Hedge Fund Investment in ETFs

Finance Working Paper N° 882/2023
March 2026

Douglas Cumming
Professor of Finance and Steven Shulman ·62 Endowed Chair for Digital Innovation

Pedro Monteiro
Kania School of Management

ECGI Working Paper Series in Finance

Hedge Fund Investment in ETFs

Working Paper N° 882/2023
March 2026

Douglas Cumming
Pedro Monteiro

we thanks to the Editor, John Doukas, 3 anonymous reviewers, and the workshop and conference participants at the Birmingham Business School, Insper, Southern Finance Association, Huddersfield Business School, Huazhong University of Science and Technology, University of South Carolina, and the Florida Atlantic University Alumni Conference.

Abstract

This paper investigates the causes and consequences of hedge fund investments in exchange-traded funds (ETFs) using U.S. data from 1998 to 2020. The findings show that transient and quasiindexer hedge funds are significantly more likely to invest in ETFs. Moreover, hedge fund firms with a greater share of assets under management in Macro, Relative Value, and Fund of Funds strategies tend to invest more in ETFs, whereas those focused on Equity Hedge and Event-Driven strategies are less inclined to do so. ETF investments are generally associated with lower hedge fund returns, consistent with the presence of agency costs.

Keywords: Hedge funds, Exchange traded funds, ETFs, Agency costs, Active investors.

JEL Classification: G23

Douglas Cumming

Professor of Finance and Steven Shulman ·62 Endowed Chair for Digital Innovation

Pedro Monteiro

Kania School of Management

Hedge Fund Investment in ETFs

Douglas Cumming
Professor of Finance and Steven Shulman '62 Endowed Chair for Digital Innovation
Stevens Institute of Technology School of Business
525 River St., Hoboken, NJ 07030, USA
dcumming@stevens.edu

Pedro Monteiro
Kania School of Management
The University of Scranton
800 Linden Street
Scranton, Pennsylvania, 18510, USA
pedro.monteiro@scranton.edu

First Draft: January 15, 2022

This Draft: March 25, 2026

Acknowledgement: We owe thanks to the Editor, John Doukas, 3 anonymous reviewers, and the workshop and conference participants at the Birmingham Business School, Insper, Southern Finance Association, Huddersfield Business School, Huazhong University of Science and Technology, University of South Carolina, and the Florida Atlantic University Alumni Conference. This paper was distributed as an ECGI working paper (Feb 2023).

Hedge Fund Investment in ETFs

Abstract

This paper investigates the causes and consequences of hedge fund investments in exchange-traded funds (ETFs) using U.S. data from 1998 to 2020. The findings show that transient and quasi-indexer hedge funds are significantly more likely to invest in ETFs. Moreover, hedge fund firms with a greater share of assets under management in Macro, Relative Value, and Fund of Funds strategies tend to invest more in ETFs, whereas those focused on Equity Hedge and Event-Driven strategies are less inclined to do so. ETF investments are generally associated with lower hedge fund returns, consistent with the presence of agency costs.

Keywords: Hedge funds, Exchange traded funds, ETFs, Agency costs, Active investors.

JEL Code: G23

"Hedge funds are using ETFs despite stigma

Hedge fund managers are the third-biggest institutional users of exchange-traded funds and exchange-traded products, but they are reluctant to talk about it."[1]

1. Introduction

Hedge funds manage pools of capital sourced from institutional investors and high net worth individuals, operating with fewer regulatory constraints than mutual funds and offering greater flexibility in investment strategies (Bessler, Drobetz, and Holler, 2015; Wang and Zheng, 2024). Exchange traded funds (ETFs) are baskets of securities - such as stocks and bonds - that trade on exchanges like individual stocks (Aggarwal and Schofield, 2014). Mutual funds likewise invest in stocks that are traded on exchanges, but unlike ETFs, mutual funds are traded once a day at the end of the day when the net asset value of a fund is known (Zitzewitz, 2006). Investors into mutual funds are retail investors, while investors into ETFs are roughly a mix of half retail and half institutional investors (Aggarwal and Schofield, 2014).

Hedge funds typically charge "2 and 20" fees with a 2% fixed fee and a 20% performance fee, albeit with much variability across funds (Clifford, 2008). In view of the high fees associated with hedge funds, it is unusual for hedge funds to invest in products that their investors could otherwise invest in directly; that is, one might see hedge fund investment in ETFs as an agency problem of delegated portfolio management (Achleitner et al. 2010; Amenc et al.,

[1] https://www.investmentnews.com/hedge-funds-are-using-etfs-despite-stigma-43012

2010; Gonzaléz et al., 2016; Sherrill et al., 2017). Institutional investors and high net worth individuals could straightforwardly design their own ETF investment portfolio without having to pay a hedge fund manager 2/20 fee. Put differently, at an initial glance the returns to ETFs do not seem to justify the fees charged by hedge fund managers, and hedge fund managerial skills are not required to pick ETFs. And if hedge fund managers are concerned with their careers (Boyson, 2010), investing in ETFs may initially seem unappealing, particularly given prevailing market sentiment.

In this paper, we contribute to the literature by offering both theoretical insights and empirical evidence on the performance implications of hedge fund investments in ETFs, as well as the underlying motivations for such investments. We consider three complementary explanations for why hedge funds invest in ETFs. First, ETF usage may reflect an agency problem: managers allocate capital to passive instruments like ETFs while still charging high fees, potentially signaling underperformance or low effort (Agency Cost Hypothesis). Second, ETFs may serve a tactical role in absorbing unexpected capital flows, providing a liquid buffer to manage temporary imbalances between inflows and illiquid positions (Liquidity Management Hypothesis). Third, ETFs may be primarily employed as part of complex investment strategies, such as long-short trades or leverage overlays, that are not captured in disclosed equity holdings (Alternative Strategies Hypothesis).

To conduct this analysis, we examine hedge fund firms based on their trading style - classified using Bushee's institutional investor framework and their investment strategies. We examine data from Hedge Fund Research (HFR), Refinitiv Institutional Holdings, and CRSP, among other sources, over the years 1998 to 2020. Joenväärä, Kauppila, Kosowski, and Tolonen (2021) review the different hedge fund databases and conclude that HFR offers the most reliable sample. Our analyses are based on “pure-play” hedge funds. For this purpose, we identify and remove managers that also report ownership on the Refinitiv Mutual Fund ownership dataset (Agarwal et al., 2012; Bali et al., 2014). The sample comprises 631 hedge funds managers, covering a total of 2,132 funds. Our data is free from survivorship bias with evidence from both living and dead funds.

We first analyze the types of hedge funds that are more likely to invest in ETFs. In theory, transient hedge funds and equity hedge funds may be especially inclined to use ETFs to support their short-term investment strategies, although this remains to be empirically validated (Bushee, 1998, 2001). These funds view ETFs as diversified, liquid instruments that can generate better returns than cash while remaining accessible for conversion into cash when required to execute investments aligned with the fund's core objectives. Prior research highlights the use of ETFs by hedge funds in short-selling strategies, suggesting that funds engaged in such activities are drawn to ETFs for their flexibility in managing short-term flows (Huang et al., 2020; Li and Zhu, 2022).

Quasi-indexer or "closet indexer" hedge funds may be more likely to invest in ETFs, as ETFs offer an efficient means of tracking market indices. These funds often adopt intentionally opaque strategies that replicate index performance while masking agency costs associated with closet indexing (Brown and Davies, 2014; Brown, Davies, and Ringgenberg, 2021). Similarly, hedge funds with a greater reliance on macro and Fund of Fund strategies might behave in a comparable manner, potentially using ETFs to gain market exposure efficiently without disclosing the limited active management underlying their strategies.

Our findings reveal that ETF holdings consistently underperform compared to non-ETF holdings; a trend evident across all hedge fund subgroups. Additionally, we demonstrate that a higher proportion of ETFs in a hedge fund's portfolio is associated with weaker overall performance, as measured by CAPM alpha, HF-7 factor alpha, raw returns, and alternative factor models. These findings are closely aligned with the agency cost perspective of delegated portfolio management, suggesting that ETF usage may reflect managerial preference for lower-effort, passive strategies rather than value-enhancing active management.

Next, we investigate whether ETF holdings serve not as a substitute for alpha generation but rather as a temporary buffer to address liquidity mismatches between capital inflows/outflows and longer-term, illiquid investments. We find that that the coefficient on unexpected flows, while higher in magnitude, is not statistically different from that on expected flows in explaining ETF allocations. This similarity suggests that ETF usage does not disproportionately spike in response to abnormal, unanticipated flows, offering little support for the view that ETFs are used systematically as temporary liquidity buffers. However, we do find that the negative impact of ETF allocations on fund performance is reduced when such allocations coincide with unexpected flows. This result supports the interpretation that, when used for liquidity management purposes, ETF investments are less detrimental to performance.

Moreover, we explore whether ETF investment is linked to hedge fund activities that extend beyond traditional equity performance, such as the use of derivatives, short-selling, leverage, or derivative-based strategies. Specifically, we examine the relationship between investment in ETFs and the hedge funds' absolute value unobserved return component ($|URC|$), which captures performance unexplained by observable factors (Agarwal et al. 2024). Our analysis shows a negative association between ETF usage and the absolute value of URC, consistent with the view that ETFs are not primarily employed as vehicles for implementing complex, non-long-equity strategies such as short-selling or derivative-based positions.

We also investigate whether our results differ by ETF type: Passive vs. Active, Broad vs. Sectoral, and Non-Leveraged vs. Leveraged. Passive, Broad, and Non-Leveraged ETFs are more strongly tied to lower returns. In all cases, ETF ownership is unaffected by abnormal capital flows and is associated with lower abnorThis paper makes three incremental contributions to the literature on hedge fund strategies and ETF usage. First, we extend the hedge fund strategy literature (e.g., Fung and Hsieh, 2001; Fung et al., 2008; Getmansky, 2012; Hodder and Jackwerth, 2007; Kosowski et al., 2007; Bollen and Pool, 2008; Bessler, Drobetz, and Holler, 2015) by providing new evidence on hedge fund investments in ETFs, a relatively underexplored topic. While Sun and Teo (2022) and Aragon et al. (2022) document ETF usage among hedge funds, we link ETF portfolio weights directly to performance using holdings-based measures.[2] Second, we introduce a flow-decomposition framework that distinguishes expected from unexpected capital flows to examine whether ETF usage is associated with liquidity management. Third, our study contributes to the emerging literature on factors influencing unobserved hedge fund returns (Agarwal et al., 2024) and to research on the use of ETFs in long-short strategies (Huang et al., 2020; Li and Zhu, 2022). Taken together, these findings shed light on the varied roles ETFs play in hedge fund strategies and their implications for performance.

[2] Sun and Teo (9 February 2022 SSRN posting) did not analyze unexpected flow and other factors that affect hedge fund investment in ETF. Our paper (6 April 2022 SSRN posting) did consider unexpected flow as a determinant of hedge fund investment. We cited Sun and Teo (9 February 2022) since we first became aware of it when we posted our paper on 6 April 2022, with the aim of professionally acknowledging contemporaneously developed work. Sun and Teo (26 May 2022SSRN posting) also examine unexpected flow (using the words in section 2.6.3: “abnormal fund flow, i.e., the difference between fund flow and predicted fund flow”, exactly as done in our version on 5 April 2022), as a determinant of hedge fund ETF investment, but do not cite the prior work posted on SSRN. It is possible that they did not see prior work using unexpected flow as a determinant of ETF investment; however, SSRN does provide a useful record of posting dates and drafts of both papers, which we are happy to share.

This paper is organized as follows. Section 2 describes the hypotheses. Section 3 introduces the data. Section 4 explains the empirical approach, presents the results, and discusses limitations and ideas for future research. Section 5 concludes.

2. Hypothesis development.

Despite their reputation for active and sophisticated investment strategies, hedge funds increasingly allocate capital to exchange-traded funds (ETFs),vehicles typically associated with passive investing. This apparent inconsistency has prompted debate over the underlying motives for such holdings. Broadly, we consider three potential explanations: agency-driven behavior, liquidity management, and sophisticated strategy

The first natural explanation for hedge fund ETF investments involves agency problems. Hedge funds are normally active investors (e.g., Brav et al., 2008, 2015; Klein and Zur, 2009; Bessler et al., 2015; Wang and Zheng, 2024). But some hedge funds may simply be passive investors, even though they charge active 2/20 fees. This practice raises concerns when it delivers no incremental value beyond what investors could obtain directly at much lower costs.

Agency frictions can be amplified under fixed-fee arrangements, typically in the form of management fees, which provide predictable income regardless of performance. However, the presence of performance-based compensation does not necessarily eliminate this conflict. Even with incentive fees in place, managers can still collect a share of gains from ETF positions that require little active skill.

Similarly, reliance on reputational incentives, the idea that managers will self-discipline to preserve future capital-raising potential, may be weak when ETF allocations are not transparent to investors, allowing passive strategies to go unnoticed. Fund-of-fund structures can weaken alignment even further, as the extra layer of intermediation reduces direct oversight and accountability, giving underlying managers greater freedom to hold ETFs without pushbacks. When monitoring mechanisms such as lock-up provisions or redemption gates are also weak, these agency frictions are magnified.

Under those conditions, persistent ETF usage that has no relation to liquidity needs, and is tied to weaker performance, is consistent with agency-driven rent extraction.

Hypothesis 1 (Agency Cost Hypothesis): Hedge funds with higher ETF investments exhibit lower performance, consistent with agency costs of delegated portfolio management.

An alternative explanation is that hedge funds use ETFs to manage short-term liquidity needs. ETFs provide a highly liquid, low-cost vehicle for parking capital temporarily, particularly in response to unexpected investor flows or market stress (Ben-David et al., 2018). Under this view, ETF holdings are not a substitute for alpha generation but rather a temporary buffer against liquidity mismatch between inflows/outflows and longer-term illiquid investments.

There is a large literature that shows hedge fund flows are, to a significant degree, quite predictable (e.g., Aitken et al., 2015; Agarwal et al., 2018; Fung et al., 2008; Getmansky et al., 2012). Future flows have been shown to depend on past performance, lock-in restrictions, market conditions, legal and institutional conditions, fund characteristics such as their strategy and fees, competition with other funds, fund manager characteristics, and misreporting behavior, among other things. Of course, capital flows are not perfectly predictable. As such, there is both an expected and unexpected component of hedge fund flow.

Therefore, we hypothesize that ETF allocations function as a transitory tool, used to temporarily park capital during periods of abnormal inflows and gradually reallocated during outflows. In this case, ETF weights would be positively associated with unexpected capital flows, but not with expected flows.

Hypothesis 2 (Liquidity Management Hypothesis): Unexpected flows will give rise to more hedge fund ETF investment, while expected hedge fund flows will be unrelated to ETF investment.

Recent research suggests that ETFs are not merely passive instruments but can play an important role in sophisticated investment strategies (Huang et al., 2020; Li and Zhu, 2022). Their flexibility allows hedge funds to incorporate them into a variety of complex, actively managed approaches. For instance, ETFs may be used in long-short strategies - such as going long a set of individual stocks while shorting a broad market ETF, or vice versa - to express relative value views. They can also serve as collateral in leveraged positions or as vehicles for tactical sector exposures and derivatives overlays. Building on this perspective, we argue that ETFs serve less as substitutes for return generation and more as tools for implementing dynamic strategies within sophisticated portfolio constructions.

Unfortunately, our dataset does not provide direct information on hedge funds' non-equity long exposures, such as derivatives positions, short-selling activity, or leverage, making it difficult to directly assess whether ETF usage is tied to more complex investment strategies. As a result, we rely on an indirect proxy: the absolute value of the unobserved return component ($|URC|$) (Agarwal et al. 2024). The URC captures the portion of fund performance unexplained by observable equity holdings. Positive or negative values of the URC suggest that returns are being generated from exposures beyond long equity positions, including potential use of leverage, short positions, or derivative instruments. Therefore, the absolute value of the URC is the appropriate measure for capturing the intensity of such non-equity activity, regardless of its direction Sections 4.4 and 4.7 take a closer look at this approach, discuss the limitations of the

|*URC*| measure, and note how access to more complete data could improve the analysis. To explore whether ETFs are being used as part of such sophisticated strategies, we test whether ETF allocations are positively associated with the absolute value of the URC. A positive relationship would suggest that ETF usage complements non-equity activity and reflects active portfolio construction beyond reported equity exposure.

Hypothesis 3 (Alternative Strategies Hypothesis): ETF investment is positively associated with the absolute value of the unobserved return component (|URC|) of hedge funds.

3. Data

3.1. Sources and Data Description.

The data examined here were obtained from several sources related to hedge funds, ETFs, institutional ownership, and stocks. Information on hedge funds ownership is not available from standard datasets. We use the Hedge Fund Research (HFR) dataset to obtain HF manager names. The list of these names is then matched with a list of hedge fund managers provided by the Refinitiv Global Ownership dataset (former Thomson-Reuters 13-F dataset). Since some hedge funds also have mutual funds, we restrict our sample to "pure-play" hedge funds (Agarwal, Jiang, Tang, and Yang, 2013). We remove all hedge funds that also have mutual funds on the Refinitiv Mutual Fund database (Griffin and Xu, 2009).[3]To avoid delisting bias, we keep hedge fund managers in the sample until the point that the manager begins to report mutual fund ownership information. Our sample list contains 631 Hedge Fund managers covering 2,132

[3] Our dataset allows us to examine if the Hedge Fund is a parent/affiliated of a holding company on the Mutual Fund ownership dataset.

funds for a period of 1998-2020.[4] Importantly, the dataset is free from survivorship bias, as it includes both live and defunct funds.

A Form 13F is filed at the management level rather than at the portfolio or individual level. Therefore, we compute the value-weighted average of Hedge fund characteristics using the asset under management reported by the HFR dataset each month[5] (Agarwal, Ruenzi, and Weigert, 2024). We compute the quarterly returns and flows, at the manager level. We control for strategy and managers' regional investment focus using the same approach[6] (Ben-David, Franzoni, and Moussawi, 2012). To avoid potential data errors, and ensure consistency and economic relevance of our 13F-based measures, we exclude hedge fund firms for which the ratio of 13F equity holdings to HFR-reported AUM exceeds ten, as well as those for which the ratio of HFR-reported AUM to HFR-reported AUM exceeds ten (Ben-David, Franzoni, and Moussawi, 2009)[7].This restriction avoids cases in which reported U.S. long equity positions represent only a negligible share of total fund assets. This filter drops about 13% of the observations. Additionally, to ensure that results are not driven by firms with insignificant holdings, we exclude managers with less than USD 5 million of AUM in a given quarter based on the HFR dataset (0.65% of the observations).

---

[4]We limit our sample to this period for two main reasons. Firstly, prior to this period, transactions involving ETFs among Hedge Funds were infrequent. The first quarter in which we observed at least 10 Hedge Fund managers reporting ETFs on their 13F filings was the quarter ending on 30-Jun-1998. Secondly, at the time the paper was written in early 2022, the most recent institutional investors' classification update by Brian Bushee only extended until 2018.
[5] Under SEC regulations, institutional investors are mandated to report their holdings on Form 13F if they exercise investment discretion over $100 million or more. Since 1980, institutions have been required to disclose all common stock positions exceeding $200,000 or 10,000 shares on a quarterly basis. It is important to note that Rule 13f-1(a)(1) stipulates the obligation to submit all four Form 13F filings, even if an institution falls below the $100 million filing threshold after initially meeting it.
[6] Fund strategy is defined by the HFR dataset and has seven different classifications: Equity Hedge, Event-Driven, Fund of Funds, Macro, Relative Value, Risk Parity, and Blockchain. For the purpose of this study, we remove Blockchain funds from our sample.
[7] We impose both restrictions to address two distinct concerns. The first mitigates potential data inconsistencies or reporting errors when 13F equity holdings appear implausibly large relative to reported AUM. The second excludes cases where U.S. long equity positions represent only a negligible share of total assets.

To examine the 13F portfolio composition, we restrict our sample to common stocks (CRSP code 11 and 10), ADRs (12, 30, and 31), and ETFs (73) reported in the 13F dataset[8]. We obtain ETFs characteristics from the CRSP Mutual Fund dataset and Bloomberg. We identify 2,362 different ETFs held by Hedge Fund managers during our sample period. We rely on the Lipper Asset Code to determine the assets' characteristics of each ETF[9]. Our sample contains 1,906 Equity ETFs, and 456 Fixed Income ETFs, including Taxable and Tax-Free Income ETFs[10]. The averages annual expense ratios among Equity and Fixed Income ETFs in our sample are 0.24% and 0.35%, respectively. The ETFs expense ratios vary substantially across types of investments. Our sample includes ETFs with annual expense ratios ranging from as low as 0.05% - such as the Vanguard Total Bond Market ETF (Ticker: BND) - to as high as 1.85%, the highest in our sample, observed for the ETF Star Buy-Write (Ticker: VEGA).

