pedersen, 2005). Empirically, Shive and Yun (2013) show that HFs profit from the predictability of flow-induced MF trades through anticipatory trading.[24] Aragon, Martin, and Shi (2019) document that HFs with locked-up capital opportunistically trade against flows of locked-up HF managers during crisis. Agarwal, Aragon, Nanda, and Wei (2022) document anticipatory trading of HFs against distressed mega HFs. Our study provides additional evidence of opportunistic HF front-running trades against ETF rebalancing events. For ETFs, HFs not only trade in anticipation of flows, as in the case of distressed HFs or MFs, but can also predict most ETF trades due to the transparency of the indices they follow. Even for rules-based ETFs, HFs could easily predict which stock will be included or excluded during the next portfolio rebalancing

[24] Chen, Hanson, Hong, and Stein (2008) show that HFs engage in front-running strategies in anticipation of flows of distressed mutual funds

event. This makes the case of ETFs unique, as they may create even larger anticipatory trading by HFs, which, in turn, can destabilize the prices of underlying securities to a greater extent.

In this section, we answer the following two questions: First, who is on the other side of ETF trades? Do HFs, which are often considered smart investors, trade in the same direction prior to ETF trades? Second, what are the broad impacts of HF anticipatory trading on underlying ETF securities?

4.1 Anticipatory trading by hedge funds

The RIT of ETFs is driven by rebalancing of the underlying index, which may be either announced in advance by the index providers or predicted by sophisticated investors, such as HFs. In anticipation of the price pressure generated by the rebalancing-induced trades of ETFs on the underlying securities, HFs, as strategic traders, may see an opportunity to engage in arbitrage trading through buying stocks prior to ETF buying and profiting by selling afterwards. For example, if a rules-based ETF follows an S&P 500 momentum index, HFs can anticipate upcoming portfolio rebalancing and front-run ETFs by buying stocks that are to be included in the index or to be increased in position and (short) selling stocks that are to be excluded or to be decreased in position. Once ETFs complete their rebalancing, HFs can complete their trade and profit from exacerbated prices by reversing their positions.

We examine whether purchasing of a stock due to ETF rebalancing in month *m* was front-run by HFs and stocks were purchased by HFs in the previous month *m*-1. Since HF holdings data are on the quarterly level and ETF RIT is calculated on a monthly basis, to make sure the test is clean, we focus on examining the calendar quarter ends for the HF NAT (March, June, September, and December) and the immediate following month for ETF RIT (April, July, October, and January). We expect anticipatory trading to happen according to the timeline demonstrated in Figure 2. We consider the first month *m* of quarter *q* to be the month during which the ETF rebalancing event happens, so we can observe the new rebalanced ETF portfolio at the end of month *m*. HFs have knowledge of ETF rebalancing in advance either due to index providers' early announcements about index reconstitution or they are able to predict such events due to index transparency. Therefore, we expect them to trade in anticipation of rebalancing during the quarter *q*-1 preceding the rebalancing event month *m*, where we can observe HF trades from 13F holdings data at the end of the quarter *q*-1. After ETFs complete rebalancing, HFs will complete their arbitrage trades in quarter *q* by reversing the initial position they took in rebalanced stocks in quarter *q*-1.

[Insert Figure 2 here]

To graphically demonstrate that HF trade in stocks rebalanced by ETFs, we plot HF NAT around ETF rebalancing events in Figure 3. The figure illustrates the evolution of HF trading around ETF purchases (sales) due to their rebalancing activities in Panel A (Panel B). The vertical blue line indicates the month in which the rebalancing event takes place. We plot NAT for two portfolios of stocks. In the first portfolio, we identify stocks that were front-run by HFs if 1) ETF RIT of stock *i* ranked in the highest (lowest) quintile in month *m*, 2) additionally in Panel A, ETF RIT is above zero, and 3) NAT of the stocks is in the highest (lowest) quintile. The second portfolio contains the rest of the stocks. The figure then plots the average NAT in Panels A.1 and B.1, abnormal long positions (AHF) in Panels A.2 and B.2, and abnormal short positions (ASI) in Panels A.3 and B.3 of HFs four quarters before the ETF rebalancing trades and four quarters after. For stocks that were front-run by HFs, there is a substantial increase in NAT in the quarter preceding rebalancing events, which indicates front-running activities by HFs. Moreover, HFs then unload their positions in quarter *q* following the completion of ETF rebalancing. This might indicate anticipatory trading behavior of HFs that profit from price distortions caused by ETF trading in underlying securities.

[Insert Figure 3 here]

We hypothesize that such front-running activities by HFs can exacerbate the price impacts of ETF RIT on stock returns. To empirically test this hypothesis, we compare returns of stocks that were rebalanced by ETFs and front-run by HFs to the rest of the stocks. Portfolio 1 contains stocks front-run by HFs, and we identify them as follows. First, for each month *m* following the end of the calendar quarter *q*-1, we sort stocks into quintiles based on their ETF RIT. Stocks that belong to the highest quintile are expected to experience the highest price pressure from RIT; therefore, we expect such stocks to be strategic trades of HFs, as shown in Figure 3. Then, we independently sort stocks into quintiles based on their NAT in quarter *q*-1. Stocks that belong to the highest quintile of RIT with RIT > 0 and at the same time belong to the quintile with the highest NAT in quarter *q*-1 are identified as HF front-run stocks in our sample. Portfolio 2 contains the rest of the stocks traded by ETFs. We calculate returns to these stocks in the month preceding the rebalancing event and the next two months. We expect stocks that are front-run by HFs to experience stronger impacts on returns.

Table 4 reports the equal-weighted returns for the two portfolios of stocks. Portfolio 1 (P1) consists of stocks bought by ETFs during the rebalancing event and front-run by HFs, and Portfolio 2 (P2) contains the rest of the stocks traded by ETFs. Panel A shows raw returns, Panel B contains CAPM-adjusted returns, and Panel C shows DGTW-adjusted returns. In Column 1 of Panel A, we calculate returns to portfolios of stocks in month *m*-1 preceding the ETF rebalancing event, when HFs trade in anticipation. Stocks that are front-run by HFs experience price pressure in month *m*-1 and generate significant returns of 1.77%, with a *t*-statistic of 2.08. During month *m*, when ETFs buy stocks due to their rebalancing trades, returns to Portfolio 1 increase to 1.88% and remain statistically significant, with a *t*-statistic of 1.91. At the same time, stocks that are not front-run by HFs do not experience a significant increase in stock returns. This shows that HFs strategically choose stocks that experience significant increases in their stock returns, which will generate higher profits for HF managers. In month *m*+1, following ETF rebalancing trades, when HFs unload their positions, the significance of returns disappears. The results remain significant after adjustment for DGTW.

Overall, we document significant price pressure prior to ETF rebalancing for stocks that are subject to HF arbitrage trading. Further, we show that HFs strategically choose stocks that are part of ETF rebalancing events to profit from the price pressure generated by ETF trades. Stocks that are front-run by HFs suffer from significant deterioration in returns during the months after ETF rebalancing, while stocks that are not part of HF front-running activities do not experience significant price pressure.

