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Doctoral Thesis

Essays on Institutional Investors and Asset Pricing

This thesis is submitted in fulfillment of the requirements for the degree of Doctor of Philosophy in Finance

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Abstract

This thesis contains two essays on the strategic trading behavior of hedge funds in two key contexts: ETF rebalancing and environmental incidents, revealing significant market impacts and the distinct roles of institutional investors. The first essay, "*ETF rebalancing, hedge fund trades, and capital markets*" the interaction between ETF rebalancing and hedge funds (HFs) trades. Our analysis reveals that the transparency and predictability inherent in ETF rebalancing provide opportunities for anticipatory trading by HFs, who gradually adjust their long and short positions ahead of ETF rebalancing. While ETF rebalancing is associated with strong price distortions of the underlying securities, we demonstrate that HFs' anticipatory trading exaggerates the price impact of non-fundamental demand, highlighting the hidden costs of ETF rebalancing. The second essay, "*Post-environmental incident drift and institutional trades: who benefits from environmental shocks?*", examines the impact of environmental incidents on stock returns and the trading patterns of various institutional investors, with a focus on hedge funds. We document a significant negative drift in stock returns following environmental incidents, persisting over one quarter. Our analysis reveals that banks, pension funds, and insurance companies exert significant selling pressure on high ESG risk stocks post-incident. In contrast, hedge funds often purchase these depressed stocks, capitalizing on the temporary price drops induced by the divestments of environmentally conscious investors. Notably, non-PRI signatory hedge funds generate positive returns from this strategy, while PRI signatories do not demonstrate similar trading behaviors. This investigation highlights the divergent strategies of institutional investors, with hedge funds playing a crucial role in providing liquidity and exploiting opportunities from climate-related risks. Overall, this thesis contributes to the understanding of ETF rebalancing dynamics and the market impacts of ESG incidents. It emphasizes the strategic roles of hedge funds in navigating these financial landscapes, offering insights into how their anticipatory and opportunistic trading behaviors can influence market efficiency and stability.

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Declaration of Authorship

I, Adina Yelekenova, declare that, except where specific reference is made to the work of others, the content of this thesis is original and has not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other University.

I further declare that Chapter 2 is co-authored with my supervisors, Dr. George Wang and Dr. Chelsea Yao, and Chapter 3 is co-authored with Prof. George Aragon at W.P. Carey School of Business, Arizona State University, and my supervisors.

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Chapter 1: Thesis introduction

Institutional investors, particularly hedge funds, play a pivotal role in the dynamics of financial markets. Their trading strategies and investment decisions significantly impact asset prices, market liquidity, and the broader financial ecosystem. Hedge funds are well known for their profit driven nature and possess superior skills to generate alpha (Agarwal, Daniel, and Naik, 2009; Agarwal, Jiang, Tang, and Yang, 2013; Aragon and Nanda, 2012; Aragon and Martin, 2012; Kosowski, Naik, and Teo, 2007; Lan, Wang, and Yang, 2013). Previous studies show that hedge funds strategically trade around events, such as technology bubble (Brunnermeier and Nagel, 2004), and in stocks sold by distressed institutional investor (Chen, Hanson, Hong, and Stein, 2008; Aragon, Martin, and Shi, 2019; Agarwal, Aragon, Nanda, and Wei, 2024). This thesis sheds light on hedge funds behavior in the two distinct market contexts, ETF rebalancing and responses to environmental incidents, that remains an open question in the literature and has not been addressed yet. We uncover the strategic trading of hedge funds around these events and show the potential hidden costs and benefits.

This thesis consists of two papers. The first paper, presented in Chapter 2 and titled *"ETF rebalancing, hedge fund trades, and capital market"*, highlights hedge funds anticipatory trading around ETF rebalancing events and shows potential hidden costs to ETF investors. The second paper, presented in Chapter 3 and titled *"Post-environmental incident drift and institutional trades: who benefits from environmental shocks?"*, shows the negative drift in stock returns following environmental incidents and focuses on the institutional trading around such events, where hedge funds end up on the buying side of high ESG risk stocks that experienced environmental incidents and derive potential profits from such trading strategy.

More specifically, the paper *"ETF rebalancing, hedge fund trades, and capital market"* (co-authored with George Wang and Chelsea Yao), examines the impact of ETF rebalancing trades on underlying securities' and focuses on the role of hedge funds anticipatory trading around rebalancing events. ETFs experienced dramatic growth in the past decade. Existing research highlights both positive and negative impact of ETFs, as a financial innovation, on capital markets, where 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). Some studies show that ETFs impose non-fundamental demand shock on underlying securities (Brown, Davies, and Ringgenberg, 2021), while others show that ETFs improve liquidity (Saglam, Tuzun, and Wermers, 2019), increase informational efficiency (Glosten, Nallareddy, and Zou, 2020), and have positive effects on real investments (Antoniou, Li, Liu, Subrahmanyam, and Sun, 2023). However, it is still unclear what are the hidden costs of ETF investing. We contribute to this literature by discovering the impact of ETF rebalancing trades, that were largely overlooked in the existing literature, due to ETFs being considered as passive investment vehicle. We also explore the role of hedge funds strategic trading and their contribution to the impact of ETF rebalancing trades on underlying securities returns.

Our analysis reveals that ETF rebalancing has a significant positive relation with contemporaneous stock returns but a negative relation with future stock returns, after controlling for flow-induced trades, inducing a “buy-high and sell-low” scenario for ETFs. This effect is more pronounced in rules-based ETFs, which rebalance more frequently due to the nature of their underlying indices. We further show that hedge funds gradually increase or decrease their positions in stocks to be included or excluded from ETFs, often leading to a temporary price pressure that hedge funds exploit for profit. This strategic trading results in a monthly outperformance for stocks bought by hedge funds ahead of ETF rebalancing events, illustrating the significant impact of hedge fund strategic trading on market prices and ETF investor costs. We also show that hedge funds use short selling and options as part of their anticipatory trading strategy. This study contributes to the literature by highlighting the hidden costs of passive investing, particularly those incurred through the interaction between ETF rebalancing and hedge fund trades. These findings extend previous research on ETF impacts on the capital market and offer new insights into the role of hedge funds in exacerbating price impacts on underlying securities.

The second paper, *“Post-environmental incident drift and institutional trades: who benefits from environmental shocks?”* (co-authored with George Aragon, George Wang, and Chelsea Yao), shifts focus to the trading behavior of institutional investors around environmental incidents. As climate change increasingly influences investor preferences, many institutional investors are pressured to divest from environmentally harmful firms and shift towards greener portfolios (Pastor, Stambaugh, and Taylor, 2023; Atta-Darkua, Glossner, Krueger, and Matos, 2023). This study examines the overall impact of environmental incidents on stock returns, how different institutional investors, especially hedge funds, react to them, and who benefits from these reactions. The shift in ESG preferences of investors has led to the higher green tilt in the portfolios of large institutional investors achieved mainly through divestment from brown firms, exits after environmental and social incidents (Gantchev, Giannetti, and Li, 2022a), and analyst downgrades following ESG incidents (Derrien, Krueger, Landier, and Yao, 2023).

Existing literature highlights the significant disagreement in ESG ratings (Avramov, Cheng, Lioui, and Tarelli, 2022; Berg, Fabisik, and Sautner, 2021; Berg, Koelbel, Pavlova, and Rigobon, 2022; Gibson, Krueger, and Schmidt, 2021; Serafeim and Yoon, 2023), therefore we focus on environmental incidents, as they provide a clear point-in-time salient shock to firms' environmental performance. We show that environmental incidents typically result in significant negative stock returns, with a pronounced negative drift persisting up to a quarter. We posit two hypotheses to explain this prolonged negative reaction: fire-selling pressure from environmentally conscious investors and investor underreaction to the incidents' implications on firm fundamentals. Our findings show that banks, pension funds, and insurance companies significantly sell high ESG risk stocks following environmental incidents, whereas hedge funds and mutual funds tend to buy these stocks, taking advantage of the downward price pressure.

We find that hedge funds' strategic trading around environmental incidents results in significant positive fund performance, especially for non-PRI signatory funds. These hedge funds often provide liquidity to selling investors and profit from the temporary price pressure caused by environmental incidents. Our analysis of short interest and options positions further indicates that hedge funds anticipate these incidents and adopt positions to capitalize on the ensuing volatility. This research contributes to the ESG literature by demonstrating hedge funds' opportunistic behavior in the face of environmental incidents. It also highlights the potential for hedge funds to play a role in mitigating the financial impacts of such incidents by providing liquidity and stabilizing prices, albeit primarily driven by profit motives.

Together, these studies illuminate the complex and often hidden interactions between hedge funds and other institutional investors within the contexts of ETF rebalancing and environmental incidents. By revealing the strategies and impacts of hedge funds in these scenarios, we contribute to a deeper understanding of the costs and market dynamics influenced by institutional investors. This thesis underscores the dual role of hedge funds as both liquidity providers and profit-driven entities, shaping the financial landscape in nuanced and significant ways.

Chapter 2: ETF Rebalancing, Hedge Fund Trades, and Capital Market

Abstract

We examine the interaction between ETF rebalancing and hedge funds (HFs) trades. Our analysis reveals that the transparency and predictability inherent in ETF rebalancing provide opportunities for anticipatory trading by HFs, who gradually adjust their long and short positions ahead of ETF rebalancing. Using the quasi-natural experiment of the index rebalancing postponement in March 2020, we establish causal evidence of HF's anticipatory trading. Furthermore, we find supportive evidence by analyzing HFs' option positions. While ETF rebalancing is associated with strong price distortions of the underlying securities, we demonstrate that HFs' anticipatory trading exaggerates the price impact of non-fundamental demand, highlighting the hidden costs of ETF rebalancing.

2.1 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 traders conducting arbitrage trades around them with large losses."

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

The dramatic change in the exchange traded funds (ETFs) market over the past decade has been accompanied by exponential growth in rebalancing activities. In 2020 alone, rebalancing trades of passive ETFs exceeded $1.4 trillion.[1] The substantial volume can be largely attributed to the rise of nontraditional ETFs, which are characterized by frequent portfolio rebalancing. The U.S. Securities and Exchange Commission (SEC) requires index-tracking ETFs to 1) align consistently with their stated objective of tracking a benchmark index while monitoring and minimizing tracking error (the divergence between the ETF's performance and its benchmark); and 2) disclose the benchmark index and clearly explain the methodology used to track it, including rules for rebalancing or reconstitution. To minimize tracking errors, ETFs often execute their rebalancing trades in bulk.[2] However, the transparency of ETFs and the predictability of their rebalancing events could make them attractive targets for systematic anticipatory trades by professional arbitrageurs, such as hedge funds (HFs).[3]

The interaction between ETF rebalancing and HFs anticipatory trading could result in both expected and unforeseen consequences for the stock market. The importance of understanding this dynamic was highlighted during the March 13, 2020 postponement of the S&P Dow Jones index rebalancing. 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] In extreme cases like this, the interaction between ETFs and HFs may

[1] We calculated the aggregate dollar value of rebalancing trades for US domestic equity ETFs in 2020 from our sample. We define rebalancing trades as the difference between the total dollar trade and the flows.

[2] As noted by Ben-David, Franzoni, and Moussawi (2017), ETF managers are evaluated on their ability to minimize tracking error, and it is widely understood within the industry that some passive ETF managers' compensation is directly tied to this metric.

[3] Previous literature shows that strategic traders can profit by front-running other institutional traders (e.g., Agarwal, Aragon, Nanda, and Wei, 2024; Aragon, Martin, and Shi, 2019; Shive and Yun, 2013).

[4] During the 2020 pandemic, the S&P Dow Jones Indices announced an unprecedented postponement of quarterly rebalancing. They claimed that this action was taken "to protect investors" and to avoid the "undesirable 'buy-high and sell-low' scenario." See www.forbes.com/sites/nathanvardi/2020/03/27/hedge-funds-suffered-losses-as-

introduce excessive non-fundamental shocks to the financial system. Despite its growing significance, the underlying dynamics of ETF-driven market movements have received limited attention in the literature. Our study aims to address this gap by investigating the implications of ETF rebalancing and its interaction with hedge fund anticipatory trading.

We begin by examining the impact of ETF rebalancing on underlying securities. Our analysis reveals that ETF rebalancing trades are significantly and positively correlated with contemporaneous stock returns but negatively correlated with future stock returns. These relations remain both economically and statistically significant, even after accounting for ETF flow–induced trades and ETF ownership. Acknowledging that certain ETFs rebalance more frequently due to the nature of their underlying indices, we classify our sample into three categories: rules-based ETFs, broad-market ETFs, and sector ETFs. Rules-based indices, which follow specific criteria such as momentum or value strategies, tend to rebalance more frequently, generating higher levels of rebalancing activity compared to sector and broad-market ETFs.[5] Our findings indicate that the negative relation between ETF rebalancing and future stock returns is most pronounced for rules-based ETFs. This underscores the critical role of ETF rebalancing in shaping future stock return patterns. These results complement earlier research documenting the non-fundamental demand shocks imposed by ETF flows (Brown, Davies, and Ringgenberg, 2021), highlighting the need to better understand the broader market implications of ETF activities.[6]

We further explore the interaction between ETF rebalancing and anticipatory trading, revealing several novel findings. First, we document that HFs gradually increase (decrease) their positions in stocks to be included in (excluded from) the ETF portfolio. This behavior aligns with reports from major financial media, suggesting that professional arbitrageurs exploit ordinary ETF investors around ETF rebalancing events. Second, stocks subject to anticipatory trading by HFs significantly outperform those not targeted by HFs, with a monthly

index-rebalancing-trade-went-awry and www.etfstrategy.com/sp-dji-delays-quarterly-index-rebalance-amid-market-chaos-10339/

[5] Rules-based ETFs rebalance their portfolios on semi-annual, quarterly, or even monthly basis (Easley, Michayluk, O'Hara, and Putnins, 2021).

[6] Previous studies have documented that inflows into ETFs exert price pressure on stocks. For instance, Brown, Davies, and Ringgenberg (2021) demonstrate that ETF flows create a non-fundamental demand shock on underlying securities. Zou (2019) finds a negative association between ETF flows and subsequent firm operating performance, sales growth, and stock returns. Dannhauser and Pontiff (2024) highlight the positive correlations between aggregate ETF flows and market returns, followed by significant reversal. Ben-David, Franzoni, and Moussawi (2018) find that ETF flows predict price reversal in the underlying stocks within a 40-day period.

outperformance of 0.6% per month during ETF rebalancing events. This finding implies that HFs' trades exert a substantial influence on prices of stocks rebalanced by ETFs.

Due to the quarterly reporting frequency of HFs' holdings, we are unable to track HFs' net arbitrage trades close to the ETF rebalancing months. To address this limitation, we analyze bi-weekly aggregate short interest in stocks sold during ETFs rebalancing. The higher frequency short interest data helps determine whether HFs build positions prior to ETF rebalancing as part of anticipatory trading or operate independently of ETF rebalancing events. Given that HFs often use short positions when bearish on the future stock returns, we focus on the abnormal short interest (ASI) in stocks sold during ETF rebalancing. Our analysis reveals a gradual increase in ASI for these stocks, with ASI remaining high two weeks before the ETFs rebalancing month, followed by an immediate decrease after ETF rebalancing. This pattern suggests that HFs engage in anticipatory trading through abnormal short-selling.

An alternative explanation for the observed relation between ETFs rebalancing and HF trades is that HFs' stock-picking skills and informed trading may drive the observed HFs trades, rather than anticipation of ETF rebalancing itself. If HFs participate in anticipatory trading activities, they would target stocks included in ETFs rebalancing portfolios. On the other hand, if their trades follow specific rules or strategies, we would observe no significant differences between their activity in rebalanced stocks and in non-rebalanced stocks with similar characteristics. Interestingly, we find that the positive relation between ETF rebalancing and HFs trades in the month preceding the ETF rebalancing month is evident only for rebalanced stocks. This provides supportive evidence that HFs trade in anticipation of ETF rebalancing.

To explore the causal relation between ETF rebalancing and HF trades, we exploit the unique event of the postponement of index reconstitutions due to the Covid-19 pandemic in March 2020. The unexpected postponement affected all S&P Dow Jones and ICE (Intercontinental Exchange) indices. Using bi-weekly short interest data, we track short positions in stocks expected to be sold during ETFs' rebalancing. Before the scheduled ETF rebalancing date, ASI in these stocks rises significantly. Strikingly, unlike in normal times—when HFs close their positions after ETF rebalancing—ASI reverts to its initial level once the postponement was announced.[7] Our finding provides causal evidence of HFs' anticipatory trading around ETF rebalancing events.

We further examine HFs holdings in call and put options to discern the nature of HF trading strategies around ETF rebalancing events. If HFs engage in speculative trading, then we expect to observed corresponding changes in their option positions in those stocks. Our findings confirm this: HFs increase call option holdings in stocks purchased by ETFs during rebalancing, anticipating upward price pressure imposed on those stocks. Furthermore, HFs increase their holdings in put option one month before ETF rebalancing, anticipating a subsequent decline in stock prices. This shift in HF option positions suggests a speculative nature of HF trading around ETF rebalancing events.

Next, we explore the impact of HFs anticipatory trading on rebalanced stock returns. To do so, we double sort stocks into quintiles based on their ETF rebalancing trades and HFs' net arbitrage trades. We show that stocks rebalanced by ETFs and bought by HFs in anticipation of rebalancing outperform non-targeted stocks by 0.6% during the rebalancing month. This finding suggests that HFs strategically select stocks experiencing significant price pressure during rebalancing month to lock in profits.

Given that both ETFs and index mutual funds (IMFs) track indices and undergo rebalancing, we assess stocks subject to rebalancing activities by both ETFs and IMFs. Stocks subject to rebalancing by both ETFs and IMFs may attract more anticipatory trades due to higher price pressure. Indeed, our findings reveal that net arbitrage trades (NAT) by HFs in stocks rebalanced in both ETFs and IMFs are approximately double the size of the corresponding trade volumes in stocks rebalanced in ETFs alone.

Finally, we estimate the approximate costs incurred by ETF investors due to HFs strategic trading around ETFs rebalancing. By comparing the price of stocks traded during ETF rebalancing with their fair market values—proxied by matched non-rebalanced stocks—we estimate an average annual loss of $5.2 billion for ETF investors.

Our paper contributes to several key strands of the existing literature. First, we build on the growing research on hedge fund strategic trading. Previous research shows that hedge funds

[7] Our finding aligns with Forbes' observation (March 17, 2020) that "*the March cancellation of scheduled rebalancing by major index providers hit some traders conducting arbitrage trades around them with large losses*."

trade around events such as technological bubbles (Brunnermeier and Nagel, 2004; Aragon and Martin, 2012), fire-sales from distressed managers (Brunnermeier and Pedersen, 2005; Chen, Hanson, Hong, and Stein, 2008; Aragon, Martin, and Shi, 2019; Agarwal, Aragon, Nanda, and Wei, 2022), and predictable mutual fund flows (Shive and Yun, 2013; Jiao, Massa, and Zhang, 2016). We extend this by demonstrating that hedge funds exploit opportunities arising from ETF rebalancing events.

Second, we contribute to the growing literature on ETF impacts on capital markets. While prior studies link high ETF ownership to increased stock volatility (Ben-David, Franzoni, and Moussawi, 2018) and ETF arbitrage to return comovement (Da and Shive, 2018), few have explored ETFs' effects on liquidity (Agarwal, Hanouna, Moussawi, and Stahel, 2018; Comerton-Forde, Sun, and Zhong, 2024; Saglam, Tuzun, and Wermers, 2019) and market efficiency (Glosten, Nallareddy, and Zou, 2020; Antoniou, Li, Liu, Subrahmanyam, and Sun, 2023)), as well as the role of ETF short-selling in liquidity provision and shareholder voting (Evans, Moussawi, Pagano, Sedunov, 2024; Evans, Karakas, Moussawi, and Young, 2025). We expand this discussion by revealing how ETF rebalancing attracts HF anticipatory trades, which, in turn, may exacerbate price impacts and impose costs on ETF investors.

Third, our research sheds light on the hidden costs of passive investing. Pedersen (2018) critiques Sharpe's (1991) zero-sum game assumption, noting that passive investors face rebalancing costs while active managers earn positive returns.[8] In particular, Pedersen (2018) note that in the real world, passive investors have to rebalance their portfolios and face rebalancing costs, while active managers collect positive returns.[9] Berk and van Binsbergen (2015) highlight transaction costs for passive investors, while Li (2024) links ETF rebalancing to high transaction fees. Our study adds to this discussion by highlighting rebalancing costs imposed by professional arbitrage traders, which previous studies have overlooked. Unlike prior work, we examine a comprehensive sample of passive ETFs and explore how their rebalancing trades impact underlying securities and ETF investors. We show that rules-based ETFs, rather than broad-market ETFs, are the main drivers of these costs. Furthermore, our

[8] Garleanu and Pedersen (2018) provide a theoretical framework in which markets can be inefficient enough for informed managers to outperform after fees.

[9] Haddad, Huebner, and Loualiche (2024) theoretically demonstrate that passive investing creates more inelastic aggregate demand curves, prompting strategic responses from other traders. Empirically, Arnott, Brightman, Kalesnik, and Wu (2022) show that trading ahead of index reconstitutions or delaying rebalancing for up to a year can reduce rebalancing costs. In contrast, Chinco and Fos (2021) argue that rebalancing cascades introduce significant noise, making it computationally difficult to predict the impact of specific trading strategies.

study is the first to use a postponed index reconstitution event (March 2020) to establish direct evidence of arbitrageurs' actions before ETF rebalancing.

Finally, our study offers fresh insights into the asset pricing implications of index-linked trading (e.g., Koijen and Yogo, 2019). Wurgler (2010) suggests that index-linked trading can distort stock prices, and Pavlova and Sikorskaya (2023) show that stocks added or removed from benchmarks experience significant long-term return shifts. Davies (2024) documents how index-linked trading contributes to variations in stock returns, with riskier stocks suffering more severe impacts. Our study extends this line of inquiry by showing that ETF rebalancing trades are negatively related to future stock returns, with the effect further amplified by anticipatory arbitrage trading.

2.2 Background and institutional details

In the last two decades, there has been a significant shift in US investment assets from active to passive funds, particularly ETFs.[10] The growth in the number of ETFs can largely be attributed to the rise of rules-based ETFs, which became popular after the 2008 financial crisis, as investors sought alternatives to MFs.

The trading of ETFs in underlying securities consists of two main components. First, ETFs trade in response to inflows or outflows. ETFs have a distinct mechanism in responding to investor flows compared to mutual funds (MFs). Unlike MFs, where managers have discretion over the allocation of flows, ETFs experience significant flow-induced pressure because all flows must be translated into trading of the underlying stock holdings (Dannhauser and Pontiff, 2024). Inflows and outflows originate in the primary market of ETFs, where ETF shares are created or redeemed in response to these flows. Second, ETF trades may be driven by the rebalancing of the underlying indices they track. This type of rebalancing event creates trading in underlying stocks, independent of 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 growing number of ETFs, especially those that track rules-based indices that rebalance frequently (semi-annually, quarterly, or monthly), the impact of ETF

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

rebalancing trades must be studied carefully, as they may generate incremental price pressure on underlying securities, worsening future stock returns even further. [11]

Unlike index mutual funds, ETFs do not have the ability to rebalance their portfolios before index reconstitution or postpone rebalancing to avoid the anticipatory trading costs imposed by arbitrageurs. This creates a unique setting in which rebalancing trades by ETFs impose additional pressure on underlying stock returns. Furthermore, the transparency of the indices ETFs track creates a perfect environment for strategic traders, such as hedge funds, to capitalize on price pressure created by rebalancing trades, which may exacerbate the negative impacts on stock returns.

We classify ETFs into three types: broad-market, rules-based, and sector ETFs. Broad-market ETFs track broad-market indices based on portfolios of U.S. stocks, with weights proportional to their market capitalization[12] Additions and deletions to broad-market indices are announced in advance and are infrequent events. Sector ETFs concentrate on stocks from a specific industry and track an industry-concentrated index. Similar to board-market indices, these indices do not experience reconstitution on a frequent basis, and events of additions and deletions are relatively rare events.[13] Rules-based ETFs track specific rules-based indices that follow a defined rule or strategy that requires more frequent portfolio rebalancing (e.g., monthly or quarterly) to ensure constituent stocks satisfy the conditions.[14] The transparency of the indices that rules-based ETFs track makes their index reconstitutions predictable events, particularly for sophisticated investors, such as HFs.

Panel A of Figure 2.1 illustrates the evolution of different ETF types between 2005 and 2020 showing the proportional distribution of total ETF assets among them. Broad-market ETFs account for the largest proportion among the three types of ETFs. However, since 2005, rules-based ETFs have been growing exponentially, reaching 30% of total ETF AUM in 2020, compared to 33% for broad-market ETFs. This trend is driven by the rise in the number of

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

[12] Examples of broad-market ETFs include Vanguard Total Stock Market Index Fund, iShares Russell 3000 ETF, and Schwab US Broad Market ETF.

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

[14] Examples of rules-based ETFs include Vanguard US Momentum Factor ETF and JPMorgan US Value Factor ETF.

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 increased; however, in terms of aggregate AUM, they remain small compared to other types of ETFs.

[Insert Figure 2.1 here]

2.3 Data and summary statistics

In this section, we outline the three main datasets used in the paper: ETF holding data, HFs data, and firm-level financial data. We define some key variables.

2.3.1 ETF holdings and rebalancing trades

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 ($0.5 < \textit{TNA/Dollar holdings} < 2$). 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.[15]

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.

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 mutual funds, 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.[16] 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 track to reduce tracking errors. We define the difference between the actual trades and the flow-induced trades as RIT:

[15] Table IA2.1 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 in broad-market ETFs by the end of 2020.

[16] Dannhauser and Pontiff (2024) 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 Dannhauser and Pontiff (2024).

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

where $Trade_{,i,m}$ is the ETF trading of stock i by all ETFs in month m. We report summary statistics of ETFs RIT and FIT trades along with their correlations in the Appendix table IA2.3. Among different types of ETFs, as anticipated, Rules-based ETFs have the highest RIT. There is low correlation between RIT and FIT trades for all types of ETFs, which highlights the importance of studying the impact of RIT trades separately.

2.3.2 Hedge fund holdings and 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 hedge fund if it satisfies the following criteria: 1) it matches the name of a fund from the Union Hedge Fund Database,[17] 2) it is one of the top hedge funds listed by industry publications, 3) on the firm's website description, hedge fund management is listed as the main business area, 4) it is listed as a hedge fund firm in Factiva, and 5) if the filer name in 13F is one of the leading personnel in a hedge fund.[18] As a result, we obtain the final sample of 1,854 unique hedge fund 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 hedge fund 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.[19] AHF is defined as the difference between the current quarter HF holdings of stock i and the average HF holdings of stock i in the past four quarters. Similarly, 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.

[17] Agarwal, Fos, and Jiang (2013) compile the Union Hedge Fund Database that merges four commercial databases: Eureka, Hedge Fund Research, Morningstar, and Lipper TASS.
[18] Agarwal, Jiang, Tang, and Yang (2013); Agarwal, Ruenzi, and Weigert (2017)
[19] Starting from September 2007, short interest data is reported twice each month. We use the last available report of the month.

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

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

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

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.

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

2.4 Hedge funds strategic trading around ETF rebalancing events

We investigate the impact of HFs' strategic trading in anticipation of ETF rebalancing events and the resulting costs imposed on ETF investors. Previous studies have largely overlooked the significance of rebalancing-induced trades in ETFs, often considering ETFs as passive investment vehicle.[20] However, ETFs are required to closely track their underlying indices to maintain low tracking error, which results in substantial volumes of rebalancing trades. The transparency of ETF holdings and the predictability of their trades make them susceptible to anticipatory trading by sophisticated investors, such as HFs. In this section, we start with examining whether ETF rebalancing trades are associated with significant price distortions of underlying securities. Second, we investigate whether and how ETF rebalancing events are prone to anticipatory trading activities by HFs.

[20] Li (2024) focuses on the transaction costs incurred from ETF rebalancing trades, whereas our study examines the direct impact on stock returns and its interaction with arbitrageurs.