Our baseline performance measures include fund returns, the Capital Asset Pricing Model (CAPM), and the Fung and Hsieh (2004) seven-factor model (FH7). We adopt CAPM and FH7 as our main benchmarks because they are widely used in the hedge fund literature and capture complementary aspects of performance. CAPM provides a simple measure of abnormal returns relative to the market, while FH7 is specifically designed to account for hedge funds' exposures to equity, bonds, currencies, commodities, and interest rates. As a robustness check, we also consider alternative factor models, including the Fama-French (1993) three-factor model (FF3), the Carhart (1997) four-factor model, the Pastor-Stambaugh (2003) liquidity factor model (PS),

[8] Baseline results reported here remain the same if we consider only common stocks and ETFs, or if the sample also includes other securities identified in the CRSP, like Certificates and Units.

[9] We obtain ETF classification on Bloomberg when there is a missing Lipper Asset code information. Similarly, we obtain expense ratio from Bloomberg when such information is missing or equal to zero on the CRSP Mutual Fund Database.

[10] Within the Lipper Asset Code, ETFs are categorized into three definitions: Equity Funds (EQ), Taxable Fixed Income Funds (TX), and Tax-Free Fixed Income Funds (MB). According to this classification, commodity ETFs like the SPDR Gold Trust ETF (GLD) are considered as Equity funds within Lipper's definition.

and the FF3 augmented with changes in market volatility, as measured by the VIX Index (FF3-Vix).

We convert all the non-USD returns into USD observations using the spot rates at end of each month. We estimate the models using 24 months of return for each fund to obtain the factor loadings. We calculate the monthly alphas as the difference between realized returns and model-fitted returns. To avoid look-ahead bias, factor loadings are estimated with data available only up to month t, and alphas are calculated at $t+1$ using these lagged estimates. We compound monthly alphas to compute the quarterly alphas. Finally, we compute the value-weighted alphas for each manager, based on the asset under management of each fund in the end of the previous quarter.

3.2. Hedge fund classification

We classify hedge fund investment profiles using two complementary dimensions: (i) investment style, based on the institutional investor classification developed by Bushee (1998), and (ii) investment strategy, defined by the characteristics of the funds managed by each hedge fund manager.[11]

Bushee's classification assigns institutional investors to one of three distinct types: transient, quasi-indexer, and dedicated. Transient investors are characterized by high portfolio turnover and broad diversification, reflecting a short-term investment orientation. Quasi-indexers tend to follow buy-and-hold or indexing strategies, maintaining high diversification but with lower turnover relative to transient investors. In contrast, dedicated investors hold large, concentrated positions in a small number of firms, indicating a long-term commitment to their portfolio

[11] We thank Brian Bushee for sharing the investor classification data on his website.

companies. Every hedge fund manager in our sample is mapped to one of the three Bushee categories.

To complement this classification, we also analyze hedge fund strategy types. Specifically, we calculate the value-weighted average AUM across fund strategies for each manager on a quarterly basis, allowing us to capture the dominant investment style pursued by each hedge fund manager.

3.3. Summary Statistics

Table 1 presents the summary statistics for the main variables in the full sample, with variable definitions provided in the Appendix A. On average, ETFs account for 4.5% of the total equity portfolio in each quarter. However, this average mask considerable right skewness in the distribution of ETF holdings: the median value of *WeightETF* is 0, while the 75th percentile is only 1.5%, suggesting that many hedge fund-quarters involve no ETF usage at all.[12]

Figure 1 illustrates the evolution of ETF use among hedge funds. Panel A shows the average portfolio weight of ETFs in reported equity holdings, which increased sharply during the first decade of the sample and has since stabilized, underscoring the long-term incorporation of ETFs into hedge fund strategies. Panel B shows the share of managers reporting ETF holdings: only 11% did so in 1998, compared with 73% by 2009. Since then, usage has leveled off, with about 50% of managers reporting ETF positions in 2020, the final year of our sample. These patterns highlight the broader integration of ETFs into institutional portfolios over this period.[13]

[12] Despite this skewness at the fund-quarter level, we find that ETF adoption is widespread at the manager level. Specifically, 67% of hedge fund managers in our sample report holding at least one ETF in their quarterly filings at some point between 1998 and 2020.
[13] We thank an anonymous reviewer for pointing this out and helping us improve the clarity of our descriptive analysis.

Further time-series variation by investor style and strategy is presented in Figures OA1 and OA2 of the Online Appendix. Figure OA1 reports results by investment style, following Bushee's (1998) classification. By 2020, the average ETF portfolio weight (*WeightETF*) reached over 8% for quasi-indexers and about 5% for transient investors. Figure OA2 presents results by hedge fund strategy, where funds are assigned to a category if at least 50% of their assets under management (AUM) fall within it. In the last full year of the sample, equity hedge and event-driven funds reported ETF allocations of roughly 3% and 1.5%, respectively, following peaks during the 2008-2009 financial crisis. Macro funds also peaked during the crisis but subsequently recovered, with ETFs accounting for about 30% of their portfolios by 2020. Relative value funds reported approximately 14% of their portfolios in ETFs, surpassing crisis-era levels. Finally, for Fund of Funds, the last year in which our sample contained such managers was 2017 (more than 50% of AUM on that strategy). In that year, the average *WeightETF* across these funds was approximately 70%.

Table 1 also includes the AUM-weighted averages of key fund manager characteristics. On average, hedge fund firms report holdings in 124 equity securities, and their total assets under management are about 1.5 times larger than the asset values disclosed in 13F filings. The funds exhibit an average annual incentive and management fee of 18.04% and 1.4%, respectively. Fund managers typically have a Lockup period of 6.14 months and require a 47-day advanced notice. The funds present an average minimum investment of $1.92 million and have an average age of 9 years. Furthermore, 34% of the AUM of funds is located offshore, and managers oversee an average of 2.5 funds each quarter. These statistics align closely with those reported by Agarwal, Ruezi, and Weigert (2024).

Detailed statistics on ETF weights are provided for the subsamples of transient, quasi-indexer, and dedicated managers, as well as for funds categorized by strategy, in Table OA3 of the online appendix. Among the subsamples, dedicated investors exhibit the lowest ETF weights relative to AUM, averaging 0.004 (or 0.4% of the total portfolio), compared to 0.042 (4.2%) for transient funds and 0.052 (5.2%) for quasi-indexer funds. By strategy, Fund of Funds and Macro funds have the highest ETF weights relative to AUM, averaging 0.257 (25.7%) and 0.197 (19.7%%), respectively. In contrast, Equity Hedge and Event Driven hedge funds show the lowest proportions of ETF weights relative to AUM, at 0.029 (2.9%) and 0.014 (1.4%), respectively.[14]

[Table 1 about here]

[Figure 1 about here]

4. Empirical Evidence

4.1. Hedge Fund Investment in ETFs

In this section, we first examine the types of ETFs used by Hedge Fund managers and present regressions that examine which types of hedge funds invest in ETFs. Table 2 presents the most popular ETF among Hedge Fund managers in our dataset. ETFs are ranked by the total AUM between 1998 and 2020. The most popular ETF in our sample is the SPDR S&P 500 ETF (Ticker: SPY), which tracks the S&P 500 index. Table 2 shows that, among the 20 most widely held ETFs by hedge funds, all are passive vehicles designed to track specific benchmarks.

[14] Hedge funds are assigned to a given strategy if at least 50% of their assets under management (AUM) are allocated to that category.

Table 3 presents fractional logit regression results for the proportion of assets under management (AUM) invested in ETFs, measured by the dependent variable *WeightETF*. This method, introduced by Papke and Wooldridge (1996), is appropriate for modeling proportion data bounded between 0 and 1, including boundary values. It ensures predicted values remain within the unit interval without requiring data transformation.[15] Importantly, the analysis in Table 3 is descriptive in nature and is not part of our identification strategy. The goal is to highlight general patterns in ETF usage across different types of hedge funds and fund characteristics, rather than to establish causal relationships. These patterns help motivate the more rigorous empirical tests presented in later sections.

Moreover, hedge fund managers that charge higher management fees, impose larger minimum investment requirements, maintain higher audited AUM levels, hold a greater share of unobservable assets, or operate fund-of-funds structures are more likely to invest in ETFs. In contrast, managers with larger total AUM, more diversified equity holdings, and greater allocations to offshore vehicles tend to exhibit a lower propensity to invest in ETFs.

The data show that hedge funds with more active portfolios, measured by *ActiveShare*, which captures the extent to which a fund's holdings deviate from those of the S&P 500 Index (Cremers and Petajisto, 2009), are less likely to invest in ETFs. This finding supports the notion that more passive funds, whose portfolios closely track the stock market index, are more inclined to use ETFs. This pattern is consistent with the agency cost hypothesis (*H1*), which links ETF usage to passive investment strategies. Additionally, *AdvanceNotice* and *Lock-upPeriod* are negatively associated with ETF investments. Since both mechanisms are designed to mitigate the

[15] Untabulated OLS regressions produce similar results to those reported in this section

impact of unexpected investor flows, this finding aligns with the liquidity management hypothesis, suggesting that hedge funds may use ETFs to manage liquidity in the absence of such contractual protection (*H2*).

We also use investors' portfolio turnover as an alternative measure of managers' investment style (Gaspar et al. 2005). Model (2) in Table 3 shows that funds with high turnover are more likely to invest in ETFs, and this effect is significant at the 1% level. In this specification, the coefficient on incentive fees turns negative and significant, suggesting that higher incentive fees motivate managers to pursue alpha-generating strategies rather than relying on passive vehicles such as ETFs. Similarly, the use of offshore vehicles may signal a focus on alternative assets and complex investment approaches that are less compatible with the transparency and standardization characteristic of ETFs.

While turnover, captured through both the transient investor classification and portfolio turnover, is typically positively related to active share, our findings reveal a break in this expected pattern: active share is negatively associated with ETF usage, while turnover is positively associated with it. This circular pattern, where turnover and active share usually move together but pull in opposite directions when it comes to ETF usage, suggests that ETFs are used in different ways, both as simple passive holding, consistent with *H1*, and as tactical, liquid tools, which can be related to *H2* and *H3*.

[Table 3 about here]

Next, we analyze the impact of hedge fund strategy and *WeightETF*. Using monthly AUM data for each fund, we calculate the weighted average AUM by strategy for each manager-quarter observation. Table 4 presents the results of a fractional logit regression assessing this factor. The findings reveal that hedge fund managers with a higher proportion of assets allocated to Macro, Relative Value, Risk Parity, and Fund of Funds strategies are more likely to invest in ETFs. In contrast, managers with greater AUM allocated to Equity Hedge and Event Driven strategies are less likely to invest in ETFs.

[Table 4 about here]

Tables OA4 and OA5 in the Online Appendix report regressions similar to those in Table 3, estimated using OLS with a logit transformation and Tobit models. The results closely mirror those presented in Tables 3 and 4.

4.2. Performance Consequences of Hedge Fund Investment in ETFs

In this section, we investigate the impact of investments in ETFs on performance. We begin by comparing the performance of ETF holdings and non-ETF holdings within each hedge fund manager, where non-ETF holdings include those by managers who have not reported any ETF holdings in the four quarters preceding the observation. This within-fund comparison approach helps control managers' characteristics and investment skills (Feng et al., 2022). Table 5 presents the univariate results of this analysis, focusing on sub-groups of hedge funds categorized by style, strategy, and asset size based on AUM. Each hedge fund is classified under a strategy if at least 50% of its assets are allocated to investments with the defining characteristics of that strategy.

On average, the quarterly returns of ETFs are 1.389% lower than those of non-ETF stocks for the entire sample of hedge funds. This trend holds true across all subgroups of hedge funds. The differences are statistically significant for most subgroups, except for the group of dedicated and hedge funds that have all of their AUM allocated in relative value and risk parity funds. Furthermore, the results indicate that ETFs consistently underperform non-ETF stocks across all sample size quartiles, with statistically significant differences at the 1% level. This return gap corresponds to roughly a 5-6 percentage point lower annual return for ETF holdings, indicating that the underperformance is economically large and not merely statistically significant. In conclusion, the findings presented in Table 5 suggest that the underperformance associated with ETFs is not limited to a particular subgroup based on investment style, size, or funds strategy.

[Table 5 about here]

Table 6 presents OLS multivariate regressions of fund performance. All models include hedge fund manager and year-quarter fixed effects[16]. The manager fixed effects control for time-invariant manager characteristics, while the year-quarter fixed effects control for time-specific market conditions, helping to isolate the impact of changes in ETF allocations on performance. Consistent with the results presented in the univariate analysis, the data indicate that investments in ETFs, measured by *WeightETF*, negatively impacts funds' CAPM alpha, FH7 factor alphas, and raw return. For the full sample, a one-standard deviation increase in *WeightETF* is associated with a decline of 0.155% in managers' CAPM alpha and 0.182% in HF7 alpha in the subsequent quarter.[17] In annualized terms, this corresponds to roughly 0.6-0.7 percentage points reduction in alpha, which is economically meaningful.

As a robustness check, we re-estimate the multivariate regressions using alternative factor models to measure performance, including the Fama-French (1993) three-factor model (FF3), the Carhart (1997) four-factor model, the Pastor-Stambaugh (2003) liquidity factor model, and an

[16] Quarter fixed effects refer to year-quarter dummies (e.g., 2006Q1, 2006Q2), capturing common time shocks.
[17] 0.137 multiplied by -1.132 and -1.333

FF3 specification augmented with monthly changes in the VIX to capture market volatility[18]. The results, reported in Table OA6 of the Online Appendix, show that the coefficient on *WeightETF* remains negative and statistically significant across all performance specifications.Online Appendix Table OA7 presents the results of OLS regressions, similar to those in Table 6, but applied to subsamples of the data categorized by funds' investment style using the Bushee (1998, 2001) classifications: transient, quasi-indexer, and dedicated investors, as well as by funds' strategies.[19] The findings suggest that investments in ETFs are associated with negative performance for transient and dedicated investors, as well as for hedge funds predominantly invested in Equity Hedge, Event Driven, and Fund of Funds strategies. In contrast, there is no evidence to suggest that ETF investments impact performance among funds with a primary focus on Macro and Relative Value strategies. [20] [21]

Overall, the evidence in this section supports the view that hedge funds perform worse when they invest in ETFs and that ETF ownership is broadly indicative of agency problems, consistent with H1.

[Table 6 about here]

4.3. Capital flows and investments in ETFs

In this section, we examine whether ETF investment is linked to abnormal capital flows, specifically testing the liquidity management hypothesis (*H2*), which suggests that ETFs serve as

---

[18] We thank an anonymous reviewer for this suggestion.

[19] Hedge funds are assigned to a given strategy if at least 50% of their assets under management (AUM) are allocated to that category.

[20] Due to the absence of observations for pure Risk Parity, this subsample is excluded from multivariate regressions that incorporate firm fixed effects

[21] As a falsification test, we reverse the specification and regress ETF usage on lagged performance measures. If reverse causality were present, poor past performance should predict higher ETF allocations. Untabulated results reveal that the coefficient on lagged performance, whether measured by CAPM alpha, HF-7 alpha, or raw return, is statistically insignificant indicating no evidence that ETF usage systematically follows underperformance.

a transitory tool for managing liquidity. We investigate whether unexpected flows lead to increased ETF allocations, while expected flows have no significant effect. A hedge fund manager estimating predicted versus unexpected flow will only do so with a margin of error. The forecasting model of a hedge fund manager is not known to an external researcher. But hedge fund managers do have access to the same prior research as academic researchers on how they can forecast their own flows. So, we may certainly expect significant overlap between academic research flow predictability and fund manager flow predictability. To this end, we expect flow predictability observed by an academic researcher to suitably proxy flow predictability by a hedge fund manager.Fund managers that receive an excess flow from one month to the next could simply hold that extra capital in the form of cash, which would not earn a rate of return. Alternatively, the fund manager could store it in equities or some other short-term liquid investment that offer some potential return while maintaining flexibility. An advantage of hedge funds investing in ETFs with the short-term excess capital flow into the fund is that ETFs offer diversification, liquidity, and possible return enhancement. This straightforward idea gives rise to our prediction that unexpected flows will give rise to more hedge fund ETF investment, while expected hedge fund flows will be unrelated to ETF investment.

A large stream of research documents the relevance of past fund flows for enabling or facilitating future fund returns (e.g., Fung et al., 2008; Luo, 2012; Agarwal et al., 2018). In respect of hedge fund investments, when there is a significant increase in unexpected flows and a commensurate increase in ETF investment to manage that expected flow in the short run, fund returns should not be harmed, and may even be enhanced. Hedge fund liquidity risk is related to return predictability (Brandon and Wang, 2013). ETF investment enables management of unexpected flows in a way that does not exacerbate liquidity risk. By contrast, agency problems explain hedge fund investment in ETFs alongside their expected flows and in ways unrelated to their unexpected flows, and these investments are expected to diminish future alpha. As such, we expect that positive changes in ETF investment alongside unexpected [expected] flows will enhance [diminish] future hedge fund alpha.

Our measure of fund flows follows that of Sirri and Tufano (1998). Similar to returns, non-USD assets under management (AUM) are converted to USD, and aggregated at manager level. To be consistent with the 13F filling frequency, we use the quarterly flow measures, adjusting the presence of a new fund or exclusion of an existent fund during the quarter. We calculate quarterly net flows (i.e., inflow net of outflows) for manager i in quarter q as follows:

$$Flow_{i,q} = \frac{AU\quad_{i,q} - AUM_{i,q-1}\ x\ (1 + Return_{i,q})}{AU\quad_{i,q-1}} \tag{1}$$

Where $AUM_{i,q}$ represents assets under management of manager i in the quarter q. In order to examine the effect of flows on equity investments, we calculated the returns adjusted net changes on ETFs and other stocks scaled by the total equity value held by the manager in the previous quarter obtained from managers' 13F filings.

We calculate expected and unexpected flows by using the methodology of Fung, Hsieh, Naik, and Ramadorai (2008).[22] Specifically, quarterly flows are modeled as a function of their own lags and lagged fund returns:

$$F_{i,q} = \alpha_i + \beta_1 R_{i,q-1} + \beta_2 F_{i,q-1} + \varepsilon_q \tag{2}$$

[22] We considered Agarwal et al. (2018) to measure flow using lagged CAPM alpha and found the results to be very similar as those reported here. Those results are available on request.

Where the quarterly flow measure $F_{i,q}$ is regressed on lagged quarterly flows $F_{i,q-1}$ and lagged quarterly returns $R_{i,q-1}$. We regress quarterly hedge fund flows on four lags of fund returns and four lags of past flows to capture the dynamic relation between performance and investor behavior. The regressions include manager fixed effects to control for time-invariant heterogeneity across managers. Standard errors are two-way clustered at the manager and year-quarter levels, which allows for arbitrary correlation of residuals within managers across time and across managers within the same quarter (Petersen, 2009).[23] [24]

The unexpected flows are then the regression residuals, while the expected flows are the predicted values. Appendix B presents the regression results for Eq.(2). All predictors are statistically significant at the 1% or 5% level, with the exception of $Flow_{t-3}$. The estimated coefficients on both lagged returns and lagged flows are positive, reflecting the persistence of flows and performance sensitivity commonly documented in the literature (Fung et al., 2008; Agarwal et al., 2018).

To measure hedge fund investments in ETFs in each quarter, we calculate the quarterly changes in ETF stocks under management minus the total return of ETF stocks over the quarter, divided by the total equity value under management in the previous quarter. This methodology allows us to capture the exact hedge fund net investment in ETFs.

Table 7 presents OLS regressions of changes in ETF holdings relative to the total equity value held by each manager. The results show that unexpected flows are significantly and

---

[23] The baseline results remain consistent even when the residuals are obtained with regressions are conducted separately for each manager. Results for this alternative approach are discussed throughout the analysis and presented in the Online Appendix.

[24] We confirm the robustness of our findings using alternative specifications to estimate expected flows, including an AR(1) model and a rolling average of the previous four quarters.

positively associated with increased ETF allocations, both in the full sample and in the subsample that excludes managers with no ETF exposure. While the coefficient on expected flows is not statistically significant, the coefficient on unexpected flows is larger in magnitude. However, the difference between the two is statistically insignificant in all specifications. This finding suggests that although hedge funds may adjust ETF allocations in response to both expected and unexpected flows, there is no compelling evidence that ETF investment is disproportionately driven by unanticipated liquidity shocks. As such, the findings offer weak support for the liquidity management hypothesis, which posits that ETFs are used primarily as tactical tools in response to unanticipated investor redemptions or inflows.

Additionally, the results show that changes in non-ETF holdings are more responsive to expected flows than to unexpected flows, as evidenced in models where changes in non-ETF holdings serve as the dependent variable. In Online Appendix Table OA8, we further explore this relationship using an alternative approach to measure expected flows, with separate regressions for each hedge fund manager The results from these alternative specifications are consistent with our main findings and offer only limited support for the view that ETF usage in hedge fund portfolios is primarily driven by liquidity management considerations.

Table OA9 on Online Appendix presents OLS regression results similar to those in Table 7, but using subsamples based on investment style, as classified by Bushee (1998, 2001), and strategy. The data indicate that the coefficient for unexpected flow is not significantly distinct from the coefficient for expected flow in any specification.