[Insert Table 4 here]

4.2 Trading of stocks rebalanced by ETFs and index mutual funds

We consider stocks that are rebalanced by both ETFs and IMFs. First, we expect to see higher anticipatory trading by HFs in stocks that experience rebalancing by both ETFs and IMFs. If ETFs and IMFs track the same indices, their rebalancing events might reinforce the pressure on the underlying securities of the same indices. Therefore, HFs have more incentives to front-run rebalancing events. Second, in comparison with ETFs, IMFs have discretion in deciding the timing of rebalancing to avoid delegation costs imposed by front-runners. We expect a more significant decrease in future returns for stocks that are rebalanced only by ETFs compared to stocks with IMF rebalancing, as IMFs' flexibility to trade after index rebalancing might reduce the negative impacts on stock returns.

Figure 4 shows NAT surrounding ETF rebalancing event for stocks rebalanced by ETFs and IMFs and stocks that are only part of ETF rebalancing trades. First, we identify stocks that are in the highest quintile of ETF RIT and, at the same time, in the highest quintile of NAT. This way, we make sure we focus only on stocks rebalanced by ETFs and front-run by HFs. Next, we divide stocks into two portfolios based on their IMF RIT. We obtain data on IMF holdings from the Thomson Reuters holdings database. We consider only calendar quarters and construct IMF RIT in a similar fashion to ETFs. For each ETF rebalancing event in month *m*, we align the IMF RIT at the end of quarter *q* since we only have quarterly data for IMFs. Then, we divide our sample into stocks that are rebalanced by both IMFs and ETFs (IMF RIT not equal to zero) and stocks that are rebalanced only by ETFs (IMF RIT equal to zero). In Panel A of Figure 5, the NAT of stocks bought by both ETFs and IMFs due to rebalancing trades is two times higher than for stocks rebalanced only by ETFs. This is not surprising, as HFs expect to profit from stocks with the highest trading pressure, which are stocks that experience the highest rebalancing-induced trading by ETFs and IMFs.

[Insert Figure 4 here]

Empirically, we test whether there is a difference in impact on underlying stock returns between ETF and IMF rebalancing events. We again select the sample of stocks that have the highest ETF RIT in month *m* and the highest NAT in quarter *q*-1. We further divide stocks into two portfolios. Portfolio 1 (P1) contains stocks with an IMF RIT > 0; this way, we make sure that stocks are on the same side of rebalancing trades by ETFs and IMFs (they are bought simultaneously by ETFs and IMFs during rebalancing events). Portfolio 2 (P2) contains the rest of the stocks. Despite the fact that NAT is higher for stocks in P1, as we have seen in Figure 5, we expect to see stronger diminishing in returns in the following months for stocks traded only by ETFs, as IMFs might still choose to rebalance in the months following index reconstitution.

Table 5 presents the results. In Column 1 of Panel B, in month *m*-1 during HF anticipatory trading, the raw returns of P1 and P2 are positive and statistically significant, with P1 returns of 1.98% and P2 returns of 1.88%. Returns during rebalancing event month *m* remain significantly positive 1.98% for stocks in P1, and returns for P2 stocks have increased to 2.19%. The difference in returns between P1 and P2 is not statistically significant; however, in economic magnitude, P2 experienced an increase in returns from *m*-1 to *m*. This is because, unlike IMFs, ETFs can only rebalance when the underlying index rebalances; therefore, the push-up in returns due to ETF RIT happens only in month *m.* In Column 3, the difference between P1 and P2 returns is 1.05%, with a *t*-statistic of 2.66. This indicates that stocks rebalanced only by ETFs experience a stronger decline in stock returns in the following month. This can again be explained by the timing of rebalancing. IMFs might choose to rebalance in the following months to avoid costs, which may reduce return reversals compared to stocks traded only by ETFs.

[Insert Table 5 here]

Overall, in this section, we have demonstrated that stocks that are part of rebalancing events by both ETFs and IMFs experience higher front-running activities by HFs. However, stocks that are only rebalanced by ETFs are subject to higher price pressure at the time of rebalancing, with a subsequent decline in returns.

5 Robustness tests

We perform several additional analyses and robustness tests for our findings. First, we test our main findings by using portfolio sorting. Second, we test whether our findings remain robust across different stock sizes. Lastly, we check whether our results are robust to controlling for ETF ownership variables, which were found to have a significant impact on underlying securities in previous studies.

5.1 Impact of ETF rebalancing: Portfolio analysis

To understand the economic impact of ETF rebalancing on underlying securities and establish the empirical implications of the findings for investors, we propose a strategy that bets against ETF rebalancing trades using portfolio sorting.

At the end of each month, we rank stocks into quintiles based on their ETF rebalancing trades, where stocks with the lowest ETF rebalancing trades are assigned to Portfolio 1 and stocks with the highest ETF rebalancing trades are assigned to Portfolio 5. We then compute the equal-weighted returns of each portfolio over the next month.[25] As we are interested in testing the previously established negative relation between future stock returns and ETF rebalancing trades, we expect a portfolio of stocks with the lowest ETF trading to outperform a portfolio of stocks with the 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.

[25] In Section 5.2, we have found that the negative relation between ETF rebalancing trades and future stock returns is more pronounced among small stocks; therefore, we use the equal-weighted strategy.

[Insert Table 6 here]

The results are reported in Table 6. At the end of each month, all stocks are sorted into quintiles based on their ETF RIT. Columns (1) and (4) present portfolios' raw returns, Columns (2) and (5) contain DGTW-adjusted returns, and Columns (3) and (6) report returns adjusted for DGTW and Amihud illiquidity measures.[26] In Column (1), the strategy that buys stocks with the lowest RIT and short sells the stocks with the highest RIT yields significant returns of 0.38%, with a *t*-statistic of 2.84 for the sample period 2005–2020, and the spread is even larger after 2010, with a monthly return of 0.47% and a *t*-statistic of 3.02 (Column (4)). The strategy generates significant returns even when we adjust for DGTW portfolio returns and Amihud illiquidity. The return spread between long and short portfolios is 0.39% for the DGTW adjusted returns (Column (2)) and 0.36% for the DGTW and Amihud illiquidity adjusted returns (Column (3)).[27]

5.2 Small vs. large stocks

Previously, we established a negative relation between ETF rebalancing trades and future stock returns. This does not preclude the possibility of a more extensive impact on certain types of stocks, such as small stocks. Davies (2022) shows theoretically and confirms empirically that the trading of index-linked products has different price impacts across stocks, where riskier stocks experience greater price impacts. In this section, we examine whether the previously documented relation is driven by small stocks.

To do so, we divide stocks into large and small, based on their market capitalization, and use the NYSE median as the threshold. We run the baseline regression specified in Equation (7) for two groups of stocks. The results of the regression are presented in Table 7. Columns (1)–(2) show that ETF rebalancing trades are associated with an increase in contemporaneous monthly stock returns across both subsamples of stocks. In Columns (3)–(4), the dependent variable is the next

[26] Similar to DGTW portfolios, we form 3 x 3 x 3 x 3 portfolios based on stock size, value, momentum, and Amihud illiquidity ratio.
[27] We repeat analysis for the aggregate value of ETF trade in Table IA.4 in the Internet Appendix.

month’s stock returns, where the estimated coefficient of ETF RIT for the large stock sample is significantly smaller compared to small stocks.