2.4.1 Rebalancing ETF trades and future stock returns

We examine the relation between ETF rebalancing trades and future returns of the underlying stocks using regression methods. Specifically, we run the Fama–MacBeth regression of the future-month stock returns on the monthly ETF rebalancing trades as follows:

$$Ret_{i,m+1} = b_0 + b_1 RIT_{i,m} + b_2 FIT_{i,m} + b_3 Controls_{i,m} + e_{i,m+1}, \tag{7}$$

where the dependent variable $Ret_{i,m+1}$ is return of stock *i* in month *m* + 1. The explanatory variable, $RIT_{i,m}$, 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. In our analysis, we control for ETF flow–induced trades $FIT_{i,m}$. To prevent potential contamination of our results by other channels, we include various control variables known to impact stock returns, as used in the previous sections. The control variables, $Controls_{i,m}$, include turnover, prior-one-month returns, prior-one-year returns, firm size, book-to-market ratio, institutional ownership, idiosyncratic volatility, and the number of analysts who cover the stock.[21] The Appendix provides details of how each variable is constructed and its data source. The *t*-statistics are computed from standard errors adjusted for autocorrelation, following Newey and West (1987).

The results are reported in Panel A of Table 2.1. In Column (1), the dependent variable is the contemporaneous month returns of the underlying securities. We observe that the estimated coefficients on both RIT and FIT are positive, and statistically and economically significant, indicating that both flow- and rebalancing-induced trading by ETFs drive stock prices upwards. Specifically, one standard deviation increase in RIT (FIT) corresponds to 0.28% (0.47%) increase in contemporaneous stock returns. In Column (2), the dependent variable is stock returns in month *m* + 1. The estimated coefficient of the ETF RIT in month *m* is -1.611, with a *t*-statistic of -4.00. Moving to Columns (3) and (4), the dependent variables are returns in months *m* + 2 and *m* +3, respectively. In these columns, the estimated coefficients on RIT are insignificant; suggesting that the reversal is short-lived. The reversal is inconsistent

[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.

with the possibility of negative returns signaling a deterioration in the fundamental value of stocks. Instead, it is more likely that the effects may reflect temporary price pressure from ETF rebalancing trades. Our study differs from Glosten, Nallaredy and Zou (2020) in the two following aspects. First, our RIT measure includes not only additions and deletions but also all the ETF trading attributed to its rebalancing activities, including adjustments in a stock's weight within an equal-weighted portfolio. Second, we examine the impact on stock returns in the months following the rebalancing event, which helps identify the full effect of ETF trades on underlying securities.[22]

[Insert Table 2.1 here]

In the case of FIT, our results align with prior research (e.g., Zou, 2019; Brown, Davies, Ringgenberg, 2021). We find that flow-induced ETF trades significantly boost contemporaneous returns, followed by a short-term reversal. Importantly, our findings indicate that flow-induced trading isn't the sole mechanism contributing to stock return reversal; rebalancing-induced trades may also play a pivotal role in amplifying the previously documented negative impact of ETF flows.

Further, we examine how the impact of ETF rebalancing trades on future stock returns may vary across different types of ETFs. Despite ETFs being generally considered passive investment vehicles, their growth in the last decade has coincided with the emergence of rules-based ETFs. Rules-based ETFs are viewed as less passive, as their portfolios are structured to adhere to specific rules-based indices or factor strategies (Easley, Michayluk, O'Hara, and Putnins, 2021), therefore, they are expected to rebalance their portfolios on a monthly, quarterly, or yearly basis, depending on the particular portfolio. Consequently, we anticipate that rules-based ETFs will exhibit higher levels of rebalancing activity compared to sector and broad-market ETFs.[23]

[22] In a recent study, Glosten, Nallaredy, and Zou (2020) discover a significant positive relation between ETF trades and contemporaneous stock returns, which is consistent with our results. They decompose ETF activity into two components: the addition and deletion of a stock into the ETF, and ETF activity associated with the creation and redemption process (flow-induced trades in our case). They find that both components exhibit a positive correlation with contemporaneous stock returns. In Table IA2.8 of the Internet appendix, we present the results of the regression of aggregate ETF trades on stock returns. We find that, in aggregate, a one standard deviation increase in ETF trading corresponds to a 0.44% increase in contemporaneous monthly stock returns and a 0.27% decrease in the next month returns.

[23] During our sample period from 2005 to 2020, Rules-based ETFs had an average turnover of 54%, whereas broad-market ETFs had an average turnover of 7% (see Table IA2.2 in the Internet Appendix).

Panel B of Figure 2.1 illustrates rolling three-year aggregate dollar rebalancing trades across the three types of ETFs: rules-based, sector, and broad-market ETFs.[24] Despite broad-market ETFs having the largest assets under management (AUM), rules-based ETFs account for the highest aggregate rebalancing trades, surpassing both broad-market and sector ETFs. This can be attributed to the nature of the underlying indices that these ETFs track.[25] In the Panel B of Table 2.1, we repeat baseline regression (7) by dividing ETFs into three categories. We find that RIT yields significant results for rules-based ETFs, given their more frequent portfolio rebalancing and higher volume of rebalancing-induced trades they experience.[26] The estimated coefficient for rules-based RIT in Column (1) is 3.06, with a *t*-statistic of 4.00. This indicates that during rebalancing events, stock prices move in the direction of ETF rebalancing–induced trading activity followed by short-term reversal, with a coefficient of -2.140 and a *t*-statistic of -2.54 in the next month.[27] We find that the negative relation remains statistically significant for broad-market ETFs.[28] 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.[29]

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[24] We categorize ETFs that track broad-market indices, such as the 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, 2023). Further, we identify rules-based ETFs using the "Strategic Beta" identifier in Morningstar, and sector ETFs are identified through Morningstar's "sector equity" classification.

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

[26] Unlike active mutual funds that employ proprietary active strategies, rules-based ETFs adhere to specific rules-based indices. This characteristic makes it relatively easier for arbitrage traders to anticipate which stocks will be included or excluded during the next portfolio rebalancing event. Consequently, arbitrage traders have an incentive to capitalize on this opportunity by purchasing stocks expected to be included in the portfolio before the ETF rebalancing date, with the aim of profiting from the temporary increase in prices. Such arbitrage behavior can potentially exert even greater price pressure on contemporaneous stock prices, leading to subsequent stock return reversals. Therefore, we anticipate observing a significant negative relation between rules-based ETF trades and future stock returns. However, this dynamic may not apply as strongly to sector ETFs, primarily due to the smaller magnitude of sector ETF trades compared to rules-based ETFs.

[27] Table IA2.9 in the Internet appendix presents the results of the regression of aggregate ETF trades across three types of ETFs on stock returns. We find that the aggregate ETF trading has a significant positive relation with contemporaneous returns and significant negative relation with future one-month stock returns for Rules-Based ETFs only.

[28] 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 the lower frequency of reconstitution of sector indices.

[29] Chen, Noronha, and Singal (2004) demonstrate 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) argues that the price effect from additions and deletions to S&P500 and Russell 2000 indices reverses over the following two months.

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. In a more recent study, Greenwood and Sammon (2024) show that abnormal returns associated with index additions and deletions from broad-market S&P and Russell indices are no longer existent in the sample period 2010 to 2020. This finding does not contradict our results. In turn, we show that the abnormal returns pattern driven by index-rebalancing events is mostly driven by rules-based ETFs. Unlike broad-market ETFs, rules-based ETFs tend to be smaller and use specific strategies and rules, where member stocks tend to be less liquid than those of broad-market ETFs.

2.4.2 Anticipatory trading by hedge funds

Previous literature theoretically shows that strategic traders profit selling stocks 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 mutual fund trades through anticipatory trading.[30] Aragon, Martin, and Shi (2019) document that HFs with locked-up capital opportunistically trade against flows of non-lockup HF managers during crisis. Agarwal, Aragon, Nanda, and Wei (2024) document anticipatory trading of HFs against distressed mega HFs.

The rebalancing trades of ETFs originate from changes to the underlying indices. The changes to underlying indices may be either announced in advance by the index providers or predicted by sophisticated investors, such as HFs. Transparency of indices that passive ETFs track may attract strategic traders who have an incentive to trade prior to ETF rebalancing events. 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 anticipation of the price fluctuations caused by rebalancing trades, HFs might choose to buy (short sell) stocks that are expected to be bought (sold) as part of ETF rebalancing events prior to ETFs. Once ETFs complete their rebalancing, HFs can complete their trade and profit from exacerbated prices by reversing their positions. Such trading activities by HFs can exacerbate the already existing price impacts of ETFs RIT on stock returns and destabilize prices prior to the rebalancing date. The impact of ETFs RIT is often overlooked in existing literature. Our

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

study aims to fill the gap by investigating the interaction between HF trading and ETF rebalancing events.

Figure 2.2 depicts the timeline of anticipatory trading. 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 HFs net arbitrage trades (NAT) (March, June, September, and December) and the immediately following month for ETF RIT (April, July, October, and January). We consider the first month *m* of quarter *q* to be the month during which ETF rebalancing event happens, so we can observe the new rebalanced ETF portfolio at the end of month *m*. HFs may gain knowledge of ETF rebalancing in advance either through early announcements by index providers regarding index reconstitution or by predicting such events due to the transparency of the index. HFs may trade in anticipation of rebalancing during the quarter $q - 1$, which precedes the rebalancing event month *m*. We can observe HF trades from 13F holdings data at the end of the quarter q - 1. After ETFs complete rebalancing, HFs may close their arbitrage trades in quarter *q* by reversing the initial position they took in rebalanced stocks in quarter q - 1.[31]

[Insert Figure 2.2 here]

Figure 2.3 plots HFs NAT to illustrate the evolution of HFs trading around ETF purchases (Panel A) and sales (Panel B) due to their rebalancing activities. resulting from their rebalancing activities. The vertical line marks the month *m* in which the rebalancing event takes place. Panel A and B display stocks that were bought (sold) by ETFs if they belong to the highest (lowest) quintile of RIT in month *m*, whereas Panel C reports stocks in Quintiles 2 – 4 of RIT. The figure then plots the average NAT of HFs three quarters before the ETF rebalancing event and three quarters after. In Panel A and B, there is a substantial increase in NAT for purchased stocks and a decrease in NAT for sold stocks in the quarter preceding rebalancing events. Moreover, HFs revert their positions in quarter *q* following the completion of ETF rebalancing. In Panel C, for stocks that do not experience rebalancing trades by ETFs, we do not observe significant changes in NAT by HFs. This finding indicates anticipatory

[31] Cui, Kolokolova, and Wang (2024) document that stocks sold by hedge funds and simultaneously bought by quasi-indexers generate an alpha of -0.33%, while stocks bought by hedge funds and simultaneously sold by quasi-indexers generate an alpha of +0.48%. We expect a similar impact on stock returns when hedge funds finish their anticipatory trading and lock in profits by reverting to their initial trade positions after the rebalancing event.

trading behavior by HFs aiming to profit from price distortions caused by ETF trading in underlying securities.

[Insert Figure 2.3]

We conduct the following Pooled OLS regression to formally investigate the relation between ETFs rebalancing trades and HFs anticipatory trading:

$$NAT_{i,q-1} = b_0 + b_1 RIT_{i,m} + b_2 FIT_{i,m} + b_3 Controls_{i,m-1} + e_{i,q-1}, \tag{8}$$

where $NAT_{i,q\text{-}1}$ is the net arbitrage trades of HFs in the calendar quarter q - 1, preceding ETF rebalancing month m, $RIT_{i,m}$ is the rebalancing induced trades of ETFs for stock i in month m. We include Year/Month fixed effect and cluster standard errors at the firm-year level.

The results are presented in Table 2.2. In Columns (1) - (3) the dependent variable is continuous NAT variable, while in Columns (4) – (6) we sort stocks into quintiles based on their NAT and use quintile rank as the dependent variable. The estimated coefficient on RIT in Column (1) is positive and statistically significant. The relation between RIT and NAT remains significant after controlling for ETFs flow-induced trades and other stock characteristics, with an estimated coefficient of 0.367 and a *t*-statistics of 2.44 in Column (3). We repeat regression and use NAT rank as the dependent variable and find similar relation. Our results further confirm that HFs may choose to trade in the same direction as ETFs prior to their rebalancing.

[Insert Table 2.2 here]

Due to the transparency of the indices ETFs track, we suggest that HFs as sophisticated investors are able to anticipate rebalancing trades and trade accordingly before the rebalancing event. To establish that HFs adjust their trades in anticipation of expected rebalancing, we decompose ETFs RIT into expected and unexpected components. To do so, we first estimate expected RIT based on the information available to HFs at the time of their trading in the quarter preceding rebalancing month m. We use information on previous stock returns, B/M ratio, firm size, its ROE, ROA, investments, gross profitability, leverage, cash flows, illiquidity, aggregate institutional ownership and volatility. We use predicted value of the regression as expected component of RIT and residual – as unexpected. We then repeat regression specified in Equation (8) by including expected and unexpected components of RIT. Results are presented in Table 2.3. We find that the positive relation between HFs trades and

RIT remains significant only for expected component of RIT, suggesting anticipatory nature of HF trades.

[Insert Table 2.3 here]

2.4.3 Short interest around ETF rebalancing

Hedge funds, as sophisticated investors, use short-selling as part of their trading strategy. Therefore, examining short positions alone can provide insights about HFs behavior around ETFs rebalancing events. [32] Several studies highlight the significance of short-selling in HFs' trading strategies. Jiao, Massa, and Zhang (2016) show that HFs employ short positions to complement their trading strategies. They find that informed HFs, which simultaneously increase their holdings in stocks while reducing short positions in those same stocks, exhibit a negative relation with mutual fund flows. Conversely, when HFs unwind their positions in stocks by simultaneously decrease holdings and short positions, it often precedes mutual funds' fire sales. Furthermore, Hwang, Liu, and Xu (2019) show that HFs tend to trade more aggressively in underpriced stocks when they have the ability to engage in short-selling. To explore, we use bi-weekly short interest data to identify whether HFs build positions prior to ETF rebalancing as part of anticipatory trading strategy, or if they trade independently of ETF rebalancing events.[33] In the former case, we expect no decrease in short interest in the two weeks leading to ETFs rebalancing. In the latter case, the high short interest at the end of quarter *q* preceding ETF rebalancing month (as we find in the previous subsection) may decrease before the rebalancing event. [34]

We construct abnormal short interest (ASI) as the difference between the current short interest at time *t* minus the average short interest over the previous 12 months, where time *t* corresponds to the two-week time period (either the 15th or the last day of each month). We then track evolution of ASI around ETFs rebalancing event. Given that HFs are more likely to

[32] Previous literature focuses on the predictability of shorting flows on stock returns and finds that short-sellers possess the ability to predict future stocks returns. Boehmer and Wu (2013) show that short-sellers contribute to the timely incorporation of information into stock prices. Diether, Lee Werner (2009) find that short-sellers trade on short-term information, while in a more recent study, Wang, Yan, and Zheng (2020) discover that long-term shorting flows exhibit higher stock return predictability. Engelberg, Reed, and Ringgenberg (2012) document that the predictive power of short-selling is twice as high on the news days.
[33] Due to the nature of HFs holdings data, we can only track their trading activities on a quarterly basis. The quarterly frequency of the data may be considered a lengthy interval when examining HFs actions. To gain more detailed insights, we leverage up bi-weekly short interests to better capture hedge fund trading activities arounds ETF rebalancing events.
[34] Comerton-Forde, Jones, and Putnins (2016) highlight two types of short sellers: liquidity providers and strategic traders. We suggest that in the case of ETF rebalancing HFs may play both roles, with strategic trading role imposing potential costs on ETF investors.

take short positions when they hold a bearish view on future stock returns, we focus on stocks that are sold during ETF rebalancing. Similar to the quarterly data, we identify stocks sold by ETFs due to rebalancing if ETF RIT of stock *i* falls within the lowest quintile in month *m*. If results obtained in previous section indicate HFs anticipatory trading of ETF rebalancing event, we expect ASI to increase up to the rebalancing month *m* and decrease after rebalancing.

[Insert Figure 2.4 here]

Figure 2.4 plots the average ASI of all stocks sold by *ETFs* during rebalancing. The vertical line indicates the month of ETF rebalancing. The figure illustrates a positive ASI in those stocks, which remains high up to fifteen days before the rebalancing event. After ETFs complete their rebalancing, ASI declines immediately, even turning negative in the following two months, indicating that short positions during these months below average. Stocks sold by ETFs experience downward price pressure during rebalancing, which may attract short-selling activity by HFs ahead of ETF rebalancing. This finding provides further supportive evidence that HFs engage in short-selling of stocks in anticipation of their exclusion from ETFs portfolios.

We find that both quarterly and bi-weekly short interest data indicate similar trading patterns by HFs around ETFs rebalancing events. One of the reasons why we are able to document HFs strategic anticipatory trading on a longer horizon where HFs choose to build positions ahead of ETFs rebalancing could be related to the recent finding by Wang, Yan, and Zheng (2020). They find that long-term shorting flows (measured over a month or quarter) have higher predictive power for future stock returns compared to short-term shorting flows. They suggest that short sellers' trade on long-term public information that is gradually reflected into prices.[35] Our results might contribute to one of the reasons this pattern is taking place. Due to transparency of ETFs portfolio composition, HFs use their superior ability of processing information and can predict stocks that are to be excluded from ETFs portfolios and short-sell those stocks ahead of ETFs and other investors, such as mutual funds.

2.4.4 Alternative explanation: Information trading by hedge funds

The above analysis suggests that HFs exploit ETFs rebalancing events by engaging in strategic anticipatory trading. An alternative interpretation of our findings is HFs' informed

[35] In an earlier study, Engelberg, Reed, and Ringgenberg (2012) find that short-sellers rarely anticipate news events. Instead, they demonstrate high skills in information processing and base their short-selling strategies on publicly available news.

trading and stock-picking skills, which are not necessarily related to ETFs rebalancing. HFs possess superior stock-picking abilities (Brunnermeier and Nagel, 2004; Kosowski, Naik, and Teo, 2007; Avramov, Kosowski, Naik, and Teo, 2011; Agarwal, Jiang, Tang, and Yang, 2013; Cao, Goldie, Liang, and Petrasek, 2016; Chen, Cliff, and Zhao, 2017), market timing expertise (Chen, 2007; Chen and Liang, 2007; Lo, 2008), and market liquidity timing skills (Cao, Chen, Liang, and Lo, 2013). Therefore, it is plausible that HFs have access to superior information about stocks that subsequently increase in value, leading to these stocks being included in ETFs. In other words, both HFs and ETFs may follow similar investment styles, such as momentum. Consequently, a stock exhibiting momentum could be purchased by both HFs and ETFs.[36]

To distinguish between anticipatory trading and stock picking, we examine whether HFs would *exclusively* buy (sell) stocks that are bought (sold) as part of ETFs rebalancing in the month preceding the rebalancing events, or if they may purchase (sell) stocks that are *not* part of ETFs' rebalancing portfolio but share similar characteristics with the rebalanced stocks. The idea is as follows: If HFs adhere to specific rules or strategies and engage in informed trading, we should expect to observe no differences in HF trades for stocks with similar characteristics; if HFs trades are driven by anticipatory trading of ETFs' rebalancing events, we should observe significant disparities in HFs trading for those stocks – HFs should *exclusively* buy (sell) stocks that are part of ETFs rebalancing portfolio.

Next, we construct the treated group (i.e., stocks involved in ETF rebalancing and traded by HFs before ETF rebalancing) and the control group (i.e., stocks not involved in ETF rebalancing but traded by HFs before ETF rebalancing). Specifically, we identify the treated group of stocks as follows: 1) stocks that are bought (sold) by ETFs during rebalancing in month m if they belong to the highest (lowest) RIT quintile in month m; and 2) stocks that are simultaneously bought (sold) by HFs in quarter q - 1 as part of anticipatory trading (if they were ranked in the top (bottom) NAT quintile in quarter q - 1). We employ propensity score matching to identify the group of stocks *not* included in the ETFs' rebalancing but possess similar characteristics (i.e., previous one-month returns, previous 11-months returns, size, B/M ratio, Amihud illiquidity, gross profits over assets, return on equity, and return on assets).

[36] Jiang, Liang, and Zhang (2022) show that hedge funds use style-shifting strategies and possess the style-timing skills.

After matching two samples, we conduct the following Pooled OLS regression with Year/Month fixed effect and standard errors clustered at the firm-year level:

$$NAT_{i,q-1} = b_0 + b_1 RIT_{i,m} + b_2 Treated_{i,m} + b_3 RIT_{i,m} \times Treated_{i,m} + b_4 FIT_{i,m} + b_5 Controls_{i,m-1} + e_{i,q-1}, \quad (9)$$

where $NAT_{i,q\text{-}1}$ is the net arbitrage trades of HFs in the calendar quarter q - 1, preceding ETF rebalancing month, $RIT_{i,m}$ is the rebalancing induced trades of ETFs for stock i in month m, $Treated_{i,m}$ is the dummy variable equal to one if the stock belong to the treated group and zero otherwise.

In Table 2.4, Columns (1) – (3) present results for stocks bought during ETF rebalancing, while Columns (4) to (6) contain results for stocks sold during ETF rebalancing. In Columns (1) and (4), the coefficients on the interaction term, RIT and Treated, are positive and statistically significant for both buy and sell samples of stocks. In Columns (3) and (5) – (6), the corresponding coefficients on the interaction term remain significant after controlling for ETFs flow-induced trade and other stock characteristics, with an estimated coefficient of 3.48 (with a *t*-statistic of 4.39) for stocks bought during rebalancing and 4.90 (with a *t*-statistic of 4.14) for the stocks sold during rebalancing. The results suggest that HFs trade in stocks that are rebalanced by ETFs and do not simultaneously buy (sell) stocks that are not part of the ETF rebalancing portfolio. This finding is inconsistent with the stock-picking interpretation of our finding.

[Insert Table 2.4 here]

2.4.5 A quasi-natural experiment: The postponement of index rebalancing in March 2020

With the Covid-19 pandemic impacting financial markets in 2020, several index providers postponed the scheduled March reconstitution of indices to later dates. This includes S&P Dow Jones and ICE (Intercontinental Exchange) data indices.[37] Specifically, S&P Dow Jones announced the postponement of "the majority of quarterly shares outstanding and investable weight factor updates" as well as "membership changes (i.e., adds/drops) for select indices". The abrupt postponement of index reconstitutions in March 2020 was an unexpected event, and hence, provides a clear setting to test whether HFs indeed trade in anticipation of ETFs rebalancing. This setting enables us to delve into the mechanism of HFs' anticipatory

[37] See, "Fragile markets prompt providers to leave benchmarks unchanged", *Financial Times*, March 26, 2020; "S&P DJI delays quarterly index rebalance amid market chaos", *ETF Strategy*, March 17, 2020; "Why index providers were right to postpone rebalances" *ETF Stream*, April 6, 2020.

trading and draw a causal interpretation of our findings. Since HF anticipatory trading activities are most likely to occur within a quarter—a period not fully captured by 13F fillings—we focus on higher-frequency short interest data to gain a clearer picture. We conjecture that HFs may increase their short interest in those stocks prior to expected rebalancing in March and reduce their positions after the announced rebalancing postponement. We posit that if HFs engage in anticipatory trading strategies, then we expect HFs to adjust their positions in the underlying stocks subjected to ETF rebalancing before anticipated index reconstitution events. S&P postponed the March index reconstitution to June 19.[38] We use the June index components as a proxy for the stocks on which HFs base their anticipatory trading related to ETFs rebalancing. We align the stocks sold during June ETFs rebalancing with their abnormal short interest two months prior to March 2020 and afterwards.

Figure 2.5 plots the ASI of stocks expected to be sold during ETF rebalancing in March 2020. The graph reveals a significant increase in ASI leading up to the expected rebalancing date, peaking on 16 March. One notable difference compared to the ASI pattern found in Figure 2.4 during normal ETF rebalancing is that in case of postponed rebalancing, ASI experience its sharpest decline by the end of March 2020 with no further deterioration. In contrast, Figure 2.4 shows a continued decline following the completion of ETF rebalancing. This evidence suggests that HFs may have taken short positions in stocks they anticipated would be rebalanced by ETFs, promptly closing their positions when the postponement was announced.

[Insert Figure 2.5 here]

The March 2020 postponement differs from typical rebalancing events, where HFs' trading adjustments occur more gradually over time. The sharp reversal in ASI highlights how HFs quickly unwound their positions when the rebalancing schedule changed, offering supportive evidence that their trading behavior was anticipatory rather than reactive. This natural experiment underscores the sensitivity of HFs' trading strategies to rebalancing expectations and provides direct evidence of their role as strategic traders exploiting ETF rebalancing events. By isolating this exogenous shock, the March 2020 test helps clarify the mechanism of anticipatory trading, strengthening the causal interpretation of our findings. However, we do acknowledge the limitation of this setting. Due to the high overall market

[38] On April 8th, S&P issued a statement, where they announced new rebalancing dates for their indices. "All SPDR ETFs that track S&P or Dow Jones indices scheduled to rebalance in March will be postponed until the next regular rebalance after close of business June 19th, except for MMTM and VLU which will rebalance after close of business April 17th and GII which is scheduled to rebalance after close of business June 30th."

volatility in March 2020, providing precise evidence of HFs' behavior in anticipation of ETF rebalancing and calculating exact costs is challenging. Nonetheless, our uncovers supportive evidence that HFs may choose to engage in anticipatory trading during ETF rebalancing events.

2.4.6 Hedge funds' utilization of options during ETF rebalancing

Hedge funds face fewer disclosure requirements, giving them the flexibility to employ various types of securities to execute their trading strategies, including derivatives.[39] HFs have the latitude to engage in speculative trading strategies involving options. This speculative aspect of HF behavior with equity options is highlighted by the research of Aragon and Martin (2012). They suggest that HFs use option holdings to capitalize on volatility timing and leverage their stock-picking expertise. In the similar spirits, we explore how HFs use options on individual securities affected by ETF rebalancing trades, as well as their holdings of ETF options.

Equity options. We start with analyzing the option positions held by HFs in stocks included in ETF rebalancing portfolios. To examine, we use the Whale Wisdom database, which provides a comprehensive dataset of reported 13F positions. To identify HFs within this dataset, we cross-reference names with the list of HFs obtained in the previous section. Following the methodology outlined in Aragon, Martin, and Shi (2019), we use the original 13F filings while excluding amendments. We filter observations using the "mv_multiplier" to retain only those with market values reported in thousands. To ensure data accuracy, we validate reported values by recalculating market values using price data from CRSP. Observations with disparities between 13F filing values and our calculated values are excluded. We focus solely on positions classified as either equity or equity options.

The HFs' net option position is calculated as the difference between their aggregate holdings of call and put options. For stocks acquired during ETF rebalancing events, we anticipate HFs to increase their net option positions prior to the rebalancing event and reduce them afterwards. Conversely, for stocks sold during ETF rebalancing trades, we expect the opposite trend. In Figure 2.6, we depict HFs' net option holdings in stocks rebalanced by ETFs before and after the rebalancing month. Stocks are sorted into quintiles based on their ETF

[39] Chen (2011) shows that 71% of hedge funds in their sample trade derivatives, in contrast to 21% of mutual funds found by Koski and Pontiff (1999).

RIT. We identify stocks that are subject to HFs option trading prior to ETF rebalancing if their ETF RIT is ranked in the highest (lowest) quintile in month *m*.

[Insert Figure 2.6 here]

Panel A of Figure 2.6 displays the HFs' net option holdings for stocks purchased by ETFs during ETF rebalancing event. HFs gradually increase their net option positions for those stocks. This increase is most notable in the quarter preceding the ETF rebalancing month, during which held by HFs the quantity of call options exceeds that of put options. That is to say, HFs augment their holdings of call options on these rebalanced stocks in anticipation of upward price pressure, while simultaneously reducing their put option positions. Similarly, as depicted in Panel B, HFs adopt the opposite approach for stocks sold during ETF rebalancing. Before the rebalancing, HFs decrease their net option positions, reflecting an increase in their holdings of put options compared to call options for stocks sold during the rebalancing period. This behavior aligns with HFs' anticipation of downward price pressure on these stocks.