[Table 7 about here]

Table 8 examines the impact of unexpected flow alongside ETF ownership on hedge fund alphas and raw returns. The data indicates that unexpected flows by themselves do not impact hedge fund alphas or raw returns in any of the econometric specifications or subsamples in the data. However, the interaction terms between *UnexpectedFlow* and *WeightETF* are positive across all performance measures. In the subsample excluding managers with no ETF exposure (NON-ETF), this interaction is statistically significant at the 10% level or better for all performance measures.

[Table 8 about here]

Online Appendix Table OA10 presents regressions similar to those in Table 8, but employing alternative measures of fund performance, including the FF3, Carhart4 , PS, and FF3-VIX factor models. Consistent with the results in Table 8, the interaction term between *UnexpectedFlow* and *WeightETF* is positive and statistically significant across all specifications. Online Appendix Table OA11 examines heterogeneity across investor style and investment strategies. Using CAPM alpha as the performance measure, all subgroups, except Macro hedge fund managers, exhibit a positive coefficient on the interaction between *UnexpectedFlow* and *WeightETF*. Statistical significance at the 10% level is observed for transient, dedicated, equity hedge, and relative value funds. These findings remain robust when performance is evaluated using FH7 alpha or raw return. Finally, Online Appendix Table OA12 also reports OLS regressions similar to those in Table 8, but based on an alternative approach to constructing expected flows, with separate regressions estimated for each hedge fund manager. The results closely mirror those in Table 8.

Overall, the results presented in this section provide no robust evidence that ETFs are systematically used for liquidity management, offering little support for *H2*. In all specifications examined the coefficient on unexpected flows is not statistically different from that of expected flows, challenging the notion that ETF allocations are a targeted response to unanticipated liquidity shocks. However, when ETFs are used in conjunction with unexpected flows, captured through interaction terms, fund performance appears less negatively affected. This suggests that while ETFs may not be systematically deployed as liquidity management tools across the hedge fund universe, their selective use in response to unexpected flows can mitigate the otherwise negative impact of ETF allocations on returns.

4.4. Investments in ETF and unobserved return component

Hedge fund returns, unlike those from pure long-equity portfolios, often reflect exposure to a diverse set of non-equity asset classes and strategies. In this section, we examine the role of such activities by analyzing their effect on the absolute value unobserved return component ($|URC|$), which captures performance not explained by reported long-equity holdings in 13F filings. Since our dataset contains only long positions in equities, we lack direct information on short positions, derivatives, or other non-equity exposures. To examine whether ETF investments are linked to these unobserved strategies, we rely on the absolute value of the URC as an indirect proxy (Agarwal et al., 2024). We calculate the absolute value of $|URC|$ as:

$$|URC_{i,t}| = |Gross\ Fund\ Firm\ Return_{i,t} - Equity\ Portfolio\ Return_{i,t}| \tag{3}$$

Where *Gross Fund Firm Returns* are defined as quarterly AUM-weighted fund returns before deducting management and incentive fees, whereas *Equity Portfolio Returns* correspond to the returns on equity holdings disclosed in 13F filings for the same quarter.[25]

[25] Because commercial databases report only net-of-fee returns, we estimate gross-of-fee returns following Agarwal, Daniel, and Naik (2009). Gross returns equal net returns plus the management fee, and, when applicable, the incentive fee, which is estimated using an algorithm that accounts for hurdle rates and high-watermark provisions.

We focus on the absolute value of the unobserved return component ($|URC|$), since non-equity activities can generate deviations in either direction from reported long-equity holdings, and the magnitude of these deviations is most informative. Both speculative and hedging uses of off-13F instruments increase $|URC|$, because such activities cause actual returns to diverge from those implied by disclosed positions. For example, if a reported long-equity position falls (rises) by 10% but is fully hedged with an unreported short or derivative position, the fund's actual return will be close to zero, while the 13F-implied return will show a −10% loss (+10% gain), yielding a $|URC|$ of 10%. This indicates substantial off-13F activity despite the absence of directional risk. If ETFs are used primarily as long-only positions reflected in 13F filings, deviations between realized returns and holdings-implied returns should be smaller on average, implying lower $|URC|$ should be close to zero,. By contrast, a positive association between ETF allocations and $|URC|$ suggests that ETFs are systematically used alongside unreported strategies, such as leverage, derivatives, or shorting, rather than as passive investments.

We note that $|URC|$ is limited, indirect, and imperfect measure of non-equity exposure. Because the expected return is based only on reported long equity holdings, $|URC|$ may also reflect model noise, reporting lags, or performance from equity positions not fully captured in the 13F portfolio. In addition, $|URC|$ does not identify the specific type of non-equity activity or its direction. That said, with the information available in public filings, it provides a practical way to investigate the extent of returns generated outside reported long equity positions.

To provide further validation of $|URC|$, we dedicate Section OA1 of the Online Appendix to examining its association with fund characteristics. There, we show that transient investors, higher portfolio turnover, and funds whose HFR descriptions explicitly reference derivatives, long-short strategies, or leverage exhibit significantly higher $|URC|$. We also document consistent patterns with other attributes linked to higher |*URC*|, including manager experience, fee structures, auditing, and minimum investment requirements. These results are consistent with prior evidence that connects hedge fund characteristics to the use of derivatives, short-selling, and leverage (Chen, 2010; Liang and Qiu, 2019; Qian et al., 2025).On one hand, hedge funds may use ETFs as a passive investment vehicle, potentially amplifying agency problems associated with inactive management. In this scenario, we would expect a negative coefficient for *WeightETF* when |*URC*| is used as the dependent variable - consistent with the agency cost hypothesis of ETF usage (*H1*). On the other hand, ETFs in hedge funds may complement investments in other non-equity asset classes. For instance, ETFs can play a critical role in long-short constructions, such as long-stock/short-ETF or vice versa (Huang et al., 2021). If ETFs are primarily used to implement such active strategies, we would expect a positive relationship between ETF allocations and the |*URC*|, supporting the alternative strategies hypothesis (*H3*).

[Table 9 about here]

Table 9 reports the impact of *WeightETF* on |*URC*|. For the full sample, the coefficient for *WeightETF* is negative and statistically significant at the 5% level. Among hedge fund manager style, the coefficient for transient investors is also negative and statistically significant at the 1% level. Across all hedge fund strategy subsamples, the coefficient for *WeightETF* remains negative, but it is statistically significant at the 1% level only in the macro hedge fund subsample.

Overall, these findings suggest that ETF usage tends to reduce the portion of hedge fund performance that is not explained by long-equity portfolio returns. This indicates that managers are more likely to use ETFs as straightforward long-only investments, rather than as components of broader non-equity strategies such as derivatives trading or short selling. These results align with the agency cost hypothesis (*H1*), indicating more passive usage of ETFs, and stand in contrast to the alternative strategy hypothesis (*H3*), which posits that ETFs are primarily used as flexible instruments to manage exposures associated with non-equity positions.

4.5. The Role of ETF Heterogeneity.

In this section, we investigate whether heterogeneity in ETF characteristics helps explain our main findings. Specifically, we examine three important dimensions: Passive vs. Active ETFs, Broad vs. Sectoral ETFs, and Non-Leveraged and Leveraged ETFs.

Although ETFs are traditionally designed as passive instruments to track broad benchmarks, they are increasingly utilized as active investment vehicles (Easley et al., 2021). Distinguishing between passive and active ETFs is important because hedge funds may use active ETFs tactically .For instance, through inverse or leveraged products, to implement market timing or hedging strategies. Persistent investment in passive ETFs, by contrast, may reflect agency-driven substitution for active management.[26][27]

The Broad vs. Sectoral distinction provides an additional perspective. Broad-market ETFs (e.g., S&P 500 or total market trackers) are more consistent with long-term, benchmark-like exposures that raise agency concerns when used persistently by hedge funds. Sectoral ETFs (e.g., financials, energy, or healthcare) instead point to tactical portfolio tilts or short-term bets on

[26] . Using CRSP Mutual Fund data, we classify ETFs by their index fund flag to separate passive from active.
[27] Approximately 10% of the ETFs in our dataset lack an index flag, preventing us from classifying them as either Passive or Active. For managers holding these ETFs, we calculate their Passive and Active shares using the portfolio-weighted values of the ETFs we are able to classify. Results remain consistent when we exclude these managers from our analysis, as confirmed by an untabulated robustness check.

specific industries. Thus, contrasting Broad and Sectoral holdings helps us assess whether ETF usage reflects strategic passivity or targeted, tactical positioning.[28]

Building on this idea, we next distinguish between Non-Leveraged and Leveraged ETFs.[29] Leveraged ETFs, available since 2006, provide amplified or inverse exposure to benchmark indexes (e.g., 2x, 3x, -2x, -3x) (DeVault et al. 2021; Davies 2022). Compared to Non-Leveraged ETFs, allocations to Leveraged ETFs are more indicative of tactical trading strategies than of simple passive exposure. In this sense, the Leveraged vs. Non-Leveraged comparison parallels the Broad vs. Sectoral distinction, as both allow us to examine whether ETF usage reflects passive benchmark replication or active tactical positioning.

Figure 2 shows that hedge fund managers have predominantly invested in passive ETF structures. On average, 92.75% of hedge fund ETF holdings are in passive vehicles, with only 7.25% allocated to active ETFs, and the share of passive ETFs has never fallen below 75% during our sample period. By contrast, the split between Broad and Sectoral ETFs has been much more balanced. In the early years of the sample, hedge fund ETF investments were concentrated in Broad ETFs, but in more recent years the allocation has stabilized at roughly 50/50 between Broad and Sectoral ETFs. A similar dynamic is observed for Non-Leveraged versus Leveraged ETFs: allocations to Leveraged ETFs were negligible at their introduction (0.43% in 2007) but have grown steadily over time, reaching more than 8% of total ETF holdings by 2020.

[Figure 2 about here]

---

[28] ETFs are classified as Broad or Sectoral using *LIPPER_ASSET_CD* categories from the CRSP Mutual Fund database.
[29] We classify ETFs as leveraged or inverse-leveraged if their names contain terms such as Leverage, Inverse, Double, Short, Ultra, UltraShort, or explicit leverage ratios (e.g., 4x, 3x, 2.5x, 2x, 1.5x, 1.25x).

Table 10 explores whether our main results on agency cost hypothesis hold under the distinction between passive versus Active, Broad versus Sectoral ETFs, and Non-Leveraged and Leveraged ETFs. Passive ETFs are associated with lower hedge fund performance, while active ETF coefficients are also negative but not statistically different from zero. . Specifically, when performance is measured by CAPM alpha, the coefficient on passive ETF holdings (*WeightPassiveETF*) is negative and statistically significant at the 1% level, while the coefficient on active ETFs (*WeightActiveETF*) is also negative but not statistically significant. The data also reveals that, while the coefficient on broad ETF holdings (*WeightBroadETF*) is negative and statistically significant across all specifications, the coefficient of sectoral ETF holding (*WeightSectoralETF*) is not statistically significant across specifications. Finally, the data also reveals that, while the coefficient of non-leveraged ETF holding (*WeightNonLeveragedETF*) is constantly negative and statistically significant in most of the specifications, the coefficient of leveraged ETF holding (*WeightLeveragedETF*) lacks statistically significance.

In Table OA13 of Online Appendix we examine whether investments in these types of ETFs respond differently to expected versus unexpected fund flows. The results are consistent with those in Section 4.3: the coefficient on unexpected flows is not significantly different from the coefficient on expected flows in any specification. This finding does not support the hypothesis that passive or active ETFs act as buffers to unanticipated capital flows. Finally, in Table OA14 of Online Appendix, we investigate whether these types of ETFs have differing impacts on the absolute value of URC (|*URC*|). The results indicate that Passive, Broad, and Non-Leveraged ETFs drive the negative relation between ETF usage and |*URC*|, while no ETF subcategory exhibits a positive association with |*URC*|.

[Table 10 about here]

In sum, the results presented further reinforce our central conclusion: hedge fund investments in ETFs align with the predictions of the agency problem hypothesis. Specifically, the patterns observed suggest that managers may be using ETFs in ways that reflect agency-driven incentives, rather than purely maximizing investor returns.

4.6. Supplementary Analysis.

In the Online Appendix, we present a series of additional tests. First, we examine the time-series pattern of our results. Figure OA3 shows that the coefficient on *WeightETF* associated with performance becomes increasingly negative over time, indicating that the effects are more pronounced in recent years as ETF usage has expanded. Similarly, Table OA15 shows that the relationship between *WeightETF* and |*URC*| becomes more negative in later subsamples. By contrast, the impact of flows on ETF allocations remains stable across time, as reported in Table OA16. Together, these results suggest that our findings are driven by the more recent ETF-dominated period rather than the early years of limited ETF activity.

In Table OA17, we examine the effect of ETF usage on funds' Sharpe ratio and on two risk measures: standard deviation and downside deviation. In multivariate regressions that use quarterly measures and include manager fixed effects and time fixed effects at the year-quarter level, a higher *WeightETF* is associated with a lower next quarter Sharpe ratio and standard deviation of returns, whereas the coefficients of downside deviation are not statistically significant. Overall, ETF use is associated with a deterioration in risk-adjusted performance, even as general volatility declines.

Finally, we also examine whether ETF usage is associated with a decrease in the number of funds a manager operates. Motivated by the idea that managers may shift toward ETFs as closure approaches, we test whether higher *WeightETF* predicts subsequent contractions in managers' fund counts.[30] Results are presented in Table OA18 in the Online Appendix. Across specifications, the coefficient on *WeightETF* is negative but statistically insignificant, indicating no systematic link between ETF use and later reductions in the number of funds managed.

4.7. Approaches in Related Papers, Limitations and Future Research

There are some differences between the approach in our paper versus that in Sun and Teo (2022), and these differences are relevant here. Sun and Teo (2022) use filing data to consider whether a hedge fund invests in ETFs. Sun and Teo (2022) perform a fund-level analysis using a dummy variable (ETF) using a sample of large institutional managers, some of which have billions of dollars of AUM.[31] Sun and Teo (2022) do not discuss fund-of-funds, and do not consider robustness to eliminating managers who also report holdings in mutual funds. In contrast, our analysis focuses on ETF portfolio weights and their interaction with non-ETF holdings. More importantly, we explore alternative hypotheses regarding hedge fund use of ETFs, offering a more nuanced examination of the role ETFs play in hedge fund strategies.

As with any empirical paper, there are limitations to our approach, which in turn gives rise to future research opportunities. First, we explored potential identification strategies, including ETF introductions and regulatory changes as instruments. However, we did not identify a clear exogenous shock or plausible instrument that satisfies both relevance and exclusion restrictions in our context. We view this as an important avenue for future research

[31] For example, in Dec-2018, Renaissance Technologies LLC, the famous Hedge Fund Manager, also known as RenTec, reported a grand total of 3,060 stocks that could be found on the CRSP dataset, with a total market value of \$90 billion. For this type of fund, ETF holdings relative to AUM is perhaps more informative than a dummy variable for ETF investment.

once more granular data on ETF availability, manager mandates, or regulatory constraints become available.

Additionally, our analyses are based on estimates of unexpected flow. To the extent that there are measurement problems with unexpected flow, there could be errors in our inferences. We have assessed robustness of our unexpected flow measurements to numerous specifications and do not see anything that would lead us to believe our estimates are biased. But future research could uncover improved estimates of flow predictability, which would in turn give rise to new scope for assessing our approach here.

Another limitation of our analysis comes from the dataset used to track hedge funds' historical ownership. The Refinitiv 13-F data does not provide short positions and derivatives, important components of hedge fund portfolios (Aragon and Spence Martin, 2012). Although our URC analysis offers evidence that ETFs are not primarily used as part of sophisticated investment strategies involving unobserved portfolio elements, this conclusion is constrained by the scope of the data. Future research with access to more comprehensive holdings data could refine and expand upon our findings related to this hypothesis.

Our analyses are based on the HFR database and the Refinitiv Institutional 13-F dataset. Reporting to HF databases is voluntary. We have assessed robustness to backfilling bias and survivorship bias, and do not have any reason to believe that our analyses suffer from data problems. The HFR dataset is the best data for hedge fund research (Joenväärä et al., 2021).

5. Conclusion

This paper provides evidence that hedge funds frequently invest in ETFs. In recent years, quasi-indexer and transient hedge fund managers have allocated approximately 7% of their disclosed equity portfolios to ETFs, and about 50% of these funds have used ETFs during this period. Our data further reveals that certain hedge fund strategies are more strongly associated with ETF investments. Notably, ETFs have accounted for as much as 30% and 14% of the total portfolios of Macro and Relative Value hedge funds, respectively.

To explore the motivations behind ETF usage, we propose and test three hypotheses: the Agency Cost Hypothesis, the Liquidity Management Hypothesis, and the Alternative Strategies Hypothesis. First, we examine the performance implications of ETF investments. Overall, we find that hedge funds investing in ETFs tend to exhibit lower alphas and raw returns, supporting the agency cost perspective. While we find no robust evidence that ETFs are primarily used as a liquidity management tool during periods of abnormal capital flows, there is some indication that hedge funds employing ETFs in response to unexpected flows tend to perform better, exhibiting higher alphas. In fact, unexpected capital flows appear to mitigate the negative association between ETF usage and performance.

Furthermore, our analysis shows that ETF usage is negatively associated with the absolute value of the unobserved return component ($|URC|$), suggesting that ETFs are largely employed as passive holdings. This finding is inconsistent with the notion that ETFs are primarily used to implement complex strategies such as short-selling, leverage, or derivative exposure. Finally, we show that our results are not driven by whether hedge funds are investing in Passive or Active ETFs specifically. To strengthen the validity of our measure, we conduct a series of tests showing that $|URC|$ is positively related to factors that are themselves positively associated with exposure to non-13F holdings.

In summary, by jointly examining ETF portfolio weights constructed from holdings data, capital-flow dynamics through a decomposition of expected and unexpected flows, and the unobserved return component of hedge fund performance, our findings are most consistent with the Agency Cost Hypothesis. The evidence suggests that hedge funds primarily use ETFs as passive investment vehicles, rather than as tools for managing abnormal liquidity needs or executing sophisticated investment strategies. The data examined here offer interesting implications for practice and policy. Institutional investors into hedge funds would improve their due diligence by examining the ETF investment policy and strategies of the hedge funds for which they consider investing. Transparency in reporting practices of hedge fund investment in ETFs and the underlying reasons could enable more efficient capital allocation and mitigate agency problems with delegated portfolio management.

References

Achleitner, A.K., Betzer, & A., Gider, J. (2010). Do Corporate Governance Motives Drive Hedge Fund and Private Equity Fund Activities? *European Financial Management, 16(5), 805-828*

Amenc, N., Martellini, L., Meyfredi, & J.C., Ziermann, V. (2010). Passive Hedge Fund Replication - Beyond Linear Case. *European Financial Management, 16(2), 191-210.*

Aitken, A.L., Clifford, C.P., & Ellis, J.A. (2015). Hedge funds and discretionary liquidity restrictions, *Journal of Financial Economics, 116, 197-218.*

Agarwal, V., Daniel,N. & Naik, N. (2004). *Flows, performance, and manage rial incentives in hedge funds*, Working paper, Georgia State University and London Business School.