[Insert Table 7 here]

Overall, we find that ETF trades have a significant and stronger impact on stock returns among small stocks. These results are consistent with the theoretical implications of Davies (2022) since small stocks are considered to be less liquid, hence riskier, and the price impact is also stronger.

5.3 Controlling for ETF ownership

Previous studies have concentrated on the relation between ETF ownership and different stock characteristics, such as volatility (Ben-David, Franzoni, and Moussawi, 2018), return comovement (Da and Shive, 2018), commonality in liquidity (Agarwal, Hanouna, Moussawi, and Stahel, 2018), and informational efficiency (Antoniou, Li, Liu, Subrahmanyam, and Sun, 2020). Unlike these studies, we focus on ETF trading activity. In this section, we control for the ETF ownership variable in our baseline regression to test whether the results in the previous sections are not driven by ETF ownership levels.

The results are reported in Table 8. The results show that after controlling for ETF ownership, the estimated coefficient on ETF rebalancing trades remains statistically significant. Even with control for ETF ownership, ETF trades exhibit a significant impact on the stock returns of underlying securities.

[Insert Table 8 here]

6 Conclusion

In this paper, we examine the implications of ETF rebalancing trades on the capital market. Specifically, we study the relation between ETF rebalancing trades and underlying stock returns. More importantly, we show that the transparency of indices ETFs follow makes them an easy target for arbitrage traders. This, in turn, imposes huge costs on ETF investors.

First, we document a significant negative relation between ETF rebalancing activities and future stock returns. The relation is most pronounced for rules-based ETFs, where rebalancing activities happen on a more frequent basis due to the nature of the underlying indices. One key contribution of our research is that we focus on the role that arbitrage traders play in enhancing the negative effect of ETF rebalancing trades on underlying securities. We document that stocks that are subject to HF front-running activities experience an increase in returns prior to ETF rebalancing events. This creates a scenario in which ETFs may be forced to rebalance at inflated prices, leaving ETF investors with higher costs. Further, we show that stocks that are subject to rebalancing by ETFs but are not part of IMF rebalancing experience a more severe decrease in future stock returns.

Overall, our study contributes to the growing literature on the impact of ETFs on underlying securities. Our results suggest that rebalancing trades by ETFs contribute to the short-term mispricing of stocks in the underlying portfolio, thereby decreasing overall market efficiency. We show that rebalancing trades come with additional costs incurred by HF arbitrage trading. The results of our study reveal the high costs ETF rebalancing trades impose on their investors.

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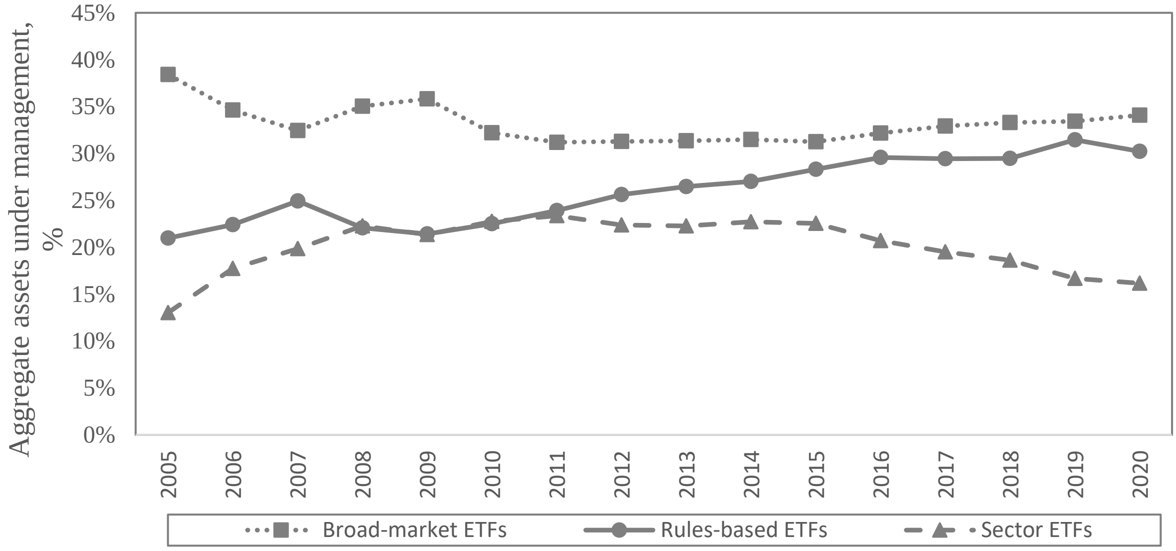
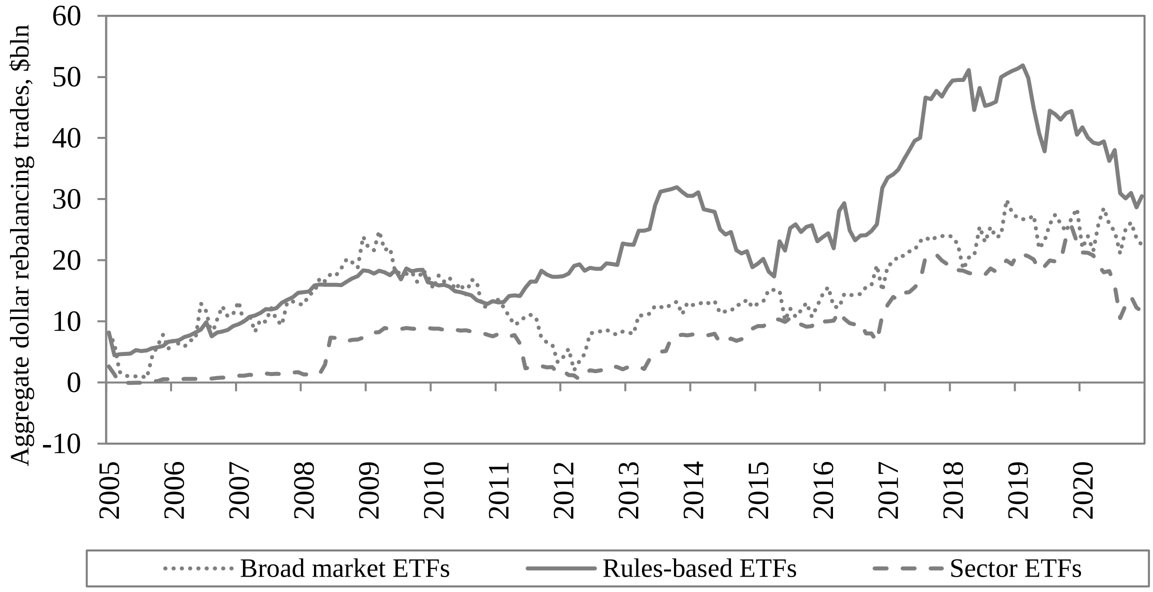
Appendix 1: Variable Definitions