Our findings—HFs strategically employ options to capitalize on ETF rebalancing events—contribute to the existing understanding of HFs behavior around volatility events in the markets. Aragon and Martin (2012) document that HFs held half of their put option positions in the technology stocks during the peak of the 2000 technological bubble, in anticipation of the eventual collapse of the bubble. Their finding highlights that HFs ability to leverage volatility timing and selectivity skills. Our investigation into HFs' use of options offers a comprehensive understanding of their trading strategies surrounding ETF rebalancing events and underscores the speculative nature of their behavior.

ETF options. We next examine whether HFs' use ETF options to cover the risks arising from their trades in stocks purchased or sold in anticipation of ETF rebalancing. Aragon, Martin, and Shi (2019) find that lockup HFs are more likely to use locked-up capital in distressed sale stocks of non-lockup managers when simultaneously hedging their risk through ETF put options. They also demonstrate that HFs using ETF options generate higher returns.[40] So far we show that HFs may choose to trade in anticipation of ETF rebalancing events by buying (or short selling) stocks ahead of ETFs. However, HFs' equity positions are susceptible to market and factor risks. To hedge these positions, HFs may engage in the derivatives market

[40] In a recent study Aragon, Chen, and Shi (2023) show that hedge funds use ETF options for volatility timing rather than market timing. However, unlike equity options, ETF options are informative about the future systematic volatility.

and utilize ETF options to reduce their risk exposure, while enhancing the upside potential of their trades. We explore whether HFs hold options of ETFs that experience high portfolio rebalancing.

We extract data on HFs' ETF option holdings from historical 13F filings. We compute the rebalancing trades (RIT) at ETF levels as the difference between the monthly change in portfolio holdings and inflows. Subsequently, we categorize ETFs into quintiles based on their RIT, with quintile 1 comprising ETFs with the lowest RIT and quintile 5 containing those with the highest RIT. To calculate HFs' options positions in ETFs, we aggregate the market value of put and call options within each ETF quintile.

The summary statistics are presented in Table 2.5. Columns (1) and (3) show the average dollar value of put and call options on ETFs by RIT quintile in HFs' portfolios. Columns (2) and (4) report the average proportion of ETFs put and call options in the aggregate HFs put and call options portfolio. Remarkably, the majority of the HFs' ETF options are concentrated in the extreme quintiles, corresponding for ETFs with the highest volume of portfolio rebalancing. On average, in Column (1), HFs hold $4.8 billion and $6.7 billion in put options on ETFs with the highest rebalancing in the quarter preceding rebalancing month, in contrast to $160 million across other ETFs. Similarly, in Column (3), the average position in call options for quintile 1 and quintile 5 ETFs is $4.33 billion. This anecdotal evidence suggests that HFs may proactively use ETF options before rebalancing events to hedge their positions in rebalancing stocks.

[Insert Table 2.5 here]

Interestingly, we observe that both call and put option positions increase simultaneously. This finding suggests that HFs may employ straddles as part of their hedging strategy. Most importantly, we demonstrate that HFs predominantly hold options in ETFs with the highest portfolio rebalancing, indicating that HFs not only time their market risk exposure but also manage their factor risks. This finding aligns with the work of Titman and Tiu (2011), which implies that better-informed HFs with superior stock-picking skills opt for lower exposure to factor risk. Overall, our analysis indicates that HFs hold options in ETFs that undergo high portfolio rebalancing, suggesting a hedging behavior.

2.5 Further tests and discussions

In this section we conduct additional tests and discuss the impact and potential cost of HFs anticipatory trading activities to ETF investors.

2.5.1 Impact of HFs anticipatory trading on rebalanced stock returns

We examine the impact of HFs anticipatory trading on returns of the stocks that are part of ETFs rebalancing portfolios. To empirically test this hypothesis, we compare returns of stocks that were rebalanced by ETFs and simultaneously traded by HFs. We do so by double sorting stocks based on their RIT and NAT and calculating each portfolios returns. First, for each month m following the end of the calendar quarter q - 1, we sort stocks into quintiles based on their ETF RIT, where Quintile 1 contains stocks sold by ETFs during rebalancing, and Quintile 5 – stocks bought by ETFs during rebalancing. 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. Second, we independently sort stocks into quintiles based on their NAT in quarter q - 1. Stocks that belong to the highest (lowest) quintile of RIT and at the same time belong to the quintile with the highest (lowest) NAT in quarter q - 1 are identified as stocks strategically traded by HFs. We calculate returns to these stocks in the month preceding the rebalancing event and the next two months. We expect stocks that are in advance traded by HFs to experience stronger impacts on returns.

Table 2.6 reports the equal-weighted returns to each portfolio of stocks.[41] Panel A reports raw returns, Panel B contains CAPM-adjusted returns, and Panel C shows FF3-adjusted returns. In Columns (1) – (3) of Panel A, we calculate returns to portfolios of stocks in month m - 1 preceding the ETF rebalancing event, when HFs trade in anticipation. Both portfolios of stocks bought by ETFs during rebalancing have significant returns in the preceding month. Stocks that are bought by HFs in anticipation of ETF rebalancing generate significant returns of 1.77%, with a t-statistic of 2.08, and stocks sold by HFs yield returns of 1.52%. Despite the difference between these two portfolios being insignificant in month m - 1, stocks bought by HFs significantly outperform stocks sold by HFs during the rebalancing month m, where HF buy-sell portfolio generates returns of 0.608 with a t-statistics of 2.32. The outperformance of ETF buy-sell portfolio remains significant only in the portfolio of stocks bought by HFs. 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

[41] As a robustness check, in unreported results, we calculate value-weighted returns. Results remain significant.

rebalancing trades, when HFs unload their positions, the significance of returns in both HF buy and HF sell portfolios disappears.[42] The results remain significant after adjustment for CAPM and Fama-French three factors.

Overall, we show that HFs, as smart investors, strategically choose stocks that are part of ETF rebalancing events to profit from the price pressure generated by ETF trades. Stocks that are traded by HFs in anticipation of rebalancing experience significant price pressure during rebalancing month, compared to other stocks in the ETF rebalancing portfolio. HFs may also be trading in the same direction as ETFs prior to their rebalancing to build up inventory to provide liquidity for ETFs during their rebalancing events. Previous literature shows that HFs play an important role in liquidity provision, which contributes to HFs performance (Jame, 2018; Cotelioglu, Franzoni and Plazzi, 2021). In the previous sections we show that HFs do not only trade on the long side, but also engage in short-selling activities prior to ETFs rebalancing and trade in derivatives markets, which can serve as supportive evidence for their strategic anticipatory trading aimed at profiting from ETF rebalancing trades.

[Insert Table 2.6 here]

2.5.2 Index additions and deletions

We delve into the characteristics of ETF rebalancing trades and examine their association with index reconstitutions. Unlike flow-induced trades, which can be attributed to the flows into and out of ETFs generated in the primary market, rebalancing-induced trades in ETFs primarily stem from underlying index reconstitutions and adjustments to portfolio weights, particularly in the case of equal-weighted ETFs. Given that all ETFs must closely track an underlying index, any alterations in the index's composition necessitate corresponding portfolio rebalancing by the ETFs themselves.

To empirically test this idea, we utilize data on the index constituents for the S&P and Russell universes of indices. It is worth noting that Compustat ceased providing data on S&P indices starting in 2020. Therefore, our dataset covers the period from 2005 to 2019. To explore

[42] In Table IA2.4 we single sort stocks based on their ETF RIT only and calculate equal-weighted returns in month $m + 1$. When considering the full portfolio of rebalancing stocks, we find significant outperformance of stocks sold by ETFs during rebalancing compared to stocks bought as part of rebalancing. These results reiterate negative relation between future one month returns and RIT in Table 2.1.

the connection between stock-level RIT and index reconstitution events, we conduct the following regression:

$$RIT_{i,m} = b_0 + b_1 Inclusion_{i,m} + b_2 Exclusion_{i,m} + b_3 Controls_{i,m} + e_{i,m}, \tag{10}$$

where the dependent variable is the RIT of stock *i* in month *m*. Inclusion (Exclusion) is a dummy variable which takes a value of 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 2.7. In Column (1), for the entire sample of ETFs, the estimated coefficient on the Inclusion dummy is 0.378 (with a *t*-statistic of 15.50). This indicates a significant increase in RIT by ETFs when a stock is added to the index. Conversely, the coefficient on the Exclusion dummy is -0.194 (with a *t*-statistic of -7.28), suggesting that RIT for a stock decrease when it is removed from the index. In Column (2), we employ alternative explanatory variables—the number of indices in which the stock was included (N_Incl) and excluded (N_Excl). Importantly, the estimated coefficients remain both economically and statistically significant. We proceed with a similar analysis for rules-based ETFs in Columns (3) and (4), broad-market ETFs in Columns (5) and (6), and sector ETFs in Columns (7) and (8). Notably, the results remain significant across all types of ETFs. The above findings provide supportive evidence that the rebalancing-induced trading activities of ETFs can be attributed to changes in the underlying indices.[43]

[Insert Table 2.7 here]

2.5.3 Difference between ETFs and index mutual funds rebalancing trades

Index mutual funds (IMFs) are often considered the closest alternative to ETFs. We investigate whether stocks that undergo rebalancing by both ETFs and IMFs experience exacerbated anticipatory trading by HFs. The idea is that if ETFs and IMFs track the same indices, their rebalancing events might amplify the pressure on the underlying securities within those indices. Consequently, HFs have a stronger incentive to engage in anticipatory trading ahead of rebalancing events. Furthermore, previous research shows that IMFs can partially avoid costs associated with index rebalancing by choosing to rebalance either at the

[43] We consider the R-squared of 15% to be a reasonable number in this case as ETF RITs capture not only inclusion and exclusion events, but it also accounts for any rebalancing due to change in weights of stocks in the portfolio of equal-weighted indices. Moreover, our sample of inclusions and exclusions only includes S&P and Russel index constituents.

announcement date or after the index rebalancing date. Green and Jame (2011) find that index funds strategically trade around index rebalancing, with 50% of trading in newly added stocks occurring either before or after the index reconstitution effective date.[44] In contrast, ETFs do not have managerial discretion such as index mutual funds.[45] Accordingly, we anticipate a more significant reduction in future returns for stocks rebalanced solely by ETFs, in contrast to stocks with IMF rebalancing, as the flexibility afforded to IMFs to trade after index rebalancing may mitigate the adverse effects on stock returns.

To explore, we obtain data on IMF holdings from the Thomson Reuters holdings database, restricting our analysis to calendar quarters, and construct IMF RIT in a manner akin to ETFs. We first identify stocks that fall into the highest quintile for both ETF RIT and HF NAT.[46] This ensures our focus solely on stocks rebalanced by ETFs and anticipated by HFs. We then segment our sample into stocks rebalanced by both IMFs and ETFs (i.e., IMF RIT not equal to zero) and stocks that are rebalanced only by ETFs (i.e., IMF RIT equal to zero). Figure 2.7 plots the average NAT in Panel A, abnormal long positions (AHF) in Panel B, and abnormal short positions (ASI) in Panel C. In Panel A, the NAT of stocks purchased by both ETFs and IMFs due to rebalancing trades is twice as high as that of stocks rebalanced solely by ETFs. This finding suggests that HFs anticipate profiting from stocks subject to the highest trading pressure, typically including stocks experiencing the most RITs by both ETFs and IMFs. The difference in NAT can be attributed to the long side of HF trades, as depicted in Panel B, where abnormal HF holdings (AHF) in stocks rebalanced by both ETFs and IMFs are double the size of AHF in stocks rebalanced solely by ETFs. In contrast, Panel C shows no noticeable difference in abnormal short positions between two samples of stocks.

[Insert Figure 2.7 here]

We then test whether there is a difference in impact on underlying stock returns between ETF and IMF rebalancing events. We select the sample of stocks that ETFs buy in month m and hedge funds buy in month m - 1 (end of quarter q - 1). We consider ETF buys in month m

[44] Such strategic trading by index funds creates tracking error. However, Elton, Gruber, and Busse (2005) show that index fund flows are not affected by their tracking error, which incentivizes index fund managers to choose their rebalancing dates strategically.
[45] Li (2024) estimates that only 7% of ETFs spread out their rebalancing trades with the majority of ETFs rebalancing at the effective date to minimize tracking error.
[46] We choose to focus on the double sorted portfolio to narrow down the behavior of hedge funds buying stocks prior to rebalancing. This allows us to track and compare trading of hedge funds in stocks subject to ETFs and IMFs rebalancing.

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 strategic anticipatory buys if NAT of stock *i* ranked in the highest quintile in month *m* – 1. We then divide the sample of stocks into two portfolios: 1) stocks that were bought by IMFs as part of their rebalancing event at the end of quarter *q* (P1), IMF RIT > 0, and 2) the rest of the stocks (P2). In other words, P1 contains stocks bought simultaneously by both ETFs and IMFs during rebalancing events.

Table 2.8 presents the results. Panel A reports raw returns, Panel B reports CAPM alphas, and Panel C includes DGTW-adjusted returns. In Column 1 of Panel A, during month *m* – 1, which encompasses HF anticipatory trading, the raw returns of P1 and P2 are 1.98% and 1.88% per month, respectively. During rebalancing event month (*m*), the raw return of P1 is 1.98%, whereas the raw return of P2 increases to 2.19%. In the month following rebalancing (*m* + 1), stocks rebalanced only by ETFs (P2) significantly underperform stocks rebalanced by both ETFs and IMFs (P1) by 1.05%, with a *t*-statistic of 2.66. Similar results are observed in Panels B and C. The findings suggest stocks involved in rebalancing events by both ETFs and IMFs tend to experience more pronounced anticipatory trading activities by HFs. Conversely, stocks rebalanced exclusively by ETFs face greater price pressure during rebalancing, leading to subsequent declines in returns.

[Insert Table 2.8 here]

2.5.4 The hidden cost of ETF rebalancing and hedge funds' anticipatory trades

The predictability of ETF rebalancing trades exposes them to strategic trading by HFs. The anticipatory trading activities by HFs may amplify rebalancing costs for ETF investors, leading to a "buy-high" and "sell-low" scenario. Previous studies have highlighted the negative impact of HFs' anticipatory trading on mutual fund alpha (Shive and Yun, 2013) and distressed mega HF portfolio returns (Agarwal, Aragon, Nanda, and Wei, 2024). Similarly, trading by HFs ahead of ETF rebalancing could result in substantial losses for ETF investors. In this section, we examine the potential costs of ETF exposure to strategic trading activities by HFs for ETF investors.[47]

[47] Li (2024) estimates the rebalancing cost for sunshine ETFs (those that track transparent indices) with an estimation shortfall of 67 bps and a price impact of -20 bps. Our approach differs as we seek to calculate the cost of hedge funds anticipatory trades around ETF rebalancing, impacting ETF investors.

We estimate the cost of ETF rebalancing by computing the difference between the price of stocks bought or sold during the ETF rebalancing event in month *m* and their fair market price. The fair market value represents the hypothetical price a stock would have if it were not subject to pressure from HF' anticipatory trading and ETF rebalancing. To approximate this fair value, we use the price of a rebalanced stock in the month preceding the rebalancing event, which is then multiplied by the equal-weighted return of a matched sample of non-rebalancing stocks. Finally, to calculate the dollar value, we multiply this result by the number of shares bought or sold during the ETF rebalancing.

To define rebalancing stocks, we implement a methodology similar to that of Starks, Venkat, and Zhu (2023). First, we categorize stocks into quintiles based on their ETF RIT and independently sort them based on HFs' net arbitrage trades (NAT) in the previous quarter (q - 1). Stocks that simultaneously belong to quintile 5 (quintile 1) of rebalanced-induced trades (RIT) and quintile 5 (quintile 1) of NAT are identified as our treated sample. To construct the control sample for each rebalanced stock, we follow these steps. For each stock bought (sold) during rebalancing, we first match it with stocks not in the extreme rebalancing portfolios (quintiles 2, 3, and 4). We then ensure that candidate matched stocks share the same two-digit SIC industry code as the treated sample. Next, we sort the candidate stocks into deciles based on the differences between their market capitalization and that of the treated stock. This generates a market capitalization rank, with candidate stocks in the lowest decile having the closest market capitalization to the treated stock. Finally, we repeat the same ranking procedure using the past 12-month stock returns prior to the rebalancing event, resulting in a return rank. For each treated stock, we select five control stocks with the lowest sum of the market capitalization rank and return rank.[48] The equal-weighted return of the control stock portfolio represents the hypothetical return for the rebalancing stocks.

We estimate the average yearly cost to an ETF investor by aggregating the calculated costs. On average, we find that ETF investors lose $5.2 billion annually in profits due to the anticipatory trading activities of HFs around ETF rebalancing events. To provide some perspective, the average yearly value of ETF rebalancing trades over our sample period is $66 billion. This means that almost 8% of the rebalancing volume represents a shadow cost that ETF investors bear as a result of HFs' strategic trading activities. Li (2024) estimates that ETFs could potentially save up to $3.9 billion in rebalancing costs by implementing smarter

[48] For robustness, we also match with 3,6, and 10 stocks, results remain economically significant.

rebalancing strategies, such as concealing rebalancing portfolios or timing their trades more effectively. Our research demonstrates that the cost of ETF rebalancing becomes even more significant when confronted with anticipatory trading by HFs. We assume that, even for self-indexing ETFs, HFs—being sophisticated investors—are capable of predicting their portfolio composition and trading in anticipation of rebalancing. Consequently, our study highlights the role of HFs' anticipatory trading as a shadow cost imposed on ETF investors during rebalancing.

2.6 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 track makes them an easy target for professional arbitragers. This, in turn, imposes higher costs on ETF investors than those documented in previous studies.

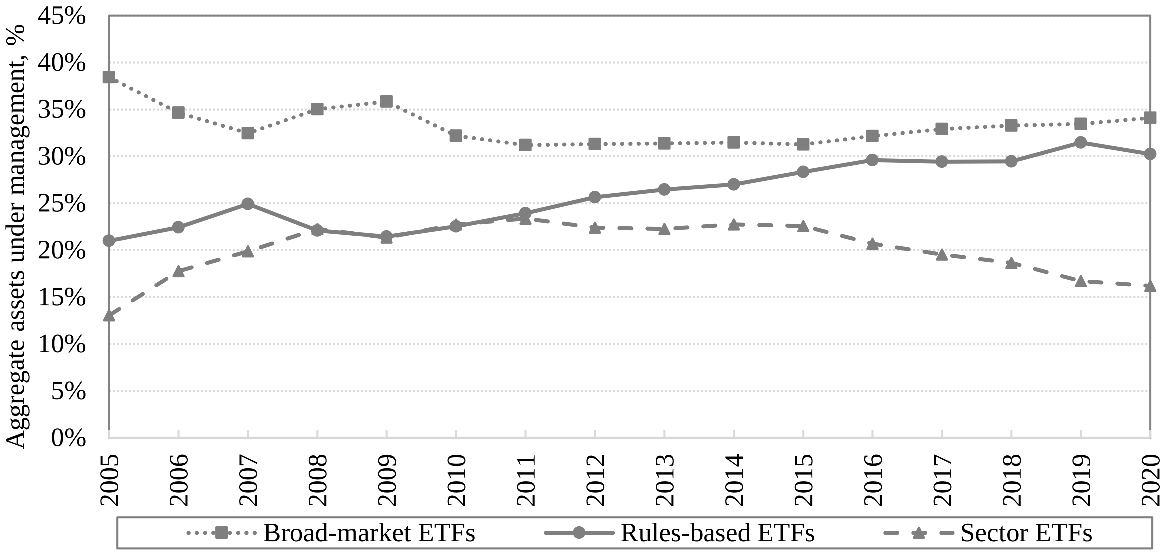
First, we document a significant negative relation between ETF rebalancing activities and future stock returns. The relation is most pronounced for rules-based ETFs, where rebalancing activities happen on a more frequent basis due to the nature of the underlying indices. One key contribution of our research is that we focus on the role that HFs play in enhancing the negative effect of ETF rebalancing trades on underlying securities. We document that stocks that are subject to HF anticipatory trading activities experience a rise in returns greater by 0.6% than those not subject to HF anticipatory trading during ETF rebalancing events. This creates a scenario in which ETFs could be forced to rebalance at inflated prices, leaving ETF investors with higher costs.

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 costs incurred by HF anticipatory trading. The results of our study reveal the hidden costs ETF rebalancing trades impose on their investors.

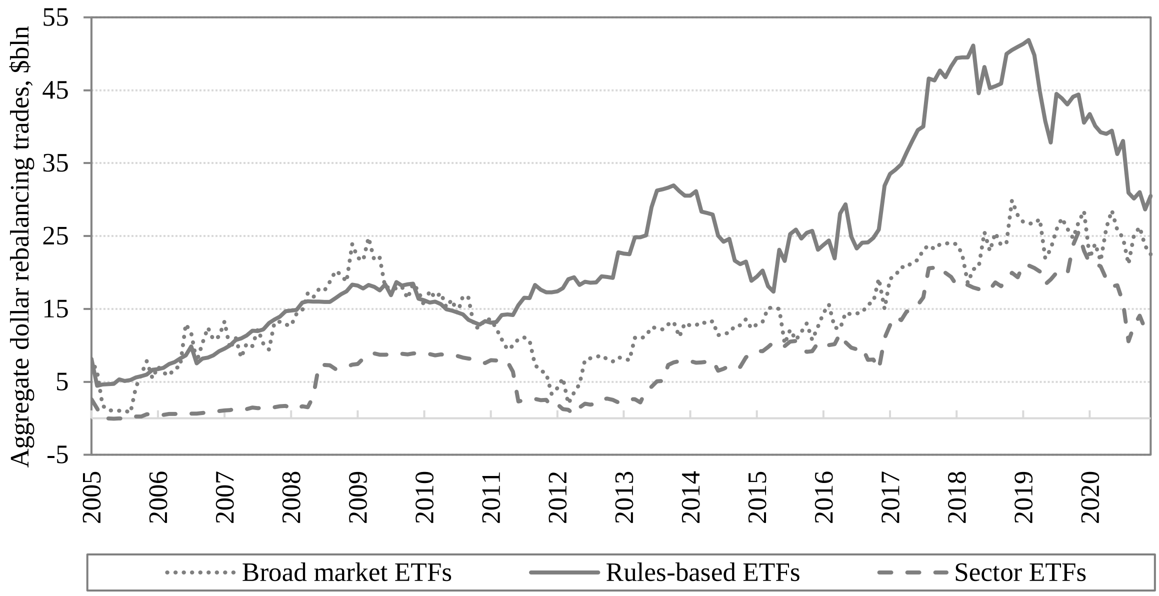
Appendix: Variable Definitions

Variable	Definition
ETF data *(Source: 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.
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.
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.
Rules-based RIT	The rebalancing-induced trades of Rules-based ETFs. We define rules-based ETFs if their “Strategic beta” identifier in Morningstar is equal to “Yes.”
Mkt RIT	The rebalancing-induced trades of Broad Market ETFs. We identify broad-market ETFs if they track broad-market indices, including S&P 500, S&P 1500, Russell 1000, Russell 3000, and NYSE/NASDAQ Composite Index.
Sector RIT	The rebalancing-induced trades of Sector ETFs. We identify sector ETFs using the Morningstar “sector equity” classification.
Hedge funds data *(Source: Thomson Reuters 13F, Compustat short interest file)*	
NAT	Net arbitrage trades by hedge funds measured as the difference between abnormal hedge fund holdings and abnormal short interest.
ASI	Abnormal short interest is calculated as the difference between current quarter short interest and average short interest in the previous four quarters.
AHF	Abnormal hedge funds holdings are measured as the difference between current quarter hedge funds holdings of a stock and average holdings in the previous four quarters.
Options data *(Source: Whale Wisdom)*	
HFs net option position	Hedge funds net option position is calculated as the difference between their aggregate holdings of call and put options.
Index data *(Source: Compustat)*	
Inclusion	A dummy variable which takes a value of one if a stock was added to one of the indices from the S&P and Russell universes of indices in a given month.

Appendix: Variable Definitions - *Continued*	
Variable	Definition
Index data *(Source: Compustat) - Continued*	
Exclusion	A dummy variable which takes a value of one if a stock was excluded from one of the indices from the S&P and Russell universes of indices in a given month.
N_Incl	The number of indices from the S&P and Russell universes of indices to which a stock was included in a given month.
N_Excl	The number of indices from the S&P and Russell universes of indices from which a stock was excluded in a given month.
Index Mutual Funds data *(Source: Thomson-Reuters)*	
IMF RIT	Hedge funds net option position is calculated as the difference between their aggregate holdings of call and put options.
Stock data *(Source: CRSP, Compustat, I/B/E/S)*	
log(SIZE)	Firm size measured as the log of market capitalization.
Turnover	Average monthly turnover over the previous quarter measured as share volume divided by total shares outstanding.
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.
#analysts	Number of analysts covering the firm.
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 estimate the value of preferred stock. We exclude negative *B/M* firms.
$Ret_{i,m-1}$	Cumulative returns in the previous month.
$Ret_{i,m-12:m-2}$	Cumulative return over 11 months preceding the beginning of the last month.
ROE	Ratio of net income and book equity, where book equity is defined as shareholders' equity minus preferred stock.
ROA	Ratio of net income to total assets
Gross profits over assets	Revenue minus costs of goods sold divided by total assets
Amihud illiquidity	Stock illiquidity defined as the average ratio of the daily absolute return to the (dollar) trading volume on that day.



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



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

Figure 2.1: AUM and rebalancing trades of US domestic ETFs by investment type
This figure illustrates the proportional AUM and the dollar value of rebalancing trades for US domestic ETFs during the sample period from January 2005 to December 2020. The ETF sample is categorized into three groups: broad-market, rules-based, and sector ETFs. Broad-market ETFs encompass those tracking broad-market indices such as the S&P 500, S&P 1500, Russell 1000, Russell 3000, and NYSE/NASDAQ Composite Index. Rules-based ETFs adhere to specific factors in their investment strategy and are identified using the "Strategic Beta" indicator in Morningstar. Sector ETFs focus on specific industries and are defined using sector equity classifications in Morningstar. Panel A displays the proportional allocation of AUM among these three types of ETFs, while Panel B illustrates the rolling three-year aggregate dollar value of rebalancing trades

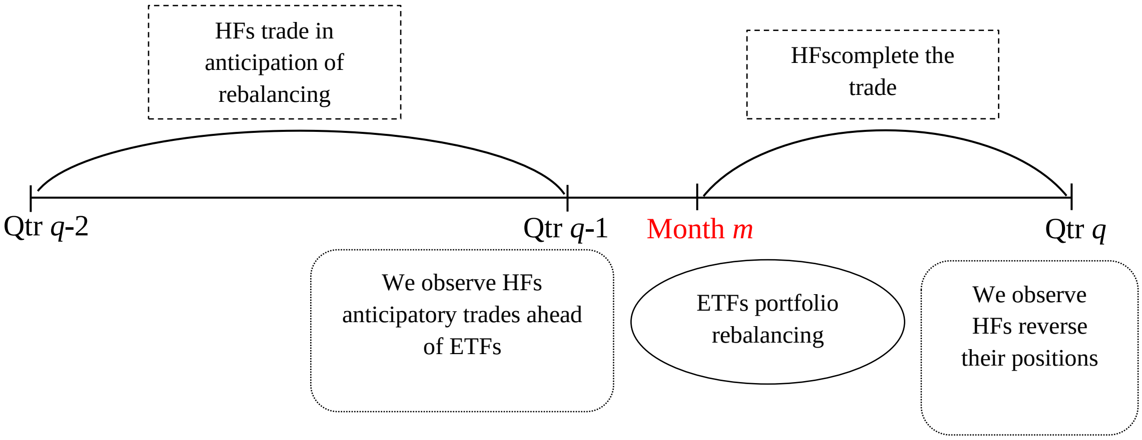
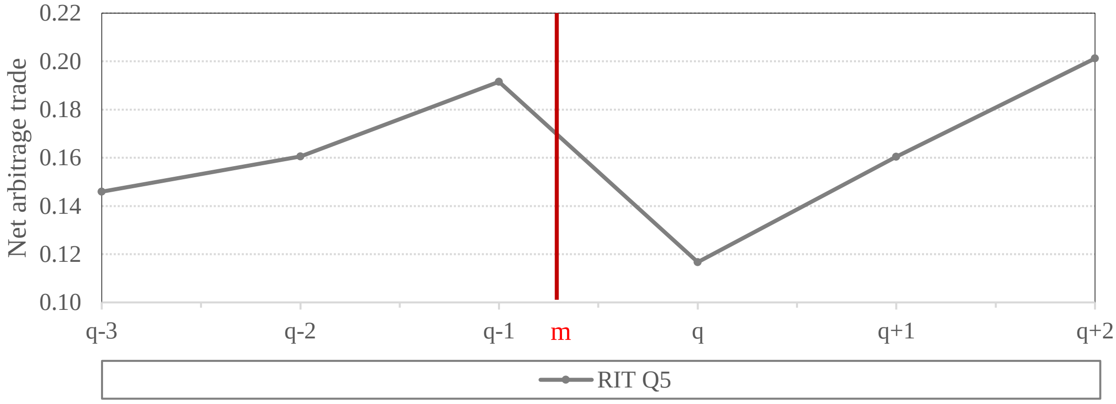
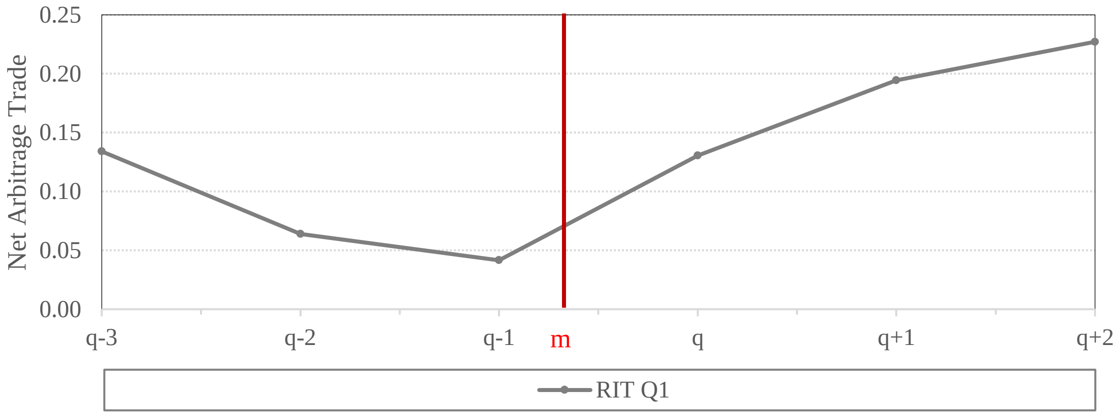


Figure 2.2: Timeline of anticipatory trading activities by hedge funds
This figure illustrates the timeline of trading by hedge funds around ETF rebalancing events. Month *m* represents the month when ETFs rebalance their portfolios. *q* - 2 and *q* - 1 refer to the quarters preceding month *m*, and *q* is the quarter following month *m*.