Aggarwal, R., & Schofield, L. (2014). The growth of global ETFs and regulatory challenges. *Advances in financial economics, 16, 77-102.*

Agarwal, V., T.C. Green, & H. Ren, (2018). Alpha or beta in the eye of the beholder: What drives hedge fund flows? *Journal of Financial Economics 127, 417-434.*

Agarwal, V., W. Jiang, Y. Tang, & B. Yang, (2013). Uncovering Hedge Fund Skill from the Portfolio Holdings They Hide. *Journal of Finance 68(2), 739-783.*

Agarwal, V. & N. Y. Naik, (2004) Risks and Portfolio Decisions involving Hedge Funds. *Review of Financial Studies, 17 (1), 63-98.*

Agarwal, V., Ruenzi, S., & Weigert,F. (2024) Unobserved Performance of Hedge Funds. *Journal of Finance 79(5), 3203-3259.*

Aragon, G., Chen, S., & Shi, Z. (2022). Volatility Timing Using ETF Options: Evidence from Hedge Funds. Available at SSRN: https://ssrn.com/abstract=4246146

Aragon, G., & Martin, J.S. (2012). A unique view of hedge fund derivatives usage: Safeguard or speculation. *Journal of Financial Economics 105(2), 436-456.*

Bali, T., Brown, S.J., & Caglayan, M.O. (2014) Macroeconomics risk and hedge fund returns. *Journal of Financial Economics 114(1), 1-19*

Ben-David, I., Franzoni, F., & Moussawi, R. (2012). Hedge Fund Stock Trading in the Financial Crisis of 2007-2009, *The Review of Financial Studies 25(1), 1-54.*

Ben-David, I., Franzoni, F., & Moussawi, R. (2018) Do ETFs Increase Volatility?, *The Journal of Finance, 73(6), 2471-2535*

Bessler, W., Drobetz, W., & Holler, J. (2015) The Returns to Hedge Fund Activism in Germany, *European Financial Management, 21 (1), 106-147.*

Bollen, N., & V.K. Pool, (2009). Do Hedge Fund Managers Misreport Returns? Evidence from the Pooled Distribution, *Journal of Finance 64(5), 2257-2288*

Bollen, N., & Pool, V.K., (2008). Conditional Return Smoothing in the Hedge Fund Industry. *Journal of Financial and Quantitative Analysis 43(2), 267-298*

Brown, D.C., & S. Davies, (2014). Closet Indexing: The Cost of Falling Asset Management Fees. Available at SSRN: https://ssrn.com/abstract=2517701

Brown, D.C., S. Davies, & Ringgenberg, M., (2021) ETF Arbitrage, Non-Fundamental Demand, and Return Predictability. *Review of Finance 25 (4), 937-972*

Boyson, N. (2010). Another look at career concerns: A study of hedge fund managers. *Journal of Empirical Finance 17(3), 283-299.*

Brav, A., W. Jiang, F. Partnoy, & R. Thomas, (2008). Hedge Fund Activism, Corporate Governance, and Firm Performance. *The Journal of Finance, 63(4), 1729-1775.*

Brandon, R.G., & Wang, S., (2013). Liquidity risk, return predictability, and hedge funds' performance: An empirical study, *Journal of Financial and Quantitative Analysis 48, 219-244.*

Bushee, B.J. (1998). The influence of institutional investors on myopic R&D investment behavior, *The Accounting Review 73(3), 305-333.*

Bushee, B.J. (2001). Do institutional investors prefer near-term earnings over long-run value? *Contemporary accounting research 18 (2), 207-246.*

Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance, 52, 57-82.*

Chen, Y. (2011) Derivatives and Risk Taking: Evidence from the Hedge Fund Industry. *Journal of Financial and Quantitative Analysis,* 46(4), 1073-1106

Clifford, C.P. (2008). Valuation creation or destruction? Hedge funds as shareholder activists, *Journal of Corporate Finance 14, 323-336.*

Cremers, K.M., Petajisto, A. (2009). How Active Is Your Fund Manager? A New Measure That Predicts Performance. *The Review of Financial Studies, 22(9), 3329-3365*

Davies, S.W. (2022). Speculation Sentiment. *Journal of Financial and Quantitative Analysis*, 57(7), 2485-2515

Devault, L., Turtle, H.J, & Wang, K. (2021). Blessing or Curse? Institutional investment in leveraged ETFs. *Journal of Banking and Finance*, 129, 106169

Easley, D., Michayluk, D., & O'Hara, M. (2021). The Active World of Passive Investing. *Review of Finance, 25,5, 1433-1471*

Fama, E.F., French, K.R. (1993) Common risk factors in the returns on stocks and bonds. J*ournal of Financial Economics*, 33,3-26

Fung, W., & Hsieh, D.A., (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies 14, 313-341.*

Fung, W., D. Hsieh, Y. Naik, & T. Ramadorai (2008). Hedge Funds: Performance, Risk, and Capital Formation, *Journal of Finance 63(4), 1777-1803.*

Gaspar, J.M., Massa, M., Matos, & P., (2005). Shareholder investment horizons and the market for corporate control. *Journal of Financial Economics 76(1), 135-165.*

Getmansky, M., (2012), The Life Cycle of Hedge Funds: Fund Flows, Size and Performance, *The Quarterly Journal of Finance 2 (1), 1250003.*

González, M.O., Papageorgiou, N.A., Skinner, & F.S,. (2016). Persistent doubt: An examination of hedge fund performance. *European Financial Management. 2016 (22), 613–639*

Griffin, J.M., & J. Xu, (2009). How Smart Are the Smart Guys? A Unique View from Hedge Fund Stock Holdings*, The Review of Financial Studies, 22(7), 2531–2570*.

Hodder, J.E. & J.C. Jackwerth, (2007). Incentive Contracts and Hedge Fund Management, *Journal of Financial and Quantitative Analysis 42, 811-826.*

Huang, S., O'Hara, & M., Zhong, Z., (2021). Innovation and Informed Trading: Evidence from Industry ETFs, *The Review of Financial Studies, 34(3), 1280-1316.*

Joenväärä, J., M. Kauppila, R. Kosowski, & P. Tolonen (2021), Hedge Fund Performance: Are Stylized Facts Sensitive to Which Database One Uses? *Critical Finance Review 10(2), 271-327.*

Klein, A., & Zur, E., (2009). Entrepreneurial shareholder activism: Hedge funds and other private investors. *Journal of Finance 64, 187-229.*

Kosowski, R., N. Naik, & M. Teo, (2007). Do hedge funds deliver alpha? A Bayesian and bootstrap analysis. *Journal of Financial Economics, 84(1), 229-264*

Li, F.W., & Zhu, Q., (2022). Short Selling ETFs. *The Review of Asset Pricing Studies, 12(4), 960-998.*

Liang, B., Qiu, L. (2018) Hedge Fund Leverage: 2002-2017. *European Financial Management*, 25(4), 908-941

Lou, D. (2012). A Flow-Based Explanation for Return Predictability, T*he Review of Financial Studies, 25(12), 3457-3489.*

Papke, L.E., & Wooldridge, J.M., (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometric 11(6), 619-632.*

Pastor, L., & Stambaugh, R., (2003). Liquidity Risk and Expected Stock Returns, *Journal of Political Economy,* 111(3), 642-685.

Petersen, M.A., (2009). Estimating standard errors in finance panel data sets: comparing approaches. *Review of Financial Studies 22, 435-480.*

Qian, J., Shi, Z., Yang, B., (2025) Short-Selling Hedge Funds. Available at SSRN: https://ssrn.com/abstract=4764190

Sherrill, D., Shirley, S., & Stark, J., (2017). Actively managed mutual funds holding passive investments: What do ETF positions tell us about mutual fund ability? J*ournal of Banking and Finance 76, 48-64*

Sirri, E.R., & P. Tufano (1998). Costly Search and Mutual Fund Flows, *Journal of Finance 53(5), 1589-1622.*

Sun, L., & M. Teo, (2022). Passive hedge funds, Working Paper, Fudan University and Singapore Management University.

Zitzewitz, E., (2006). How Widespread Was Late Trading in Mutual Funds? *American Economic Review 96(2), 284-289.*

Wang, F., & Zheng, L. (2024). Do find managers time momentum? Evidence from mutual fund and hedge fund returns. *European Financial Management, 30(1), 55-91*

Appendix A

Definitions of Variables

Variable	Source	Definition
WeightNonETF Stocks	Refinitiv Institutional Holdings 13-F database & CRSP	Weight of managers' aggregated portfolio invested in Common stocks (CRSP Code 10 and 11) and ADRs (12,30 and 31). Quarterly observation
WeightETF	Refinitiv-13F, CRSP, and CRSP Mutual Fund databases	Weight of managers' aggregated portfolio invested in ETFs (CRSP code 73). Quarterly observation
WeightPassiveETF	Refinitiv-13F, CRSP, and CRSP Mutual Fund databases	Portfolio weight allocated to Passive ETFs, defined as those with an index flag equal to 'D'—in each manager's aggregated holdings.
WeightActiveETF	Refinitiv-13F, CRSP, and CRSP Mutual Fund databases	Portfolio weight allocated to Active ETFs, defined as those with an index flag other than 'D'—in each manager's aggregated holdings
WeightBroadETF	Refinitiv-13F, CRSP, and CRSP Mutual Fund databases	Portfolio allocated to Broad ETFs, using LIPPER_ASSET_CD categories.
WeightSectoralETF	Refinitiv-13F, CRSP, and CRSP Mutual Fund databases	Portfolio allocated to Sectoral ETFs, using LIPPER_ASSET_CD categories.
WeightLeveragedETF	Refinitiv-13F, CRSP, and CRSP Mutual Fund databases	Portfolio allocated to Leveraged ETFs. We classify ETFs as leveraged or inverse-leveraged if their names contain terms such as Leverage, Inverse, Double, Short, Ultra, UltraShort, or explicit leverage ratios (e.g., 4x, 3x, 2.5x, 2x, 1.5x, 1.25x).
WeightNonLeveragedETF	Refinitiv-13F, CRSP, and CRSP Mutual Fund databases	Portfolio allocated to ETFs that are not leveraged.
WeightBlock	Refinitiv-13F and CRSP	Weight of manager's aggregated portfolio invested in block holdings common stocks – once the HF manager surpasses the 5% firm's ownership threshold, the stock is classified as block hold.
Non-ETF	Refinitiv-13F	Non-ETF managers - managers that have not reported any ETF in the four quarters prior the observation
Low-ETF	Refinitiv-13F	If manager is not classified as Non-ETF user - the group below the median proportion of portfolio invested in ETFs over four quarters period

High-ETF	Refinitiv-13F	The group above the median proportion of portfolio invested in ETFs over four quarters periods
Raw Return	HFR	AUM-weighted quarterly raw return at the manager-level.
CAPM Alpha	HFR and Kenneth French's website	Quarterly Capital Asset Pricing Model Alpha, using 24 months to compute factor loadings; Alphas are compounded from the monthly residual returns within each quarter to obtain a quarterly measure.
FH7Alpha	HFR and David Hsieh website	Quarterly FH 7-factor alpha (Fung and Hsieh, 2004).
FF3 Alpha	HFR and Kenneth French's website	Quarterly Fama French 3-factor Alpha. (Carhart,1997)
Carhart4 Alpha	HFR and Kenneth French's website	Quarterly Carhart 4-factor Alpha. (Fama andFrench, 1993)
PS Alpha	HFR and Kenneth French's and Robert Stambaugh's websites	Quarterly Pastor-Stambaugh factor Alpha. FF3 model augmented with PF liquidity factor (Pastor & Stambaugh,2003)
FF3-Vix Alpha	HFR, Kenneth French's websites and Bloomberg.	Quarterly FF3-Vix Alpha. FF3 model augmented with monthly changes on VIX index factor.
13F Non-ETF Return	Refinitiv-13F and CRSP	Value-weighted quarterly return on hedge fund 13F holdings excluding ETFs, based on end-of-quarter portfolio weights and subsequent stock returns.
13F ETF Return		Value-weighted quarterly return on hedge fund 13F ETF holdings, based on end-of-quarter portfolio weights and subsequent ETF returns.
|URC|	Refinitv 13-Fand HFR (Agarwal et al. 2009)	The absolute value of gross-of-fee returns minus the equity portfolio return
Active Shares	Refinitiv-13F	The deviation of portfolio holdings from the holdings of the S&P 500 Index. The approach is similar to that of Cremers and Petajisto (2009). For each HF manager, the value-weighted sum of the deviations in each stock is summer up across stocks and divided by two. A value closer to 1 indicates that the manager is highly active compared to benchmark. A value close to zero indicates that the manager follows the benchmark closely.

Transient	Brian Bushee's web page	A variable that indicates if the Hedge Fund manager is classified as transient institutional investor
Quasi-Indexer	Brian Bushee's web page	A variable that indicates if the Hedge Fund manager is classified as quasi-indexer institutional investor
Dedicated	Brian Bushee's web page	A variable that indicates if the Hed Fund manager is classified as dedicated institutional investor
Turnover	Refinitiv-13F	Manager quarterly turnover rate (more details on Gaspar et al. 2005,2012).
Flow	HFR	Asset-Weight aggregated quarterly flows.
ΔNonETF Holdings	HFR, Refinitiv-13F and CRSP	Quarterly changes in Non-ETF stocks under management less the total return of Non-ETF stocks over the quarter divided by the total equity value under management in the previous quarter (t-1).
ΔETF Holdings	HFR, Refinitiv-13F and CRSP	Quarterly changes in ETF stocks under management less the total return of ETF stocks over the quarter divided by the total equity value under management in the previous quarter (t-1).
Non-ETF	Refinitiv-13F	Non-ETF User - managers that have not reported any ETF in the four quarters prior the observation
Low-ETF	Refinitiv-13F	If manager is not classified as Non-ETF user - the group below the median proportion of portfolio invested in ETFs over four quarters period
High-ETF		The group above the median proportion of portfolio invested in ETFs over four quarters periods
LogAsset	Refinitiv-13F and CRSP	Logged assets under management (AUM) in each quarter.
Number_Securities	Refinitiv-13F and CRSP	The total number of different securities held by the manager in each quarter - Common stocks, ADRs and ETFs.
UnobservedAssetsRatio	Refinitiv-13F and HFR	Total assets under management from the HFR dataset divided by the total value of equities reported in Form 13F filings

Incentive fee	HFR	The AUM-weighted carried interest performance fee in percentage for management compensation.
Management fee	HFR	The AUM-weighted fixed fee in percentage for management compensation
Auditing	HFR	The percentage of managers' AUM allocated in audited funds.
Offshore	HFR	The percentage of managers' AUM allocated in Offshore vehicles in each quarter.
Advance Notice	HFR	The number of days required for redemptions.
Lockup Period	HFR	The length of time that new investor cannot redeem assets
Age (years)	HFR	The number of years between the current date minus the funds' inception day
Minimum Investment	HFR	Funds' minimum investment required.
Number of Funds	HFR	The number of live funds that the manager has in each quarter.
Fund of Fund Dummy	HFR	A dummy variable equal to one if the investor has some fund of fund reported in the HFR dataset in a given quarter.
Sharpe Ratio	HFR	Weighted-average Sharpe Ratio for each hedge fund manager. The Sharpe ratio is the quarter's excess return (r-rf) divided by the within-quarter standard deviation of monthly excess return converted to quarterly scale. Values reported on a quarterly, non-annualized basis.
DerivativeFlag	HFR	Funds are flagged with a dummy variable equal to one if their strategy description contains any of the following terms: derivative, option, future, swap, forward, overlay, or synthetic. We then compute an AUM-weighted measure at the manager's level, aggregating across funds according to each fund's size
LongShortFlag	HFR	Funds are flagged with a dummy variable equal to one if their strategy description contains any of the following terms: long-short, long short, market neutral, and low net exposure.

LeverageFlag	HFR	Funds are assigned a dummy variable equal to one if they report any use of leverage according to the HFR leverage flag

Appendix B

Regression output for expected flows

Predictor variables:	Dependent Variable: $Flow_t$
$Return_{t-1}$	0.289***
	(10.941)
$Return_{t-2}$	0.214***
	(7.992)
$Return_{t-3}$	0.141***
	(5.753)
$Return_{t-4}$	0.116***
	(5.473)
$Flow_{t-1}$	0.138***
	(6.275)
$Flow_{t-2}$	0.089***
	(5.379)
$Flow_{t-3}$	0.023
	(1.238)
$Flow_{t-4}$	0.038*
	(1.951)
Observations	13302
R-squared	0.171
Manager FE	Yes

This table presents the results from estimating Equation (2). Hedge fund managers' quarterly flows are regressed on four quarterly lags of raw returns and four quarterly lags of flows. All models include firm fixed effects, and standard errors are clustered at the manager and year-quarter levels.

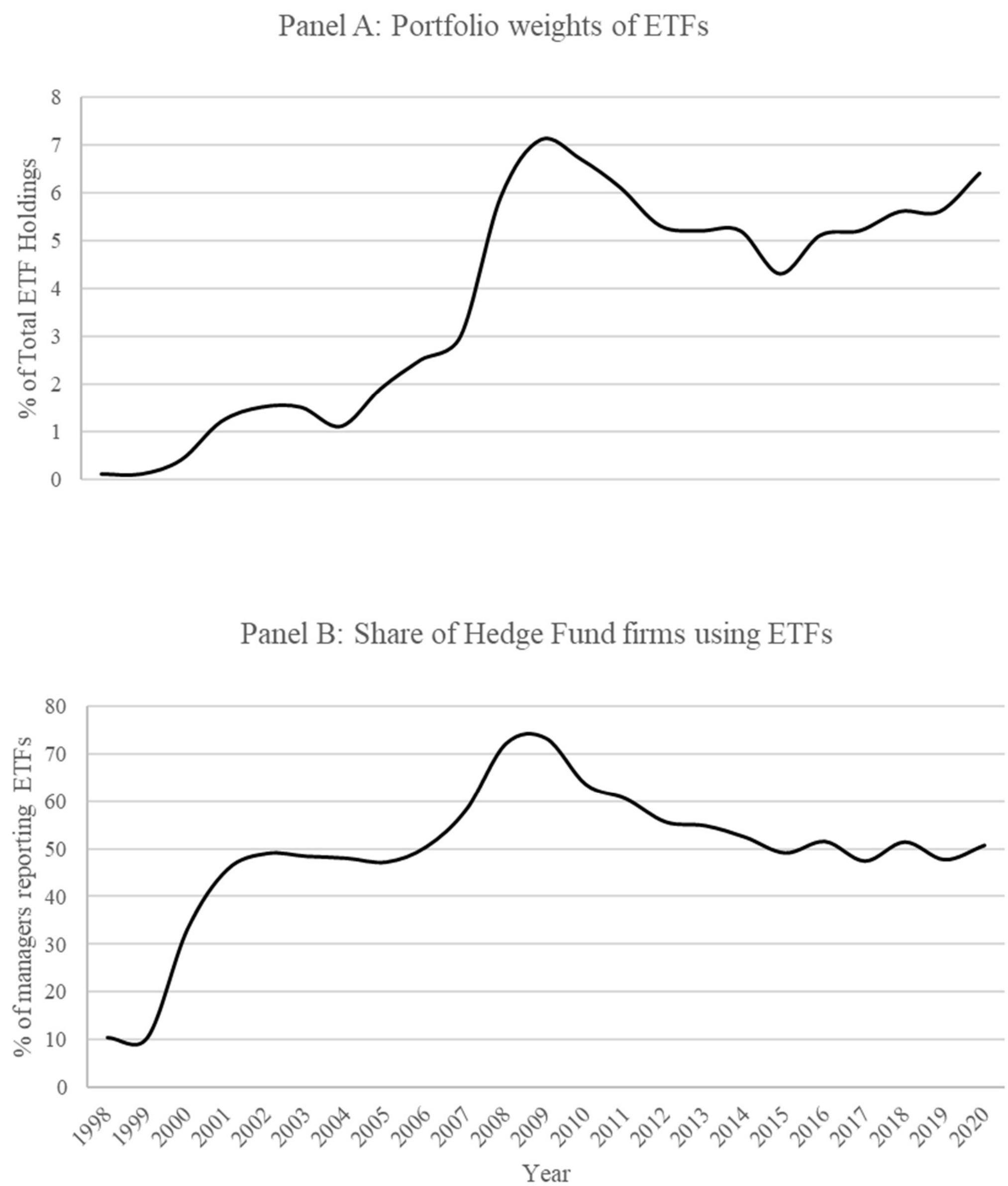

Figure 1 - This figure shows the evolution of ETF usage in hedge fund equity portfolios between 1998 and 2020. Panel A plots the average ETF portfolio weight; Panel B shows the share of hedge fund firms reporting ETF holdings in 13F filings

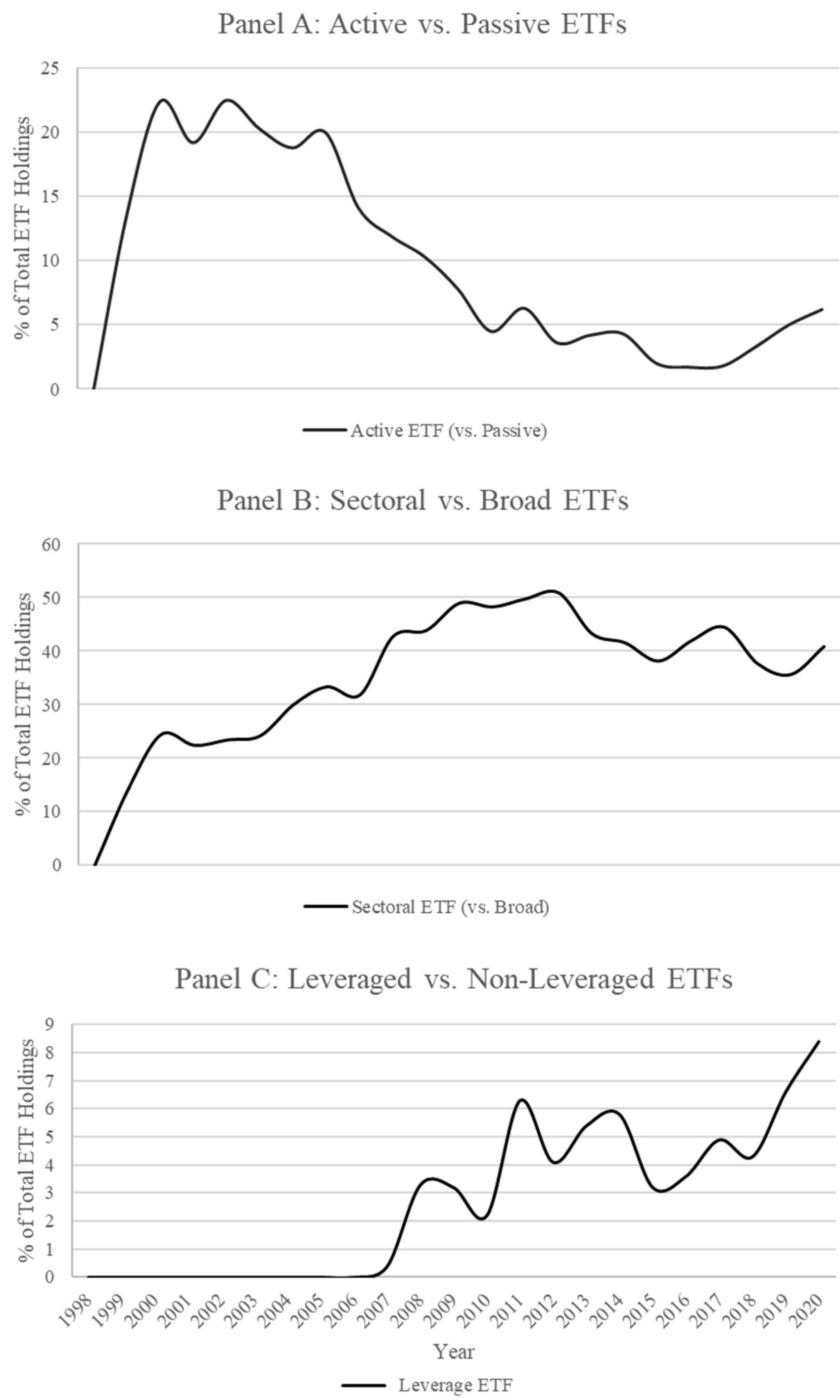

Figure 2 - This figure presents the share of hedge fund ETF holdings across different ETF categories from 1998 to 2020. Panel A reports the percentage of holdings in Active ETFs (with Passive ETFs as the complement). Panel B reports the percentage of holdings in Sectoral ETFs (with Broad ETFs as the complement). Panel C reports the percentage of holdings in Leveraged ETFs (with Non-Leveraged ETFs as the complement).