Variable	Description	Source
ETF trade	The net shares purchased by ETFs 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.	Morningstar Direct, Thomson-Reuters, CRSP Mutual Fund, CRSP securities
ETF FIT	The flow-induced trades of ETFs measured as the aggregate number of shares held by ETFs in the previous quarter multiplied by the flows in the current quarter, divided by total shares outstanding at current quarter end.	Morningstar Direct, Thomson-Reuters, CRSP Mutual Fund, CRSP securities
ETF RIT	The rebalancing-induced trades of ETFs measured as the difference between ETF trade and ETF flow-induced trades.	Morningstar Direct, Thomson-Reuters, CRSP Mutual Fund, CRSP securities
NAT	Net arbitrage trades by hedge funds measured as the difference between abnormal hedge fund holdings and abnormal short interest.	Thomson Reuters 13F, Compustat short interest file
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 the 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 redemption (PSTKRV), liquidation (PSTKL), or par value (PSTK) to	CRSP, Compustat

	estimate the value of preferred stock. We exclude negative *B/M* firms.	
$Ret_{i,m-1}$	Cumulative returns in the previous month.	CRSP
$Ret_{i,m-12:m-2}$	Cumulative return over 11 months preceding the beginning of the last month.	CRSP



Panel A: AUM of US equity ETFs by investment type (%)



Panel B: Aggregate dollar rebalancing trades across three types of ETFs

Figure 1: AUM and rebalancing trades of US domestic ETFs by investment type

This figure shows the proportional AUM and dollar value of the rebalancing trades of US domestic ETFs for the sample period of January 2005 and December 2020. ETF sample is divided into broad market, rules-based and sector ETFs. We classify ETFs that track broad-market indices, such as S&P 500, S&P 1500, Russel 1000, Russel 3000, and NYSE/NASDAQ Composite Index, as broad-market ETFs. Rules-based ETFs follow specific factors in their investment strategy and are identified using the "Strategic Beta" indicator in Morningstar. Sector ETFs follow a specific industry and are defined using sector equity classification in Morningstar. Panel A shows the proportional allocation of AUM between three types of ETFs. Panel B shows the rolling three-year aggregate dollar value of rebalancing trades.

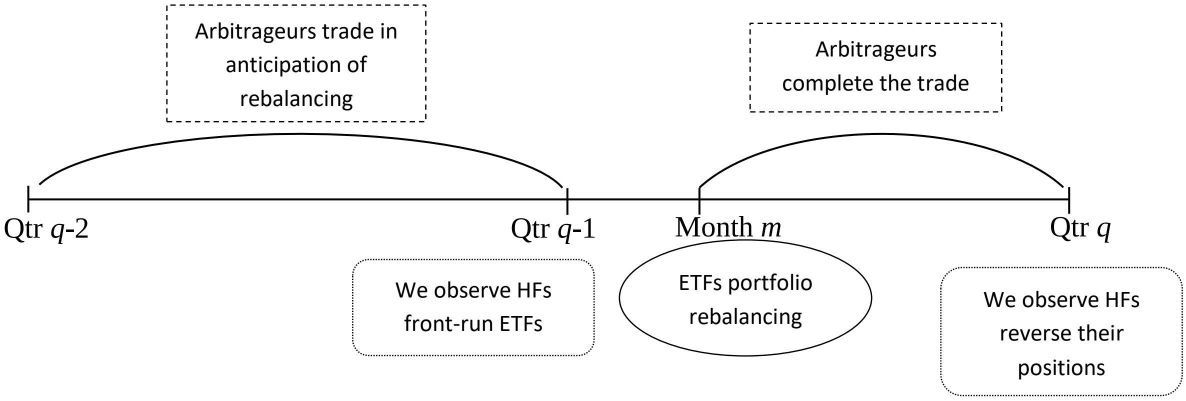
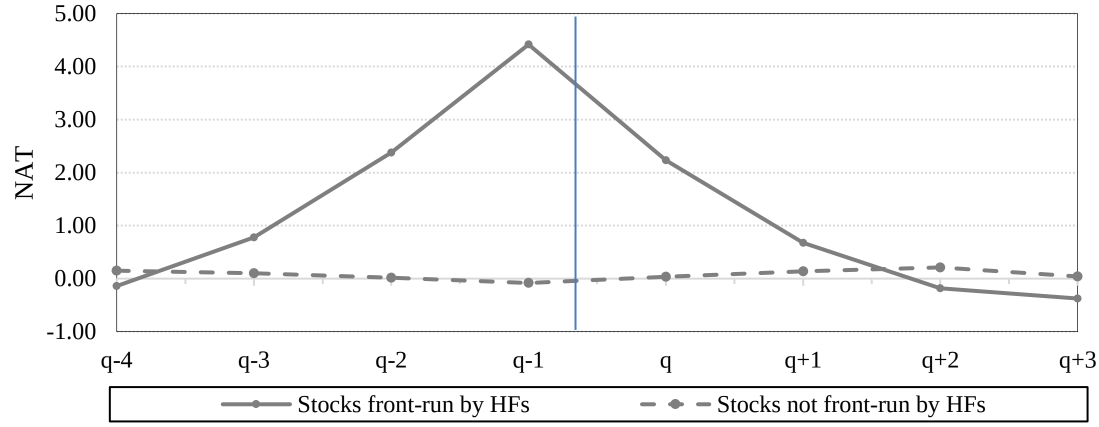


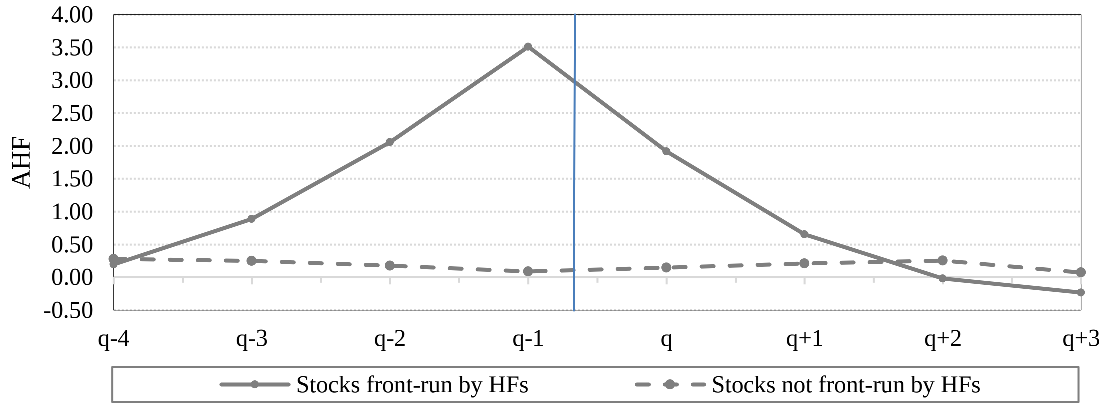
Figure 2: Timeline of anticipatory trading activities by HFs

This figure shows the timeline of trading by hedge funds around ETF rebalancing events. Month m is the month when ETFs rebalance their portfolios. q-2 and q-1 denote quarters preceding month m, and q is the quarter following month m.