Panel A: Hedge funds net arbitrage trades of stocks **purchased** as part of ETF rebalancing



Panel B: Hedge funds net arbitrage trades of stocks **sold** as part of ETF rebalancing



Panel C: Hedge funds net arbitrage trades of stocks not rebalanced by ETFs

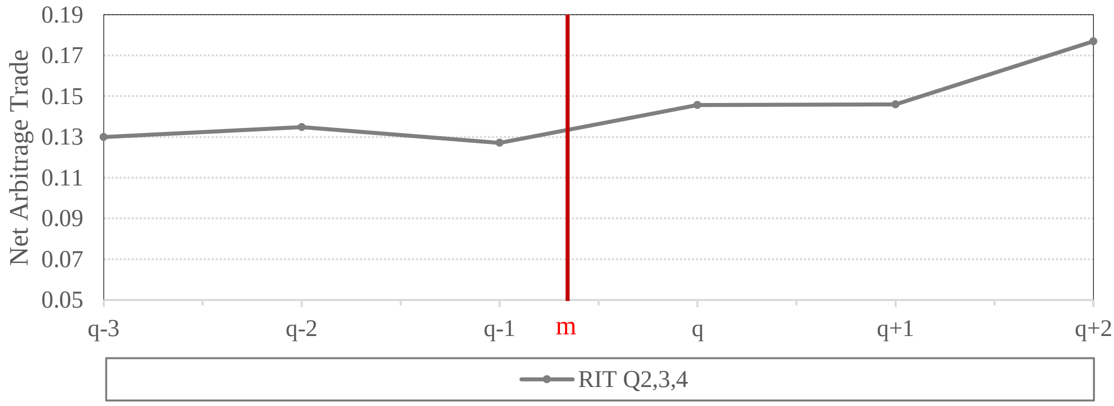


Figure 2.3: Hedge fund trading in stocks rebalanced by ETFs

This figure illustrates the evolution of hedge funds trading in stocks traded by ETFs during portfolio rebalancing. The sample period is 2005-2020. The vertical red line indicates the month *m*, during which ETF rebalancing takes place. We depict the net arbitrage trade (NAT) for stocks that were rebalanced by ETFs in the calendar quarter preceding the ETF rebalancing month, as well as for non-rebalanced stocks. NAT is calculated as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). The figure then presents the average NAT for stocks bought by ETFs during rebalancing in Panel A, for sold stocks in Panel B, and for other non-rebalanced stocks in Panel C. We define stocks bought (sold) by ETFs as part of rebalancing if they belong to the highest (lowest) quintile of RIT, and the rest of the stocks treat as non-rebalanced portfolios.

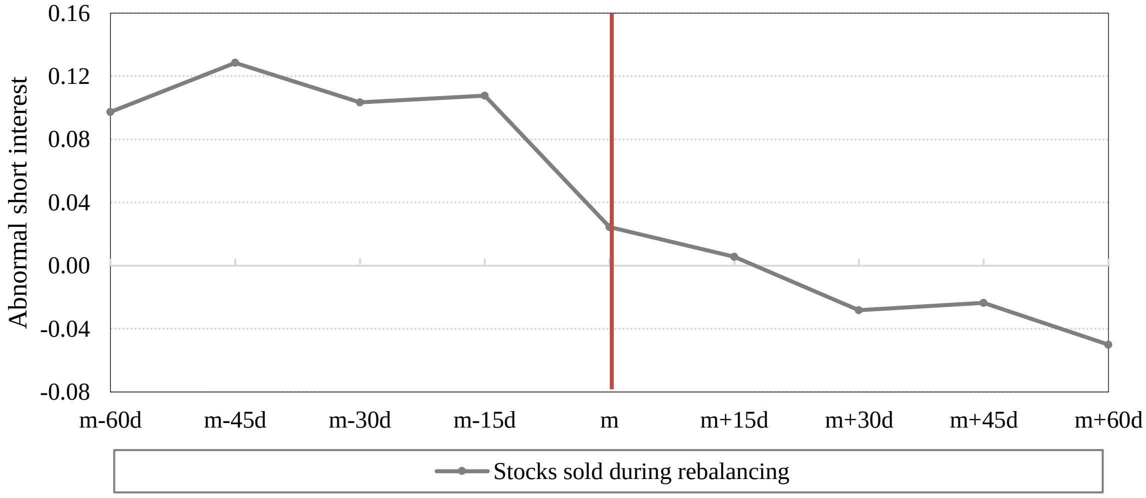


Figure 2.4: Short positions of stocks rebalanced by ETFs
This figure illustrates the abnormal short interest (ASI) of stocks that were sold during ETF rebalancing. The sample period is 2005-2020. The vertical red line marks the month of the ETF rebalancing. ASI is calculated as the difference between the short interest in the current month and the average short interest over the previous year. We utilize the bi-weekly short interest data and display ASI of stocks sold during the ETF rebalancing event for two months before and two months after the rebalancing.

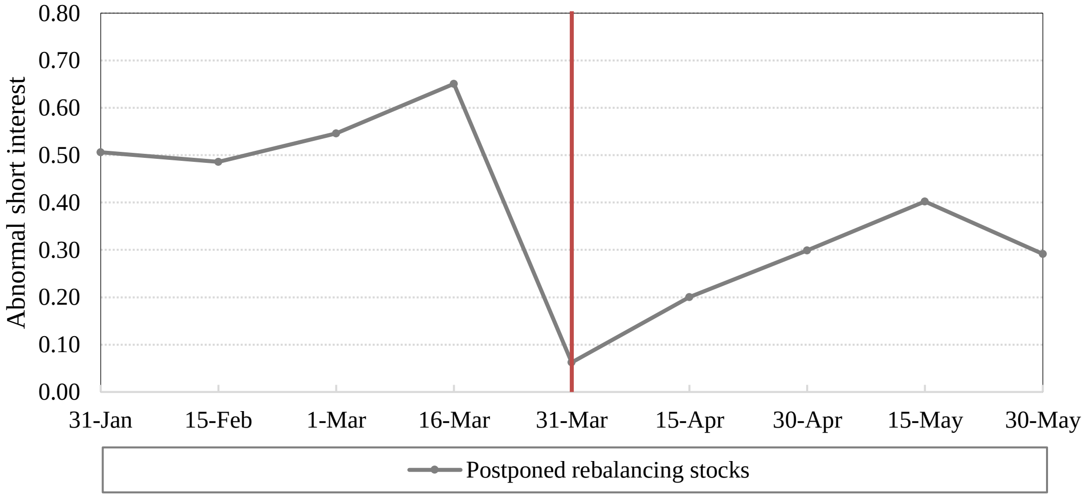
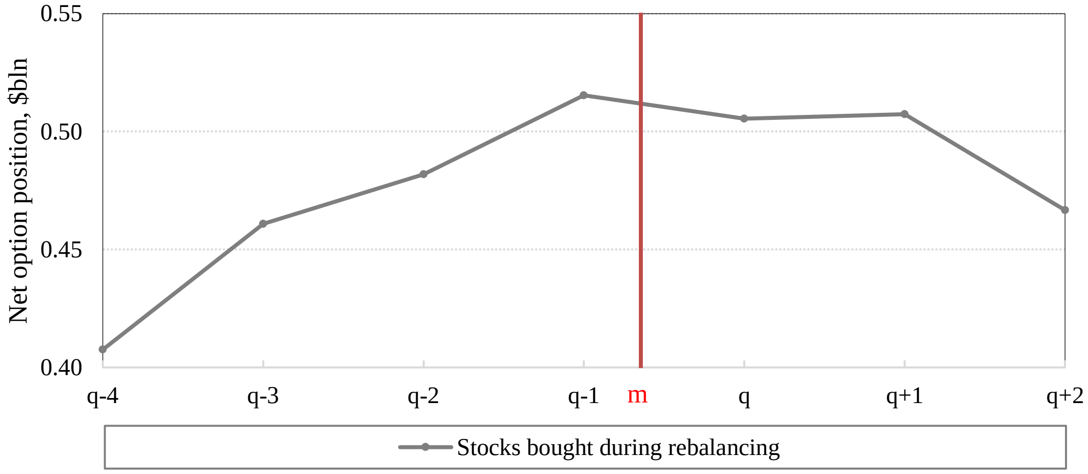


Figure 2.5: Short positions of stocks in the postponed index rebalancing portfolio in March 2020
This figure illustrates the abnormal short interest (ASI) of stocks that were not sold due to the postponed index rebalancing in March 2020. We proxy stocks that were part of the postponed index rebalancing portfolio by stocks that were eventually sold during the rebalancing in June 2020. The ASI of these stocks is tracked from January to May 2020. The vertical red line marks the initial rebalancing month. ASI is calculated as the difference between the short interest in the current month and the average short interest over the previous year.

Panel A: Aggregate **net option position** of hedge funds in stocks **purchased** during ETF rebalancing



Panel B: Aggregate **net option position** of hedge funds in stocks **sold** during ETF rebalancing

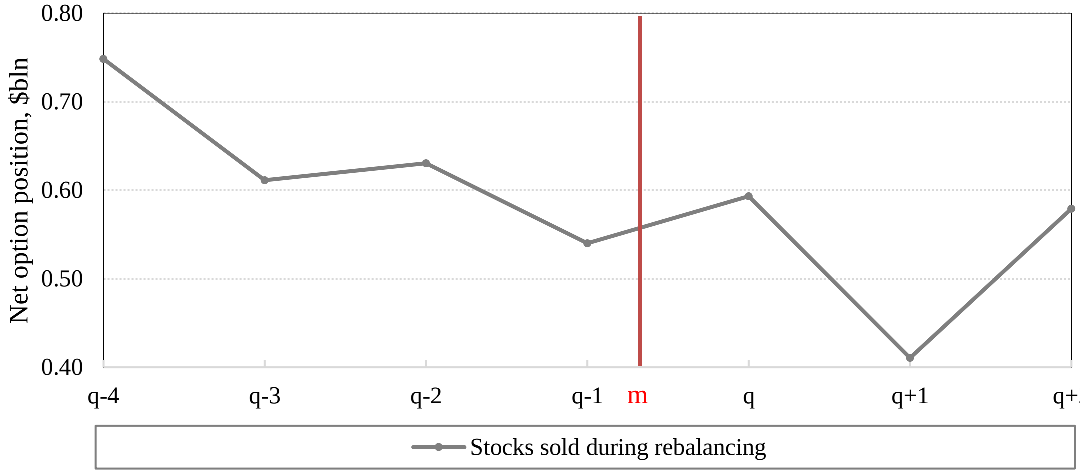


Figure 2.6: Hedge fund option holdings surrounding ETF rebalancing events

This figure illustrates the evolution of hedge funds' net options positions in stocks that were purchased and sold during ETF rebalancing events. The sample period is 2005-2020. The vertical red line indicates the month of the ETFs rebalancing event. In Panel A (Panel B), we plot the aggregate net option positions of hedge funds for stocks that were purchased (sold) by ETFs during the rebalancing. Net options position is calculated as the difference between call and put options.

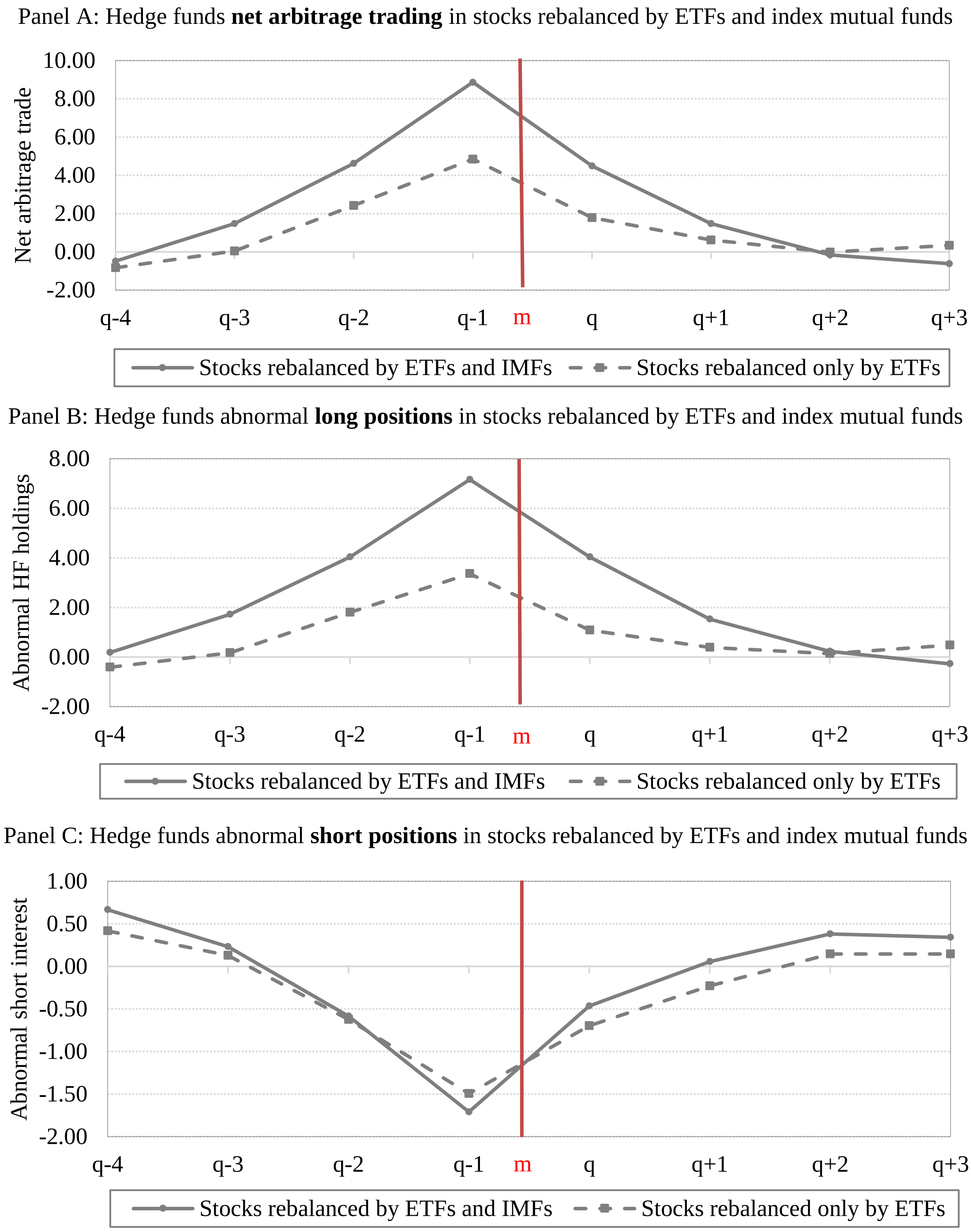


Figure 2.7: Hedge fund trades of stocks rebalanced by ETFs and index mutual funds

This figure illustrates the evolution of hedge fund (HF) trading in stocks rebalanced by ETFs and index mutual funds (IMFs). The sample period is 2005-2020. The vertical red line marks the month in which we observe high ETF rebalancing induced trades (RIT) for a given stock. For each ETF rebalancing month, we match IMF RIT at the end of the quarter corresponding to the rebalancing month. We then depict the net arbitrage trade (NAT) for stocks that were purchased by ETFs and simultaneously bought by HFs in the quarter *q* - 1. NAT is calculated as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). Further, stocks are categorized into two portfolios: 1) stocks that undergo rebalancing by IMFs in quarter *q;* 2) stocks that are not rebalanced by IMFs. The figure then plots the NAT in Panel A, AHF in Panel B, and ASI in Panel C of hedge funds for the four quarters before the ETF rebalancing trades and four quarters after.

Table 2.1: ETF rebalancing trades and future stock returns

This table reports the results of Fama–MacBeth regressions of the monthly returns of underlying securities on ETF rebalancing trades. The sample period spans 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 trades by ETFs of stock *i* in month *m*, measured as the difference between monthly ETF trades and flow-induced trades (FIT). We control for $FIT_{i,m}$, which denotes stock-level monthly flow-induced trades. In Panel A, results are reported for the entire ETF sample. In Panel B ETF sample is categorized into three groups. 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. Other control variables include previous one month returns ($Ret_{i,m-1}$), one year returns ($Ret_{i,m-12:m-2}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and the 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.

Panel A: All ETFs				
	$Ret_{i,m}$	$Ret_{i,m+1}$	$Ret_{i,m+2}$	$Ret_{i,m+3}$
	(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	Yes	Yes	Yes	Yes
Adjusted R^2	0.090	0.041	0.041	0.039
Panel B: ETFs by investment type				
	$Ret_{i,m}$	$Ret_{i,m+1}$	$Ret_{i,m+2}$	$Ret_{i,m+3}$
	(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 $RIT_{i,m}$	-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	Yes	Yes	Yes	Yes
Adjusted R^2	0.101	0.047	0.040	0.036

Table 2.2: Hedge funds anticipatory trading before ETF rebalancing

This table reports the results of Pooled OLS regressions of the hedge funds NAT on ETF rebalancing trades. The sample period is from January 2005 to December 2020. In Columns (1) – (3), the dependent variable is a continuous measure, defined as hedge funds' NAT in quarter q - 1, preceding the ETFs' rebalancing month m. This is measured as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). In Columns (4) – (6), the dependent variable is the quintile rank formed according to the corresponding continuous measure. $RIT_{i,m}$ is monthly rebalancing-induced trading of stock i 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 returns ($Ret_{i,m\text{-}1}$), one year returns ($Ret_{i,m\text{-}12:m\text{-}2}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and the 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

Dep var	$NAT_{i,q-1}$					
	Continuous measure			Quintile rank		
	(1)	(2)	(3)	(4)	(5)	(6)
$RIT_{i,m}$	0.352***	0.359**	0.367**	13.399***	13.902**	14.204**
	(3.29)	(2.43)	(2.44)	(3.00)	(2.03)	(2.03)
$FIT_{i,m}$			0.422			16.844
			(0.85)			(0.69)
Controls	No	Yes	Yes	No	Yes	Yes
Year/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.038	0.041	0.041	0.000	0.002	0.002

Table 2.3: Predictability of ETF rebalancing trades and hedge funds anticipatory trading

This table reports the results of regressions of the hedge funds NAT on expected and unexpected components of ETF rebalancing trades. The sample period is from January 2005 to December 2020. The dependent variable is hedge funds NAT in quarter *q* - 1, preceding the ETFs' rebalancing month *m*. This is measured as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). $RIT_{i,m}$ is monthly rebalancing-induced trading of stock *i* by ETFs in month *m*, measured as the difference between monthly ETF trades and flow-induced trades (FIT). We decompose RIT into expected and unexpected component. We estimate expected component based on the information available to HFs in month *m* - 2, which includes stock characteristics and previous 3 months rebalancing trades. Residual from the estimated regression is then proxied as a unexpected component of RIT. In Columns (5) and (6) we control for $FIT_{i,m}$, which is stock-level monthly flow-induced trades. Other control variables include previous one month returns ($Ret_{i,m-1}$), one year returns ($Ret_{i,m-12:m-2}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and the 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

Dep var	$NAT_{i,q-1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Expected RIT $_{i,m}$	2.424**	2.798*	2.789*		2.537**	2.893*
	(2.20)	(1.81)	(1.81)		(2.30)	(1.87)
Unexpected RIT $_{i,m}$	0.139	0.123		0.122	0.146*	0.131
	(1.59)	(1.42)		(1.41)	(1.68)	(1.51)
FIT $_{i,m}$					-0.398**	-0.477***
					(-2.50)	(-2.99)
Controls	No	Yes	Yes	Yes	No	Yes
Year/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.056	0.058	0.058	0.058	0.056	0.058

Table 2.4: Hedge funds anticipatory trading in stocks rebalanced by ETFs: treated vs control

This table reports the results of Pooled OLS regressions of the hedge funds NAT on ETF rebalancing trades for treated and control stocks. The sample period is from January 2005 to December 2020. Dependent variable is hedge funds NAT in quarter *q* - 1 preceding ETFs rebalancing month *m*, measured as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). $RIT_{i,m}$ 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). Treated stocks are identified as stocks that meet the following criteria: for buy (sell) sample 1) ETF rebalancing trades of stock *i* ranked in the highest (lowest) quintile in month *m* and 2) NAT of stock *i* ranked in the highest (lowest) quintile in quarter *q* - 1. We use propensity score matching to identify control sample of stocks using the following stock characteristics: momentum, size, B/M ratio, illiquidity, gross profitability, ROE, ROA. Columns (1) – (3) report results for the sample of stocks in bought during rebalancing (Q5 RIT), and Columns (4) – (6) report results for sold stocks (Q1 RIT). We control for $FIT_{i,m}$, which is stock-level monthly flow-induced trades. Other control variables include previous one month returns ($Ret_{i,m-1}$), one year returns ($Ret_{i,m-12:m-2}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and the 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.

Dep var	$NAT_{i,q-1}$					
	Buy			Sell		
	(1)	(2)	(3)	(4)	(5)	(6)
$RIT_{i,m}$ x $Treat_{i,m}$	2.352***	3.469***	3.482***	4.790***	4.874***	4.901***
	(3.02)	(4.36)	(4.39)	(8.14)	(4.10)	(4.14)
$RIT_{i,m}$	-1.706***	-2.203***	-2.209***	-3.850***	-4.031***	-4.005***
	(-3.23)	(-3.38)	(-3.39)	(-9.16)	(-4.39)	(-4.36)
$Treat_{i,m}$	0.043***	0.041***	0.041***	-0.042***	-0.042***	-0.042***
	(32.85)	(29.17)	(28.94)	(-24.76)	(-25.25)	(-25.17)
$FIT_{i,m}$			0.445			0.823**
			(1.15)			(2.08)
Controls	No	Yes	Yes	No	Yes	Yes
Year/Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.413	0.407	0.407	0.403	0.432	0.432

Table 2.5: Average option positions of hedge funds in ETFs

This table reports the average option positions held by HFs in ETFs over the sample period from 2005 to 2020. ETFs are categorized into quintiles based on their aggregate portfolio rebalancing trades (RIT). Quintile 1 comprises ETFs with the lowest rebalancing trades, while quintile 5 includes ETFs with the highest rebalancing activity. Rebalancing trades of ETFs are measured as the difference between the total aggregate trades in the previous month and the aggregate flow-induced trades. For each quintile of ETF, we compute the average market value of put and call options held by hedge funds in the quarter preceding the rebalancing month. We also report the proportion of put and call option within the ETFs as a share of the aggregate put and call option portfolio of all hedge funds.

	Put options		Call options	
RIT rank	$ mln	Proportion, %	$ mln	Proportion, %
	(1)	(2)	(3)	(4)
1 – low RIT ETFs	4,822	15.60	1,866	6.13
2	19	0.07	23	0.05
3	27	0.05	12	0.03
4	114	0.29	23	0.07
5 – high RIT ETFs	6,757	20.82	2,468	7.54

Table 2.6: Returns of stocks subject to ETF rebalancing and anticipatory trading by HFs

This table reports the equal-weighted monthly returns of stocks rebalanced by ETFs and traded by hedge funds. We first sort stocks into quintiles based on their RIT during rebalancing month m, where Quintile 1 (Low) contains stocks sold during ETF rebalancing, and Quintile 5 (High) contains stocks bought by ETFs during rebalancing. Next, we independently sort stocks into quintiles based on their NAT in quarter $q – 1$, preceding rebalancing month m, where Quintile 1 (Low) contains stocks with lowest NAT, and Quintile 5 (High) contains stocks with highest NAT. NAT is the net position of hedge funds in the stock measured as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). We then calculate equal-weighted returns for high and low, and high-low portfolios in months $m – 1$ in Columns (1) – (3), month m in Columns (4) – (6), and months $m + 1$ in Columns (7) – (9). Panel A reports raw returns, Panel B reports CAPM alphas, and Panel C includes FF3-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

	NAT								
	m-1			**m**			**m+1**		
	Low	High	High - Low	Low	High	High - Low	Low	High	High - Low
RIT	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low	-0.165	1.133	1.298***	1.013	1.158	0.145	0.487	1.230	0.743***
	(-0.20)	(1.31)	(4.22)	(0.97)	(1.27)	(0.56)	(0.57)	(1.61)	(2.91)
High	1.542*	1.775**	0.233	1.24	1.848*	0.608**	0.269	0.933	0.664***
	(1.71)	(2.06)	(0.82)	(1.21)	(1.90)	(2.32)	(0.32)	(1.19)	(2.73)
High - Low	1.707***	0.642*	-1.065**	0.227	0.690**	0.462	-0.217	-0.297	-0.079
	(4.97)	(1.81)	(-2.62)	(0.71)	(2.07)	(1.26)	(-0.82)	(-1.16)	(-0.25)

Panel B: CAPM alpha

	NAT								
	m-1			**m**			**m+1**		
	Low	High	High - Low	Low	High	High - Low	Low	High	High - Low
RIT	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low	-0.832**	0.429	1.157***	0.609	0.785	0.073	-0.649*	0.200	0.745***
	(-2.24)	(1.13)	(3.73)	(0.58)	(0.87)	(0.27)	(-1.81)	(0.67)	(2.98)
High	0.826*	1.062***	0.132	0.858	1.432	0.471*	-0.869**	-0.137	0.628**
	(1.94)	(3.11)	(0.46)	(0.84)	(1.48)	(1.76)	(-2.61)	(-0.51)	(2.59)
High - Low	1.554***	0.529	-1.129***	0.146	0.544	0.294	-0.324	-0.441*	-0.221
	(4.49)	(1.47)	(-2.78)	(0.45)	(1.60)	(0.79)	(-1.20)	(-1.71)	(-0.68)

Panel C: FF3 adjusted returns

	NAT								
	m-1			**m**			**m+1**		
	Low	High	High - Low	Low	High	High - Low	Low	High	High - Low
RIT	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low	-1.142***	0.114	1.147***	0.734	1.066	0.229	-0.454*	0.412*	0.763***
	(-4.29)	(0.36)	(3.62)	(0.65)	(1.09)	(0.81)	(-1.78)	(1.76)	(2.92)
High	0.47	0.743***	0.164	0.813	1.433	0.517*	-0.760***	-0.117	0.540**
	(1.49)	(3.05)	(0.56)	(0.73)	(1.37)	(1.79)	(-3.35)	(-0.62)	(2.12)
High - Low	1.502***	0.52	-1.092**	-0.024	0.263	0.184	-0.41	-0.632**	-0.326
	(4.19)	(1.39)	(-2.59)	(-0.07)	(0.75)	(0.46)	(-1.41)	(-2.34)	(-0.94)

Table 2.7: 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 returns ($Ret_{i,m-1}$), one year returns ($Ret_{i,m-12:m-2}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and the 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.