Table 1
Summary Statistics – Quarterly Observations

	N	Mean	Std. Dev.	Median	p5	p25	p75	p95
Panel A. Composition of Equity Holdings								
WeightNonETF	14950	0.955	0.137	1.000	0.732	0.985	1.000	1.000
WeightETF	14950	0.045	0.137	0.000	0.000	0.000	0.015	0.268
WeightPassiveETF	14950	0.041	0.134	0.000	0.000	0.000	0.009	0.255
WeightActiveETF	14950	0.002	0.017	0.000	0.000	0.000	0.000	0.003
WeightBroadETF	14950	0.029	0.111	0.000	0.000	0.000	0.001	0.175
WeightSectoralETF	14950	0.014	0.056	0.000	0.000	0.000	0.000	0.070
WeightNonLeveragedETF	14950	0.043	0.136	0.000	0.000	0.000	0.014	0.263
WeightLeveragedETF	14950	0.001	0.010	0.000	0.000	0.000	0.000	0.000
Panel B. Performance, Risk, and Unobserved Returns								
Funds' Return (%)	14505	1.553	7.500	1.724	-11.366	-1.558	4.992	13.140
13F Non-ETF Return (%)	14941	3.018	13.330	3.514	-20.442	-2.717	9.675	22.913
13F ETF Return (%)	6108	1.525	11.810	2.426	-19.220	-2.883	7.020	17.267
CAPM Alpha (%)	14372	0.171	5.121	0.283	-9.180	-2.426	2.806	9.249
FH7 Alpha (%)	14372	0.314	5.782	0.361	-10.282	-2.650	3.205	10.735
FF3 Alpha (%)	14372	0.109	5.107	0.216	-9.202	-2.548	2.674	9.166
Carhart Alpha (%)	14372	0.269	5.135	0.351	-9.198	-2.362	2.896	9.463
PS Alpha (%)	14372	0.148	5.220	0.196	-9.245	-2.578	2.791	9.478
VIX Alpha (%)	14372	0.063	5.000	0.091	-9.804	-2.717	2.644	9.176
Sharpe Ratio	14503	0.735	2.314	0.460	-2.250	-0.519	1.599	4.688
Volatility (%)	14503	4.909	4.256	3.649	0.736	1.996	6.373	13.579
Downside Volatility (%)	11830	3.432	3.932	2.120	0.093	0.825	4.510	11.467
|URC|	14373	6.170	6.039	4.214	0.326	1.731	8.719	19.256
Panel C. Funds' characteristics								
Weight Block	14950	0.065	0.147	0.000	0.000	0.000	0.052	0.382
Turnover	14950	0.222	0.156	0.191	0.018	0.092	0.326	0.551
Active Share	14875	0.920	0.114	0.963	0.685	0.896	0.993	1.000
AUM ($Million)	14950	907.481	1912.275	273.985	33.665	116.278	752.200	4027.593
Number Securities	14950	124.425	209.204	50.000	9.000	25.000	115.000	560.000
UnobservedAssetsRatio	14950	1.509	1.682	1.021	0.117	0.462	1.751	5.261
Incentive Fee (%)	14834	18.042	5.095	20.000	2.986	20.000	20.000	20.000
Management Fee (%)	14850	1.395	0.410	1.500	0.900	1.000	1.549	2.000
Auditing	14950	0.928	0.233	1.000	0.209	1.000	1.000	1.000
Offshore	14950	0.338	0.394	0.126	0.000	0.000	0.679	1.000
Advance Notice (days)	14917	47.475	24.319	45.000	10.000	30.000	60.000	90.000
Lockup Period (months)	14907	6.143	7.225	3.000	0.000	0.000	12.000	13.484
Age (Years)	14950	9.015	5.456	8.057	1.951	4.819	12.037	20.011
Min Investments ($Million)	14933	1.924	3.079	1.000	0.250	0.635	1.474	5.000
Number of Funds	14950	2.525	2.053	2.000	1.000	1.000	3.000	7.000
Fund of Fund Dummy	14950	0.040	0.197	0.000	0.000	0.000	0.000	0.000
DerivativeFlag	14950	0.286	0.416	0.000	0.000	0.000	0.000	1.000
LongShortFlag	14950	0.078	0.246	0.000	0.000	0.000	0.000	0.943
LeverageFlag	14939	0.587	0.463	.962	0.000	0.000	1.000	1.000
Flow Total (%)	13302	0.119	14.672	-0.225	-19.064	-4.154	3.287	18.656
Expected Flow (%)	13302	0.119	6.073	-0.142	-8.574	-3.023	2.867	9.124
Unexpected Flow (%)	13302	0.000	13.356	-0.334	-17.266	-4.536	3.768	15.562
Panel D. Investment Styles and Strategies								
Transient	14665	0.657	0.475	1.000	0.000	0.000	1.000	1.000
Quasi-Indexer	14665	0.293	0.455	0.000	0.000	0.000	1.000	1.000
Dedicated	14665	0.030	0.170	0.000	0.000	0.000	0.000	0.000
Equity_Hedge	14950	0.657	0.455	1.000	0.000	0.000	1.000	1.000

Event_Driven	14950	0.164	0.361	0.000	0.000	0.000	0.000	1.000
Macro	14950	0.048	0.201	0.000	0.000	0.000	0.000	0.487
Relative_Value	14950	0.100	0.279	0.000	0.000	0.000	0.000	1.000
Risk_Parity	14950	0.004	0.053	0.000	0.000	0.000	0.000	0.000
Fund_of_funds	14950	0.027	0.151	0.000	0.000	0.000	0.000	0.000

This table summarizes the statistics for the sample of 631 hedge fund managers from 1998 to 2020. Equity composition is based on managers' 13F filings. Performance and risk measures are quarterly, constructed by compounding monthly returns within each calendar quarter. All metrics are aggregated to the manager, quarter level using AUM-weighted averages across the manager's funds, with weights from HFR-reported quarterly AUM. Variables are defined in Appendix A.

Table 2
Most Popular ETFs among Hedge Fund Managers

Rank	Fund Name	Benchmark	Expense Ratio	Ticker
1	SPDR S&P ETF Trust	S&P 500	0.10%	SPY
3	SPDR Gold Trust:	Gold bullion	0.40%	GLD
3	Vanguard International EM Index	FTSE EM	0.18%	VWO
4	iShares MSCI EM Index	MSCI EM	0.70%	EEM
5	iShares MSCI EAFE Index	MSCI EAFE	0.34%	EFA
6	SPDR S&P Midcap 400 ETF Trust	S&P Midcap 400	0.24%	MDY
7	iShares Russell 2000 ETF	Russell 2000	0.20%	IWM
8	iShares Core S&P 500 Index	S&P 500	0.08%	IVV
9	Invesco QQQ	Nasdaq-100	0.20%	QQQ
10	iShares iBoxx High Yield Corp Bonds	Markit iBoxx Liquid HY Index	0.50%	HYG
11	iShares iBoxx Investment Grade Corp Bond	Markit iBoxx Liquid IG Index	0.15%	LQD
12	VanEck Vectors Gold Miners	NYSE Arca Gold Miner	0.53%	GDX
13	iShares Core MSCI Emerging Market	MSCI EM Investable Market Index	0.14%	IEMG
14	Vanguard 500 Index Fund	S&P 500	0.04%	VFIAX
15	Financial Sector SPDR Fund	Financial Sector S&P 500	0.19%	XLF
16	Energy Select Sector SPDR Fund	Energy Sector S&P 500	0.19%	XLE
17	iShares Russell 1000 Value Index	Russell 1000 Value	0.20%	IWD
18	iShares Brazil	MSCI 25/50 Brazil	0.69%	EWZ
19	iShares S&P MidCap 400 Index	S&P 400 MidCap Index	0.16%	IJH
20	Vanguard FTSE Developed Market	FTSE Developed Market Index	0.09%	VEA

This table lists the ETFs with the largest aggregate 13F dollar holdings in our sample. Rankings sum positions across managers and quarters. Columns: Benchmark (tracked index), Expense ratio (total), Ticker (symbol). Data are PERMNO-level. When an ETF changed name/CUSIP, we report the latest name for that PERMNO (e.g., PowerShares QQQ → Invesco QQQ, 2018).

Table 3

Fractional logit regression Analysis of Investment Style: Weight ETF as the Dependent Variable

Dep. variable	*$WeightETF_t$*	
	(1)	(2)
$Transient_t$	0.523***	
	(2.610)	
$Quasi\text{-}Indexer_t$	0.196	
	(0.969)	
$Turnover_t$		0.613***
		(2.726)
$ActiveShares_t$	-4.737***	-4.551***
	(-16.302)	(-16.63)
$AvgFlow_{t,t-5}$	0.007***	0.006**
	(2.636)	(2.411)
$Ln(AUM)_t$	-0.305***	-0.300***
	(-11.084)	(-10.83)
$Ln(NumberSecurities)_t$	-0.255***	-0.235***
	(-6.624)	(-6.246)
UnobservedAssetsRatio	0.121***	0.144***
	(6.820)	(8.308)
$IncentiveFee_t$ (%)	-0.006	-0.011**
	(-1.342)	(-2.456)
$ManagementFee_t$ (%)	0.245***	0.276***
	(2.659)	(2.941)
$Auditing_t$	0.368***	0.436***
	(3.603)	(4.143)
$Offshore_t$	-0.191**	-0.274***
	(-2.462)	(-3.476)
$AdvanceNotice_t$	-0.009***	-0.009***
	(-5.129)	(-5.542)
$LockupPeriod_t$	-0.066***	-0.063***
	(-13.901)	(-13.71)
Age_t	0.095*	0.067
	(1.919)	(1.387)
$Ln(MinimumInvestment)_t$	0.408***	0.363***
	(10.909)	(9.537)
$Ln(NumberFunds)_t$	0.001	0.0699
	(0.020)	(1.485)
$FOFDummy_t$	1.699***	1.585***
	(14.303)	(13.23)
_cons	-7.826***	-7.186***
	(-7.616)	(-7.040)
Observations	13,400	13,625
Pseudo R^2	0.142	0.139
YearQtr FE	Yes	Yes

This table presents the results of a fractional logit regression of the determinants of the quarterly weight managers' total portfolio invested in ETFs. Coefficients are reported in terms of fractional logit regression coefficients. The dependent *WeightETF* Variable is the total market value of the ETFs held by hedge fund managers, divided by the total asset under management (AUM) reported by the invested at the end of a quarter. All other explanatory variables are defined in Appendix. Column (1) presents the results when the investment style is measured by Bushee's classification (Bushee 1998). Comparison category is Dedicated HFs. Columns (2) present the results when the investment style is measured by portfolio turnover (Carhart,1997; Gaspar et al. 2005). Dummy variables are included for the observation year-quarter. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table 4
Fractional logit regression Analysis of Fund Strategy: Weight ETF as the Dependent Variable

Dep. Variable	*$WeightETF_t$*					
	(1)	(2)	(3)	(4)	(5)	(6)
$Equity\_Hedge_t$	-0.820***					
	(-12.377)					
$Event\_Driven_t$		-1.118***				
		(-11.956)				
$Macro_t$			1.706***			
			(20.401)			
$Relative\_Value_t$				0.281***		
				(3.085)		
$Risk\_Parity_t$					1.964***	
					(5.813)	
$Fund\_of\_Funds_t$						2.835***
						(9.112)
Other Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,625	13,625	13,625	13,625	13,625	13,625
Pseudo R^2	0.149	0.146	0.163	0.139	0.141	0.147
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of a fractional logit regression analyzing the determinants of the quarterly weight of hedge fund managers' total portfolios allocated to ETFs. The key variable of interest is the value-weighted average of hedge fund characteristics, calculated using the AUM reported by the HFR dataset for funds employing the following strategies: Equity Hedge, Event-Driven, Fund of Funds, Macro, Relative Value, and Risk Parity. The dependent variable, WeightETF, represents the total market value of ETFs held by hedge fund managers divided by the total assets under management (AUM) reported at the end of each quarter. Dummy variables for the observation year are included. Robust t-statistics are shown in parentheses, with significance levels indicated as ***p<0.01, **p<0.05, and *p<0.1.

Table 5

Within-fund NON_ETF versus ETF performance: Value-weighted quarterly performance

Type of HF Manager	N	13F Non-ETF Return (%)	13F ETF Return (%)	Diff	St Err	t value
Full Sample	6099	2.913	1.525	1.389	0.154	9.047***
High-ETF	3481	2.763	1.549	1.214	0.179	6.756***
Low-ETF	2618	3.113	1.492	1.621	0.266	6.093***
Transient	4143	2.831	1.381	1.450	0.187	7.766***
Quasi-Indexer	1726	3.091	1.779	1.312	0.283	4.641***
Dedicated	81	4.420	2.514	1.906	1.291	1.477
Equity_Hedge	3572	3.328	1.565	1.763	0.213	8.270***
Event_Driven	656	2.009	0.819	1.190	0.526	2.260**
Macro	568	2.735	1.585	1.151	0.392	2.940***
Relative_Value	888	1.881	1.541	0.340	0.380	0.896
Risk_Parity	51	3.348	1.258	2.090	0.689	3.033***
Fund_Of_Funds	305	2.924	2.342	0.582	0.287	2.030**
Rank_Size1	1620	3.014	1.313	1.701	0.324	5.257***
Rank_Size2	1208	3.232	1.644	1.588	0.339	4.692***
Rank_Size3	1352	2.791	1.804	0.987	0.332	2.980***
Rank_Size4	1919	2.714	1.431	1.283	0.252	5.091***

This table provides a summary of the within fund return differences between the hedge fund portfolios of Non-ETF stocks (including common stocks and ADRs) and ETF stocks. The hedge fund managers are divided into two groups based on their proportion of investments in ETFs: High-ETF represents managers with an investment proportion above the median, while Low-ETF represents those with a proportion below the median over four quarters. Hedge fund managers are classified as Transient, Quasi-indexer, and Dedicated based on Bushee's (1998) classification. The sample by strategy is organized based on the total AUM for each fund strategy at the manager level, following the approach described by Ben-David et al. (2010). Funds are categorized in each group if 50% of their assets or more are classified under the corresponding strategy corresponding strategy. The Rank Size sample is divided based on the portfolio size, which is determined by the assets under management (AUM) for each hedge fund manager on a quarterly basis, using the HR dataset. Rank_Size1 represents the bottom quartile, while Rank_Size4 represents the top quartile. Statistical significance is denoted by ***, **, and *, representing 1%, 5%, and 10% significance levels, respectively.

Table 6
Performance measured by CAPM Alpha, FH7 Factor Alpha, and Raw returns are dependent variable.

	Full Sample			Excluding Non-ETF Managers		
Dependent Variable	CAPM $Alpha_{t+1}$	FH7 $Alpha_{t+1}$	Raw $Return_{t1+}$	CAPM $Alpha_{t+1}$	FH7 $Alpha_{t+1}$	Raw $Return_{t1+}$
	(1)	(2)	(3)	(4)	(5)	(6)
$WeightEtf_t$	-1.132*	-1.333*	-2.568***	-1.502**	-1.601*	-2.907**
	(-1.888)	(-1.861)	(-2.636)	(-2.207)	(-1.978)	(-2.619)
$WeightBlock_t$	-0.569	-0.822	-0.945	0.265	-0.785	-0.640
	(-0.816)	(-0.900)	(-1.205)	(0.239)	(-0.521)	(-0.432)
$Turnover_t$	-0.120	-0.140	0.342	-0.514	-0.795	-0.083
	(-0.247)	(-0.261)	(0.514)	(-0.988)	(-1.226)	(-0.098)
$ActiveShares_t$	-2.071	0.207	0.212	-3.477*	-2.046	-2.341
	(-1.077)	(0.119)	(0.100)	(-1.681)	(-0.959)	(-1.024)
$Ln(AUM)_t$	-0.903***	-0.891***	-1.164***	-0.971***	-0.960***	-1.102***
	(-6.789)	(-6.803)	(-6.991)	(-6.081)	(-5.237)	(-5.699)
$Ln(NumberSecurities)_t$	0.035	0.088	0.029	0.013	-0.049	-0.087
	(0.251)	(0.516)	(0.161)	(0.069)	(-0.230)	(-0.419)
UnobservedAssetsRatio	0.024	0.000	-0.050	0.040	0.068	-0.078
	(0.459)	(0.007)	(-0.582)	(0.561)	(0.885)	(-0.739)
$IncentiveFee_t$	0.046	0.047	0.018	0.019	0.018	0.008
	(1.366)	(1.326)	(0.334)	(0.468)	(0.428)	(0.147)
$ManagementFee_t$	0.184	0.198	0.134	0.340	0.065	0.480
	(0.349)	(0.398)	(0.221)	(0.544)	(0.096)	(0.676)
$Auditing_t$	0.239	0.041	0.101	0.643	0.590	0.464
	(0.392)	(0.079)	(0.114)	(0.752)	(0.689)	(0.405)
$Offshore_t$	0.562	-0.196	0.303	0.677	0.498	-0.227
	(1.086)	(-0.344)	(0.538)	(0.970)	(0.633)	(-0.247)
$AdvanceNotice_t$	0.017*	0.004	0.018	0.008	0.002	-0.001
	(1.939)	(0.547)	(1.526)	(0.471)	(0.094)	(-0.035)
$LockupPeriod_t$	-0.002	-0.027	0.012	-0.026	0.003	-0.036
	(-0.043)	(-0.707)	(0.325)	(-0.449)	(0.043)	(-0.510)
Age_t	-0.227	-0.284	-0.202	-0.154	-0.152	-0.433
	(-1.231)	(-1.317)	(-0.933)	(-0.631)	(-0.609)	(-1.395)
$Ln(MinimumInvestment)_t$	0.485***	0.324*	0.315	0.327	0.496*	0.155
	(3.193)	(1.930)	(1.558)	(1.509)	(1.935)	(0.661)
Ln(NumberFunds)	0.058	0.021	0.132**	0.114**	0.048	0.181**
	(1.450)	(0.452)	(2.451)	(1.988)	(0.763)	(2.582)
$FOFDummy_t$	0.019	0.239	-0.908	-0.476	0.601	-1.324
	(0.014)	(0.230)	(-0.491)	(-0.319)	(0.532)	(-0.851)
$Alphas\text{-}Returns_t$	0.025	-0.014	-0.013	0.003	-0.045	-0.040
	(0.998)	(-0.613)	(-0.409)	(0.099)	(-1.621)	(-0.870)
_cons	-0.933	0.150	4.045	4.716	-1.148	12.712**
	(-0.232)	(0.034)	(0.721)	(0.887)	(-0.227)	(2.424)
Observations	14,003	14,003	14,172	7,395	7,395	7,474
R-squared	0.198	0.154	0.422	0.234	0.196	0.444
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of OLS regressions on the determinants of managers' performance, measured by CAPM alphas, FH7 alphas, and raw returns, for the full sample from 1998 to 2020. All explanatory variables are defined in Appendix Table 1. Quarterly alphas are constructed by first estimating factor loadings using the 24 months preceding each quarter, then obtaining monthly alphas and compounding them to compute quarterly values. Columns (1)–(3) report results for the full sample, while Columns (4)–(6) restrict the sample to managers who have invested in ETFs during at least one of the four quarters prior to the observation (i.e., excluding Non-ETF users). We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset. All regressions include manager and calendar year–quarter fixed effects. Standard errors are clustered at both the manager and calendar year–quarter levels, and robust t-statistics are reported in parentheses. Statistical significance is denoted as ***p<0.01, **p<0.05, and *p<0.1.