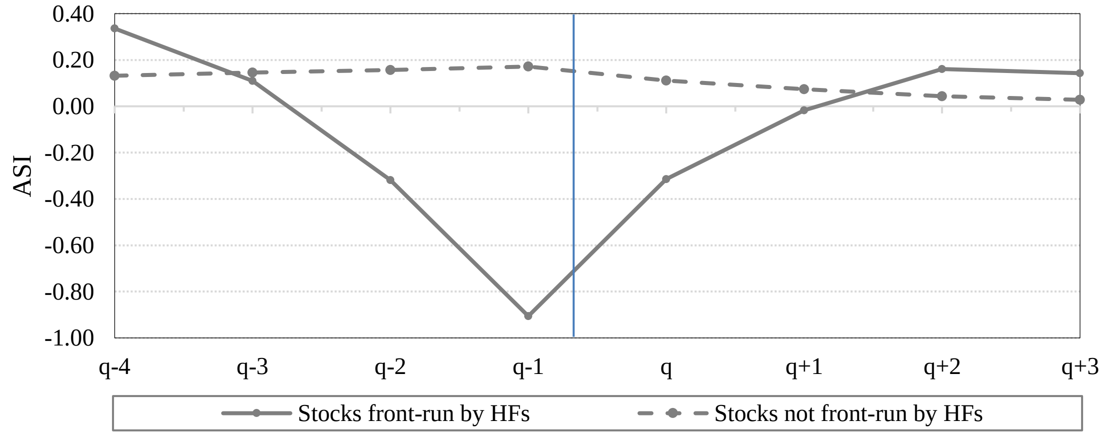
Panel A.1: HF **net arbitrage trades** surrounding ETF rebalancing induced purchases



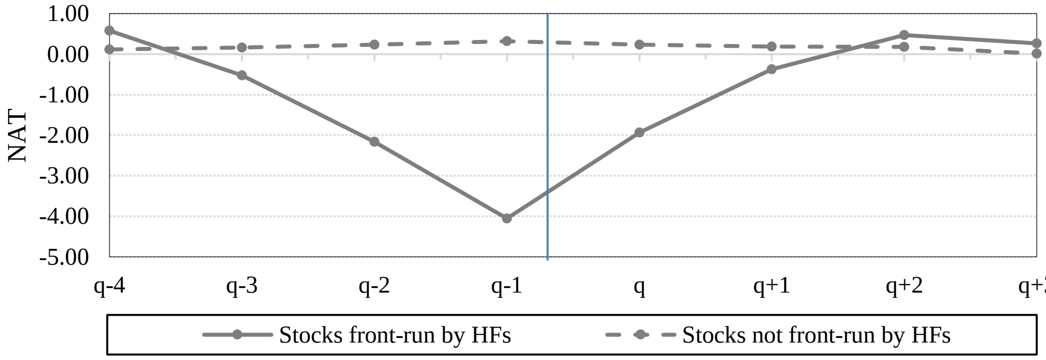
Panel A.2: HF abnormal **long positions** surrounding ETF rebalancing–induced purchases



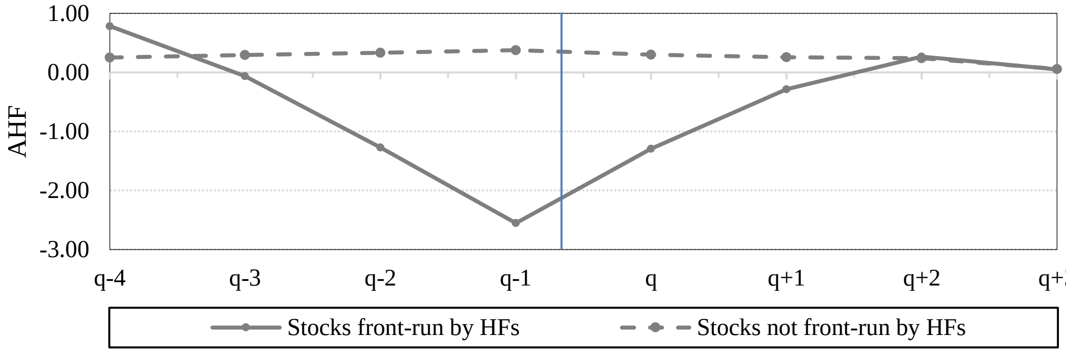
Panel A.3: HF abnormal **short positions** surrounding ETF rebalancing–induced purchases



Panel B.1: HF **net arbitrage trades** surrounding ETF rebalancing–induced sales



Panel B.2: HF abnormal **long positions** surrounding ETF rebalancing–induced sales



Panel B.3: HF abnormal **short positions** surrounding ETF rebalancing–induced sales

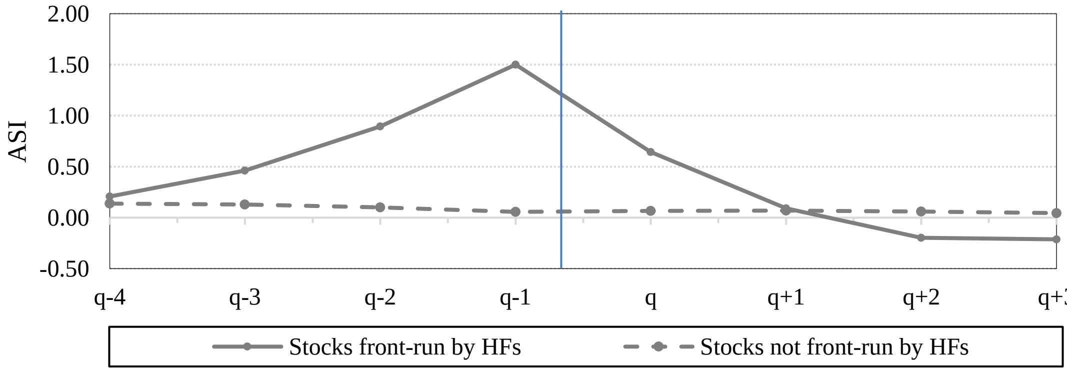
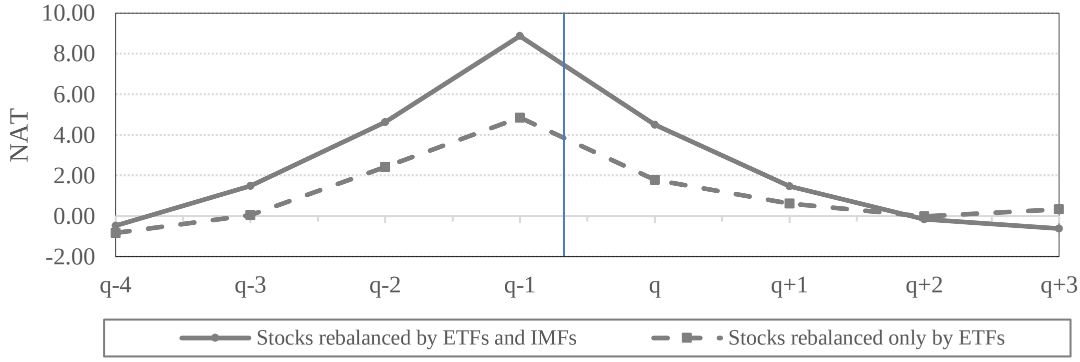