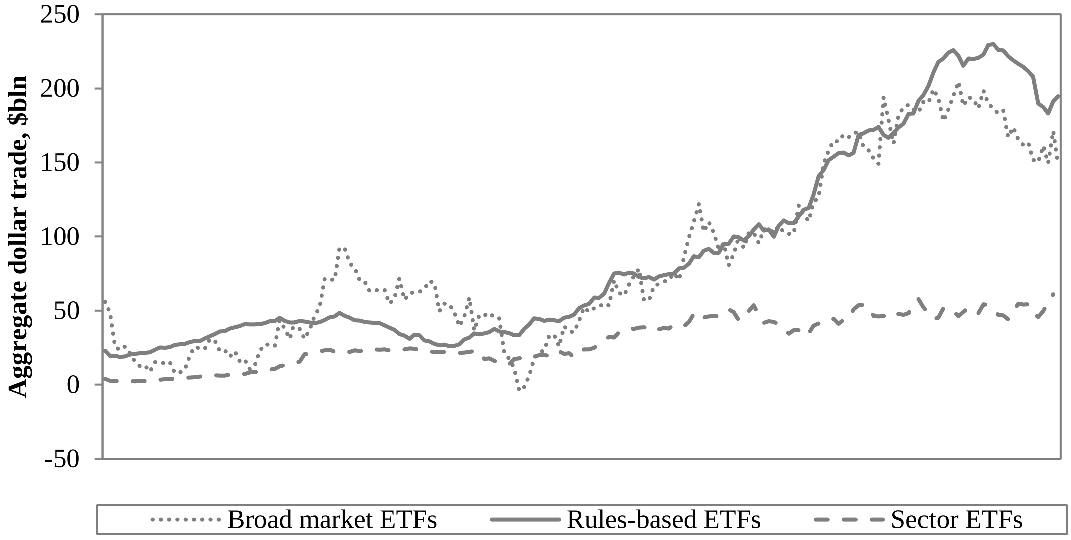
Dep var	$RIT_{i,m}$							
	All ETFs		Rules-based ETFs		Board-market ETFs		Sector ETFs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Inclusion_{i,m}$	0.378***		0.240***		0.029***		0.055***	
	(15.50)		(21.00)		(11.55)		(5.95)	
$Exclusion_{i,m}$	-0.194***		-0.198***		-0.030***		-0.047***	
	(-7.28)		(-12.05)		(-8.50)		(-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	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.151	0.161	0.142	0.145	0.165	0.174	0.053	0.053

Table 2.8: Hedge funds trading of stocks rebalanced by ETFs and index mutual funds

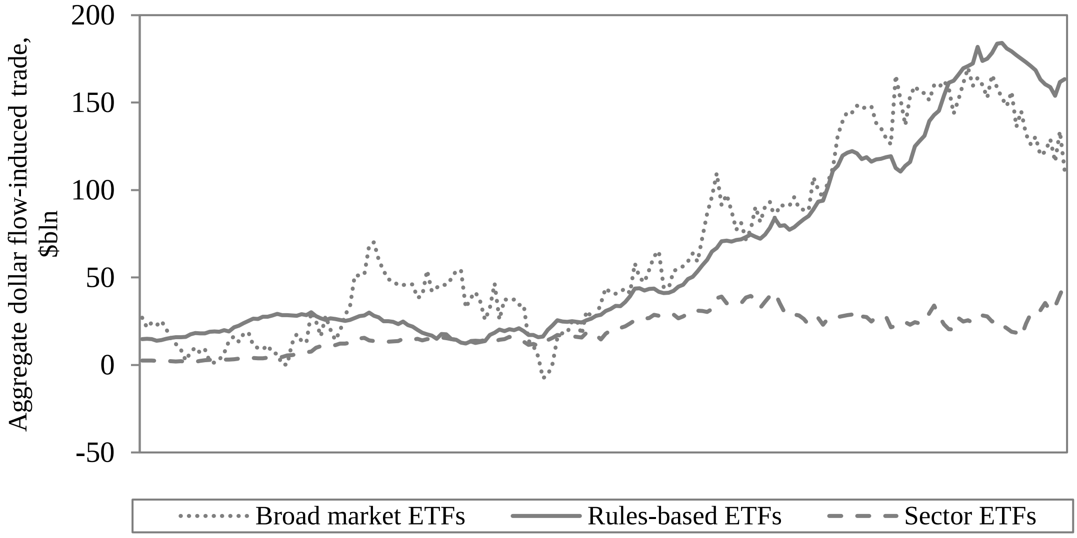
This table reports the equal-weighted monthly returns of stocks rebalanced by ETFs and IMFs subject to hedge funds front-running. We identify stocks that were purchased by ETFs due to its rebalancing event in month *m*. We consider ETF buys as stocks that meet the following two conditions: 1) ETF rebalancing 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 hedge funds in the stock measured as the difference between abnormal hedge fund holdings (AHF) and abnormal short interest (ASI). 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.

Panel A: Raw returns				
	m -1	m	m + 1	m + 2
	(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 A: CAPM alpha				
	m - 1	m	m + 1	m + 2
	(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				
	m - 1	m	m+1	m+2
	(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)

Internet Appendix: Additional Figures and Tables



Panel A: Aggregate dollar trades across three types of ETFs



Panel B: Aggregate dollar flow induced trades across three types of ETFs

Figure IA2.1: Aggregate dollar trade of US domestic ETFs by type

This figure shows the rolling 3-year aggregate dollar value of trading by US domestic ETFs for the sample period of January 2005 and December 2020. ETFs 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 factor in their investment strategy and identified using "Strategic Beta" indicator in Morningstar. Sector ETFs follow specific industry and defined using Sector equity classification in Morningstar. Panel A shows aggregate dollar trades measured as the monthly change in fund holdings and aggregated across each ETF type. Panel B shows aggregate dollar flow-induced trades, calculated as the dollar change in holdings proportional to ETF flows.

Table IA2.1: Summary Statistics of ETFs

This table presents descriptive statistics of ETFs for the sample period of 2005-2020. 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.

		Number of stock holdings			Total AUM ($ bln)		
Year	No. ETFs	Broad-market ETFs	Rules-based ETFs	Sector ETFs	Broad-market ETFs	Rules-based ETFs	Sector ETFs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2005	144	1480	397	67	74	41	25
2006	241	1500	388	55	86	56	44
2007	296	1496	368	60	103	79	63
2008	312	1471	372	67	113	71	72
2009	335	1460	355	69	106	64	63
2010	366	1440	382	70	122	85	86
2011	438	1304	385	69	150	115	113
2012	439	1340	397	69	176	144	126
2013	431	1437	389	77	246	208	175
2014	448	1452	370	77	319	274	230
2015	517	1487	389	77	364	330	263
2016	610	1675	342	67	412	379	265
2017	687	1365	336	60	564	504	334
2018	749	1289	335	65	676	598	378
2019	812	1302	316	72	760	715	379
2020	909	1298	312	70	882	782	418

Table IA2.2: ETF Turnover

This table presents average yearly turnover of ETFs for the sample period of 2005-2020. Column 1 contains average turnover for the whole sample of ETFs. Columns (2), (3), and (4) show the average yearly turnover for broad-market, rules-based, and sector ETFs respectively. Yearly turnover ratio is obtained from Morningstar.

	Turnover (%)			
Year	**All ETFs**	**Broad-market ETFs**	**Rules-based ETFs**	**Sector ETFs**
	(1)	(2)	(3)	(4)
2005	15.34	9.67	22.37	11.67
2006	21.38	4.87	32.17	17.05
2007	25.45	5.20	30.18	25.10
2008	43.67	5.86	51.09	37.54
2009	51.22	7.87	64.80	45.17
2010	39.25	5.54	51.09	33.84
2011	34.68	8.39	43.97	31.19
2012	41.95	9.23	48.48	34.86
2013	40.95	6.75	49.26	32.82
2014	45.31	7.05	50.09	41.99
2015	45.25	4.16	51.31	37.08
2016	51.89	5.27	64.11	38.83
2017	54.27	6.18	59.77	39.03
2018	53.10	6.27	57.65	39.81
2019	76.18	5.27	91.15	58.92
2020	68.18	7.91	103.47	41.73
Average	44.25	6.59	54.44	35.41

Table IA2.3: ETF trades summary statistics

This table presents the summary statistics of the ETF trades for the sample period of 2005-2020.. Panel A presents summary statistics of the RIT and FIT trades (measured in %) of ETFs by type, where *RIT* is stock-level monthly rebalancing-induced trades by ETFs, measured as the difference between monthly ETF trades and flow-induced trades (FIT). *FIT* is stock-level monthly flow-induced trades. Panel B shows correlation between ETFs RIT and FIT for each ETF type. $*$,$**$, $***$ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Summary statistics						
Variable	**N**	**Mean**	**Std Dev**	**Min**	**Median**	**Max**
	(1)	(2)	(3)	(4)	(5)	(6)
All ETFs						
RIT	839,466	0.025	0.179	-0.924	0.001	1.296
FIT	839,477	0.016	0.083	-0.222	0.001	0.348
ETFs by investment type						
Rules-based RIT	732,108	0.010	0.090	-0.480	0.001	0.581
Rules-based FIT	732,108	0.007	0.028	-0.073	0.003	0.128
Mkt RIT	851,085	0.002	0.018	-0.169	0.000	0.178
Mkt FIT	851,085	0.003	0.014	-0.053	0.001	0.081
Sector RIT	475,960	0.007	0.109	-0.747	0.000	0.909
Sector FIT	475,960	0.005	0.053	-0.190	0.000	0.282

Panel B: Correlation matrix of RIT and FIT				
	All ETFs RIT	Rules-based RIT	Mkt RIT	Sector RIT
	(1)	(2)	(3)	(4)
All ETFs FIT	0.027***			
Rules-based FIT		0.002***		
Mkt FIT			0.092***	
Sector FIT				0.045***

Table IA2.4: 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 in month $m + 1$, where month m is ETF rebalancing month. 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 IA2.5: ETF rebalancing trades and future stock returns

This table reports the results of Fama–MacBeth regressions of the monthly returns of underlying securities on ETF rebalancing trades. The sample period spans 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 trades by ETFs of stock *i* in month *m*, measured as the difference between monthly ETF trades and flow-induced trades (FIT). We control for $FIT_{i,m}$, which denotes stock-level monthly flow-induced trades. In Panel A, results are reported for the entire ETF sample. In Panel B ETF sample is categorized into three groups. 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. Other control variables include previous one month returns ($Ret_{i,m-1}$), one year returns ($Ret_{i,m-12:m-2}$), log(SIZE), turnover, idiosyncratic volatility, log(B/M), and the 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.

Panel A: All ETFs				
	$Ret_{i,m}$	$Ret_{i,m+1}$	$Ret_{i,m+2}$	$Ret_{i,m+3}$
	(1)	(2)	(3)	(4)
$RIT_{i,m}$	**1.455*** **	**-1.616*** **	**-0.570***	-0.196
	(3.24)	**(-4.04)**	**(-1.93)**	(-0.50)
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.094	0.042	0.036	0.034
Panel B: ETFs by investment type				
	$Ret_{i,m}$	$Ret_{i,m+1}$	$Ret_{i,m+2}$	$Ret_{i,m+3}$
	(1)	(2)	(3)	(4)
Rules-based $RIT_{i,m}$	**3.066*** **	**-2.037*** *	**-1.231***	-1.071
	(3.56)	**(-2.49)**	**(-1.81)**	(-1.23)
Mkt $RIT_{i,m}$	6.268	**-7.859*** **	**-5.230*** *	3.026
	(0.86)	**(-2.74)**	**(-1.99)**	(0.92)
Sector $RIT_{i,m}$	11.169	5.559	-0.965	0.090
	(0.98)	(0.76)	(-0.20)	(0.01)
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.093	0.042	0.035	0.032

Table IA2.6: 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.

Dep vars	$Ret_{i,m}$	$Ret_{i,m+1}$	$Ret_{i,m+2}$	$Ret_{i,m+3}$
	(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

Table IA2.7: 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.

Dep vars	$Ret_{i,m}$		$Ret_{i,m+1}$		$Ret_{i,m+2}$	
	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 IA2.8: ETF trades and future stock returns

This table reports the results of Fama-MacBeth regressions of monthly returns on monthly trading of ETFs. 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. $Ret_{i,q+1}$ is cumulative stock return over the next quarter q+1. $Trade_{i,m}$, $Trade_{i,m+1}$, $Trade_{i,m+2}$, 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 returns ($Ret_{i,m-12:m-3}$), 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.

Dep vars	$Ret_{i,m}$	$Ret_{i,m+1}$	$Ret_{i,m+2}$	$Ret_{i,m+3}$	$Ret_{i,q+1}$
	(1)	(2)	(3)	(4)	(5)
$Trade_{i,m}$	2.188***	-1.353***	-0.238	0.590	-1.652
	(4.68)	(-4.02)	(-0.47)	(1.57)	(-1.54)
$Trade_{i,m+1}$			-1.369**	-0.621	
			(-2.64)	(-0.74)	
$Trade_{i,m+2}$				-1.013*	
				(-1.80)	
$Controls_{i,m}$	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.090	0.041	0.041	0.039	0.045

Table IA2.9: 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. 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, 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 3 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 "Sector Equity" Morningstar Category. $Trade_{i,m+1}$, $Trade_{i,m+2}$, are monthly trading of stocks by ETFs in months 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 returns ($Ret_{i,m-12:m-3}$), 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.

Dep vars	$Ret_{i,m}$	$Ret_{i,m+1}$	$Ret_{i,m+2}$	$Ret_{i,m+3}$
	(1)	(2)	(3)	(4)
Rules-based Trade $_{i,m}$	3.018***	-1.473**	-1.510	-0.314
	(3.34)	(-2.39)	(-1.62)	(-0.42)
Mkt Trade $_{i,m}$	-1.072	-3.294	0.298	0.832
	(-0.19)	(-1.65)	(0.08)	(0.11)
Sector Trade $_{i,m}$	6.336	0.317	-4.498	-2.523
	(1.25)	(0.07)	(-0.94)	(-0.73)
Trade $_{i,m+1}$			-1.266**	-0.639
			(-2.34)	(-0.92)
Trade $_{i,m+2}$				-1.046**
				(-2.07)
Controls $_{i,m}$	Yes	Yes	Yes	Yes
Adj R^2	0.95	0.044	0.045	0.045

Chapter 3: Post-environmental incident drift and institutional trades: who benefits from environmental shocks?

Abstract

This paper examines the impact of environmental incidents on stock returns and institutional investors' trading patterns around such events, focusing on the strategic behavior of hedge funds. We show significant negative drift in stock returns following environmental incidents that persists over one quarter. We document significant selling by banks, pension funds, and insurance companies, particularly in high ESG risk stocks. In contrast, hedge funds often purchase these stocks, capitalizing on temporary price pressure as a result of divestment from environmentally conscious investors. Our analysis reveals that non-PRI hedge funds generate positive returns from this strategy, whereas PRI signatories do not exhibit similar trading behavior. This study enhances understanding of ESG incidents' market impacts and highlights the divergent strategies of institutional investors, with hedge funds playing a pivotal role in providing liquidity and exploiting opportunities arising from climate-related risks.

3.1 Introduction

With climate change posing a significant threat to humanity, all institutional investors are under the increasing pressure from the public to take actions to alleviate the impacts of climate change by changing their investment strategies to incorporate climate concerns. The shift in ESG preferences of investors has led to the higher green tilt in the portfolios of large institutional investors achieved mainly through divestment from brown firms (Pastor, Stambaugh, and Taylor, 2023; Atta-Darkua, Glossner, Krueger, and Matos, 2023), exits after environmental and social incidents (Gantchev, Giannetti, and Li, 2022a), and analyst downgrades following ESG incidents (Derrien, Krueger, Landier, and Yao, 2023). However, it is still unclear how different institutional investors react to ESG incidents. With the growing awareness of ESG ratings disagreement, environmental incidents provide a clearer signal to investors and a point-in-time shock to firms' environmental performance. In this paper we uncover trading patterns of different types of institutional investors around environmental incidents, and who stands to benefit from them.

Environmental incidents may have significant negative impact on stock returns. Previous studies show that stocks, that experienced ESG incidents experience abnormal negative returns in the two-day window around environmental incident date and in the same month (Groen-Xu and Zeume, 2021; Gantchev, Giannetti, and Li, 2022a). We analyze stock returns, following environmental incidents on a longer horizon and find significant negative drift in stock returns that persists up to one quarter. Negative impact on returns is more pronounced among stocks that have low ESG risk profile. We posit two hypotheses that can explain prolonged negative reaction to environmental incidents. First, stocks that experienced environmental incidents may suffer from selling pressure imposed by environmentally conscious investors. If socially responsible investors start selling incident stocks in large amounts, the impact can be equal to fire-selling of Coval and Stafford (2007), which can manifest in negative stock returns. Second hypothesis is underreaction, where investors may underreact to the negative implications incidents might have on firm fundamentals, resulting in long-term negative future returns.

We study institutional investors trading around environmental incidents to test whether there is significant fire selling pressure imposed by them and if so, who stands to benefit from it. We start by examining the aggregate trading for each type of institutional investor. We find that banks, pensions funds, and insurance companies exhibit significant selling in incident stocks. Interestingly, we find that selling pressure is concentrated in stocks with high ESG risk profiles. When considering low ESG risk firms, we do not find selling by these institutions, on the other hand, they tend to buy low ESG risk firms despite their exposure to incidents. This is consistent with finding of Huynh and Xia (2023), who show that stocks with strong environmental profiles experience lower selling pressure when disaster strikes. On the buying side, we find that hedge funds and mutual funds engage in buying stocks following the incidents. Several studies have explored mutual funds trading in incident stocks and find that only non-committed ESG mutual funds (Lowry, Wang, and Wei, 2023) and mutual funds with high concentration of incident stocks in their portfolios (Beschwitz, Filali-Adib, and Schmidt, 2023) sell incident stocks. However, there is a gap in the literature on the hedge funds trading in incident stocks, therefore, we next explore hedge funds trading around environmental incidents and whether they benefit from it.

Hedge funds face lower pressure to abide by Environmental, Social, and Governance (ESG) standards in their investment strategies. Several media outlets report that hedge funds see an opportunity when other institutional investors divest from fossil fuel companies and end up on the buying side.[1] According to Hedge Fund Research, hedge fund industry collectively managed US$4.01 trillion by the end of 2021. Therefore, in our efforts to combat climate change, hedge funds may be a key player to allocate capital in the financial market and should be involved in green efforts to achieve the goal collectively.

Hedge funds are well known for their profit driven nature, that is rooted in their fee structure (Agarwal, Daniel, and Naik, 2009; Aragon and Nanda, 2012; Lan, Wang, and Yang, 2013). To maximize their profits, hedge funds are motivated to generate alpha and implement strategic trading to achieve the target.[2] Previous studies show that hedge funds strategically trade in stocks sold by distressed institutional investor (Chen, Hanson, Hong, and Stein, 2008; Aragon, Martin, and Shi, 2019; Agarwal, Aragon, Nanda, and Wei, 2024). In the current market, where institutional investors face a significant pressure to allocate capital to greener firms, hedge funds may see an opportunity arising from the divestment of environmentally conscious investors and trade on the other side to lock-in profits. When environmental incident

[1] See "Hedge funds cash in as green investors dump energy stocks", *Financial Times*, October 7, 2021.

[2] Previous studies show that hedge fund managers possess superior skill, where hedge funds performance is persistent and cannot be explained by luck (Kosowski, Naik, and Teo, 2007; Aragon and Martin, 2012; Agarwal, Jiang, Tang, and Yang, 2013; Cao, Goldie, Liang, and Petrasek, 2016; Jiao, Massa, and Jang, 2016; Chen, Cliff, and Zhao, 2017). Hedge funds strategically traded during technology bubble by investing in technology stocks and reducing their positions before the bubble burst (Brunnermeier and Nagel, 2004).

strikes, we found that several institutional investors, including banks, divest from incident stocks. At the same time, we found a negative drift in stock returns following incidents. These, in turn, may motivate hedge funds to profit from temporary downward price pressure and purchase incident stocks.

On the other hand, hedge funds may choose to divest from firms that experience environmental incidents. This can be due to one of the following. First, environmental incidents may cause investors to revise their projections regarding a company's future cash flows, thereby influencing the firm’s fundamental value (Pastor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021; Ardia, Bluteau, Boudt, and Inghelbrecht, 2023). In this case, hedge funds may want to divest from such firms. Second, hedge funds may face significant pressure from their investors to implement socially responsible investment strategies and divest from brown stocks. Large proportion of hedge fund investors are endowment funds, who in turn face pressure from their stakeholders to adopt responsible investment policies (Aragon, Jiang, Joenvaara, Tiu, 2023). Third, hedge funds may be motivated to attract flows from responsible investors. Previous research shows that hedge fund investors tend to chase past fund performance, despite past performance not reflecting future fund returns (Agarwal, Daniel, and Naik, 2004; Baquero and Verbeek, 2022), which may motivate some hedge funds to misreport their returns (Agarwal, Daniel, and Naik, 2011). However, socially responsible investors are willing to forgo financial performance for their social preference (Riedl and Smeets, 2017), and research shows that mutual funds with highest sustainability ratings attract higher flows (Hartzmark and Sussman, 2019). This may motivate hedge funds to invest in greener portfolios to attract socially responsible investors. One way for investment managers to signal their orientation towards sustainable investing is to endorse the United Nations Principles for Responsible Investment (PRI). Liang, Sun, and Teo (2022) show that hedge funds managed by PRI signatories attract higher flows and collect larger fees. Therefore, hedge funds may reduce their exposure to incident firms to attract socially responsible investors, implying even higher selling pressure imposed on such stocks.

We uncover several new findings in our paper. First, we examine trading patterns of hedge funds in stocks with environmental incidents. To do so, we use fund-security level hedge fund trades and regress it on the environmental incidents. We find a strong positive relation between individual hedge fund trades and environmental incidents. The relation holds only for the sample of NonPRI signatory hedge funds, while hedge funds managed by PRI signatories do not engage in trading of stocks with environmental incidents. However, there is a heterogeneity in stocks that experience environmental incidents. We show that stocks with low ESG risk profile experience lower selling from other institutional investors and more significant negative drift in returns. Therefore, we expect hedge funds to avoid buying stocks with low ESG risk profile. We find that indeed hedge funds exhibit lower trading in stocks with low ESG risk profile after environmental incidents.

Hedge funds may serve as liquidity providers to other institutional investors who are divesting from incident stocks. At the same time, hedge funds may profit from buying incident stocks sold by other institutional investors. To find whether hedge funds trade on the other side of institutional investors, we examine the relation between hedge fund trades and stocks with environmental incidents sold by different types of institutional investors. Our results suggest that hedge funds buy incident stocks from banks, pension funds, insurance companies, and endowment funds. Interestingly, PRI hedge funds also trade on the other side of some institutional investors. Results align with the idea that committed ESG funds do not shun away from firms after they experienced incidents, but instead provide liquidity to selling investors (Lowry, Wang, Wei, 2023). However, some PRI hedge funds may not necessarily align with ESG principles (Liang, Sun, and Teo, 2022), and hence buy incident stocks. Overall, we find that hedge funds tend to buy incident stocks sold by other institutional investors.

Next, we explore the profitability of the hedge funds trading strategy around environmental incidents. We conduct fund level analysis and test whether hedge funds that buy stocks following environmental incidents generate significant returns. We use hedge funds long-equity portfolio returns and show that NonPRI hedge funds that buy incident stocks generate significant positive returns over the next quarter. We fail to find similar results for PRI signatories, which is consistent with findings by Liang, Sun, and Teo (2022) that PRI signatory hedge funds with low ESG portfolio exposure underperform. Overall, our study shows that hedge funds are smart investors and exploit opportunities when trading brown stocks, which reflects in their performance.

Finally, we examine strategic trading by hedge funds in incident stocks by exploring short interest and option positions. If hedge funds want to capitalize on the price movement of incident stocks following environmental incidents, but do not hold long positions in the stock, they could do so by acquiring a short position. We find that short interest increases in the month preceding environmental incidents and remain high during the incident month, with subsequent reversal. Results suggest that short sellers are able to anticipate negative news and trade in advance. We also examine directional and non-directional option holdings of hedge funds in incident stocks. According to our results, hedge funds tend to hold straddle positions in stocks with environmental incidents. We do not find significant holdings of directional option positions in incident stocks. Unlike other events, such as earnings announcements and corporate news, there is uncertainty in market reaction to environmental incidents due to the diverse investor preferences. Therefore, we suggest that hedge funds' use of straddle positions allows them to profit from stock price volatility following the incident regardless of the price direction. Overall, we show that hedge funds may try to benefit from the impact environmental incidents may have on stock market in derivatives market and through short selling.

Our study contributes to three main strands of literature. First, we contribute to the literature that studies ESG incidents and their impact on the market. Several studies use natural disasters and ESG incidents to examine investors' reaction to unexpected climate events and find that such events prompt selling by responsible investors and have impact on stock returns (Huynh and Xia, 2023; Huynh, Li, and Xia, 2024; Gantchev, Giannetti, and Li, 2022a). Studies find that firms with past ESG incidents are more likely to experience incidents in the future, have lower profitability (Glossner, 2021), and experience significant analyst downgrades on both short and long-term horizons (Derrien, Krueger, Landier, and Yao, 2023). We contribute to this literature by examining the trading pattern of different institutional investors around environmental incident to partially explain the continuous negative return drift after the incident. We show the implications of negative impact on stock returns and find that hedge funds may profit from such price movements.

Second, we contribute to the growing body of research on the institutional investors' preferences and trading patterns towards ESG. Pastor, Stambaugh, and Taylor (2023) find that on average institutional investors' portfolios have a green tilt, which can mainly be attributed to large institutions, while Starks, Venkat, and Zhu (2023) find that ESG-oriented institutional investors tend to have longer investment horizons. Studies also show that institutions reduce exposure to carbon intensive firms (Bolton and Kacperczyk, 2021; Choi, Gao, and Jiang, 2020). Atta-Darkua, Glossner, Krueger, and Matos (2023) show that climate-conscious investors mainly use portfolio re-weighting to green their portfolios, and find no evidence of engagement. Such divestment strategy by socially responsible investors has lower efficiency in improving firm's environmental policies and has limited effects on stock prices (Broccardo, Hart, and Zingales, 2022; Berk and van Binsbergen, 2021). We are among the first studies to provide an in-depth examination of hedge fund behavior towards climate change and their trading in response to environmental incidents.

Third, we contribute to the large body of research on strategic trading by hedge funds. Previous research shows that hedge funds strategically trade around events such as technological bubble both in equity and derivatives market (Brunnermeier and Nagel, 2004; Aragon and Martin, 2012), trade in anticipation of fire-sales from distressed fund managers (Brunnermeier and Pedersen, 2005; Chen, Hanson, Hong, and Stein, 2008; Aragon, Martin, and Shi, 2019; Agarwal, Aragon, Nanda, and Wei, 2024), and in anticipation of predictable flow-induced mutual fund trade (Shive and Yun, 2013; Jiao, Massa, and Zhang, 2016). We contribute to this literature by examining how hedge funds react to climate change risks and whether it affects their trading behavior. We show that hedge funds, as profit driven investors, exploit opportunities arising from selling pressure imposed by environmentally conscious investors on brown stocks by purchasing them. At the same time, hedge funds recognize the detrimental effect climate risks may have on firms' future cash flows, and avoid investing in stocks, where such risks may materialize.