Table 7
Unexpected and Expected flows and changes on ETFs holdings

	Full Sample				Excluding Non-ETF Managers			
Dependent Variable	ΔETF Holdings$_t$		ΔNonETF Holdings$_t$		ΔETF Holdings$_t$		ΔNon-ETF Holdings$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(A) UnexpectedFlow$_t$	0.013**	0.015**	0.262***	0.252***	0.023**	0.026**	0.235***	0.217***
	(2.152)	(2.472)	(7.112)	(6.879)	(2.246)	(2.432)	(5.732)	(5.108)
(B) ExpectedFlow$_t$	0.003	0.006	0.395***	0.574***	0.004	0.000	0.272**	0.559***
	(0.228)	(0.426)	(4.913)	(5.752)	(0.150)	(0.015)	(2.572)	(4.003)
(A) minus (B)	0.010	0.009	-0.133*	-0.322***	0.019	0.026	-0.037	-0.342**
	(0.670)	(0.600)	(-1.760)	(-3.330)	(0.710)	(0.910)	(-0.370)	(-2.530)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,124	13,123	13,124	13,123	7,196	7,184	7,196	7,184
R-squared	0.104	0.244	0.038	0.184	0.110	0.272	0.033	0.211
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes
YearQtr FE	No	Yes	No	Yes	No	Yes	No	Yes

This table presents the results of an OLS regression of the determinants of changes on ETFs and Non-ETF stocks adjusted by the return in each quarter. Changes are scaled by the total asset under management reported by the investor in the previous quarter (t-1). To measure unexpected and expected flow, we rely on the methodology presented by Fung et al. (2008). (A) minus (B) represents the difference between coefficients of Unexpected Flows (A) and Expected Flows (B). All other explanatory variables are defined in Appendix Table 1. Columns (1)-(4) present the results for the total sample. Columns (5)-(8) report the results of the sample excluding managers that did not invest in ETFs in the four-quarter previous the observation (NonETF=1). We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset We use manager and year-quarter fixed effect. Standard errors are clustered at the manager and year-quarter levels. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table 8
Expected and Unexpected Flows and fund Performance measured.

	Full Sample			Excluding Non-ETF managers		
	CAPM Alpha$_{t+1}$	FH7 Alpha$_{t+1}$	Raw Return$_{t1+}$	CAPM Alpha$_{t+1}$	FH7 Alpha$_{t+1}$	Raw Return$_{t1+}$
	(1)	(2)	(3)	(4)	(5)	(6)
WeightEtf$_t$	-1.179*	-1.299*	-2.609***	-1.459**	-1.650**	-2.843***
	(-1.852)	(-1.755)	(-3.285)	(-2.240)	(-2.179)	(-3.480)
UnexpectedFlow$_t$* Weigh Etf$_t$	0.054**	0.041	0.063**	0.051**	0.042*	0.060**
	(2.474)	(1.597)	(2.306)	(2.356)	(1.664)	(2.213)
ExpectedFlow$_t$* WeightEtf$_t$	-0.084	-0.048	0.069	-0.090	-0.081	0.099
	(-1.068)	(-0.593)	(0.798)	(-1.312)	(-1.024)	(1.161)
UnexpectedFlow$_t$	0.002	0.006	0.000	0.002	0.003	-0.000
	(0.483)	(1.482)	(0.094)	(0.381)	(0.650)	(-0.051)
ExpectedFlow$_t$	-0.028**	0.006	-0.012	-0.036**	0.010	-0.037*
	(-2.047)	(0.414)	(-0.713)	(-2.183)	(0.534)	(-1.665)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,697	12,697	12,725	6,940	6,940	6,960
R-squared	0.195	0.149	0.426	0.235	0.194	0.448
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of an OLS regression of the determinants of managers' performance, measured by CAPM and FH7 alphas and raw performance, and unexpected and expected flows for 1998-2020. To measure unexpected and expected flow, we rely on the methodology presented by Fung et al. (2008). All the models include all HF control variables presented in the Appendix. Columns (1)-(3) present the results for the total sample. Columns (4)-(6) report the results of the sample excluding managers that have not invested in ETFs in the four-quarter previous the observation (Non-ETF) users. We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset. We use manager and year-quarter fixed effect. Standard errors are clustered at the manager and year-quarter levels. Robust t-statistics errors are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table 9
The Effect of ETFs on Hedge Funds' Unobserved Return Component (URC)

Dep. Variable	$\|URC\|_{t+1}$									
Subsample	Full Sample	Excluding Non-ETF	Transient	Quasi-Indexers	Dedicated	Equity Hedge	Event Driven	Macro	Relative Value	Fund of Funds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$WeightEtf_t$	-1.354**	-1.803**	-1.537**	-1.304	-6.007	-0.505	1.650	-3.643***	-1.118	2.205
	(-1.978)	(-2.436)	(-2.035)	(-0.557)	(-0.548)	(-0.498)	(0.697)	(-3.561)	(-0.696)	(0.447)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,151	7,494	9,206	4,134	417	9,352	2,317	707	1,358	255
R-squared	0.454	0.495	0.478	0.419	0.563	0.483	0.428	0.596	0.474	0.625
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of an OLS regression examining the impact of ETF allocations on Hedge Funds' absolute Unobserved Return Component (|URC|). The URC is defined as the difference between a hedge fund's reported gross-of-fee return and its long-equity portfolio return (Gross Fund Firm $Return_{i,t}$ - Equity PF $Return_{i,t}$) (Agarwal et al., 2024). The dependent variable is the absolute value of the URC. Column (1) shows results for the full sample, while Column (2) excludes Non-ETF Hedge Funds. Columns (3), (4), and (5) present results for Transient, Quasi-Indexer, and Dedicated hedge funds, respectively. Column (6) presents the results for the sample of Equity Hedge investors, while Column (7) focuses on Event Driven hedge funds. Columns (8), (9), and (10) report the results for Relative Value, Macro, and Fund of Funds (FoFs) hedge funds, respectively. Funds are categorized in each group if 50% of their assets or more are classified under the corresponding strategy. All models include control variables specific to the hedge fund firm. Strategy is controlled for by using assets under management at the manager level, each quarter, based on the HRF dataset. We apply calendar year-quarter fixed effects, and standard errors are clustered at the manager and year levels. Robust t-statistics are reported in parentheses: ***p<0.01, **p<0.05, *p<0.1.

Table 10
The role of ETF Heterogeneity

Types of ETFs:	Passive vs. Active			Broad vs. Sectoral			Non-Leveraged vs. Leveraged		
Dep. variable:	CAPM $Alpha_{t+1}$	FH7 $Alpha_{t+1}$	Raw $Return_{t1+}$	CAPM $Alpha_{t+1}$	FH7 $Alpha_{t+1}$	Raw $Return_{t1+}$	CAPM $Alpha_{t+1}$	FH7 $Alpha_{t+1}$	Raw $Return_{t1+}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$WeightPassiveETF_t$	-1.234**	-1.122	-2.793***						
	(-2.037)	(-1.436)	(-3.266)						
$WeightActiveETF_t$	-0.787	-0.058	-1.699						
	(-0.224)	(-0.016)	(-0.211)						
$WeightBroadETF_t$				-1.420*	-1.681*	-3.044***			
				(-1.852)	(-1.797)	(-2.688)			
$WeightSectoralETF_t$				-0.701	0.444	-2.017			
				(-0.591)	(0.382)	(-1.342)			
$WeightNonLeveragedETF_t$							-1.211*	-1.336*	-2.783***
							(-1.943)	(-1.834)	(-2.736)
$WeightLeveragedETF_t$							2.279	-1.226	6.646
							(0.514)	(-0.357)	(1.353)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,003	14,003	14,172	14,003	14,003	14,172	14,003	14,003	14,172
R-squared	0.198	0.154	0.422	0.198	0.154	0.422	0.198	0.154	0.422
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the results of OLS regressions examining the impact of ETF characteristics on hedge fund performance, measured by CAPM alpha, Fama–French 7-factor alpha (FH7 alpha), and raw returns. Models (1)–(3) distinguish between passive and active ETF ownership, models (4)–(6) between broad and sectoral ETF ownership, and models (7)–(9) between non-leveraged and leveraged ETF ownership. ETF weights are defined as the share of the portfolio allocated to each category; for instance, *WeightPassive* represents the percentage of the portfolio invested in passive ETFs, while *WeightActive* captures the share in active ETFs. All regressions include manager and year–quarter fixed effects, and control for investment strategy using strategy-level AUM from the HRF dataset. Variable definitions are provided in Appendix A. Standard errors are clustered at both the manager and calendar year–quarter levels, and robust t-statistics are reported in parentheses. Statistical significance is denoted as ***p<0.01, **p<0.05, and *p<0.1.

Hedge Fund Investment in ETFs

ONLINE APPENDIX

The following tables are included in the online appendix, offering supplementary details on the data and additional robustness checks.

Section OA1. Validation of |URC| as a Proxy for Non-Equity Exposure

In this section, we provide further validation of the absolute value of the unobserved return component (|*URC*|) as a proxy for hedge funds' non-equity exposures. Our objective is to test whether exposures associated with non-equity instruments, such as derivatives, short-selling activity, and leverage, are positively correlated with |*URC*|.

Although our dataset does not provide direct measures of non-equity exposures, Hedge Fund Research (HFR) includes detailed manager-reported strategy descriptions (*Strategy_Description*), which outline each fund's approach and objectives. We manually review these descriptions to identify clues suggesting the use of non-equity instruments and construct two binary indicators: *DerivativeFlag* and *LongShortFlag*. Specifically, a fund is flagged as *DerivativeFlag* = 1 if its description includes terms such as derivative, option, future, swap, or forward. Similarly, a fund is flagged as *LongShortFlag* = 1 if the description references long-short, market neutral, or low net exposure.

In addition, HFR provides a field indicating whether the fund utilizes leverage. From this, we construct *LeverageFlag*, equal to one if HFR reports that the fund employs leverage. Because our analysis is conducted at the manager-level, we compute AUM-weighted averages of each flag across funds managed by the same manager.

Summary statistics (Table 1) show that, on average, managers allocate 28.6% of AUM to funds explicitly mentioning derivative exposures, 7.8% to funds identifying long-short exposures, and 58.7% to funds reporting the use of leverage.

Table OA1 reports whether these flags are associated with |*URC*|. Both *DerivativeFlag* and *LongShortFlag* are positively and statistically significantly related to |*URC*|. The coefficient on *LeverageFlag* is positive but not statistically significant. These results support our expectation that non-long-equity instruments are positively associated with |*URC*|.

We also find that Transient managers and portfolio turnover are positively related to |*URC*|, while Quasi-Indexers are negatively related. This is consistent with the view that short trading horizons and high-frequency trading are linked to non-equity exposures such as derivatives and short-selling (Qian et al., 2025). Strategy-level analysis, presented in Table OA2, further reveals that Macro, Equity Hedge, and Relative Value funds are most strongly associated with derivatives use, while Event-Driven funds are less so. Coefficient estimates show that Macro funds have the strongest positive association with |*URC*|, whereas Event-Driven funds have the weakest, consistent with prior literature (Chen, 2010; Qian et al., 2025).

In addition, other factors attributable to non-equity exposures are positively related to |URC|, including *UnobservedAssetRatio*, minimum investment, *WeightBlock*, number of securities reported in 13F filings, management and incentive fees, auditing, lockup periods, and the presence of a Fund of Funds structure. By contrast, *ActiveShares*, total AUM, advance notice period, and number of funds managed are negatively associated with |*URC*|.

These findings are broadly consistent with prior research. For example, Chen (2010) shows that minimum investment requirements, fees, auditing, and fund age are positively associated with derivatives use, while lockup and notice periods are negatively associated. Our results align with the latter regarding notice periods. Liang and Qiu (2019) document that stronger governance is positively associated with leverage use, consistent with our finding that auditing is positively related to $|URC|$.

Overall, the results presented in this section corroborate the validity of $|URC|$ as a proxy for non-equity exposures. This supports our interpretation that, while not perfect, $|URC|$ captures exposures beyond observable U.S. equities, reflecting hedge funds' use of derivatives, short-selling, and leverage that are otherwise difficult to measure directly.

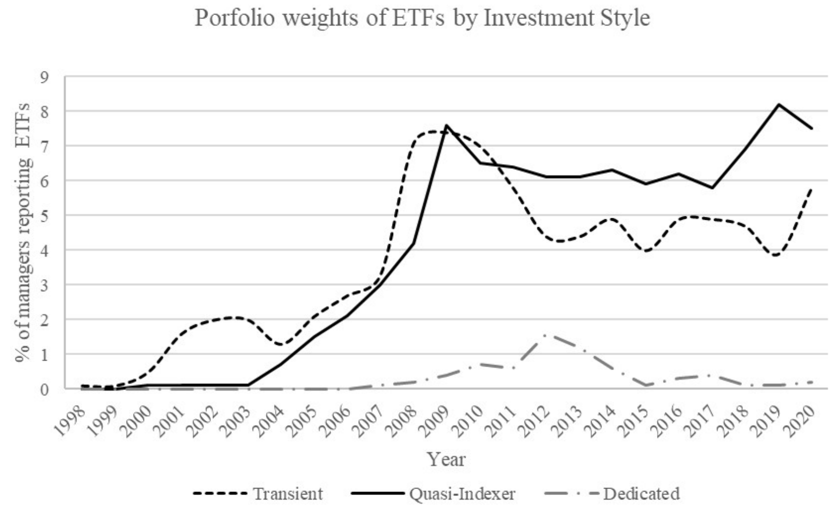

Figure OA1. The figure shows the percentage of managers' equity holdings invested in ETFs from 1998 to 2020, separately for Transient (dashed line), Quasi-Indexer (solid line), and Dedicated (dash–dot line) managers. The vertical axis measures the average ETF portfolio weight, and the horizontal axis denotes calendar years.

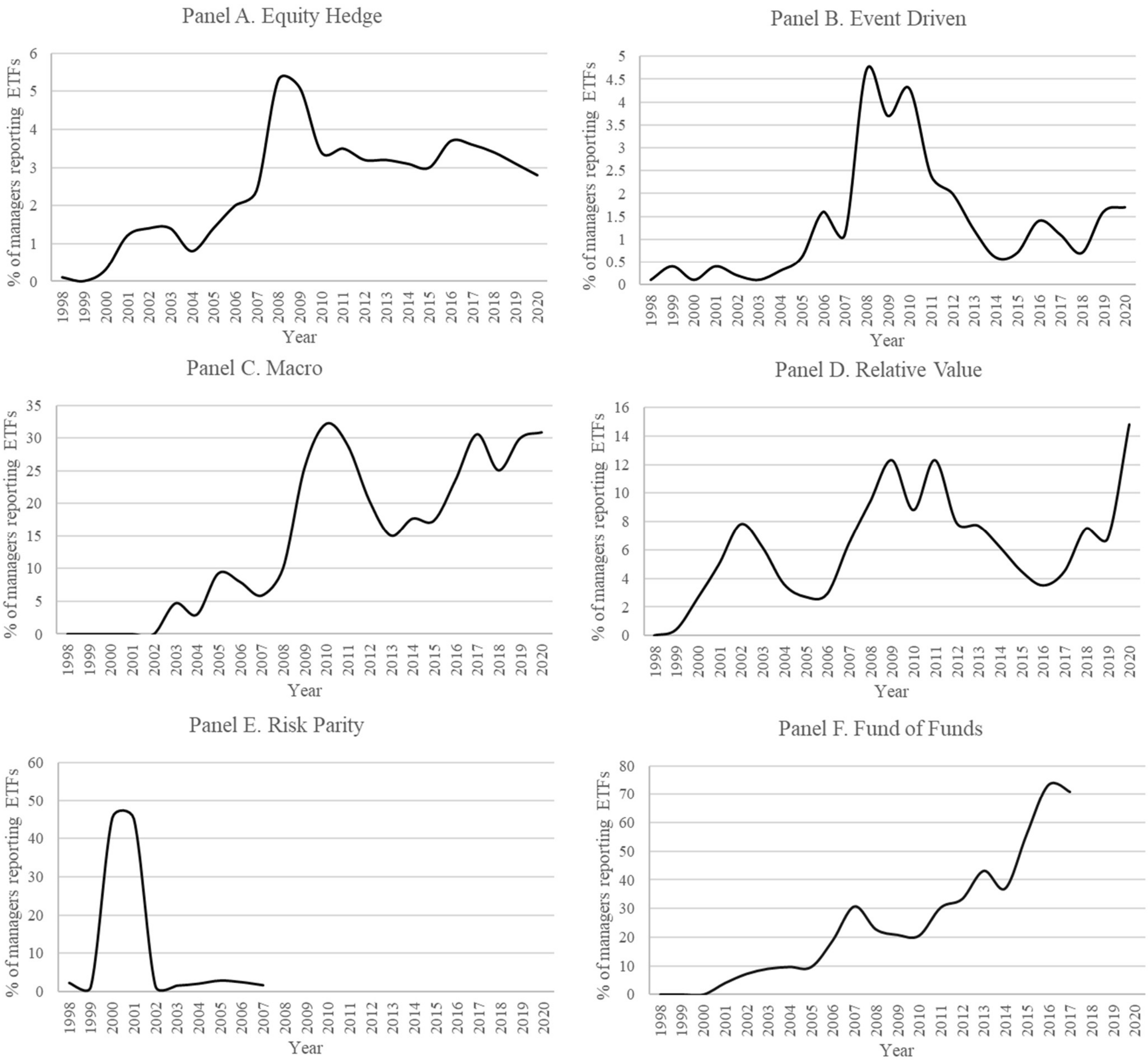

Figure OA2 - The figure plots the percentage of managers' equity holdings invested in ETFs from 1998 to 2020, separately for six hedge fund strategies. Panel A shows Equity Hedge, Panel B Event Driven, Panel C Macro, Panel D Relative Value, Panel E Risk Parity, and Panel F Fund of Funds. Hedge funds are assigned to a given strategy if at least 50% of their assets under management (AUM) are allocated to that category. The vertical axis reports the average ETF portfolio weight, and the horizontal axis denotes calendar years.

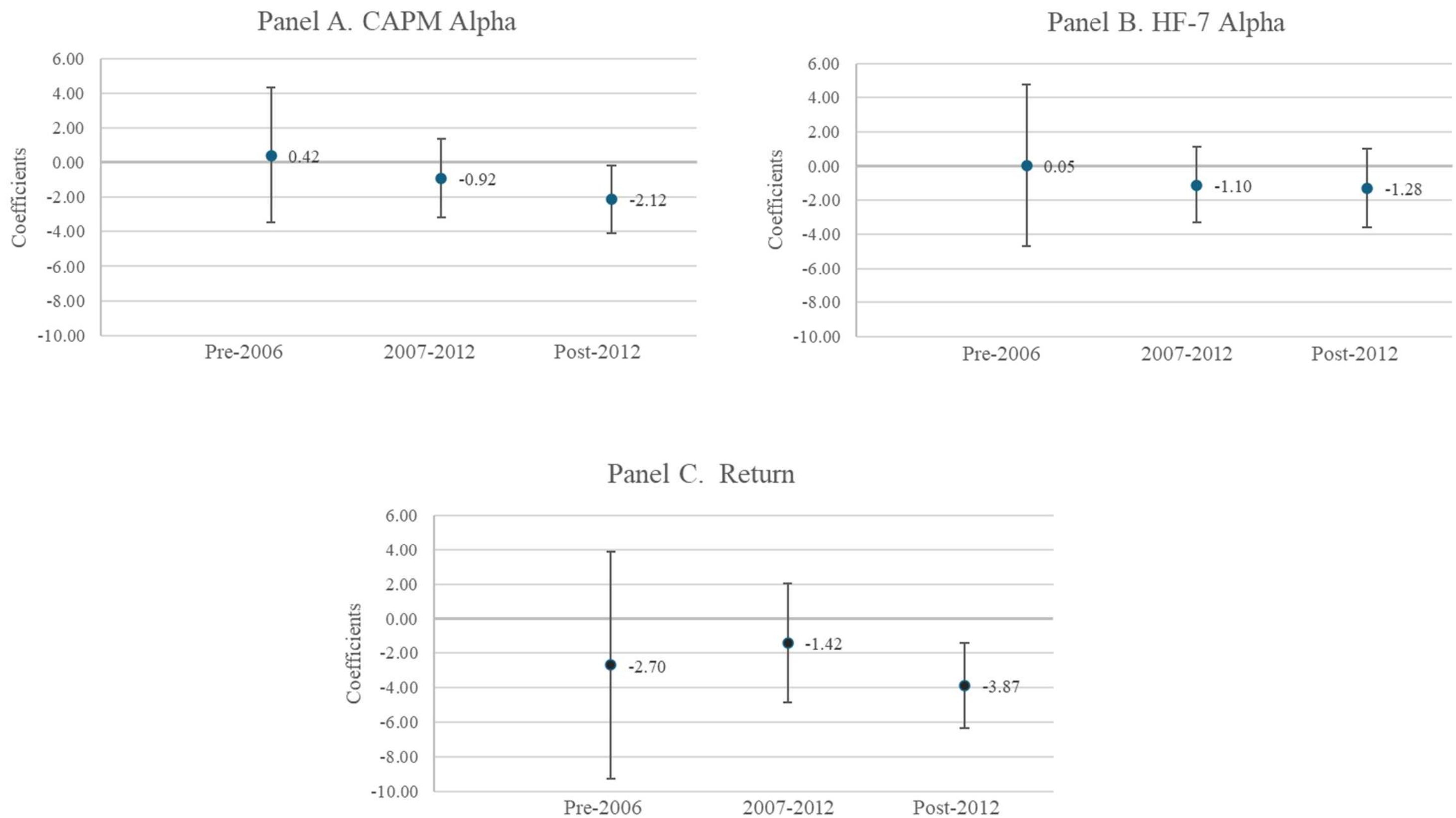

Figure OA3 - This figure plots the estimated coefficients of *WeightETF* from regressions where hedge fund performance is the dependent variable. Panel A reports results using CAPM alphas, Panel B using HF-7 factor model alphas, and Panel C using raw returns, all measured at a quarterly frequency. Estimates are shown separately for the Pre-2006, 2007–2012, and Post-2012 periods. Regressions include control variables as well as firm and year-quarter fixed effects. Dots represent coefficient estimates, and vertical bars denote 90% confidence intervals