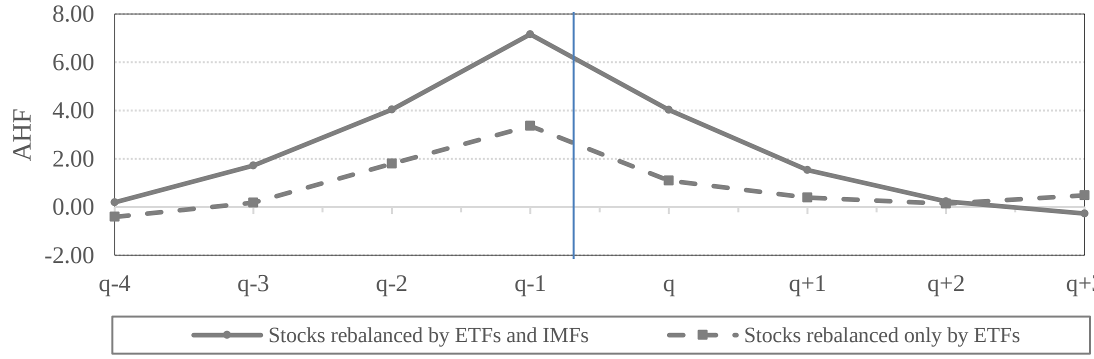
Figure 3: Hedge fund trades surrounding ETF rebalancing events

This figure illustrates the evolution of hedge fund trading around ETF purchases due to their rebalancing activities. The vertical blue line indicates the month in which we observe the high (low) RIT of a stock in Panel A (Panel B). We plot the net arbitrage trade (NAT) for stocks that were purchased (sold) by ETFs and, at the same time, were front-run and bought (sold short) by HFs in the calendar quarter preceding the ETF rebalancing event and for stocks that were not front-run by HFs. NAT is measured as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). The figure then plots the average net arbitrage trades (NAT) in Panels A.1 and B.1, abnormal long positions (AHF) in Panels A.2 and B.2 and abnormal short positions (ASI) in Panels A.3 and B.3 of HFs four quarters before the ETF rebalancing trades and four quarters after.

Panel A: HFs' **net arbitrage trading** in stocks rebalanced by ETFs and index mutual funds



Panel B: HFs' abnormal **long positions** in stocks rebalanced by ETFs and index mutual funds



Panel C: HFs' abnormal **short positions** in stocks rebalanced by ETFs and index mutual funds

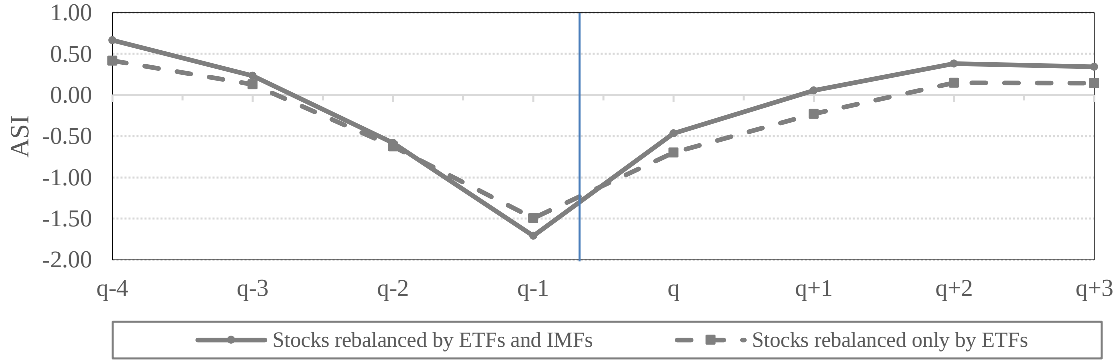


Figure 4: HF trades of stocks rebalanced by ETFs and index mutual funds

This figure illustrates the evolution of hedge fund trading of stocks rebalanced by ETFs and index mutual funds (IMFs). The vertical blue line indicates the month in which we observe the high ETF RIT of a stock. For each ETF rebalancing event, we match IMF RIT at the end of quarter. We plot the net arbitrage trade (NAT) for stocks that were purchased by ETFs and, at the same time, were front-run and bought by HFs in the quarter *q*-1. NAT is measured as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). Further, stocks are divided into two portfolios: 1) stocks that experience rebalancing by IMFs in quarter *q;* 2) stocks that are not rebalanced by IMFs. The figure then plots the average net arbitrage trades (NAT) in Panel A, abnormal long positions (AHF) in Panel B, and abnormal short positions (ASI) in Panel C of HFs four quarters before the ETF rebalancing trades and four quarters after.

Table 1: ETF rebalancing trades and future stock returns

This table reports the results of Fama–MacBeth regressions of the monthly returns of the underlying securities on ETF rebalancing trades. The sample period is from January 2005 to December 2020. $Ret_{i,m}$, $Ret_{i,m+1}$, $Ret_{i,m+2}$, $Ret_{i,m+3}$ are contemporaneous and next months' returns. $RIT_{i,m}$ is monthly rebalancing-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 previous one month ($Ret_{i,m-1}$) and one year returns ($Ret_{i,m-12:m-2}$), 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 percentiles. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Ret_{i,m}$	**$Ret_{i,m+1}$**	**$Ret_{i,m+2}$**	**$Ret_{i,m+3}$**
	(1)	(2)	(3)	(4)
$RIT_{i,m}$	**1.555*****	**-1.611*****	-0.255	0.315
	(3.24)	**(-4.00)**	(-0.55)	(0.69)
$FIT_{i,m}$	5.883***	-2.483**	-0.349	0.995
	(5.18)	(-2.49)	(-0.27)	(0.61)
$Controls_{i,m}$	Yes	Yes	Yes	Yes
Adj R^2	0.090	0.041	0.041	0.039

Table 2: ETF rebalancing trades and future stock returns: ETFs classified by investment type