3.2 Data and sample

In this section, we outline the three main datasets used in the paper: environmental incidents data, and hedge funds holdings data, and hedge funds options data.

3.2.1 Environmental incidents

We obtain data on environmental incidents from RepRisk. RepRisk compiles information on daily updates of negative news counts. The data spans from 2007. RepRisk daily screens over 100,000 media and third-party sources in 23 languages. The incidents are classified into 28 ESG issues, including pollution poor employment conditions, discrimination, child labor, supply chain problems, etc., that are further divided into more specific thematic 73 topic tags. The classification is performed using proprietary methodology based on AI and human analysis. Risk incidents are evaluated based on three parameters: severity, reach, and novelty. Severity of an incident reflects the extent of its impact, the consequences, and whether the incident is a result of systematic issue or was caused by an accident, negligence, or intent. Incidents can be classified as high, medium, or low severity. The reach of the information source the incident was covered in, where limited reach sources include local media or governmental bodies, and small NGO; medium reach sources are most national and regional media, international NGOs, and national and international governmental bodies; and high reach sources are global media outlets such as New York Times, etc. RepRisk also provides an indicator of whether an incident is related to environmental, social, or governance issues. In our study, we focus on environmental incidents only and cover the whole sample of such incidents.[3]

Table B.1 in Appendix B reports summary statistics of environmental incidents from 2007 to 2021, categorized by severity, reach, and novelty. Panel A shows the average number of environmental incidents per year. We see a steady increase in the number of incidents every year. This may be due to the heightened attention to the incidents and higher report rates. The number of high severity incidents is significantly lower and on average is about 3% of the total number of incidents. Panel B provides characteristics of stocks that experience environmental incidents in our sample period. On average every company experiences around 4 to 5 incidents per year, with majority of them being developments of the old incidents. There is no significant difference in the size of the firms that experience low, medium, or high severity incidents. However, as expected, stocks with high severity incidents tend to have higher RepRisk Risk rating compared to other stocks. They also have higher analyst coverage, suggesting that these firms may attract greater market attention. RepRisk also provide the RepRisk Rating (RRR), which is a letter rating from AAA to D, that reflects the risk exposure of a company benchmarked against the peer group and sector of a company. Companies with RRR of AAA have the lowest ESG risk exposure, and companies with RRR of D have the highest ESG risk exposure. We use companies' RRR to separate between companies with low and high ESG risk profile to examine their impact on hedge funds decision making when trading stocks with environmental incidents.

3.2.2 Hedge fund holdings

We obtain HF quarter-end holdings from the Thomson Reuters 13F equity portfolio holdings database. To identify hedge funds in the 13F institutional database, we extract the list of HF firms by following 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,[4] 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

[3] We include results using high reach environmental incidents only in the Table B.3 of the Appendix B.

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

business area, 4) it is listed as a HF firm in Factiva, and 5) if the filer name in 13F is one of the leading personnel in a HF.[5] As a result, we obtain the final sample of 1,854 unique HF firms from 13F filing institutions.

3.2.3 Hedge fund options

Most standard commercial databases, like Thomson Reuters, do not provide information on complete 13f positions and only include stock holdings. To obtain option holdings data from 13f, we use Whale Wisdom database that offers a complete set of reported 13F positions, including stock, option, and other types of securities. We extract 13f position of hedge funds using the sample of hedge funds obtained in the previous section and cross-reference names. We follow Aragon, Martin, and Shi (2019) and use the original 13F filings by excluding amendments. We filter observations using the "mv_multiplier" to retain only those with market values reported in thousands. To ensure data accuracy, we validate reported values by calculating market values using price data from CRSP. Observations with disparities between 13F filing values and our calculated values are removed. We focus solely on positions classified as either equity or equity options.

3.3 Post-environmental incident drift

With the rising investor awareness on climate change and a global push to action, environmental performance of the company is becoming an important signal to investors. We zoom into the environmental incidents as a point-in-time shock to the environmental performance of the firms. Using environmental incidents helps us avoid the existing disagreement in the ESG ratings documented in the literature and provides a clear signal about the firms' fundamentals and compliance with environmental standards.[6] Previous research uses RepRisk ESG incidents as a salient shock to firms' ESG profiles and shows that stocks that experienced an ESG incident have lower abnormal returns, with stronger effect for high severity events (Groen-Xu and Zeume, 2021). Such firms have more incidents in the future, have lower profitability (Glossner, 2021), and experience downgrades by analysts at both short- and long-term horizons (Derrien, Krueger, Landier, and Yao, 2023). We contribute to this literature by studying the long-term impact of environmental incidents on stock returns across different ESG risk firms.

[5] Agarwal, Jiang, Tang, and Yang (2013); Agarwal, Ruenzi, and Weigert (2017)
[6] Avramov, Cheng, Lioui, and Tarelli (2022); Berg, Fabisik, and Sautner (2021); Berg, Koelbel, Pavlova, and Rigobon (2022); Gibson, Krueger, and Schmidt (2021); Serafeim and Yoon (2023).

3.3.1 *The impact of environmental incidents on the stock market*

In this section we examine the impact of environmental incidents on stock returns. We posit two main hypotheses. First, we hypothesize that environmental incidents may impose selling pressure from investors who care about firms' ESG characteristics, similar to fire-selling of Coval and Stafford (2007). According to fire sales hypothesis, environmental incidents may trigger forced selling by institutional investors, which may result in significant price drops during selling period, followed by a period of positive returns due to the buying force of liquidity providers, such as hedge funds.[7] Alternative hypothesis is investors underreaction (Jiang and Zhu, 2017; Ben-Rephael, Da, and Israelsen, 2017). If investors do not consider ESG factors as important, it may lead to underreaction to the negative implications incidents might have on firm fundamentals, resulting in long-term negative drift in future returns. The two scenarios are not necessarily mutually exclusive, as underreaction may only partially explain the impact on stock returns for specific types of stocks.

To test the hypotheses, we examine the relation between environmental incidents and stock returns by running the following pooled OLS regression:

$$RET_{i,t+1} = a_0 + b_1 E\_incident_{i,t} + b_2 Controls_{i,t} + e_t \quad (1)$$

where dependent variable $RET_{i,t+1}$ is the returns of stock i in month $t + 1$. $E\_incident_{i,t}$ is a dummy variable equal to 1 if stock i experienced an environmental incident in month t, and 0 otherwise. Controls are measured as of the prior month t and include previous one- and eleven-month returns, log of market capitalization, book-to-market ratio, volatility, ROE, investments, sales growth, and EPS growth. We also include year/month fixed effects and cluster standard errors at the firm and year levels. Additionally, we estimate the regression using contemporaneous returns, and returns in the next two months as dependent variables.

Results are presented in Panel A of Table 3.1. In Column (1) the dependent variable is returns in contemporaneous month t. The relation between environmental incident dummy and returns is negative and statistically significant, with an estimated coefficient of -0.521 and a t-statistics of -2.19. In Column (2) the dependent variable is future returns in month $t + 1$. The relation between stock returns and environmental incidents remains negative and becomes

[7] Huynh and Xia (2023) show that investors overreact to climate risk exposure of firms, causing bond and stock prices to drop when disaster strikes, resulting in higher future returns. Ardia, Bluteau, Boudt, and Inghelbrecht (2023), using news about climate change, find that on days with high climate change concerns, brown firms' prices decrease and associated with an increase in their discount rate.

more significant, with an estimated coefficient of -0.514 and a *t*-statistics of -2.83. We further estimate regression for returns in month t +2 and t + 3 and find that returns fail to fully reverse, despite coefficient becoming less significant.

[Insert Table 3.1 here]

The negative relation between stock returns and incidents is consistent with results found in Groen-Xu and Zeume (2021), where they find negative relation between contemporaneous stock returns and incident dummy. These results indicate that stocks experience a significant negative drift following environmental incidents. Similar to Post-earnings announcement drift anomaly, stock prices do not experience an instantaneous adjustment after an environmental incident, but rather drift down for up to three months following an incident, which is contrary to the efficient market hypothesis (Fama, 1970). In unreported results we calculate returns to the portfolio of stock with environmental incidents without controlling for different firm characteristics as in the regression, and confirm that stocks with environmental incidents have significantly negative returns, CAPM and DGTW adjusted alphas in the first quarter following the incidents. Such post-incident drift presents an opportunity for investors to potentially profit from the downward returns trend.

One possible explanation for the extended negative price drift following environmental incidents is investor underreaction. If investors have limited attention to the environmental performance of firms, prices may fail to adjust fully immediately after the incident, resulting in a prolonged negative drift. Pedersen, Fitzgibbons, and Pomorski (2021) show in their theoretical model that in an economy with a substantial number of investors who do not incorporate ESG information into their investment decisions, ESG stocks may have higher expected future returns. In the case of environmental incidents, where investors fail to see the impact of ESG on a firm's future profits and fundamentals, this can manifest in negative future returns. Derrien, Krueger, Landier, and Yao (2023) show that ESG incidents result in analysts' forecast downgrades on both short term and long-term horizons. Alternatively, in the presence of ESG-conscious investors, underreaction may occur if an incident comes as a surprise. This can happen with low ESG risk stocks, where the occurrence of an incident is unexpected and rare. We study the returns of different ESG risk profile stocks in the next section.

3.3.2 The difference in post-environmental incident drift in low and high ESG risk stocks

In previous section we establish the negative relation between environmental incidents and future stock returns, with negative drift continuing throughout the next quarter. At first, these results may appear to be inconsistent with the selling pressure hypothesis. If investors care about firm's environmental characteristics, we expect them to divest from such stocks imposing temporary downward selling pressure on stock prices, followed by subsequent reversal. However, we fail to see immediate price reversal following the incidents. Huynh and Xia (2023) find that stocks with high environmental scores are less likely to experience selling pressure. This could be either due to investors underreaction or incentives of fund managers to engage with such firms rather than shun away from them (Lowry, Wang, and Wei, 2023; Beschwitz, Filali Adib, and Schmidt, 2023). Therefore, we posit that underreaction to environmental incidents is most likely to happen for stocks with low ESG risk profile, while stocks with high ESG risk may be subject to selling pressure.

We use RepRisk Rating (RRR) to identify risk level of stocks. RRR is a letter rating that evaluates company's risk exposure relative to its peer group, sector, and country affiliations.[8] We identify stocks as low ESG risk stocks if they have a RRR of A and higher, and high ESG risk stocks if they have RRR of BBB and lower. To empirically test we repeat baseline regression, but this time we include an interaction with ESG risk dummy. The new regression looks as follows:

$$RET_{i,t+1} = a_0 + b_1 E\_incident_{i,t} \times Low\_ESG\_risk_{i,t} + b_2 E\_incident_{i,t} + \\ + b_3 Low\_ESG\_risk_{i,t} + b_4 Controls_{i,t} + e_{i,t} \quad (2)$$

where *Low_ESG_risk* is a dummy variable equal to 1 if RRR of stock *i* in month *t* is A or above, and 0 otherwise. The main coefficient of interest is b_1. We expect the relation between future returns and interaction variable to be negative, signifying the negative impact incidents have on future firm value (Derrien, Krueger, Landier, and Yao, 2023; Glossner, 2021).

Panel B of Table 3.1 presents the results. In Column (1) the dependent variable is contemporaneous stock returns. The relation between stock returns and incidents is negative for both low ESG risk stocks and the rest of the sample. However, there is a striking difference when we run regression on future stock returns. In Column (2), the dependent variable is next

[8] Beschwitz, Adib, and Schmidt (2023) use RRR to identify mutual funds trading in high and low ESG risk stocks.

month stock returns, and the estimated coefficient on the interaction variable is -0.488 with a *t*-statistics of -2.23. The relation remains negative and statistically significant in month $t + 2$, with an estimated coefficient of -0.692 and a *t*-statistics of -2.15 in Column (3). After controlling for low ESG risk dummy, the coefficient on environmental incident dummy reverts and becomes positive in two-month period. In Panel C we repeat regression for high ESG risk stocks, where we use high ESG risk dummy if the RRR of a stock is BBB or below. We find significant reversal in stock returns in month $t + 1$, with the estimated coefficient of 0.414 and a *t*-statistics of 1.75. Returns become more significant in month $t + 2$ with an estimated coefficient of 0.552.

Results indicate that environmental incidents have different impact on stock returns conditional on the level of ESG risk exposure. Firms with low ESG risk exposure that experience an incident are initially overpriced, which results in the negative future stock returns that persist due to investors underreaction and failure to respond to the long-term impact incidents have on firm value. For high ESG risk stocks, incidents have a different impact on stock returns where stocks experience negative returns in the contemporaneous month, followed by a reversal. These results may be due to the selling pressure imposed on high ESG risk stocks by environmentally conscious investors.

Overall, our findings reveal a significant negative drift of stock prices after environmental incidents that persists over the following quarter. The drift may be caused by the initial underreaction of investors to the information, especially in the low ESG stocks, where incidents are an unexpected event.

3.4 Institutional trading around environmental incidents

In this section we examine how institutional investors trade on the environmental incidents. Several studies use natural disasters and ESG incidents to examine investors' reaction to unexpected climate events and find that such events prompt selling by responsible investors and have impact on stock returns. Huynh, Li, and Xia (2024) show that fund managers exposed to air pollution underweight stocks of firms with high carbon emissions, where such stocks subsequently outperform. Gantchev, Giannetti, and Li (2022a) find that environmentally conscious investors reduce exposure to stocks with high environmental and social risks, while there is no significant selling from other investors. We aim to identify the sellers and buyers of the stocks with environmental incidents.

3.4.1 Aggregate institutional trading in stocks with environmental incidents

If institutional investors care about environmental characteristics of the companies, then we expect a significant selling by institutions following environmental incidents. According to our first hypothesis, if stocks are sold by substantial amount of environmentally conscious investors, they should experience downward price pressure immediately after the incident. This, in turn, may create trading opportunities for investors that do not incorporate ESG metrics into their investment decisions. Hedge funds are well known for their profit-driven nature, and therefore, may try to profit from the downward price pressure imposed by selling investors.

To examine trading around environmental incidents for different types of institutional investors, we extract institutional holdings from Thomson Reuters (TR) 13F database. Using TR institution type and Brian Bushee classification[9], we identify the following eight categories: 1) banks - type 1 institutions by the TR classification; 2) insurance companies - type 2 institutions by the TR classification; 3) mutual fund management companies - type 3 institutions by the TR classification; 4) independent investment advisors - type 4 institutions by the TR classification; 5) pension funds – Brian Bushee classification identified from type 5 institutions by the TR classification; 6) university and foundation endowments - Brian Bushee classification identified from type 5 institutions by the TR classification; and (7) hedge funds – manually identified as described in section 3.2.2. For each institution type we calculate the aggregate trade for each stock i in quarter q as the quarterly difference in shares held, divided by the shares outstanding at the end of quarter q. We include not only the change in existing positions, but also initiating buys and terminating sales to account for all the trading.

We hypothesize that hedge funds do not adhere to ESG selection criteria in their investment decisions. However, there are some hedge funds that signal their commitment to responsible investments to investors by becoming a United Nations Principles for Responsible Investment (PRI) signatory. PRI signatories must endorse six fundamental principles of responsible investments.[10] Pastor, Stambaugh, Taylor (2023) show that PRI signatories tilt their portfolios toward green stocks. At the same time, Liang, Sun, and Teo (2022) find that

[9] Brian Bushee classification obtained from the website: https://accounting-faculty.wharton.upenn.edu/bushee/

[10] The six principles are: (I) to incorporate ESG issues into investment analysis and decision-making processes; (II) to be active owners and incorporate ESG issues into ownership policies and practices; (III) to see appropriate disclosure on ESG issues by the entities in which they invest; (IV) to promote acceptance and implementation of the Principles within the investment industry; (V) to work together to enhance effectiveness in implementing the Principles; (VI) to report their activities and progress towards implementing the Principles.

hedge funds managed by PRI signatories underperform despite attracting significant flows and collecting larger fees. Therefore, it is important to differentiate between hedge funds managed by PRI signatories, we call them PRI hedge funds, and non-PRI hedge funds. To do so, we obtain a list of PRI signatories from the PRI website that contains signatory name, signature date, headquarter, and category (investment manager, asset owner, or service provider). We manually match the names of PRI signatories with hedge fund management company names and headquarter countries. We identify 100 PRI hedge fund companies in our sample. We then separately calculate aggregate trade for PRI and non-PRI hedge funds.

To empirically test how different institutions trade on environmental incidents, we run the following logistic regression for each type of institution:

$$Buy\_dummy_{i,q}(Sell\_dummy_{i,q}) = a_0 + b_1 E\_incident_{i,q} + b_2 Controls_{i,q} + e_{i,q} \tag{3}$$

where *Buy_dummy (Sell_dummy)* is a dummy variable equal to one if aggregate institutional trade of stock *i* in quarter *q* is greater than (less than) zero, and zero otherwise. Control variables are measured as of the prior quarter *q* - 1 and include stock *i*'s quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. We include time fixed effect and cluster standard errors at the firm and quarter level.

Table 3.2 presents the results. In Panel A the dependent variable is buy dummy, and in Panel B the dependent variable is sell dummy. Columns (1) and (2) present results for subsample of PRI and non-PRI signatory hedge funds. Strikingly, PRI and non-PRI hedge funds have opposite results, where PRI hedge funds have significant negative coefficient on environmental incident dummy, indicating that such hedge funds significantly reduce buying in stocks that experienced environmental incident. In the meantime, non-PRI hedge funds engage in buying incident stocks with an estimated coefficient on incident dummy of 0.097. Results confirm our hypothesis that PRI signatory hedge funds avoid stocks with heightened environmental risks, while other hedge funds do not see environmental incidents as a prompt to sell and instead engage in trading such stocks. We will study in section 3.5 whether hedge funds profit from buying environmental stocks.

Apart from hedge funds, mutual funds engage in significant buying following an incident with an estimated coefficient of 0.118. In a recent study, Beschwitz, Adib, and Schmidt

(2023) show that mutual funds only sell stocks with environmental incidents if they have a high proportion of holdings in stocks with environmental incidents, conditional on the stocks having low ESG risk. However, we show that on the aggregate level, mutual funds tend to buy incident stocks. One possible explanation is that mutual funds are committed investors and provide liquidity for investors on the selling side. Lowry, Wang, and Wei (2023) show that committed ESG mutual funds do not exhibit selling behavior following ESG incidents and in aggregate increase ownership in stocks with severe incidents, suggesting liquidity provision channel. In case of non-ESG mutual funds, they may try to derive profits from the expected negative price pressure on incident stocks.

Among other institutional investors banks and insurance companies significantly decrease their positions in stocks with environmental incidents with significant negative estimated coefficients. At first, our findings might seem to be controversial with previously documented results in Pastor, Stambaugh, and Taylor (2023), where they document significant brown tilt in banks portfolios. However, they show that large institutional investors are significantly greener. In our case, we consider aggregate selling by banks, which might be driven by large banks. Banking sector is currently experiencing growing pressure to incorporate ESG screening, with initiatives such as Net-Zero Banking Alliance that already has 144 member banks from 44 countries, including largest American banks like Bank of America, JPMorgan Chase, and Morgan Stanley.[11] In a recent study, Kacperczyk and Peydro (2022) use Science Based Targets Initiative (SBTi) to classify ESG committed banks and show that such banks restrict funding to polluting firms and instead allocate more funds to greener firms. One of the impeding issues that slows down the greening of the banking sector is difficulty in identifying ESG complying firms due to ambiguity and dispersion in existing ESG metrics. Environmental incidents, on the other hand, provide a clear signal about the firms' compliance with ESG attracting banks' attention to poor ESG performance and triggering banks selling.[12]

[11] See https://www.unepfi.org/net-zero-banking/members/.

[12] To illustrate, we study two examples of environmental incidents and plot trading by hedge funds and banks around incident dates in Figure B.1 of Appendix B. We choose two distinct incidents from RepRisk, first one in the early years of our sample period on November 4, 2009, for an oil giant Chevron Corporation (Panel A). RepRisk only provides information on the countries linked to the incidents, and which of the 28 ESG issues, 73 topic tags, or UNGC principles the incident violates. Using available information, we manually searched for news articles related to these incidents. The incident is related to the famous lawsuit between Ecuador government and Chevron's acquired in 2001 subsidiary, Texaco Petroleum, regarding oil pollution in Amazon region. We plot trading 3 quarters before and after the incident. There is a sharp increase in trading by hedge funds following incident, where their holdings increase by 4%. At the same time, banks significantly decrease their holdings in Chevron also by 4%.

Similarly, insurance industry is taking action to address climate change by allocating capital to green assets. One of the initiatives is UN Principles for Sustainable Insurance, that currently has 162 signatories worldwide.[13]

At last, to cover the scope of all investments, we calculate ownership by non 13F filing institutions. Institutions filing Form 13F must have at least $100 million in equity and other publicly traded securities. Therefore, our sample excludes any investors that do not satisfy the $100 million threshold and all the retail investors. To complement the picture, we proxy ownership by non 13F filing institutions and other investors by taking the difference between stocks' shares outstanding and aggregate ownership across all 13F institutions. We further calculate aggregate trading by non 13F filers for each stock as the change in quarterly ownership, divided by shares outstanding. We repeat regression (3) for non 13F filers. Results are reported in Column 9 of Table 3.2. Strikingly, non 13F filers buy stocks with environmental incidents. These results are not surprising as non-filing investors do not disclose their portfolio holdings and face lower pressure to comply with ESG investing.

[Insert Table 3.2 here]

3.4.2 Different trading response by institutions to environmental incidents in stocks with low and high ESG risk

In section 3.3 we find that stocks experience negative drift in returns following environmental incidents. The drift is mostly pronounced in stocks with low ESG risk, that may be partially explained by market underreaction. At the same time, we find that hedge funds buy stocks after incidents. If hedge funds are smart investors and trade to profit from environmental incidents, we expect them to avoid buying stocks with low ESG risk after incidents and instead buy stocks with high ESG risk. Meanwhile, if other environmentally-conscious investors underreact to environmental incidents in low ESG risk stocks, we expect them to sell only stocks with high ESG risk profile.

Second incident is in the most recent year of our sample period, on January 3, 2021, for Mondelez International, one of the largest snacks company in food and beverage sector (Panel B). Mondelez uses palm oil in production of its well-known Cadbury chocolate bars, Oreos cookies, and Ritz crackers. The palm oil is sourced from Malaysia and Indonesia, which was long linked to the use of child labor, deforestation, and destruction of Orangutan habitat. After the incident date, there is a significant aggregate buying from hedge funds, and simultaneously selling by banks, where the amount of buying trades from hedge funds is roughly similar to the selling from banking sector, around 1% of shares outstanding.

[13] See https://www.unepfi.org/insurance/insurance/signatory-companies/

To test, we repeat regression specified in equation (3) and add interaction variable between environmental incident dummy and low or high ESG risk dummy. Table 3.3 reports the results. Panel A includes results for low ESG risk stocks, and Panel B reports results for high ESG risk stocks. In Panel A, for regression with buy dummy as a dependent variable, the coefficient on the interaction variable for non-PRI hedge funds is statistically insignificant, and even negative. This confirms our hypothesis that hedge funds avoid stocks that experienced environmental incidents if they have low ESG risk. For sell dummy as a dependent variable, the coefficient is positive, indicating that hedge funds on aggregate sell such stocks. In contrast, PRI hedge funds for buy dummy have significant positive coefficient on interaction variable. This further highlights the underreaction hypotheses, where PRI signatories rely on the low ESG risk score and do not divest from companies even after experiencing an environmental incident. In a similar fashion, institutional investors that avoided buying environmental incidents on aggregate, including banks, pension funds and insurance companies, exhibit significant buying in regards to low ESG risk stocks.

For hedge funds the picture is opposite in high ESG risk stocks (Panel B of Table 3.3). Non-PRI hedge funds have significant positive relation between buy dummy and interaction variable. Results align with the idea that hedge funds, as smart investors, recognize that high ESG risk stocks experience a temporary price pressure after incidents, followed by positive returns, highlighting hedge funds profit-driven nature. Unlike their peers, PRI signatory hedge funds do not involve in buying high ESG risk stocks. Strikingly, despite negative coefficient on interaction variable for pension funds and insurance companies, it is statistically insignificant. This indicates that overall, these institutions avoid high ESG risk stocks. The main selling force behind high ESG risk stocks following incidents is non-13F filing investors with an estimated coefficient on sell dummy regression of 0.170. Non-13F filers only react to environmental incidents by selling high ESG risk stocks, while there is no such reaction to low ESG risk stocks.

Non-13F filers include smaller investors that hold less than $100 million in equity and other publicly traded securities, which incorporates retail traders. While such traders may sell shares during periods of heightened uncertainty or ESG-related incidents, HFs and MFs appear to capitalize on these opportunities by taking the opposite side of the trade. This aligns with the literature on liquidity provision and institutional trading behavior, which often highlights the ability of sophisticated investors to profit from price dislocations caused by less-informed trading. We note, however, that this finding does not necessarily imply predatory trading by HFs or MFs but rather reflects their role as liquidity providers in a market where retail investors might react more strongly to negative ESG events.

In the next section we examine whether hedge funds profit from their trading activity around environmental incidents.

[Insert Table 3.3 here]

3.5 Hedge funds profiting from trading on environmental incidents

In this section we examine whether hedge funds profit from trading in stocks that experience environmental incidents. Previous studies show that hedge funds engage in strategic trading to profit from downward pressure on stock prices imposed by distressed selling of mutual funds (Chen, Hanson, Hong, and Stein, 2008), non-lockup hedge funds during crisis (Aragon, Martin, and Shi, 2019), and distressed mega hedge funds (Agarwal, Aragon, Nanda, and Wei, 2024). We anticipate hedge funds to buy stocks with environmental incidents that are sold by other institutional investors, to profit from temporary selling pressure imposed on stocks.

3.5.1 Hedge fund trades and environmental incidents

In the previous section we examine aggregate trading by institutional investors for each stock, where we identified hedge funds to be on the buying side of environmental incident stocks. When measuring aggregate hedge fund trades, it allocates more weight to larger funds with larger trades, and may net out buy and sell trades across different hedge funds. Individual fund-security level analysis gives equal weight to each hedge fund, which allows us to understand hedge funds behavior and evaluate profitability of their trading.

First, we start our analysis by examining the relation between individual hedge fund trades and occurrence of environmental incidents. Following aggregate results from Section 3.4, we expect hedge funds to buy stocks with environmental incidents. To empirically test the relation between hedge fund trades and environmental incidents using the following regression specification:

$$HFtrade_{j,i,q} = a_0 + b_1 E\_incident_{i,q} + b_2 Controls_{j,i,q-1} + e_{j,i,q} \tag{4}$$

where dependent variable $HFtrade_{j,i,q}$ is the trade of hedge fund j in stock i in quarter q. The main independent variable of interest is $E\_incident_{i,q}$, which is a dummy variable equal to 1 if a company had an environmental incident in quarter q. Control variables are measured as of the prior quarter q - 1 and include hedge fund j's trading in stock i, the logarithm of the size of hedge fund j measured by its equity portfolio value, and stock i's quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. Fund fixed effects and quarter fixed effects are included to control for unobservable institutional characteristics and macroeconomic conditions, respectively. Standard errors are clustered by institution and quarter. We expect coefficient b_1 to be positive if hedge funds buy stocks that experienced an environmental incident in the previous quarter.