Table OA1
Investment Style and Other Determinants of Hedge Fund |URC|

Dep. variable	*|URC|*	
	(1)	(2)
Transient	0.693***	
	(2.859)	
Quasi-Indexer	-0.798***	
	(-3.261)	
Turnover		3.712***
		(11.202)
DerivativeFlag	0.304***	0.297***
	(2.839)	(2.771)
LongShortFlag	0.438***	0.369**
	(2.655)	(2.188)
LeverageFlag	0.065	0.144
	(0.668)	(1.489)
UnobservedAssetsRatio	0.554***	0.531***
	(14.680)	(14.148)
ManagerAge	0.354**	0.481***
	(2.574)	(3.481)
WeightBlock_t	4.530***	4.612***
	(10.707)	(11.230)
ActiveShares_t	-1.048**	-1.034**
	(-2.040)	(-2.010)
Ln(AUM)_t	-0.138***	-0.103**
	(-3.167)	(-2.371)
$\text{Ln(NumberSecurities)}_t$	0.183***	0.093
	(3.067)	(1.507)
IncentiveFee (%)	0.029***	0.019*
	(2.832)	(1.808)
ManagementFee (%)	0.553***	0.640***
	(3.914)	(4.508)
Auditing	0.911***	0.921***
	(5.167)	(5.206)
Offshore	-0.011	0.033
	(-0.081)	(0.245)
AdvanceNotice	-0.010***	-0.010***
	(-4.652)	(-4.804)
LockupPeriod	0.025***	0.025***
	(3.795)	(3.864)
Ln(MinimumInvestment)	0.119**	0.135***
	(2.319)	(2.607)
Ln(NumberFunds)	-0.636***	-0.614***
	(-7.865)	(-7.562)
FOFDummy	0.966***	1.000***
	(4.068)	(4.212)
_cons	3.072***	2.293**
	(3.150)	(2.387)
Observations	14019	14160
Pseudo R^2	0.328	0.323

YearQtrFE FE	Yes	Yes

This table reports the results from OLS regressions examining the determinants of hedge funds' absolute Unobserved Return Component (|URC|). The URC is defined as the difference between a hedge fund's reported gross-of-fee return and its long-equity portfolio return (Gross Fund Firm Return$_{i,t}$ - Equity PF Return$_{i,t}$) (Agarwal et al., 2024). Column (1) presents the results when the investment style is measured by Bushee's classification (Bushee 1998). Comparison category is Dedicated HFs. Columns (2) present the results when the investment style is measured by portfolio turnover (Carhart,1997; Gaspar et al. 2005). Dummy variables are included for the observation year-quarter. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table OA2

Investment Strategy and Other Determinants of Hedge Fund |URC|

Dep. Variable	$\|URC\|_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
EquityHedge	0.463***					
	(3.874)					
EventDriven		-1.564***				
		(-11.846)				
Macro			1.695***			
			(7.004)			
RelativeValue				0.606***		
				(3.329)		
RiskParity					1.154*	
					(1.929)	
FundofFunds						-0.489
						(-0.901)
Other Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14160	14160	14160	14160	14160	14160
Pseudo R^2	.318	.324	.319	.317	.317	.317
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the results from OLS regressions examining the determinants of hedge funds' absolute Unobserved Return Component (|URC|). The URC is defined as the difference between a hedge fund's reported gross-of-fee return and its long-equity portfolio return (Gross Fund Firm Returni,t - Equity PF Returni,t) (Agarwal et al., 2024). Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table OA3

ETF Weight – by hedge fund style and strategy – Quarterly Observations

Variable:	*WeightETF*							
	N	Mean	Std. Dev.	Median	p5	p25	p75	p95
Transient	9633	0.042	0.128	0.000	0.000	0.000	0.017	0.248
Quasi-Indexer	4298	0.052	0.153	0.000	0.000	0.000	0.015	0.368
Dedicated	438	0.004	0.016	0.000	0.000	0.000	0.000	0.021
Equity_Hedge	9861	0.029	0.102	0.000	0.000	0.000	0.008	0.164
Event_Driven	2426	0.014	0.056	0.000	0.000	0.000	0.001	0.070
Macro	738	0.197	0.275	0.047	0.000	0.000	0.314	0.833
Relative_Value	1436	0.070	0.156	0.006	0.000	0.000	0.051	0.395
Risk_Parity	51	0.156	0.322	0.019	0.011	0.014	0.029	0.899
Fund_of_funds	356	0.257	0.310	0.030	0.000	0.001	0.580	0.733

This table reports descriptive statistics on ETF weights (WeightETF) for subsamples of transient, quasi-indexer, and dedicated managers, as well as for hedge funds categorized by strategy. Investment style follows the institutional investor classification of Bushee (1998). Hedge funds are assigned to a given strategy if at least 50% of their assets under management (AUM) are allocated to that category.

Table OA4

OLS and Tobit Regression Analysis of Investment Style: ETF Weight as the Dependent Variable

Dep. variable	*$WeightETF_t$*			
Regression:	OLS-Logit Transformed		Tobit	
	(1)	(2)	(3)	(4)
$Transient_t$	0.522***		0.046***	
	(2.867)		(3.177)	
$Quasi\text{-}Indexer_t$	0.083		0.016	
	(0.429)		(1.059)	
$Turnover_t$		2.795***		0.099***
		(10.408)		(5.563)
$ActiveShares_t$	-9.537***	-9.870***	-0.459***	-0.458***
	(-21.085)	(-23.593)	(-17.510)	(-17.826)
$AvgFlow_{t,t-5}$	0.015***	0.016***	0.001***	0.001***
	(4.406)	(4.735)	(3.291)	(3.251)
$Ln(AUM)_t$	-0.514***	-0.494***	-0.028***	-0.027***
	(-10.674)	(-10.706)	(-12.100)	(-11.750)
$Ln(NumberSecurities)_t$	0.925***	0.834***	0.023***	0.023***
	(18.722)	(16.839)	(8.217)	(8.061)
UnobservedAssetsRatio	0.324***	0.314***	0.015***	0.016***
	(9.774)	(9.603)	(8.680)	(9.071)
$IncentiveFee_t$ (%)	-0.008	-0.021**	-0.001**	-0.002***
	(-0.869)	(-2.218)	(-2.552)	(-3.694)
$ManagementFee_t$ (%)	0.423***	0.325***	0.029***	0.030***
	(3.236)	(2.687)	(4.044)	(4.109)
$Auditing_t$	0.252	0.334*	0.023***	0.027***
	(1.275)	(1.724)	(3.095)	(3.580)
$Offshore_t$	-0.070	-0.175**	-0.013**	-0.021***
	(-0.794)	(-2.020)	(-2.097)	(-3.168)
$AdvanceNotice_t$	-0.011***	-0.010***	-0.001***	-0.001***
	(-5.335)	(-5.082)	(-5.564)	(-5.885)
$LockupPeriod_t$	-0.064***	-0.062***	-0.005***	-0.005***
	(-13.604)	(-13.693)	(-13.430)	(-13.391)
Age_t	0.660***	0.690***	0.026***	0.026***
	(8.728)	(9.414)	(6.508)	(6.518)
$Ln(MinimumInvestment)_t$	0.247***	0.214***	0.031***	0.028***
	(3.588)	(3.204)	(9.754)	(8.722)
$Ln(NumberFunds)_t$	0.234***	0.276***	0.002	0.006
	(4.585)	(5.127)	(0.441)	(1.580)
$FOFDummy_t$	2.321***	2.350***	0.178***	0.174***
	(7.719)	(8.204)	(12.890)	(12.452)
_cons	-6.547***	-5.439***	-0.459***	-0.458***
	(-6.174)	(-5.332)	(-17.510)	(-17.826)
Observations	13400	13625	13,400	13,625
Pseudo R^2	0.227	0.234	0.360	0.349
YearQtr FE	Yes	Yes	Yes	Yes

This table reports regression results examining the determinants of the quarterly share of hedge fund managers' portfolios invested in ETFs. In Columns (1) and (2), the dependent variable is the logit transformation of the ETF weight, defined as the total market value of ETFs held by a hedge fund manager divided by the manager's total assets under management (AUM) at the end of each quarter. To accommodate zero allocations, the ETF weight is adjusted by adding 0.00001 prior to the logit transformation. Reported coefficients in Columns (1)–(2) are OLS estimates on the logit scale. Columns (3) and (4) present Tobit regressions of the ETF weight itself, with the dependent variable bounded between 0 and 1. This specification treats zero ETF allocations as censored outcomes rather than fractional ones, serving as an additional robustness check. All explanatory variables are defined in Appendix. Column (1) and Column (3) measure investment style using Bushee's (1998) classification, with Dedicated hedge funds as the omitted category. Column (2) and Column (4) measure investment style using portfolio turnover (Carhart, 1997; Gaspar et al., 2005). Year-quarter fixed effects are included in all specifications. Robust t-statistics are reported in parentheses, with significance levels denoted as ***p<0.01, **p<0.05, and *p<0.1.

Table OA5
OLS Logit-Transformed and Tobit Regression Analysis of Investment Style: ETF Weight as the Dependent Variable

Dep. Variable	*WeightETF$_t$*					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. OLS Logit-Transformed Regression						
Equity_Hedge	-1.272***					
	(-12.775)					
Event_Driven		-0.496***				
		(-5.044)				
Macro			2.564***			
			(10.854)			
Relative_Value				1.838***		
				(13.150)		
Risk_Parity					1.060**	
					(2.507)	
Fund_of_Funds						4.446***
						(7.411)
Other Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,625	13,625	13,625	13,625	13,625	13,625
Pseudo R^2	0.237	0.230	0.237	0.237	0.229	0.232
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B. Tobit Regression						
Equity_Hedge	-0.073***					
	(-12.450)					
Event_Driven		-0.057***				
		(-8.337)				
Macro			0.177***			
			(12.910)			
Relative_Value				0.067***		
				(8.331)		
Risk_Parity					0.158***	
					(2.682)	
Fund_of_Funds						0.343***
						(10.555)
Other Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13625	13625	13625	13625	13625	13625
Pseudo R^2	0.364	0.352	0.380	0.354	0.347	0.363
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents regression results analyzing the determinants of the quarterly share of hedge fund managers' portfolios allocated to ETFs. Panel A reports OLS regressions where the dependent variable is the logit transformation of the ETF weight, defined as the total market value of ETFs held by a hedge fund manager divided by the manager's total assets under management (AUM) at the end of each quarter. To accommodate zero allocations, the ETF weight is adjusted by adding 0.00001 prior to the logit transformation. Reported coefficients are estimated on the logit scale. Panel B reports Tobit regressions of the ETF weight itself, bounded between 0 and 1, which treat zero allocations as censored values. This specification provides an alternative robustness check to the fractional logit model. The key explanatory variable in both panels is the value-weighted average of hedge fund characteristics, calculated using AUM from the HFR dataset for funds classified under the following strategies: Equity Hedge, Event-Driven, Fund of Funds, Macro, Relative Value, and Risk Parity. Year-quarter fixed effects are included in all regressions. Robust t-statistics are reported in parentheses, with significance levels denoted as ***p<0.01, **p<0.05, and *p<0.1.

Table OA6
Alternative measures of performance as dependent variable

	Full Sample				Excluding Non-ETF Managers			
Dependent variable	FF3 $Alpha_{t+1}$	Carhart4 $Alpha_{t+1}$	PS $Alpha_{t+1}$	FF3-Vix $Alpha_{t+1}$	FF3 $Alpha_{t+1}$	Carhart4 $Alpha_{t+1}$	PS $Alpha_{t+1}$	FF3-Vix $Alpha_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$WeightEtf_t$	-1.190**	-1.267*	-1.171*	-0.922*	-1.192**	-1.547**	-1.230*	-1.058*
	(-2.132)	(-1.901)	(-1.948)	(-1.664)	(-2.037)	(-2.046)	(-1.969)	(-1.823)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,003	14,003	14,003	14,003	7,395	7,395	7,395	7,395
R-squared	0.165	0.173	0.159	0.165	0.220	0.219	0.207	0.217
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents OLS regression results on the determinants of managers' performance over the full sample period from 1998 to 2020, where performance is measured by alphas estimated from four models: the Fama–French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Pastor–Stambaugh liquidity model (PS), and an FF3 specification augmented with monthly changes in the VIX (FF3–VIX). Quarterly alphas are constructed by first estimating factor loadings using the 24 months preceding each quarter, then computing monthly alphas, which are compounded to obtain quarterly values. Models (1)-(4) present the results for the total sample. Models (4)-(8) report the results of the sample excluding managers that have not invested in ETFs in the four-quarter previous the observation (Non-ETF=1). All regressions include a set of control variables. We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset. Manager and year–quarter fixed effects are included. Standard errors are clustered at both the manager and year–quarter levels, and robust t-statistics are reported in parentheses. Statistical significance is denoted as ***p<0.01, **p<0.05, and *p<0.

Table OA7

Investment style, Fund strategy, ETF allocation and performance

Strategy:	Transitory	Quasi-Indexer	Dedicated	Equity Hedge	Event Driven	Macro	Relative Value	Fund of Funds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Performance CAPM Alpha								
$WeightEtf_t$	-1.209*	-0.500	-33.577**	-1.959*	-2.113	1.875	0.192	-3.298
	(-1.688)	(-0.275)	(-2.747)	(-1.731)	(-0.930)	(1.249)	(0.163)	(-1.368)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,009	4,125	397	9,204	2,312	683	1,322	325
R-squared	0.189	0.235	0.478	0.195	0.316	0.235	0.391	0.623
Panel B. FH7 Alpha								
$WeightEtf_t$	-1.446*	-0.550	-41.308**	-1.552	-6.418**	0.873	0.429	-3.658
	(-1.736)	(-0.332)	(-2.830)	(-1.114)	(-2.125)	(0.545)	(0.305)	(-1.263)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,009	4,125	397	9,204	2,312	683	1,322	325
R-squared	0.160	0.155	0.453	0.155	0.254	0.235	0.305	0.625
Panel C. Raw return								
$WeightEtf_t$	-2.804***	1.602	-15.007	-3.115**	-5.875**	-0.262	0.072	-0.600
	(-3.049)	(0.533)	(-1.126)	(-2.059)	(-2.171)	(-0.153)	(0.046)	(-0.222)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,014	4,149	403	9,322	2,332	689	1,342	330
R-squared	0.365	0.554	0.638	0.442	0.531	0.241	0.423	0.811

This table presents the results of OLS regressions analyzing the determinants of hedge fund managers' performance across different fund strategies. Panel A measures performance using CAPM alpha, Panel B uses FH7 alpha, and Panel C evaluates performance based on raw returns. Models (1)–(3) report results for subsamples of hedge funds' investment style based on Bushee's (1998) classification: Transitory, Quasi-Indexer, and Dedicated, respectively. Models (4)–(8) present regressions for subsamples corresponding to the following strategies: Equity Hedge, Event-Driven, Fund of Funds, Macro, Relative Value, and Risk Parity. Hedge funds are assigned to a given strategy if at least 50% of their assets under management (AUM) are allocated to that category. The analysis incorporates manager and year-quarter fixed effects. Standard errors are clustered at the manager and year-quarter levels. Robust t-statistics are shown in parentheses, with significance levels denoted as ***p<0.01, **p<0.05, and *p<0.1.

Table OA8

Unexpected and Expected flows and changes on ETFs holdings – Manager-level Flow Regressions

	Full Sample				Excluding Non-ETF Managers			
Dependent Variable	ΔETF Holdings$_t$		ΔNonETF Holdings$_t$		ΔETF Holdings$_t$		ΔNon-ETF Holdings$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(A) Unexpected Flow$_t$	0.011	0.014*	0.255***	0.243***	0.020	0.024*	0.198***	0.184***
	(1.356)	(1.765)	(6.559)	(6.367)	(1.444)	(1.779)	(4.814)	(4.478)
(B) Expected Flow$_t$	0.010*	0.010	0.332***	0.347***	0.016	0.017	0.315***	0.344***
	(1.844)	(1.469)	(5.842)	(5.867)	(1.627)	(1.336)	(4.698)	(4.856)
(A) minus (B)	0.001	0.004	-0.077	-0.104*	0.004	0.007	-0.117*	-0.160**
	(0.030)	(0.320)	(-1.350)	(-1.800)	(0.240)	(0.400)	(-1.780)	(-2.510)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,489	12,489	12,489	12,489	6,899	6,894	6,899	6,894
R-squared	0.094	0.214	0.041	0.161	0.101	0.243	0.034	0.185
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes
YearQtr FE	No	Yes	No	Yes	No	Yes	No	Yes

This table presents the results of an OLS regression of the determinants of changes on ETFs and Non-ETF stocks adjusted by the return in each quarter. Changes are scaled by the total asset under management reported by the investor in the previous quarter (t-1). Unexpected and expected flows are measured following Fung et al. (2008), with separate flow regressions estimated for each manager. (A) minus (B) represents the difference between coefficients of Unexpected Flows (A) and Expected Flows (B). All other explanatory variables are defined in Appendix Table 1. Columns (1)-(4) present the results for the total sample. Columns (5)-(8) report the results of the sample excluding managers that did not invest in ETFs in the four-quarter previous the observation (NonETF=1). We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset We use manager and year-quarter fixed effect. Standard errors are clustered at the manager and year-quarter levels. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table OA9

Unexpected and Expected flows and changes on ETFs holdings – subsamples analysis

Panel A. Subsamples by investment horizon

Dependent variable	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Investment Style:	Transient		Quasi-Indexers		Dedicated	
(A) UnexpectedFlow$_t$	0.019**	0.317***	0.005	0.154**	-0.004	0.091
	(2.285)	(6.955)	(0.936)	(2.388)	(-0.762)	(0.585)
(B) ExpectedFlow$_t$	0.005	0.689***	-0.016	0.238	0.012	0.711
	(0.274)	(5.436)	(-0.676)	(1.391)	(0.663)	(1.612)
(A) minus (B)	0.014	-0.372***	0.021	-0.084	-0.016	-0.620
	(0.680)	(-3.440)	(1.190)	(-0.850)	(-0.670)	(-1.270)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,519	8,519	3,920	3,920	360	360
R-squared	0.254	0.180	0.139	0.244	0.400	0.380
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Subsamples by funds' strategy

Dep Variable:	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel B. Funds' strategy:	Equity Hedge		Event Driven		Relative Value		Macro		Fund of Funds	
(A) Unexpected Flow	0.014*	0.245***	-0.012	0.463***	0.035	0.084	0.033*	0.137	0.077	-0.092
	(1.849)	(5.605)	(-1.136)	(3.911)	(0.925)	(0.982)	(1.712)	(1.458)	(1.202)	(-1.276)
(B) Expected Flow	0.004	0.537***	0.006	0.844**	0.06	0.425	-0.049	0.121	0.100	0.032

					2					
	(0.305)	(5.366)	(0.158)	(2.263)	(0.413)	(0.657)	(-0.523)	(0.219)	(0.423)	(0.085)
(A) minus (B)										
	0.010	-0.292***	-0.018	-0.381	-0.027	-0.341	0.082	0.016	-0.023	-0.124
	(0.810)	(-3.820)	(-0.580)	(-1.280)	(-0.170)	(-0.780)	(0.940)	(0.040)	(-0.080)	(-0.320)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,593	8,593	2,134	2,134	653	653	1,278	1,278	306	306
R-squared	0.196	0.152	0.478	0.235	0.337	0.325	0.421	0.374	0.341	0.546
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of an OLS regression of the determinants of changes on ETFs and Non-ETF stocks adjusted by the return in each quarter. Changes are scaled by the total asset under management reported by the investor in the previous quarter (t-1). To measure unexpected and expected flow, we rely on the methodology presented by Fung et al. (2008). Panel A reports results for subsamples of hedge funds' investment style based on Bushee's (1998) classification: Transitory, Quasi-Indexer, and Dedicated, respectively. Panel B presents regressions for subsamples corresponding to the following strategies: Equity Hedge, Event-Driven, Fund of Funds, Macro, Relative Value, and Risk Parity. Hedge funds are assigned to a given strategy if at least 50% of their assets under management (AUM) are allocated to that category. (A) minus (B) represents the difference between coefficients of Unexpected Flows (A) and Expected Flows (B). All other explanatory variables are defined in Appendix Table 1.