This table reports the results of Fama–MacBeth regressions of monthly returns on monthly rebalancing-induced trading of ETFs. The sample period is from January 2005 to December 2020. $Ret_{i,m}$, $Ret_{i,m+1}$, $Ret_{i,m+2}$, and $Ret_{i,m+3}$ are contemporaneous and next months' returns. $RIT_{i,m}$ is the monthly rebalancing-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. ETF sample is divided into three categories. Rules-based ETFs defined by Morningstar Strategic Beta group. Broad-market ETFs 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 the "Sector Equity" Morningstar Category. Control variables include previous one month ($Ret_{i,m-1}$) and one year returns ($Ret_{i,m-12:m-2}$), 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 percentiles. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\mathbf{Ret_{i,m}}$	$\mathbf{Ret_{i,m+1}}$	$\mathbf{Ret_{i,m+2}}$	$\mathbf{Ret_{i,m+3}}$
	(1)	(2)	(3)	(4)
Rules-based $RIT_{i,m}$	**3.060*** **	**-2.140** **	-1.028	-0.674
	(4.00)	**(-2.54)**	(-1.66)	(-0.90)
Rules-based $FIT_{i,m}$	-1.071	0.725	-1.584	-2.929
	(-0.32)	(0.17)	(-0.44)	(-1.10)
Mkt $RITt_{i,m}$	-4.784	-9.201***	-3.754	4.456
	(-1.18)	(-3.44)	(-1.42)	(1.58)
Mkt $FIT_{i,m}$	2.280	2.475	24.342*	16.002
	(0.07)	(0.20)	(1.82)	(0.88)
Sector $RIT_{i,m}$	-0.908	-0.377	8.654	-5.936
	(-0.18)	(-0.04)	(1.16)	(-0.89)
Sector $FIT_{i,m}$	11.738**	1.485	-13.098	13.742
	(2.08)	(0.21)	(-1.43)	(1.41)
Controls $_{i,m}$	Yes	Yes	Yes	Yes
Adj R^2	0.101	0.047	0.040	0.036

Table 3: ETFs rebalancing and changes in the underlying indices

This table reports the results of Fama–MacBeth regressions of monthly rebalancing-induced trades by ETFs on the dummy variables of index inclusion or exclusion events. The sample contains all the additions and deletions to the universes of S&P and Russell indices for the period from January 2005 to December 2019. $RIT_{i,m}$ is monthly rebalancing-induced trading of stocks by ETFs in month m, measured as the difference between monthly ETF trades and flow-induced trades (FIT). $Inclusion_{i,m}$ ($Exclusion_{i,m}$) is the dummy variable equal to 1 if a stock was included (excluded) in one of the indices in month m and 0 otherwise. $N\_Incl_{i,m}$ ($N\_Excl_{i,m}$) is the variable that defines the number of indices in which a stock was included (excluded). The results are presented for the whole sample of ETFs and for the three categories: rules-based, broad-market, and sector ETFs. Rules-based ETFs defined by Morningstar Strategic Beta group. Broad-market ETFs 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 the "Sector Equity" Morningstar Category. Control variables include previous one month ($Ret_{i,m-1}$) and one year returns ($Ret_{i,m-12:m-2}$), log(SIZE), turnover, and log(B/M). Financial stocks (SIC codes 6000-6999) are excluded from the sample. All variables are winsorized at the 1st and 99th percentiles. *,**, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

	$RIT_{i,m}$							
	All ETFs		**Rules-based ETFs**		**Board-market ETFs**		**Sector ETFs**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Inclusion_{i,m}$	0.378***		0.240***		0.029***		0.055***	
	(15.50)		(21.00)		(11.55)		(5.95)	
$Exclusion_{i,m}$	-0.194***		-0.198***		-0.030***		-0.047***	
	(-7.28)		(-12.05)		(-8.50)		(-5.49)	
$N\_Incl_{i,m}$		0.038***		0.066***		0.028***		0.008***
		(15.60)		(14.99)		(11.98)		(5.84)
$N\_Excl_{i,m}$		-0.015***		-0.055***		-0.027***		-0.007***
		(-2.90)		(-7.66)		(-7.83)		(-4.62)
$Controls_{i,m}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Adj\ R^2$	0.151	0.161	0.142	0.145	0.165	0.174	0.053	0.053

Table 4: ETF rebalancing vs arbitrage trades by hedge funds

This table reports the equal-weighted monthly returns of stocks rebalanced by ETFs and subject to HF arbitrage trades. We identify stocks that were purchased by ETFs due to its rebalancing event in month *m.* We examine whether purchasing of a stock by an ETF in month *m* was front-run by HF and stocks were bought by HFs in the previous month *m*-1. We consider ETF buys as stocks that meet the following two conditions: 1) ETF rebalancing trades of stock *i* ranked in the highest quintile in month *m* and 2) ETF rebalancing trades are above zero. We consider hedge fund front-run buys as stocks that meet the following condition: NAT of stock *i* ranked in the highest quintile in month *m*-1, where NAT is the net position of HFs in the stock measured as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). The 13F holdings are observed in March, June, September, and December (i.e., month *m*-1), and ETF rebalancing trades in month *m* would be April, July, October, and January. We form two portfolios: portfolio 1 (P1) containing stocks that were front-run and bought by HFs in the previous month and portfolio 2 (P2) containing the rest of the stocks rebalanced by ETFs. We also report returns to the strategy that goes long on P1 and short sells P2. Panel A reports raw returns, Panel B reports CAPM alphas, and Panel C includes DGTW-adjusted returns. The results are presented for the sample period 2005–2020. $*$,$**$, $***$ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Raw returns				
	m-1	**m**	**m+1**	**m+2**
	(1)	(2)	(3)	(4)
P1: ETFs buy in *m* and HFs front-run in *m*-1	**1.77****	**1.88***	0.93	1.02
	(2.08)	**(1.91)**	(1.19)	(1.26)
P2: HFs do not front-run in *m*-1	0.92	1.12	0.75	1.03
	(1.25)	(1.33)	(1.06)	(1.39)
P1 – P2	**0.86*****	**0.75*****	0.18	-0.01
	(3.86)	**(2.65)**	(0.82)	(-0.06)
Panel B: CAPM alpha				
	m-1	**m**	**m+1**	**m+2**
	(1)	(2)	(3)	(4)
P1: ETFs buy in *m* and HFs front-run in *m*-1	**1.69****	1.46	-0.14	0.76
	(2.04)	(1.58)	(-0.51)	(0.82)
P2: HFs do not front-run in *m*-1	0.79	0.79	-0.22	0.76
	(1.13)	(0.94)	(-0.99)	(0.91)
P1 – P2	**0.80*****	**0.57****	-0.01	-0.11
	(3.57)	**(2.07)**	(-0.07)	(-0.64)
Panel C: DGTW adjusted returns				
	m-1	**m**	**m+1**	**m+2**
	(1)	(2)	(3)	(4)
P1: ETFs buy in *m* and HFs front-run in *m*-1	**0.51*****	**0.77*****	0.03	-0.01
	(2.81)	**(2.74)**	(0.20)	(-0.05)
P2: HFs do not front-run in *m*-1	-0.06	0.09	-0.01	0.03
	(-0.99)	(1.09)	(-0.16)	(0.57)
P1 – P2	**0.57*****	**0.69****	0.04	-0.04
	(3.00)	**(2.36)**	(0.24)	(-0.23)

Table 5: HFs arbitrage trading of stocks rebalanced by ETFs and index mutual funds