Panel A of Table 3.4 presents the results of regression. In Column (1) we run the regression for the full sample of hedge funds. The relation between hedge fund trades and environmental incident dummy is positive and significant with an estimated coefficient of 0.008 and a *t*-statistics of 3.19. As discussed in section 3.2, there is a certain heterogeneity among hedge funds, which can affect their trading behavior and preferences when it comes to trading on environmental issues. Therefore, we run regression separately for PRI and non-PRI hedge fund samples. Results are presented in Columns (2) and (3) respectively. The coefficient is positive and statistically stronger when we exclude the sample of PRI signatory hedge funds and consider only non-PRI peers in Column (3), with estimated coefficient of 0.009 and a *t*-statistic of 3.7. For PRI hedge funds the relation between hedge fund trades and environmental incident dummy is negative despite being statistically insignificant. Results align with the idea that PRI signatory hedge funds avoid stocks with environmental incidents. There might still be some heterogeneity in the PRI signatory hedge funds as shown by Liang, Sun, and Teo (2022), but on average they do not engage in trading around environmental incidents unlike their peers.[14]

[Insert Table 3.4 here]

We hypothesize that hedge funds are motivated to buy stocks that experienced an environmental incident due to the selling pressure from other institutions. However, according to underreaction hypothesis, investors may underestimate the adverse effect incidents may have

[14] We also separate the sample of hedge funds based on their equity portfolio size; however, we do not find significant differences in the coefficients. In Table B.1 of Appendix B, we regress hedge fund trades on the environmental incident dummy only for high severity incidents, results are similar to the full incident sample.

on long term firm value, which can manifest in negative future stock returns. Cao, Titman, Zhan, and Zhang (2023) show that socially responsible institutions are less likely to react to quantitative mispricing signals, resulting in overpricing of stocks held by such institutions. Therefore, we posit that underreaction to environmental incidents is most likely to happen for stocks with low ESG risk profile. In Section 3.3 we show that stocks experience prolonged negative returns after environmental incidents, where negative returns are concentrated in stocks with low ESG risk profile. The difference in the market reaction to environmental incidents and difference in their impact on stock returns may influence hedge funds behavior towards incident stocks. Previous research shows that hedge funds tend to buy undervalued stocks (Cao, Chen, Goetzmann, and Ling, 2018). Using market misvaluation measure, Kokkonen and Suominen (2015) show that hedge funds invest more in undervalued stocks than overvalued when the misvaluation spread is high, which confirms the argument of Stulz (2007) that hedge funds play a significant role in correcting market mispricing. According to underreaction hypothesis, we expect stocks with low ESG risk to be overvalued following ESG incident. As a result, we hypothesize that hedge funds, as smart investors, avoid buying overpriced stocks with low initial risk profile and might instead sell them due to the expected negative effect on their future returns.

We estimate hedge fund trading in stocks with low ESG risk exposure that experienced environmental incidents using the following specification:

$$\begin{aligned} HFtrade_{j,i,q} = a_0 + b_1 Low\_ESG\_risk_{i,q} * E\_incident_{i,q} + b_2 E\_incident_{i,q} \\ + b_3 Low\_ESG\_risk_{i,q} + b_4 Controls_q + e_q \end{aligned} \tag{5}$$

where *Low_ESG_risk* is a dummy variable equal to 1 if RRR of stock *i* in quarter *q* is A or above, and zero otherwise. We use same control variables as in equation (6). If stocks with low initial ESG risk exposure experience an environmental incident, this will have a surprise effect on investors, causing underreaction and long-term negative returns. This in turn, should results in hedge funds selling of such stocks. Therefore, we expect coefficient on interaction variable to be negative.

Results are reported in Panel B of Table 3.4. Column (1) presents results for the full sample of hedge funds, and Columns (2) and (3) include results for subsamples of PRI and NonPRI signatory hedge funds. The estimated coefficient on the interaction variable between low ESG risk dummy and environment incident dummy is -0.003 with a *t*-statistics of 1.97.

The coefficient on incident dummy remains positive and statistically significant. Results indicate that hedge funds avoid incident stocks if they have low ESG rating. The negative relation with interaction variable is more pronounced for PRI signatory hedge funds (Column (2)), while the relation is negative, but statistically insignificant for the sample of NonPRI signatory hedge funds. The significant selling from PRI hedge funds may be due to their larger positions in stocks with low ESG risk exposure, as these are the target firms. Therefore, when such stocks experience an environmental incident, this triggers selling by PRI hedge funds, as incidents may have a significant negative impact on firm value (Derrien, Krueger, Landier, and Yao, 2023; Glossner, 2021).

3.5.2 Hedge fund trades on the other side of institutional investors

Previously in Section 3.4 we find that institutional investors such as banks and insurance companies sell stocks following environmental incidents. We suggest that hedge funds trade on the other side of investors selling stocks with environmental incidents. Hedge funds may trade strategically to profit from short-term price pressure, at the same time providing liquidity to investors selling the stocks. Unlike other investors, hedge funds have incentives in

We carry out formal tests to empirically identify whether hedge funds buy stocks that are sold by other institutional investors following environmental incidents, providing liquidity. We regress hedge fund trades on the interaction variable between environmental incidents dummy and institutional investors selling dummy for each type of investor. Specifically, we run the following pooled OLS regression of individual hedge fund trades of stocks *i* in quarter *q* on the interaction variable between institutions selling dummy and environmental incidents in quarter *q*:

$$\begin{aligned} HFtrade_{j,i,q} = {} & a_0 + b_1 Banks\_sell_{i,q} * E\_incident_{i,q} + b_2 MF\_sell_{i,q} * E\_incident_{i,q} \\ & + b_3 Pension\_sell_{i,q} * E\_incident_{i,q} + b_4 Indep\_adv\_sell_{i,q} * E\_incident_{i,q} \\ & + b_5 Insurance\_sell_{i,q} * E\_incident_{i,q} + b_6 Endowment\_sell_{i,q} * E\_incident_{i,q} \\ & + b_7 Controls_{q-1} + e \end{aligned} \tag{6}$$

where $HFtrade_{j,i,q}$ is the trade of hedge fund *j* in stocks *i* in quarter *q*, and *E_incident* is a dummy variable equal to 1 if a company had an environmental incident in quarter *q*. *Banks_sell* is a dummy variable equal to 1 if aggregate banks trade in stock *i* in quarter *q* is less than zero, and zero otherwise. Aggregate banks trading is measured as the difference between the shares of stock i held by all banks in the end of quarter q and shares held in the end of quarter q - 1, divided by the shares outstanding in the end of quarter q. We include sell dummy for all types of institutional investors, measured in a similar way. Controls are measured as of the prior quarter q - 1 and include hedge fund j's trading in stock i, the logarithm of the size of hedge fund j as measured by its long equity portfolio value, and stock i's quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. We also control for each institutional investors sell dummy separately. Fund and quarter fixed effects are included to control for unobservable institutional characteristics and macroeconomic conditions, respectively. We cluster standard errors by institution and quarter.

Table 3.5 reports the results. Column (1) contains results of the regression for the full sample of hedge funds. According to results, we can suggest that hedge funds provide liquidity to those institutional investors, who sell stocks with environmental incidents, by trading on the other side. Among the selling investors are banks, pension funds, insurance companies, and endowment funds. After controlling for the interaction variables, the coefficient on environmental incident dummy becomes statistically insignificant. Interestingly, PRI hedge funds in Column (2) also trade on the other side of some institutional investors, including mutual funds, banks, pensions funds, and insurance companies. However, the estimated coefficient on the environmental incident dummy remains negative and statistically significant (-0.187 with a *t*-statistic of 1.98). Results may seem contradictory to the aggregate selling by PRI hedge funds we found in section 3.4. However, literature shows that committed mutual funds do not sell stocks of the firms with environmental incidents and instead provide liquidity to selling investors (Lowry, Wang, Wei, 2023). We observe similar behavior among PRI hedge funds. On the other hand, not all PRI hedge funds may align with ESG principles (Liang, Sun, and Teo, 2022), hence buying incident stocks from selling institutions.

[Insert Table 3.5 here]

3.5.3 Performance of hedge funds that trade on environmental incidents

In this section we explore whether hedge funds profit from trading on the negative environmental stock events. It is well documented in the literature, that hedge funds are smart investors and possess skill (Brunnermeier and Nagel, 2004; Kosowski, Naik, and Teo, 2007; Avramov, Kosowski, Naik, and Teo, 2011; Chen, Cliff, and Zhao, 2017; Agarwal, Jiang, Tang, and Yang, 2013; Cao, Bradley, Liang, and Petrasek 2016). Hedge funds also play an important role in liquidity provision, which can partially explain hedge funds' performance (Jame, 2018; Cotelioglu, Franzoni and Plazzi, 2021). We suggest that hedge funds trade on the other side of investors selling stocks with environmental incidents. Hedge funds may trade strategically to profit from short-term price pressure, at the same time providing liquidity to investors selling the stocks. We expect hedge funds to profit from such trading activity.

First, we identify hedge funds that trade on environmental incidents using regression specification (5). We estimate the model on a rolling basis using previous four-quarter period as an estimation window. We regress each individual hedge fund trades on the stocks' environmental incident dummy in each quarter, where the estimated coefficient is hedge funds environmental incident beta, denoted by $\beta_{j,q}$. Second, we use the estimated environmental betas to examine performance of hedge funds with high betas. Due to the heterogeneity in hedge fund preferences, we found no significant trading on environmental incidents in hedge funds managed by PRI signatories. Therefore, to separate between these two fund samples, we introduce dummy variable that is equal to 1 if hedge fund is a non-PRI signatory fund and 0 otherwise. This will let us find the clearer relation between hedge fund trading in incident stocks and its impact on their performance. To examine, we run the following regression:

$$\begin{aligned} RET_{j,q+1} = a_0 + b_1\beta_{j,q} \times NonPRI\_dummy_{j,q} + b_2\beta_{j,q} + \\ + b_3 NonPRI\_dummy_{j,q} + b_4 Controls_{j,q} + e_{j,q} \end{aligned} \tag{7}$$

where dependent variable $RET_{j,q+1}$ is the raw returns of hedge fund j's long-equity portfolio in quarter $q + 1$, estimated as the value-weighted aggregate return of its equity holdings. Fund level control variables are estimated at the previous quarter q and include hedge fund returns and logarithm of hedge fund long-equity portfolio size. We include time fixed effect and cluster standard errors at the fund level. If hedge funds are smart investors and buy stocks with environmental incidents to profit from temporary downward price pressure, we expect the coefficient on interaction variable to be significant and positive.

Results are presented in Table 3.6. In Column (1) the dependent variable is hedge fund returns in the next quarter $q + 1$, and in Column (2) the dependent variable is cumulative returns in the next three quarters. The relation between the interaction variable and fund returns is positive and statistically significant, with the estimated coefficient of 0.161 and a t-statistics of 2.43. This implies that non-PRI signatory hedge funds that buy stocks that experienced an environmental incident significantly outperform other funds. Overall, our results indicate that hedge funds are smart investors and strategically choose to trade in stocks with environmental incident, which in turn reflects on the higher performance of such hedge funds.

[Insert Table 3.6 here]

3.6 Hedge funds strategic trading around environmental incidents

So far, we considered only long equity positions of institutional investors and hedge funds to analyze their trading patterns around environmental incidents. However, long positions do not provide the full picture. Among institutional investors, hedge funds face less strict regulations compared to mutual funds, and use sophisticated arbitrage strategies, including short selling and derivatives usage. If hedge funds anticipate significant downward impact on stock returns following incidents and they do not hold positions of the stocks in their portfolios, they may engage in short selling to profit from anticipated price decrease. In this section we discover whether hedge funds engage in shorting or option trading around environmental incidents.

3.6.1 Short interest around environmental incidents

Several studies show short sellers informed trading around events such as earnings announcements and corporate news events. Christophe, Ferri, and Hsieh (2010) find that short sellers increase their positions three days prior to the public release of analyst downgrades, which is strongly related to significant downward price movement in the subsequent period. Engleberg, Reed, and Ringgenberg (2012) analyze short selling around corporate news events and show that short sellers possess superior public information processing skills and able to profit from short selling around news events. We found that stocks experience significant decrease in their returns following environmental incidents, which can attract short sellers. Zhan and Zhang (2022) show that short sellers are unwilling to short overpriced stocks with high ESG scores due to the uncertainty in the long-side investor preferences and trading patterns, which increases synchronization risk (Abreu and Brunnermeier, 2002). However, environmental incidents provide a clear indication about environmental performance of the firms, reducing such risk. RepRisk gathers information on environmental incidents from publicly available news outlets, NGOs and governmental bodies reports. Sophisticated investors, such as hedge funds, may anticipate these events as information may not be necessarily new and unpredictable. We hypothesize that hedge funds, as profit-driven investors, may want to capitalize on the short-term mispricing in stocks with environmental incidents and increase short positions prior to environmental incident.[15]

To examine our hypothesis, we obtain stock level short interest data from Compustat. Starting from September 2007, short interest data is reported twice each month. Since our sample period for environmental incidents starts in 2007, we use bi-monthly short interest data for higher frequency analysis. We construct stock level short interest ratio (SI) as the number of shares sold at time *t*, that corresponds to the bi-monthly frequency, divided by shares outstanding at time *t.* We use daily CRSP security data to obtain shares outstanding. To study the short interest around environmental incidents, we follow framework in Engelberg, Reed, and Ringgenberg (2012) and run the following panel regression:

$$SI_{i,t} = a_0 + b_1 E\_incident_{i,t} + b_2 Controls_{i,t-1} + e_{i,t} \qquad (8)$$

where $SI_{i,t}$ is short volume ratio of stock *i* at time *t*. Since data on environmental incidents is daily, we align environmental incidents with short interest if they happened between time *t* and time *t* - 1.[16] We control for two daily lag returns to account of the documented short sellers' response to previous returns.[17] We also include firm and month fixed effects.

Results are reported in Table 3.7. We run regression for short interest one month before and one month after the incident. We find that for the short interest in *t* - 2, the estimated coefficient on environmental incident dummy is negative, however, the relation becomes positive and statistically significant for short interest ratio at time *t* - 1, preceding incident date. In Column (3), where we estimate regression for the SI corresponding to the incident date, the relation remains positive and significant. Results corroborate our hypothesis that institutional investors, such as hedge funds, may anticipate negative environmental news and short sell stocks that may experience negative impact on their stock returns following incidents. Columns (4) and (5) estimate regression for SI at a longer horizon after the incident. We find that there exists a subsequent reversal in the short interest of stocks that experience environmental incidents.

[15] Short selling plays an important role in hedge funds trading strategies (Jiao, Massa, and Zhang, 2016; Hwang, Liu, and Xu, 2019).
[16] For example, if an incident happened on 10th of March, we align it with short interest in the middle of March, and if the incident happened on 20th of March, we align it with short interest at the end of the month.
[17] In untabulated results we also rerun regression with controls for previous 5 day returns, returns for the previous period between t and t-1, and for previous months returns. Results remain unchanged.

Overall, our results show that institutional investors may trade not only on the long side, but also use short selling to profit from the negative impact environmental incidents may have on the stock returns. Some events can be anticipated; therefore, short sellers may open short positions right before and during the incident time, and cover their short positions soon after the incident.

[Insert Table 3.7 here]

3.6.2 Options usage by hedge funds

Hedge funds use options as part of their arbitrage strategies. Aragon and Martin (2012) show that that hedge funds engage in option trading to profit from volatility timing and stock selection skills. There is also an evidence of hedge funds skillful use of options in green stocks. Aragon, Jiang, Joenvaara, and Tiu (2024) show that bullish option positions of hedge funds in green stocks predict stocks poor performance. In this section we investigate hedge funds options use around environmental incidents. Zhan and Zhang (2022) highlight the unwillingness of short sellers to bet against overpriced ESG stocks. Due to uncertainty in investors reaction to environmental performance of firms, we expect hedge funds to use options to hedge their long and short positions in stocks with environmental incidents.

We follow Aragon and Martin (2012) and calculate the following variables: 1) $Dir_{i,q}$ is the the proportion of hedge fund advisors disclosing directional option position on underlying security *i* at the end of quarter *q*; 2) $NonDir_{i,q}$ is the proportion of advisors disclosing non directional option position. Similarly, we define $Bull_{i,q}$ for directional call option positions, $Bear_{i,q}$ for directional put option positions, $PPut_{i,q}$ and $Straddle_{i,q}$ for protective puts and straddles respectively. We then run the following regression for each stock *i* in quarter *q*:

$$Bull_{i,q} = a_0 + b_1 E\_incident_{i,q} + b_2 Controls_{i,q-1} + e_{i,q} \tag{9}$$

We repeat regression for all types of option positions and for the next quarter q. Results are reported in Table 3.8. Panel A include results for quarter *q*, and Panel B – for quarter *q* + 1. In Panel B from Columns (1) and (2), the coefficient on environmental incident dummy for directional options positions is insignificant, while the coefficient for non-directional options is positive and statistically significant. When decomposing further, results suggest that hedge funds tend to hold straddle positions in stock with environmental incidents in the quarter corresponding to the incident quarter. This confirms our assumption that hedge funds avoid directional option trading in stocks with environmental incidents due to existing uncertainty in market reaction, and instead use straddle positions that allow hedge funds to profit from stock price volatility following the incident regardless of the direction. In Panel B we repeat analysis for option positions in quarter $q + 1$. Results remain largely the same with the relation being statistically significant and positive for the proportion of advisors holding straddles. One striking difference is that in Column (4), the coefficient on bull options positions is now positive and statistically significant. This indicates that hedge funds increase holdings in directional call positions one quarter after the incident. This may suggest that hedge funds anticipate prices to go up on a longer horizon after the incident.

Overall, in this section we show that hedge funds try to capitalize on the stock price movements following environmental incidents by employing straddles and call option positions.

[Insert Table 3.8 here]

3.7 Conclusion

In conclusion, our study sheds light on the intricate dynamics of institutional investors' trading behaviors around environmental incidents, with a particular focus on hedge funds. We find that while banks, pension funds, and insurance companies tend to divest from high ESG risk profiles following environmental incidents, hedge funds often act as liquidity providers by purchasing these stocks. This behavior underscores hedge funds' strategic approach to capitalizing on the temporary price depressions caused by selling pressures from more environmentally conscious investors. Our findings suggest that hedge funds exploit these opportunities to generate significant positive returns, particularly when trading non-PRI hedge funds' portfolios. Conversely, PRI signatory hedge funds do not exhibit the same trading patterns, highlighting a divergence in strategy based on ESG commitments.

Furthermore, our research contributes to the broader understanding of ESG incidents' impact on market dynamics and institutional investors' strategic responses. By examining the prolonged negative return drift following environmental incidents and the varied responses of different investor types, we provide nuanced insights into the financial implications of climate-related risks. Our study reveals that hedge funds' trading strategies around such incidents are driven by profit motives, as they anticipate and respond to the market movements created by other institutional investors' divestment actions. This strategic behavior not only impacts the immediate market response to environmental incidents but also underscores the critical role of hedge funds in the evolving landscape of ESG investing.

Appendix A: Variable Definitions

Variable	Definition
Environmental Incidents *(Source: RepRisk)*	
$E\_incident_{i,t}$	Dummy variable equal to one, if stock *i* in month *t* experienced an environmental incident, and zero otherwise. We use environmental incident flag in RepRisk to identify environmental incidents.
$Low\_ESG\_risk_{i,t}$	Dummy variable equal to one if stock *i* in month *t* has RepRisk Rating (RRR) of A, AA, or AAA, and zero otherwise.
$High\_ESG\_risk_{i,t}$	Dummy variable equal to one if stock *i* in month *t* has RepRisk Rating (RRR) of BBB or below, and zero otherwise.
Hedge funds data *(Source: Thomson Reuters 13F, Principles for Responsible Investment, Whale Wisdom)*	
HF $trade_{j,i,q}$	Individual hedge fund *j* trades of stock *i* in quarter *q*, measured as the change in shares held by hedge fund *j* (i.e., number of shares bought minus the number of shares sold by all hedge funds) from quarter *q*-1 to quarter *q* divided by total shares outstanding of stock *i* at the end of quarter *q*.
Buy $dummy_{i,q}$	Dummy variable equal to one if aggregate hedge funds trade of stock *i* in quarter *q* is greater than zero, and zero otherwise. Where aggregate hedge funds trades is measured as the changes in shares held by all hedge funds from quarter *q*-1 to quarter *q* divided by total shares outstanding at the end of quarter *q*.
Sell $dummy_{i,q}$	Dummy variable equal to one if aggregate hedge funds trade of stock *i* in quarter *q* is less than zero, and zero otherwise.
Dir/NonDir	Proportion of hedge fund advisors that disclose a directional/non-directional option position on the underlying security out of all advisors that report at least one stock or option position in the security.
Bear/Bull	Proportion of hedge fund advisors that disclose a directional put/call option position on the underlying security out of all advisors that report at least one stock or option position in the security. A put option position is classified as directional if the advisor does not simultaneously report a position in a call option or a common stock. A call option position is classified as directional if the advisor does not simultaneously report a position in a put option on the same underlying security.
Straddle/PPut	Proportion of hedge fund advisors that disclose a straddle/protective put option position on the underlying security out of all advisors that report at least one stock or option position in the security.

Appendix: Variable Definitions - *Continued*	
Variable	Definition
Other institutional investors data *(Source: Thomson Reuters 13F)*	
Buy dummy$_{i,q}$	Dummy variable equal to one if aggregate institutional trade of stock *i* in quarter *q* is greater than zero, and zero otherwise. We measure buy dummy variable for each type of institution, including banks, pension funds, mutual funds, independent investment advisors, pension funds, insurance companies, and endowments.
Sell dummy$_{i,q}$	Dummy variable equal to one if aggregate institutional trade of stock *i* in quarter *q* is less than zero, and zero otherwise.
Short Interest data *(Source: Compustat)*	
SI	Short interest ratio measured as the ratio between the number of shares sold short at the end of the quarter and the total number of shares outstanding.
Stock data *(Source: CRSP, Compustat)*	
log(SIZE)	Firm size measured as the log of market capitalization.
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 estimate the value of preferred stock. We exclude negative *B/M* firms.
Ret$_{i,t-1}$	Cumulative returns in the previous month.
Ret$_{i,t-2:t-12}$	Cumulative return over 11 months preceding the beginning of the last month.
ROE	Ratio of net income and book equity, where book equity is defined as shareholders' equity minus preferred stock.
ROA	Ratio of net income to total assets
Gross profits over assets	Revenue minus costs of goods sold divided by total assets
Illiquidity	Stock illiquidity defined as the average ratio of the daily absolute return to the (dollar) trading volume on that day.
Volatility	Standard deviation of stock returns in the past 12 months.
Sales growth	Dollar change in annual firm revenues normalized by previous month's market capitalization.
EPS growth	Dollar change in annual earnings per share, normalized by the firm's equity price.

Appendix B: Additional tables and figures

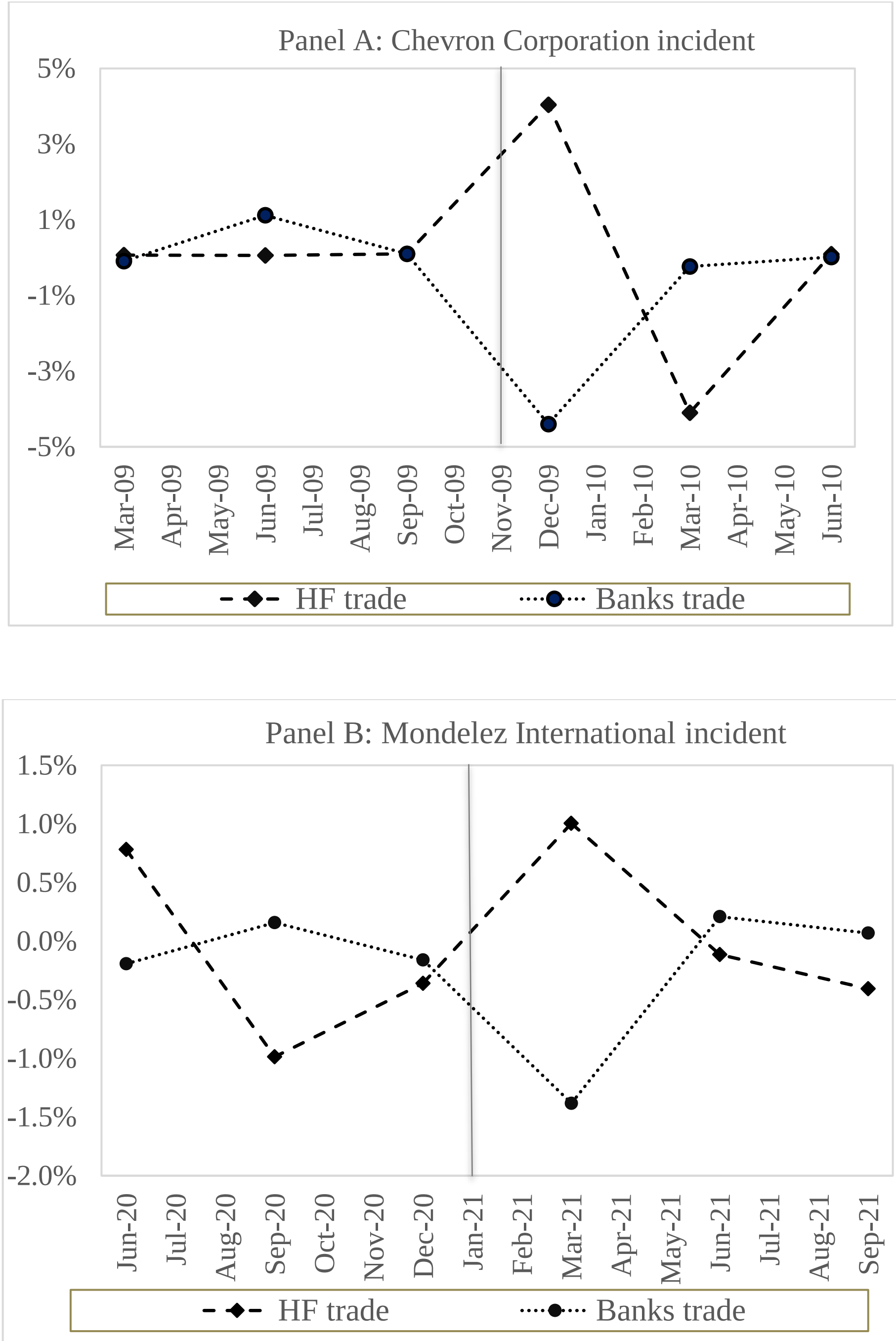


Figure B.1: Institutional trading around environmental incidents: case studies
This figure shows two cases of trading by hedge funds and banks around environmental incidents. Environmental incidents data is gathered from RepRisk dataset. Panel A shows trading around incident of Chevron Corporation on November 4, 2009, and Panel B shows trading around incident of Mondelez International on January 3, 2021. Trading is calculated as the quarterly change in aggregate shares held by hedge funds (banks), scaled by stock's shares outstanding.

Table B.1: Summary Statistics

This table presents the summary statistics of environmental incidents for the sample period January 2007 – December 2021. Panel A reports average number of environmental incidents per year based on incident severity, reach, and novelty. Panel B reports characteristics of the stocks that experience different types of environmental incidents. Stock characteristics include stock size, B/M ratio, Amihud Illiquidity, returns over incident quarter q and in the previous quarter q – 1, institutional ownership, hnumber of analysts following the stock, and RepRisk RRI rating.