Table OA10

Expected and Unexpected Flows and alternative measures of fund Performance measured

	Full Sample				Excluding Non-ETF Managers			
Dependent variable	FF3 Alpha$_{t+1}$	Carhart4 Alpha$_{t+1}$	PS Alpha$_{t+1}$	FF3-Vix Alpha$_{t+1}$	FF3 Alpha$_{t+1}$	Carhart4 Alpha$_{t+1}$	PS Alpha$_{t+1}$	FF3-Vix Alpha$_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WeightEtf$_t$	-1.270**	-1.357**	-1.291*	-0.947	-1.189*	-1.577**	-1.313*	-0.901
	(-2.034)	(-2.084)	(-1.934)	(-1.483)	(-1.787)	(-2.371)	(-1.915)	(-1.374)
UnexpectedFlow$_t$* WeightEtf$_t$	0.044*	0.053**	0.044*	0.055**	0.045**	0.050**	0.045*	0.054**
	(1.780)	(2.366)	(1.897)	(2.514)	(2.024)	(2.232)	(1.943)	(2.472)
ExpectedFlow$_t$*WeightEtf$_t$	-0.128	-0.053	-0.143**	-0.093	-0.112	-0.044	-0.139*	-0.082
	(-1.438)	(-0.746)	(-1.970)	(-1.346)	(-1.604)	(-0.630)	(-1.936)	(-1.190)
UnexpectedFlow$_t$	0.003	0.000	0.002	0.003	0.000	0.000	-0.000	0.002
	(0.638)	(0.128)	(0.568)	(0.797)	(0.057)	(0.068)	(-0.081)	(0.341)
ExpectedFlow$_t$	-0.007	-0.013	-0.018	-0.005	-0.029*	-0.027	-0.032*	-0.023
	(-0.482)	(-1.077)	(-1.468)	(-0.426)	(-1.690)	(-1.574)	(-1.832)	(-1.354)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,697	12,697	12,697	12,697	6,940	6,940	6,940	6,940
R-squared	0.164	0.169	0.158	0.162	0.220	0.218	0.207	0.216
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents OLS regression results on the determinants of managers' performance, and unexpected and expected flows for 1998-2020, where performance is measured by alphas estimated from four models: the Fama–French three-factor model (FF3), the Carhart four-factor model (Carhart4), the Pastor–Stambaugh liquidity model (PS), and an FF3 specification augmented with monthly changes in the VIX (FF3–VIX). To measure unexpected and expected flow, we rely on the methodology presented by Fung et al. (2008). All the models include all HF control variables presented in the Appendix. Models (1)-(4) present the results for the total sample. Models (5)-(8) report the results of the sample excluding managers that have not invested in ETFs in the four-quarter previous the observation (Non-ETF) users. We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset. We use manager and year-quarter fixed effect. Standard errors are clustered at the manager and year-quarter levels. Robust t-statistics errors are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table OA11

Expected and Non-Expected Flows Performance measured – Investor type and Fund strategy.

Strategy:	Transient	Quasi-Indexer	Dedicated	Equity Hedge	Event Driven	Macro	Relative Value	Fund of Funds
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Performance CAPM Alpha								
$WeightEtf_t$	-1.321*	-0.171	-45.727	-2.260**	-2.242	2.279	0.556	-6.450
	(-1.929)	(-0.086)	(-1.146)	(-2.038)	(-0.964)	(1.416)	(0.458)	(-1.336)
$UnexpectedFlow_t$* $WeightEtf_t$	0.055*	0.052	13.573*	0.058**	0.135	-0.118	0.204***	0.078
	(1.948)	(1.190)	(1.697)	(2.109)	(1.094)	(-1.201)	(2.804)	(1.447)
$ExpectedFlow_t$* $WeightEtf_t$	-0.121	-0.013	-3.605	-0.132	-0.012	0.079	-0.137	-0.267
	(-1.046)	(-0.093)	(-0.431)	(-1.390)	(-0.040)	(0.353)	(-0.728)	(-1.149)
$UnexpectedFlow_t$	0.002	-0.000	0.034	0.004	0.014*	0.011	-0.028***	-0.000
	(0.396)	(-0.018)	(1.107)	(1.001)	(1.775)	(0.688)	(-3.277)	(-0.011)
$ExpectedFlow_t$	-0.027	-0.027	-0.049	-0.014	-0.082***	-0.041	-0.044	0.117
	(-1.563)	(-1.143)	(-0.478)	(-0.938)	(-2.761)	(-0.656)	(-1.067)	(0.914)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,262	3,818	351	8,322	2,061	632	1,226	299
R-squared	0.187	0.242	0.458	0.196	0.302	0.233	0.413	0.655
Panel B. FH-7 Alpha								
$WeightEtf_t$	-1.362	-0.655	-72.527	-1.219	-5.716**	0.475	0.949	-6.185
	(-1.504)	(-0.283)	(-1.576)	(-0.942)	(-2.108)	(0.262)	(0.670)	(-1.154)
$UnexpectedFlow_t$* $WeightEtf_t$	0.068*	-0.006	15.634*	0.043	0.012	-0.071	0.189**	0.092
	(1.952)	(-0.115)	(1.695)	(1.340)	(0.086)	(-0.641)	(2.234)	(1.543)
$ExpectedFlow_t$* $WeightEtf_t$	-0.106	0.033	-6.263	-0.146	0.267	-0.062	0.135	-0.454*
	(-0.791)	(0.203)	(-0.650)	(-1.316)	(0.752)	(-0.246)	(0.617)	(-1.762)
$UnexpectedFlow_t$	0.004	0.004	0.050	0.007	0.020**	0.006	-0.019*	-0.004
	(0.813)	(0.572)	(1.395)	(1.340)	(2.073)	(0.307)	(-1.873)	(-0.159)
$ExpectedFlow_t$	0.011	-0.002	-0.074	0.015	-0.081**	0.026	0.009	0.228
	(0.606)	(-0.079)	(-0.631)	(0.859)	(-2.335)	(0.371)	(0.186)	(1.596)

Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,262	3,818	351	8,322	2,061	632	1,226	299
R-squared	0.158	0.159	0.458	0.152	0.250	0.218	0.317	0.657
Panel C. Raw return								
$WeightEtf_t$	-2.852***	1.827	-36.727	-3.606***	-4.756*	-0.457	0.139	-3.834
	(-3.128)	(0.747)	(-0.734)	(-2.626)	(-1.697)	(-0.250)	(0.084)	(-0.715)
$UnexpectedFlow_t$* $WeightEtf_t$	0.073	0.043	15.964	0.072**	-0.115	-0.107	0.136	0.086
	(1.529)	(0.799)	(1.594)	(2.126)	(-0.771)	(-0.958)	(1.370)	(1.444)
$ExpectedFlow_t$* $WeightEtf_t$	-0.015	0.163	-3.521	-0.002	0.875**	-0.151	0.069	-0.173
	(-0.104)	(0.942)	(-0.336)	(-0.017)	(2.383)	(-0.583)	(0.268)	(-0.671)
$UnexpectedFlow_t$	-0.001	0.003	0.032	0.005	0.015	-0.007	-0.040***	0.006
	(-0.208)	(0.326)	(0.830)	(1.024)	(1.499)	(-0.374)	(-3.385)	(0.221)
$ExpectedFlow_t$	-0.028	0.008	-0.006	-0.002	0.025	-0.050	-0.103*	0.325**
	(-1.261)	(0.239)	(-0.045)	(-0.118)	(0.653)	(-0.696)	(-1.724)	(2.143)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,289	3,818	351	8,342	2,062	636	1,229	299
R-squared	0.372	0.557	0.649	0.452	0.524	0.235	0.438	0.831

This table presents the results of OLS regressions analyzing the determinants of hedge fund managers' performance across different fund strategies. Panel A measures performance using CAPM alpha, Panel B uses FH7 alpha, and Panel C evaluates performance based on raw returns. Models (1)–(3) report results for subsamples based on Bushee’s (1998) classification: Transitory, Quasi-Indexer, and Dedicated, respectively. Models (4)–(8) present regressions for subsamples corresponding to the following strategies: Equity Hedge, Event-Driven, Fund of Funds, Macro, Relative Value, and Risk Parity. Hedge funds are assigned to a given strategy if at least 50% of their assets under management (AUM) are allocated to that category .The analysis incorporates manager and year-quarter fixed effects. Standard errors are clustered at the manager and year levels. Robust t-statistics are shown in parentheses, with significance levels denoted as ***p<0.01, **p<0.05, and *p<0.1.

Table OA12

Expected and Unexpected Flows and fund Performance measured - Manager-level Flow Regressions

	Full Sample			Excluding Non-ETF managers		
	CAPM Alpha$_{t+1}$	FH7 Alpha$_{t+1}$	Raw Return$_{t1+}$	CAPM Alpha$_{t+1}$	FH7 Alpha$_{t+1}$	Raw Return$_{t1+}$
	(1)	(2)	(3)	(4)	(5)	(6)
WeightEtf$_t$	-0.849	-1.037	-2.131***	-1.177*	-1.416*	-2.351***
	(-1.339)	(-1.385)	(-2.656)	(-1.766)	(-1.832)	(-2.825)
UnexpectedFlow$_t$* WeightEtf$_t$	0.076**	0.092***	0.110***	0.067**	0.080**	0.106***
	(2.357)	(2.731)	(3.040)	(2.333)	(2.399)	(2.969)
ExpectedFlow$_t$* WeightEtf$_t$	0.015	0.003	0.026	0.023	0.012	0.039
	(0.421)	(0.062)	(0.559)	(0.598)	(0.274)	(0.809)
UnexpectedFlow$_t$	-0.001	0.002	-0.004	0.001	0.005	-0.005
	(-0.167)	(0.419)	(-0.728)	(0.183)	(0.708)	(-0.705)
ExpectedFlow$_t$	0.002	0.011*	0.003	-0.003	0.003	-0.002
	(0.276)	(1.741)	(0.411)	(-0.398)	(0.372)	(-0.203)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,168	12,168	12,191	6,698	6,698	6,715
R-squared	0.187	0.141	0.422	0.225	0.186	0.441
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of an OLS regression of the determinants of managers' performance, measured by CAPM and FH7 alphas and raw performance, and unexpected and expected flows for 1998-2020. Unexpected and expected flows are measured following Fung et al. (2008), with separate flow regressions estimated for each manager). All the models include all HF control variables presented in the Appendix. Columns (1)-(3) present the results for the total sample. Columns (4)-(6) report the results of the sample excluding managers that have not invested in ETFs in the four-quarter previous the observation (Non-ETF) users. We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset. We use manager and year-quarter fixed effect. Standard errors are clustered at the manager and year-quarter levels. Robust t-statistics errors are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table OA13
The role of ETF Heterogeneity – Flow analysis

	ΔPassive ETFs$_t$ (1)	ΔActive ETFs$_t$ (2)	ΔBroad ETFs (3)	ΔSectoral ETFs (4)	ΔNon-Leveraged ETFs (5)	ΔLeveraged ETFs (6)
Panel A. Full Sample						
(A) UnexpectedFlow	0.012**	-0.000	0.008*	0.002	0.012**	0.000
	(2.380)	(-0.122)	(1.919)	(1.044)	(2.389)	(0.669)
(B) ExpectedFlow	0.007	-0.001	-0.005	0.004	0.006	-0.000
	(0.624)	(-0.838)	(-0.631)	(0.949)	(0.549)	(-0.860)
(A) - (B)	0.005	0.001	0.013	-0.002	0.006	0.000
	(0.350)	(0.720)	(1.490)	(-0.540)	(0.480)	(1.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,123	13,123	13,123	13,123	13,123	13,123
R-squared	0.214	0.025	0.184	0.065	0.218	0.045
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B. Excluding Non ETF users.						
(A) UnexpectedFlow	0.021**	-0.000	0.014*	0.003	0.021**	0.000
	(2.374)	(-0.002)	(1.897)	(1.075)	(2.386)	(0.710)
(B) ExpectedFlow	0.010	-0.001	-0.012	0.005	0.007	-0.000
	(0.404)	(-0.889)	(-0.722)	(0.514)	(0.291)	(-0.764)
(A) - (B)	0.011	0.001	0.026	-0.002	0.014	0.000
	(0.450)	(0.810)	(1.510)	(-0.170)	(0.620)	(0.920)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,184	7,184	7,184	7,184	7,184	7,184
R-squared	0.237	0.035	0.206	0.076	0.241	0.056
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports OLS regressions examining the determinants of quarterly changes in ETF holdings. We analyze how hedge funds' changes in allocations to different types of ETFs are associated with expected and unexpected investor flows, with changes scaled by the fund's total AUM in the prior quarter (t–1). Expected and unexpected flows are computed following Fung et al. (2008). The difference between the coefficients on unexpected and expected flows is reported as (A) – (B). Panel A presents results for the full sample. Panel B present the results of the sample excluding managers that did not invest in ETFs in the four-quarter previous the observation. (NonETF=1). Models (1)–(2) distinguish between passive and active ETFs, models (3)–(4) between broad and sectoral ETFs, and models (5)–(6) between non-leveraged and leveraged ETFs. All regressions include manager and year-quarter fixed effects, and control for strategy using strategy-level AUM from the HRF dataset. Robust t-statistics are reported in parentheses. Statistical significance is denoted by ***p<0.01, **p<0.05, and *p<0.1.

Table OA14
The role of ETF Heterogeneity – URC Analysis.

Dep Var.	$\|URC\|_{t+1}$					
	Full sample			Excluding NonETF managers		
	(1)	(2)	(3)	(4)	(5)	(6)
$WeightPassiveETF_t$	-1.058			-1.486**		
	(-1.532)			(-1.998)		
$WeightActiveETF_t$	-3.721			-3.610		
	(-0.872)			(-0.855)		
$WeightBroadETF_t$		-1.076			-1.647*	
		(-1.260)			(-1.847)	
$WeightSectoralETF_t$		-1.367			-1.400	
		(-1.397)			(-1.247)	
$WeightNonLeveragedETF_t$			-1.138*			-1.524**
			(-1.648)			(-2.025)
$WeightLeveragedETF_t$			-10.528			-13.007**
			(-1.544)			(-1.987)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,151	14,151	14,151	7,494	7,494	7,494
R-squared	0.454	0.454	0.454	0.495	0.495	0.495
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of an OLS regression examining the impact of ETF allocations on Hedge Funds' absolute Unobserved Return Component (|URC|). The URC is defined as the difference between a hedge fund's reported gross-of-fee return and its long-equity portfolio return *(Gross Fund Firm Return*$_{i,t}$ *- Equity PF Return*$_{i,t}$) (Agarwal et al., 2024). The dependent variable is the absolute value of the URC. Columns (1)-(3) present the results for the total sample. Columns (4)-(6) report the results of the sample excluding managers that did not invest in ETFs in the four-quarter previous the observation (NonETF=1). Model (1) distinguishes between passive and active ETF ownership, model (2) between broad and sectoral ETF ownership, and model (3) between non-leveraged and leveraged ETF ownership. ETF weights are defined as the share of the portfolio allocated to each category; for instance, *WeightPassive* represents the percentage of the portfolio invested in passive ETFs, while *WeightActive* captures the share in active ETFs. All regressions include manager and year–quarter fixed effects, and control for investment strategy using strategy-level AUM from the HRF dataset. Variable definitions are provided in Appendix A. Standard errors are clustered at both the manager and calendar year–quarter levels, and robust t-statistics are reported in parentheses. Statistical significance is denoted as ***p<0.01, **p<0.05, and *p<0.1.

Table OA15

The Effect of ETFs on Hedge Funds' Unobserved Return Component (URC) – Time series analysis

Dep. Variable	$\lvert URC\rvert_{t+1}$		
Subsample	Pre-2006	2006-2012	Post-2012
	(1)	(2)	(3)
$WeightEtf_t$	0.959	-0.155	-3.229***
	(0.527)	(-0.137)	(-3.161)
Controls?	Yes	Yes	Yes
Observations	2,769	5,141	6,221
R-squared	0.533	0.473	0.465
Manager FE	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes

This table presents the results of an OLS regression examining the impact of ETF allocations on Hedge Funds' absolute Unobserved Return Component (|URC|). The URC is defined as the difference between a hedge fund's reported gross-of-fee return and its long-equity portfolio return (Gross Fund Firm $Return_{i,t}$ - Equity PF $Return_{i,t}$) (Agarwal et al., 2024). The dependent variable is the absolute value of the URC. Column (1) shows results for the sample pre-2006. Column (2) shows results for the sample between 2006 and 2012. Column (3) shows results for the sample post-2012.Strategy is controlled for by using assets under management at the manager level, each quarter, based on the HRF dataset. We apply calendar year-quarter fixed effects, and standard errors are clustered at the manager and year levels. Robust t-statistics are reported in parentheses: ***p<0.01, **p<0.05, *p<0.1.

Table OA16

Unexpected and Expected flows and changes on ETFs holdings – Time series analysis

Subsample	Pre-2006		2006-2012		Post-2012	
Dependent variable	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$	ΔETF Holdings$_t$	ΔNonETF Holdings$_t$
	(1)	(2)	(3)	(4)	(5)	(6)
(A) UnexpectedFlow$_t$	-0.000	0.073*	0.019**	0.298***	0.027	0.327***
	(-0.150)	(1.712)	(2.369)	(4.355)	(1.417)	(5.530)
(B) ExpectedFlow$_t$	0.013	0.346	0.004	0.591***	0.002	0.487**
	(1.104)	(1.513)	(0.127)	(2.849)	(0.055)	(2.466)
(A) minus (B)	-0.013	-0.273	0.015	-0.293	0.025	-0.160
	(-1.300)	(-1.210)	(0.420)	(0.137)	(0.810)	(-0.840)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,234	2,234	4,744	4,744	6,112	6,112
R-squared	0.274	0.262	0.345	0.254	0.265	0.192
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of an OLS regression of the determinants of changes on ETFs and Non-ETF stocks adjusted by the return in each quarter. Changes are scaled by the total asset under management reported by the investor in the previous quarter (t-1). To measure unexpected and expected flow, we rely on the methodology presented by Fung et al. (2008). (A) minus (B) represents the difference between coefficients of Unexpected Flows (A) and Expected Flows (B). All other explanatory variables are defined in Appendix Table 1. Columns (1)-(2) shows results for the sample pre-2006. Columns (3)-(4) shows results for the sample between 2006 and 2012. Columns (5)-(6) shows results for the sample post-2012We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset We use manager and year-quarter fixed effect. Standard errors are clustered at the manager and year-quarter levels. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table OA17

Multivariate regressions - Sharpe Ratio & Risk Metrics by ETF Usage

	Full Sample			Excluding Non-ETF Managers		
Dependent Variable	Sharpe $Ratio_{t+1}$	Std. $Deviation_{t+1}$	Downside $Deviation_{t+1}$	Sharpe $Ratio_{t+1}$	Std. $Deviation_{t+1}$	Downside $Deviation_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$WeightEtf_t$	-0.650**	-1.296**	-0.239	-0.677**	-1.417**	-0.249
	(-2.321)	(-2.058)	(-0.534)	(-2.218)	(-2.169)	(-0.480)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,262	14,262	11,626	7,497	7,497	6,188
R-squared	0.318	0.513	0.553	0.341	0.524	0.576
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results of an OLS regression of ETF usage on managers' Sharpe Ratio, standard deviation, and downside deviation. The dependent variables are true quarterly measures constructed from the three monthly observations within quarter t. The Sharpe ratio is defined as the mean of the monthly excess returns in quarter t divided by the sample standard deviation of those monthly excess returns. Standard deviation is the sample standard deviation of monthly excess returns in quarter t. Downside deviation is computed with a 0% excess-return target as the square root of the average of squared negative monthly excess returns in quarter t. Excess returns equal total returns minus the monthly risk-free rate. The unit of observation is fund-quarter; quarters with fewer than three monthly observations are excluded. Columns (1)-(3) present the results for the total sample. Columns (4)-(6) report the results of the sample excluding managers that have not invested in ETFs in the four-quarter previous the observation (Non-ETF=1). All regression include manager-level control variable. We also control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset. We use manager and year-quarter fixed effect. Standard errors are clustered at the manager and year-quarter levels. Robust t-statistics errors are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table OA18

ETF use and the number of funds managed.

Dep. Variable	Number of $Funds_{t+1}$		Log(Number of $Funds_{t+1}$)	
	(1)	(2)	(3)	(4)
$WeightEtf_t$	0.229	0.439	0.017	0.078
	(0.742)	(1.433)	(0.195)	(0.933)
Controls	No	Yes	No	Yes
Observations	14,294	14,081	14,294	14,081
R-squared	0.789	0.819	0.840	0.866
Strategy Control	No	Yes	No	Yes
Manager FE	Yes	Yes	Yes	Yes
YearQtr FE	Yes	Yes	Yes	Yes

This table reports regressions of next-quarter Number of Funds (Models 1–2) and log(Number of Funds) (Models 3–4) on *WeightETF*. The sample is at the manager–quarter level. All specifications include manager and year–quarter fixed effects. Standard errors are clustered at the manager and year-quarter levels. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

About ECGI

european corporate governance institute

ECGI Working Paper Series in Finance

https://www.ecgi.global/publications/working-papers