This table reports the equal-weighted monthly returns of stocks rebalanced by ETFs and IMFs and subject to HF front-running. We identify stocks that were purchased by ETFs due to its rebalancing event in month *m*. We consider ETF buys as stocks that meet the following two conditions: 1) ETF rebalancing trades of stock *i* ranked in the highest quintile in month *m* and 2) ETF rebalancing trades are above zero. We consider hedge fund front-run buys as stocks that meet the following condition: NAT of stock *i* ranked in the highest quintile in month *m* – 1, where NAT is the net position of HFs in the stock measured as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). The 13F holdings are observed in March, June, September, and December (i.e., month *m*-1), and ETF rebalancing trades in month *m* would be April, July, October, and January. We further divide stocks into two portfolios: 1) stocks that were bought by index mutual funds (IMFs) as part of their rebalancing event at the end of quarter *q* (P1) and 2) the rest of the stocks (P2). We also report returns to the strategy that goes long on P1 and short sells P2. Panel A reports raw returns, Panel B reports CAPM alphas, and Panel C includes DGTW-adjusted returns. The results are presented for the sample period 2005–2020. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

	m-1	**m**	**m+1**	**m+2**
Panel A: Raw returns				
	(1)	(2)	(3)	(4)
P1: Stocks bought by ETFs and IMFs	**1.98****	**1.98****	1.01	0.81
	(2.33)	**(1.99)**	(1.36)	(1.00)
P2: Stocks bought only by ETFs	**1.88***	**2.19***	-0.04	0.48
	(1.79)	**(1.94)**	(-0.05)	(0.53)
P1 – P2	0.11	-0.21	**1.05*****	0.32
	(0.22)	(-0.44)	**(2.66)**	(0.81)
Panel B: CAPM alpha				
	(1)	(2)	(3)	(4)
P1: Stocks bought by ETFs and IMFs	**1.88****	**1.60***	0.21	0.60
	(2.30)	**(1.73)**	(0.77)	(0.67)
P2: Stocks bought only by ETFs	**1.85***	**1.82***	**-0.79****	0.33
	(1.79)	**(1.74)**	**(-1.98)**	(0.32)
P1 – P2	-0.07	-0.32	**0.90****	0.17
	(-0.15)	(-0.67)	**(2.40)**	(0.43)
Panel C: DGTW adjusted returns				
	(1)	(2)	(3)	(4)
P1: Stocks bought by ETFs and IMFs	**0.60****	**0.75****	**0.35***	-0.06
	(2.44)	**(2.16)**	**(1.89)**	(-0.25)
P2: Stocks bought only by ETFs	0.65	**0.98****	-0.31	-0.35
	(1.42)	**(2.25)**	(-0.93)	(-1.11)
P1 – P2	-0.05	-0.23	**0.67***	0.29
	(-0.09)	(-0.47)	**(1.93)**	(0.79)

Table 6: Betting against ETF rebalancing trades: Portfolio analysis

This table reports the equal-weighted monthly returns for Long, Short, and Long-Short portfolios sorted on ETF rebalancing trades. At the end of each month, all stocks are sorted into quintiles based on their ETF RIT. Columns (1) and (4) present portfolios' raw returns, Columns (2) and (5) contain DGTW adjusted returns, and Columns (3) and (6) include DGTW + Illiquidity adjusted returns for portfolios sorted based on monthly ETF RIT, respectively, using Morningstar data and one-month holding period. The long (short) portfolio contains stocks with the lowest (highest) ETF RIT. Long-Short portfolio is formed by taking a long position in the stocks with the lowest ETF RIT and taking a short position in the stocks with the highest ETF RIT. The results are presented for the whole sample period (2005–2020) and for the second half of the sample (2010–2020). $*$,$**$, $***$ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

	2005-2020			**2010-2020**		
	Raw	**DGTW**	**DGTW and Illiquidity**	**Raw**	**DGTW**	**DGTW and Illiquidity**
	(1)	(2)	(3)	(4)	(5)	(6)
Low	1.124**	0.204***	0.156**	1.353**	0.147**	0.102
	(2.48)	(2.80)	(2.25)	(2.57)	(2.03)	(1.37)
High	0.744	-0.182**	-0.199**	0.885	-0.278***	-0.291***
	(1.49)	(-2.28)	(-2.39)	(1.54	(-3.65)	(-3.16)
Low-High	**0.379*** **	**0.386*** **	**0.355*** **	**0.468*** **	**0.425*** **	**0.393*** **
	(2.84)	**(3.51)**	**(3.43)**	**(3.02)**	**(4.09)**	**(3.48)**

Table 7: Subsample analysis: Small and large firms

This table reports the results of Fam–MacBeth regressions of the monthly returns of the underlying securities on ETF rebalancing trades. The sample period is from January 2005 to December 2020. Stocks in the sample are divided into two subsamples based on their size. We use the NYSE median as the breakpoint. $Ret_{i,m}$, $Ret_{i,m+1}$, $Ret_{i,m+2}$ are contemporaneous and the next months' returns. $RIT_{i,m}$ is the rebalancing 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 previous one month ($Ret_{i,m-1}$) and one year returns ($Ret_{i,m-12:m-2}$), 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 percentiles. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Ret_{i,m}$		$Ret_{i,m+1}$		$Ret_{i,m+2}$	
	Large stocks	**Small stocks**	**Large stocks**	**Small stocks**	**Large stocks**	**Small stocks**
	(1)	(2)	(3)	(4)	(5)	(6)
$RIT_{i,m}$	**0.795***	**1.003***	**-0.580***	**-2.009*****	1.255	-0.416
	(1.75)	**(1.80)**	**(-1.73)**	**(-3.60)**	(1.26)	(-0.79)
$FIT_{i,m}$	5.800***	5.307***	0.006	-2.764**	0.008	-1.132
	(2.82)	(3.63)	(0.00)	(-2.47)	(0.01)	(-0.74)
$Controls_{i,m}$	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.133	0.101	0.090	0.038	0.098	0.037

Table 8: ETF trades and future stock returns: control for ETF ownership

This table reports the results of Fama–MacBeth regressions of the monthly returns of the underlying securities on ETF rebalancing trades. The sample period is from January 2005 to December 2020. $Ret_{i,m}$, $Ret_{i,m+1}$, $Ret_{i,m+2}$, $Ret_{i,m+3}$ are contemporaneous and the next months' returns. $RIT_{i,m}$ is the monthly rebalancing-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, and for ETF ownership in month *m.* Other control variables include previous one month ($Ret_{i,m-1}$) and one year returns ($Ret_{i,m-12:m-2}$), 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 percentiles. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Ret_{i,m}$	**$Ret_{i,m+1}$**	**$Ret_{i,m+2}$**	**$Ret_{i,m+3}$**
	(1)	(2)	(3)	(4)
$RIT_{i,m}$	**1.930*** **	**-1.321*** **	-0.450	-0.194
	(4.12)	**(-3.04)**	(-1.50)	(-0.46)
$FIT_{i,m}$	7.228***	-1.517	-0.489	1.344
	(5.18)	(-1.35)	(-0.55)	(1.25)
$ETFownership_{i,m}$	-0.347***	-0.038	-0.066	-0.081
	(-3.23)	(-0.57)	(-1.02)	(-1.26)
$Controls_{i,m}$	Yes	Yes	Yes	Yes
Adj R^2	0.096	0.046	0.039	0.036