Panel A: Number of environmental incidents by year

Year	Total	Severity			Reach			Novelty	
		Low	Med	High	Low	Med	High	Old	New
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2007	397	202	175	20	98	276	23	172	225
2008	987	436	515	36	441	505	41	356	631
2009	685	390	263	32	226	410	49	357	328
2010	819	311	471	37	311	438	70	470	349
2011	1259	765	464	30	507	632	120	847	412
2012	1547	877	661	9	706	757	84	931	616
2013	1593	996	589	8	774	712	107	926	667
2014	1963	1125	807	31	993	865	105	1207	756
2015	1987	1093	880	14	1073	829	85	1157	830
2016	1311	754	547	10	655	548	108	674	637
2017	1749	1144	568	37	861	804	84	1019	730
2018	1607	980	598	29	848	633	126	968	639
2019	1878	1189	633	56	945	780	153	1115	763
2020	1962	1394	518	50	982	836	144	1205	757
2021	1889	1305	526	58	990	590	309	1186	703
Total	21633	12961	8215	457	10410	9615	1608	12590	9043

Panel B: Summary statistics									
		Severity			Reach			Novelty	
Var	**Total**	**Low**	**Med**	**High**	**Low**	**Med**	**High**	**Old**	**New**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Avg # of incidents per company	19.32	14.09	10.72	3.22	11.35	12.41	5.64	24.45	8.20
# of incidents per year per stock	4.59	3.57	2.86	1.48	2.97	3.21	2.04	5.18	2.25
Stock Size	10.33	10.36	10.27	10.90	10.26	10.33	10.85	10.60	9.96
B/M	0.54	0.53	0.54	0.48	0.54	0.54	0.50	0.54	0.53
Illiquidity	0.02	0.02	0.02	0.00	0.03	0.01	0.00	0.02	0.03
Ret q-1	0.03	0.03	0.03	0.00	0.03	0.02	0.05	0.03	0.03
Ret q	0.03	0.03	0.02	0.03	0.02	0.03	0.03	0.03	0.03
RRI risk rating	35.66	35.41	35.77	40.87	34.49	36.24	39.77	37.11	33.60
Institutional ownership	0.62	0.61	0.64	0.57	0.62	0.62	0.61	0.61	0.64
# analysts	17.44	17.63	17.14	17.75	17.32	17.27	19.53	17.85	16.88

Table B.2: Aggregate Institutional Trades and Environmental Incidents

This table presents the results of logit regressions of aggregate institutional trades on the environmental incidents. Dependent variable is buy trade dummy in panel A, and sell dummy in panel B. Buy (sell) dummy variable is equal to one if aggregate institutional trade of stock *i* in quarter *q* - 1 is greater (less) than zero, and zero otherwise, where quarter *q* corresponds to the incident quarter. We conduct analysis for each type of institutional investor, where HFs separated into PRI and NonPRI HF signatories. In Column (9) we include aggregate trade for investors that are not 13F filing institutions. *E_incident* is a dummy variable equal to 1 if a company had an environmental incident in quarter *q*. *Controls* measured as of the quarter *q* - 2 include stock *i*'s quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. We include time fixed effect. Standard errors are clustered by firm and quarter. The sample period is from January 2007 to December 2021. *,**, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep Var	**Panel A: Buy dummy$_{i,q-1}$**								
	PRI HFs	**NonPRI HFs**	**Banks**	**Mutual funds**	**Independent investment advisors**	**Pension funds**	**Insurance companies**	**Endowments**	**Non 13F**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
E_Incident$_{i,q}$	**-0.152****	**0.100****	**-0.143****	**0.159*****	-0.060	0.020	**-0.119****	0.009	**0.160*****
	(-2.13)	**(2.53)**	**(-1.89)**	**(3.36)**	(-1.07)	(0.28)	**(-2.11)**	(0.15)	**(3.40)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.123	0.016	0.082	0.040	0.023	0.049	0.039	0.089	0.045
Dep Var	**Panel B: Sell dummy$_{i,q-1}$**								
	PRI HFs	**NonPRI HFs**	**Banks**	**Mutual funds**	**Independent investment advisors**	**Pension funds**	**Insurance companies**	**Endowments**	**Non 13F**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
E_Incident$_{i,q}$	0.114	**-0.106*****	0.068	**-0.182*****	0.050	-0.035	0.075	**-0.114*****	**-0.163*****
	(1.63)	**(-2.16)**	(0.9)	**(-3.89)**	(0.87)	(-0.49)	(1.37)	**(-1.84)**	**(-3.43)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.138	0.016	0.082	0.042	0.023	0.050	0.041	0.095	0.045

Table B.3: Hedge Fund Trades and High Severity Environmental Incidents

This table presents the results of regressions of individual hedge fund trades of stocks *i* in quarter *q* on the environmental incidents. *HF trade*$_{j,i,,q}$ is the trade of hedge fund *j* in stocks *i* in quarter *q*, and *Highsev_E_incident* is a dummy variable equal to 1 if a company had a high severity environmental incident in quarter *q*. We also repeat regression for the subsample of PRI and Non-PRI hedge funds. *Controls* measured as of the prior quarter *q* - 1 include hedge fund *j*'s trading in stock *i*, the logarithm of the size of hedge fund *j* as measured by its equity portfolio value, and stock *i*'s quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. Fund fixed effects and quarter fixed effects are included to control for unobservable institutional characteristics and macroeconomic conditions, respectively. Standard errors are clustered by institution and quarter. The sample period is from January 2007 to December 2021. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep Var	**HF trade$_{j,i,q}$**		
	All HFs	**PRI HFs**	**NonPRI HFs**
	(1)	(2)	(3)
Highsev_E_Incident$_{i,q}$	**0.004****	0.006	**0.004****
	(2.18)	(1.09)	**(2.26)**
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj R-sq	0.0138	0.2496	0.0128

Table 3.1: Environmental incidents and stock returns

This table presents the results of regressions of monthly stock returns on the occurrence of environmental incidents. $RET_{i,t}$ is the returns of stock *i* in month *t*. $E\_incident_{i,t}$ is a dummy variable equal to 1 if stock *i* experienced an environmental incident in month *t* and 0 otherwise. *Controls* are measured as of the prior month *t* - 1 and include previous one- and eleven-month returns, log of market capitalization, book-to-market ratio, volatility, ROE, investments, log of PPE, sales growth, and EPS growth. Year/month fixed effects are also included, and standard errors are clustered at the firm and year levels. Panel B includes interaction variable with low-risk dummy variable, and Panel C includes interaction variable with high risk dummy variable. Low (high) risk dummy variable is equal to 1 if stock's RepRisk Rating is A and above (BBB and below), and 0 otherwise. The sample period is January 2007 to December 2021. *,**, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Unconditional test				
Dep Vars	**$Ret_{i,t}$**	**$Ret_{i,t+1}$**	**$Ret_{i,t+2}$**	**$Ret_{i,t+3}$**
	(1)	(2)	(3)	(4)
$E\_incident_{i,t}$	**-0.521****	**-0.514*****	**-0.454***	-0.314
	(-2.19)	**(-2.83)**	**(-1.68)**	(-1.60)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R^2	0.171	0.170	0.170	0.172
Panel B: Conditional on low ESG risk				
Dep Vars	**$Ret_{i,t}$**	**$Ret_{i,t+1}$**	**$Ret_{i,t+2}$**	**$Ret_{i,t+3}$**
	(1)	(2)	(3)	(4)
$E\_incident_{i,t}$ x $Low\_ESG\_risk_{i,t}$	-0.065	**-0.488****	**-0.692****	-0.310
	(-0.16)	**(-2.23)**	**(-2.15)**	(-0.85)
$E\_incident_{i,t}$	-0.305	-0.137	0.013	0.005
	(-0.89)	(-0.80)	(0.04)	(0.03)
$Low\_ESG\_risk_{i,t}$	**0.364*****	**0.371*****	**0.373*****	**0.379*****
	(2.95)	**(3.71)**	**(2.90)**	**(3.30)**
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R^2	0.171	0.170	0.171	0.172
Panel C: Conditional on high ESG risk				
Dep Vars	**$Ret_{i,t}$**	**$Ret_{i,t+1}$**	**$Ret_{i,t+2}$**	**$Ret_{i,t+3}$**
	(1)	(2)	(3)	(4)
$E\_incident_{i,t}$ x $High\_ESG\_risk_{i,t}$	-0.026	**0.414***	**0.552***	0.194
	(-0.07)	**(1.75)**	**(1.86)**	(0.50)
$E\_incident_{i,t}$	-0.405	**-0.659****	**-0.693****	-0.327
	(-1.69)	**(-2.51)**	**(-2.09)**	(-0.91)
$High\_ESG\_risk_{i,t}$	**-0.283****	**-0.301*****	**-0.263****	**-0.292****
	(-2.43)	**(-3.61)**	**(-2.54)**	**(-2.30)**
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Adj R^2	0.171	0.170	0.171	0.172

Table 3.2: Aggregate Institutional Trades and Environmental Incidents

This table presents the results of logit regressions of aggregate institutional trades on the environmental incidents. Dependent variable is buy trade dummy in panel A, and sell dummy in panel B. Buy (sell) dummy variable is equal to one if aggregate institutional trade of stock *i* in quarter *q* is greater (less) than zero, and zero otherwise. We conduct analysis for each type of institutional investor, where HFs separated into PRI and NonPRI HF signatories. In Column (9) we include aggregate trade for investors that are not 13F filing institutions. *E_incident* is a dummy variable equal to 1 if a company had an environmental incident in quarter *q*. *Controls* measured as of the prior quarter *q* - 1 include stock *i*'s quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. We include time fixed effect. Standard errors are clustered by firm and quarter. The sample period is from January 2007 to December 2021. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep Var	**Panel A: Buy dummyi,q**								
	PRI HFs	**NonPRI HFs**	**Banks**	**Mutual funds**	**Independent investment advisors**	**Pension funds**	**Insurance companies**	**Endowments**	**Non 13F**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$E\_Incident_{i,q}$	**-0.161****	**0.097***	**-0.142****	**0.118****	-0.046	0.000	**-0.142*****	0.006	**0.148*****
	(-1.98)	**(1.72)**	**(-1.90)**	**(2.47)**	(-0.93)	(0.00)	**(-2.85)**	(0.08)	**(3.07)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.124	0.016	0.081	0.040	0.022	0.049	0.040	0.087	0.045
Dep Var	**Panel B: Sell dummy$_{i,q}$**								
	PRI HFs	**NonPRI HFs**	**Banks**	**Mutual funds**	**Independent investment advisors**	**Pension funds**	**Insurance companies**	**Endowments**	**Non 13F**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$E\_Incident_{i,q}$	0.114	**-0.102***	0.066	**-0.138*****	0.034	-0.012	**0.098****	**-0.156****	**-0.151*****
	(1.42)	**(-1.81)**	(0.88)	**(-2.88)**	(0.66)	(-0.17)	**(2.02)**	**(-2.26)**	**(-3.11)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.138	0.016	0.081	0.042	0.023	0.050	0.041	0.094	0.045

Table 3.3: Aggregate Institutional Trades and Environmental Incidents of low and high ESG risk firms

This table presents the results of logit regressions of aggregate institutional trades on the environmental incidents for stocks with low ESG risk profile in Panel A, and high ESG risk profile in Panel B. Dependent variables are buy and sell trade dummies. Buy (sell) dummy variable is equal to one if aggregate institutional trade of stock *i* in quarter *q* is greater (less) than zero, and zero otherwise. We conduct analysis for each type of institutional investor, where HFs separated into PRI and NonPRI HF signatories. In Column (9) we include aggregate trade for investors that are not 13F filing institutions. *E_incident* is a dummy variable equal to 1 if a company had an environmental incident in quarter *q*. Low (high) risk dummy variable is equal to 1 if stock's RepRisk Rating is A and above (BBB and below), and 0 otherwise. *Controls* measured as of the prior quarter *q* - 1 include stock *i*'s quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. We include time fixed effect. Standard errors are clustered by firm and quarter. The sample period is from January 2007 to December 2021. *,**, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Low ESG risk firms								
Dep var	**Buy dummy$_{i,q}$**								
	PRI HFs	**NonPRI HFs**	**Banks**	**Mutual funds**	**Independent investment advisors**	**Pension funds**	**Insurance companies**	**Endowments**	**Non 13F**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low_ESG_risk$_{i,q}$ x E_Incident$_{i,q}$	**0.191****	**-0.121***	**0.162****	-0.024	0.071	**0.199*****	**0.147****	-0.088	-0.055
	(2.06)	**(-1.65)**	**(1.97)**	(-0.31)	(1.11)	**(2.58)**	**(1.94)**	(-1.10)	(-0.91)
E_Incident$_{i,q}$	-0.244***	0.120**	-0.218**	0.079	-0.092	-0.103	-0.198***	-0.010	0.199***
	(-2.75)	(1.88)	(-2.49)	(1.32)	(-1.47)	(-1.26)	(-2.97)	(-0.12)	(3.49)
Low_ESG_risk$_{i,q}$	-0.042	-0.030**	-0.045**	-0.093***	-0.044***	-0.073***	-0.014	-0.110***	0.061***
	(-1.37)	(-2.42)	(-2.22)	(-6.01)	(-2.95)	(-3.34)	(-0.80)	(-3.71)	(3.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.124	0.016	0.081	0.040	0.023	0.049	0.040	0.088	0.045

Dep Var	**Sell dummy$_{i,q}$**								
	PRI HFs	**NonPRI HFs**	**Banks**	**Mutual funds**	**Independent investment advisors**	**Pension funds**	**Insurance companies**	**Endowments**	**Non 13F**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low_ESG_risk$_{i,q}$ x E_Incident$_{i,q}$	-0.155	**0.122***	-0.127	0.035	-0.070	**-0.203*****	**-0.121***	-0.042	0.059
	(-1.65)	**(1.68)**	(-1.57)	(0.46)	(-1.08)	**(-2.68)**	**(-1.70)**	(-0.52)	(0.97)
E_Incident$_{i,q}$	0.190**	-0.124*	0.137	-0.099*	0.081	0.097	0.150**	-0.101	-0.203***
	(2.17)	(-1.93)	(1.57)	(-1.67)	(1.28)	(1.19)	(2.35)	(-1.47)	(-3.52)
Low_ESG_risk$_{i,q}$	0.051*	0.034***	0.057***	0.099***	0.046***	0.083***	0.025	0.095***	-0.061***
	(1.65)	(2.72)	(2.82)	(6.31)	(3.11)	(3.84)	(1.37)	(2.99)	(-3.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.138	0.0165	0.081	0.042	0.023	0.050	0.041	0.095	0.045

	Panel B: High ESG risk firms								
Dep var	**Buy dummy$_{i,q}$**								
	PRI HFs	**NonPRI HFs**	**Banks**	**Mutual funds**	**Independent investment advisors**	**Pension funds**	**Insurance companies**	**Endowments**	**Non 13F**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High_ESG_risk$_{i,q}$ x E_Incident$_{i,q}$	0.036	**0.141***	0.016	**0.154****	0.035	-0.118	-0.099	**0.141***	**-0.174****
	(0.36)	**(1.88)**	(0.17)	**(2.02)**	(0.53)	(-1.36)	(-1.12)	**(1.73)**	**(-2.43)**
E_Incident$_{i,q}$	-0.092	-0.007	-0.090	0.031	-0.039	0.075	-0.061	-0.113	0.190***
	(-1.13)	(-0.11)	(-1.33)	(0.53)	(-0.94)	(1.23)	(-1.38)	(-1.50)	(3.85)
High_ESG_risk$_{i,q}$	-0.197***	0.019	-0.125***	-0.031	-0.061**	0.004	-0.033	0.062*	0.149***
	(-6.03)	(0.75)	(-3.83)	(-1.27)	(-2.35)	(0.10)	(-1.23)	(1.71)	(5.31)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.124	0.016	0.081	0.040	0.022	0.049	0.040	0.088	0.045
Dep Var	**Sell dummy$_{i,q}$**								
	PRI HFs	**NonPRI HFs**	**Banks**	**Mutual funds**	**Independent investment advisors**	**Pension funds**	**Insurance companies**	**Endowments**	**Non 13F**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High_ESG_risk$_{i,q}$ x E_Incident$_{i,q}$	-0.062	**-0.146***	-0.035	**-0.160****	-0.037	0.109	0.083	0.006	**0.170****
	(-0.63)	**(-1.94)**	(-0.39)	**(-2.11)**	(-0.54)	(1.25)	(1.00)	(0.07)	**(2.36)**
E_Incident$_{i,q}$	0.073	0.006	0.039	-0.040	0.029	-0.082	0.038	-0.123*	-0.190***
	(0.88)	(0.09)	(0.58)	(-0.69)	(0.67)	(-1.35)	(0.87)	(-1.60)	(-3.85)
High_ESG_risk$_{i,q}$	0.175***	-0.021	0.099***	0.018	0.058**	-0.003	0.010	-0.087**	-0.150***
	(5.14)	(-0.82)	(2.96)	(0.71)	(2.21)	(-0.07)	(0.40)	(-2.27)	(-5.37)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.138	0.017	0.081	0.042	0.023	0.050	0.041	0.094	0.045

Table 3.4: Individual Hedge Fund Trades and Environmental Incidents

This table presents the results of regressions of individual hedge fund trades of stocks *i* in quarter *q* on the environmental incidents. Panel A presents results for the full sample of environmental incidents, Panel B includes the interaction variable of Low-risk dummy and environmental incidents. $HF\ trade_{j,i,,q}$ is the trade of hedge fund *j* in stocks *i* in quarter *q*. *E_incident* is a dummy variable equal to 1 if a company had an environmental incident in quarter *q*. *Low_ESG_risk* is a dummy variable equal to 1 if a company's RepRisk rating in quarter *q* is AAA, AA, or A, and zero otherwise. We also repeat regression for the subsample of PRI, Non-PRI, Small, and Large hedge funds. *Controls* measured as of the prior quarter *q* - 1 include hedge fund *j*'s trading in stock *i*, the logarithm of the size of hedge fund *j* as measured by its equity portfolio value, and stock *i*'s quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. Fund fixed effects and quarter fixed effects are included to control for unobservable institutional characteristics and macroeconomic conditions, respectively. Standard errors are clustered by institution and quarter. The sample period is from January 2007 to December 2021. *,**, *** indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Unconditional test			
Dep Var	**$HF\ trade_{j,i,q}$**		
	All HFs	**PRI HFs**	**NonPRI HFs**
	(1)	(2)	(3)
$E\_Incident_{i,q}$	**0.008*** **	-0.038	**0.009*** **
	(3.19)	(-1.28)	**(3.70)**
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj R-sq	0.014	0.245	0.013
Panel B: Conditional on low ESG risk			
Dep Var	**$HF\ trade_{j,i,q}$**		
	All HFs	**PRI HFs**	**NonPRI HFs**
	(1)	(2)	(3)
$Low\_ESG\_risk_{i,q}$ x $E\_Incident_{i,q}$	**-0.003***	**-0.011*** **	-0.002
	(-1.97)	**(-2.03)**	(-1.51)
$E\_Incident_{i,q}$	**0.003*** **	-0.011	**0.003*** **
	(2.99)	(-0.88)	**(2.53)**
$Low\_ESG\_risk_{i,q}$	0.001	0.017	0.000
	(0.69)	(1.61)	(-0.21)
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj R-sq	0.010	0.282	0.007

Table 3.5: Hedge Funds trade on the other side of institutional investors

This table presents the results of regressions of individual hedge fund trades of stocks *i* in quarter *q* on environmental incidents and institutional sell trades. *HF trade*$_{j,i,,q}$ is the trade of hedge fund *j* in stocks *i* in quarter *q*, and *E_incident* is a dummy variable equal to 1 if a company had an environmental incident in quarter *q*. We interact incident dummy with sell dummy for each institution type, where sell dummy equal to one if aggregate institutional trade is less than zero in quarter *q*, and zero otherwise. We also repeat regression for the subsample of PRI and Non-PRI hedge funds. *Controls* measured as of the prior quarter *q* - 1 include hedge fund *j*'s trading in stock *i*, the logarithm of the size of hedge fund *j* as measured by its equity portfolio value, and stock *i*'s quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. Fund fixed effects and quarter fixed effects are included to control for unobservable institutional characteristics and macroeconomic conditions, respectively. Standard errors are clustered by institution and quarter. The sample period is from January 2007 to December 2021. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep Var	**HF $trade_{j,i,q}$**		
	All HFs	**PRI HFs**	**NonPRI HFs**
	(1)	(2)	(3)
$Banks\_sell_{i,q}$ x $E\_Incident_{i,q}$	**0.010*** **	**0.087** **	**0.008*** **
	(2.75)	**(2.34)**	**(2.76)**
$MF\_sell_{i,q}$ x $E\_Incident_{i,q}$	0.003	**0.037** **	0.000
	(0.74)	**(2.09)**	(-0.16)
$Pension\_sell_{i,q}$ x $E\_Incident_{i,q}$	**0.012*** **	**0.048*** **	**0.009*** **
	(3.28)	**(2.61)**	**(4.49)**
$Indep\_adv\_sell_{i,q}$ x $E\_Incident_{i,q}$	-0.002	0.013	-0.004
	(-0.48)	(0.94)	(-1.28)
$Insurance\_sell_{i,q}$ x $E\_Incident_{i,q}$	**0.009***	**0.088** **	**0.003***
	(1.67)	**(2.20)**	**(1.82)**
$Endowment\_sell_{i,q}$ x $E\_Incident_{i,q}$	**0.004** **	-0.006	**0.003** **
	(2.22)	(-0.47)	**(1.99)**
$Banks\_sell_{i,q}$	-0.013	-0.123	-0.007
	(-2.03)	(-1.84)	(-2.51)
$MF\_sell_{i,q}$	-0.003	-0.076*	0.002
	(-0.58)	(-1.72)	(0.67)
$Pension\_sell_{i,q}$	-0.013***	-0.071**	-0.009***
	(-2.96)	(-2.10)	(-3.84)
$Indep\_adv\_sell_{i,q}$	0.005	-0.037	0.007***
	(1.39)	(-1.29)	(2.92)
$Insurance\_sell_{i,q}$	-0.009	-0.109*	-0.003*
	(-1.54)	(-1.85)	(-1.89)
$Endowment\_sell_{i,q}$	-0.005***	-0.032*	-0.004**
	(-2.98)	(-1.94)	(-2.80)
$E\_Incident_{i,q}$	-0.016	-0.187**	-0.006
	(-1.50)	(-1.98)	(-1.26)
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj R-sq	0.014	0.263	0.022

Table 3.6: Trading on environmental incidents and hedge fund performance

This table presents the results from regressions of hedge funds' long-equity portfolio performance during quarter $q + 1$ or quarters $q + 1$ through $q + 3$ on their environmental incident β measured as of quarter q. The dependent variables are the raw returns of hedge fund j's long-equity portfolio. The independent variables include environmental incident β and its interaction term with an indicator variable denoting NonPRI signatory hedge funds. We regress hedge fund trading on the stocks' environmental incident dummy to estimate individual HFs' environmental incident βs in each quarter. One-quarter lagged control variables include the logarithm of a fund's long-equity portfolio value, and raw fund returns, and a dummy variable indicating NonPRI signatory. t-statistics computed with standard errors clustered by fund are reported in parentheses. The sample period is January 2007 to December 2021. $*$,$**$, $***$ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep Vars	**$Ret_{j, q+1}$**	**$Ret_{j,q+1:q+3}$**
	(1)	(2)
$Beta_{j,q}$ x $NonPRI\_Dummy_{j,q}$	**0.161****	0.279
	(2.43)	(0.94)
$Beta_{j,q}$	**-0.160*****	-0.238
	(-3.16)	(-0.92)
$NonPRI\_Dummy_{j,q}$	0.325	1.069
	(1.50)	(1.12)
Fund Controls	Yes	Yes
Time FE	Yes	Yes
Adj R^2	0.495	0.479

Table 3.7: Short interest around environmental incidents

This table presents the results from regressions that examines stocks' short interest around environmental incidents. In each regression specification the dependent variable is bi-monthly short interest ratio of a stocks. Since short interest in Compustat is reported on a bi-monthly period, we denote this time period as *t.* All regressions include firm and time fixed effects. We include past two daily lags of returns to control for previously documented response of short sellers to past returns. t-statistics computed with standard errors clustered by firm and time and reported in parentheses. The sample period is January 2007 to December 2021. ∗,∗∗, ∗∗∗ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep vars	**SI (t-2)**	**SI (t-1)**	**SI (t)**	**SI (t+1)**	**SI (t+2)**
	(1)	(2)	(3)	(4)	(5)
$E\_incident_{i,t}$	-0.314***	0.314***	0.315***	-0.300***	0.172**
	(-3.72)	(3.63)	(3.78)	(-3.41)	(2.15)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Adj R-sq	0.355	0.355	0.355	0.355	0.355

Table 3.8: Options use by hedge funds around environmental incidents

This table presents the results from regressions that examines options usage by hedge funds in stocks that experienced an environmental incident. The dependent variables are the proportion of hedge fund advisors disclosing certain option positions. *Dir* is the proportion of advisors disclosing a directional option position on underlying security *i* among all advisors that holds at least one stock or option position in that security. We similarly define the proportion of advisors disclosing nondirectional (NonDir), directional call (Bull), directional put (Bear), straddle (Straddle), and protective put (PPut) option positions. In Panel A dependent variable are measure as of quarter $q-1$, preceding the quarter of environmental incident, Panel B repeats regression for option positions in concurrent quarter q. *E_incident* is a dummy variable equal to 1 if a company had an environmental incident in quarter q. *Controls* measured as of the prior quarter q - 1 include stock *i*'s quarterly returns, cumulative returns in the prior four-quarter period, logarithm of market capitalization, book-to-market ratio, and Amihud illiquidity measure. All regressions include firm and time fixed effects. t-statistics computed with standard errors clustered by firm and time and reported in parentheses. The sample period is January 2007 to December 2021. $*$,$**$, $***$ indicates statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Options use in quarter *q* - 1						
Dep vars	**Dir**	**NonDir**	**Bear**	**Bull**	**Straddle**	**PPut**
	(1)	(2)	(3)	(4)	(5)	(6)
$E\_incident_{i,q}$	0.061	**0.253*** **	0.027	0.034	**0.223*** **	0.031
	(1.28)	**(4.23)**	(0.92)	(0.81)	**(4.72)**	(1.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sq	0.278	0.437	0.213	0.249	0.420	0.136

Panel B: Options use in quarter *q*						
Dep vars	**Dir**	**NonDir**	**Bear**	**Bull**	**Straddle**	**PPut**
	(1)	(2)	(3)	(4)	(5)	(6)
$E\_incident_{i,q}$	0.082	**0.321*** **	0.003	**0.079* **	**0.285*** **	0.035
	(1.52)	**(4.91)**	(0.12)	**(1.72)**	**(5.29)**	(1.59)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sq	0.276	0.440	0.182	0.249	0.423	0.136

Chapter 4: Thesis conclusion

This thesis provides an in-depth analysis of hedge funds' strategic interactions with other institutional investors in two significant market contexts: ETF rebalancing and environmental incidents. Through a series of empirical studies, we have elucidated the profound and often covert impact that hedge funds exert on market dynamics and investor behavior.

In the first study, we investigate the relation between ETF rebalancing activities and hedge fund arbitrage trading. Our findings reveal that ETF rebalancing trades, driven by the necessity to align with underlying indices, create predictable price movements that hedge funds exploit. The transparency of rebalancing schedules enables hedge funds to front-run these trades, resulting in temporary price pressure and subsequent market inefficiencies. Specifically, we find that stocks targeted for inclusion in ETFs experience an initial price increase followed by a decline post-rebalancing, reflecting a buy-high and sell-low pattern. This behavior imposes hidden costs on ETF investors.

Hedge funds' anticipatory trading is further highlighted during the unique event of the March 2020 index reconstitution postponement due to the Covid-19 pandemic. This event provide a natural experiment to examine hedge funds anticipatory trading around ETF rebalancing events. We show that HFs traded in anticipation of scheduled March rebalancing, however, upon announcement of postponement of index rebalancing, HFs rushed to close their positions. Our analysis extended the understanding of how hedge funds' trading strategies around ETF rebalancing contribute to price distortions and impose further costs on ETF investors.

The second study focused on the reaction of institutional investors to environmental incidents, exploring how hedge funds differentiate themselves from other institutional players. We find that environmental incidents trigger significant negative stock returns, which can be partially explained by selling pressure imposed by environmentally conscious institutional investors, such as banks, pension funds, and insurance companies. We find that HFs often take contrarian positions and buy stocks that experienced an incident. Hedge funds' opportunistic trading around environmental incidents allows them to exploit the downward price pressure caused by other investors' fire-selling. We find that non-PRI signatory HFs, in particular, exhibit a pronounced tendency to capitalize on these incidents.

The findings from these studies contribute significantly to the literature on institutional investor behavior, market efficiency, and ESG investing. By dissecting the interactions between hedge funds and other institutional investors, we have highlighted the hidden costs and market distortions that arise from strategic trading activities. These insights have practical implications for regulators, policymakers, and investors seeking to understand the broader impacts of institutional trading on market stability and efficiency. For regulators and policymakers, the evidence of hedge funds' anticipatory trading around ETF rebalancing and environmental incidents suggests a need for greater scrutiny and potential regulation to mitigate adverse market impacts. For investors, understanding these dynamics can inform better investment strategies and risk management practices, particularly in passive investment vehicles and ESG-focused portfolios.

In conclusion, this thesis highlights the pivotal role of hedge funds in shaping market dynamics through their strategic interactions with other institutional investors. By shedding light on the hidden costs and behaviors that drive market outcomes, this work contributes to a more nuanced understanding of the financial landscape and the critical role of institutional investors in maintaining market efficiency and stability.

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