Hedge Fund Investment in ETFs

Finance Working Paper N° 882/2023

February 2023

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ECGI Working Paper Series in Finance

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This paper examines the causes and consequences of hedge fund investments in exchange traded funds (ETFs) using U.S. data from 1998 to 2018. The data indicate that transient and quasi-indexer hedge funds are substantially more likely to invest in ETFs. ETF investment is in general associated with worse hedge fund returns, consistent with agency costs. However, some hedge funds invest in ETFs when there is an abnormal increase in capital flow relative to past performance. ETF investment associated with abnormal inflow does not appear to be an agency cost of delegated portfolio management.

Keywords: Hedge funds, Exchange traded funds, ETFs, Agency costs, Active investors, Delegated portfolio management

JEL Classifications: G23

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First Draft: January 15, 2022

This Draft: January 31, 2023

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Hedge Fund Investment in ETFs

Abstract

This paper examines the causes and consequences of hedge fund investments in exchange traded funds (ETFs) using U.S. data from 1998 to 2018. The data indicate that transient and quasi-indexer hedge funds are substantially more likely to invest in ETFs. ETF investment is in general associated with worse hedge fund returns, consistent with agency costs. However, some hedge funds invest in ETFs when there is an abnormal increase in capital flow relative to past performance. ETF investment associated with abnormal inflow does not appear to be an agency cost of delegated portfolio management.

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*"**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 (Hodder and Jackwerth, 2007). Exchange traded funds (ETFs) are baskets of stocks that trade on exchanges in the same way that stocks are traded (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. Institutional investors and high net worth individual could straightforwardly design their own ETF invest portfolio without having to pay a hedge fund manager 2/20. Put differently, at an initial glance the returns to ETFs do not seem to justify the

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

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), investment in ETFs might seem at first glance to be bad idea in view of market sentiment.[2]

In this paper, we advance the literature by providing theory and evidence for why hedge funds invest in ETFs, and by providing theory and evidence underlying the performance consequences of hedge fund investment in ETFs. We show that ETFs underperform non-ETF holdings. We posit that the main explanation for hedge fund ETF investments is related to the notion of "unexpected flow". Institutional investment into hedge funds is predictable, to a degree, based on past performance, lockup periods, fee structures, and the economic and intuitional environment (Agawral, Green, and Ren, 2018; Getmansky, 2012). Hedge fund managers base their investment decisions on expected capital under management (Agarwal and Naik, 2004; Bollen and Pool, 2009). An ETF is a liquid and diversified investment that can be somewhat tailored to a hedge fund strategy in a way that balances the portfolio and earns a short-term return that is better than holding cash. And if there is a negative shock to expected flow, then the ETF holdings can be reduced commensurate with the capital has been withdrawn by institutional investors.

To examine the idea that flow drives hedge fund ETF investment, we consider two main types of hedge funds that are more likely to invest in ETFs, but for very different reasons. First*,* *quasi-indexer, or closet indexer hedge funds* are more likely to invest in ETFs because ETFs better enable the fund to track the market index. In general, "closet indexers" are funds with obtuse strategies designed to merely track a market index (Brown and Davies, 2014). We hypothesize

[2] *Ibid.*

that unexpected flow will be statistically relevant to closet index hedge fund ETF allocations, but the economic significance of this effect will not be pronounced as the fund pursues obtuse strategies to hide their closet indexing agency costs.

Second, *transient hedge funds* are more likely to invest in ETFs as a tool that fulfills their short-term investment strategies (Bushee, 1998, 2001). For example, event driven funds can use ETFs as investments that are diversified, earn a better return than cash, and are liquid so that they can exchanged when cash is needed to carry out an event driven investment consistent with the main objective of the fund. We hypothesize that unexpected flow will be statistically relevant to transient hedge fund ETF allocations, and the economic significance of this effect will be very pronounced as the funds are not obscuring their investment strategies but instead using the ETFs as a temporary store of value.

In short, our theory of hedge fund ETF investment posits flow as the main reason for engaging in ETFs. Of course, another explanation for ETF investment is simply agency costs. Hedge funds manage capital on behalf of intuitional investors, and a very long literature documents many pronounced agency problems with delegated asset management. Passive ETF investment by hedge funds is not much different than hedge funds forming portfolios largely based on the five big U.S. tech companies,[3] as investors into hedge funds could simply invest in those companies themselves without being charged the hefty hedge fund fees.

Our theory has implications for performance consequences of hedge fund investment in ETFs. In general, we may expect performance to be worse among hedge funds that invest in ETFs due to the agency problems of inactive investment. But we could go further than that. Here, we

[3] https://www.fool.com/investing/2021/10/24/hedge-funds-confidence-in-five-big-tech-companies/

hypothesize that hedge funds with allocations to ETFs in ways *consistent* with their *unexpected* flow will perform *better* than hedge funds with allocations to ETFs in ways that are *inconsistent* with their *unexpected* flow.

We test our predictions using data from Hedge Fund Research (HFR), Refinitiv Institutional Holdings, and CRSP, among other sources, over the years 1998 to 2018. 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. The sample comprises 531 hedge funds managers, covering a total of 2,353 funds. Our data are free from survivorship bias with evidence from both living and dead funds.

The data examined offer strong evidence of the performance implications of ETF investment. Consistent with the agency hypothesis, we first show that ETFs underperform non-ETF stocks, based on the quarterly performance of the portfolio holdings reported by the hedge fund managers. On average, ETFs present a 1.14% lower returns than non-ETFs stocks. The economic significance is such that a 1-standard deviation increase in ETF weights cause a 0.24% drop in raw returns. The data also indicates that a 1-standard deviation increase in ETF weights causes a decrease on CAPM and 7-factor alpha, and this effect is statistically significant among hedge funds that invest in ETFs.

The data examined also offer strong evidence consistent with our theory regarding the implication of capital flow on ETF allocation. We show that the negative impact of ETF on return and alpha is reduced when portfolio allocation on ETF is accompanied by capital flows. This effect is more pronounced when we consider unexpected flows. Hedge funds with a 1-standard deviation increase in unexpected flow have an approximately 10.15% higher allocation to ETFs in the following period, and this effect is consistently significant at the 5% level. By contrast, expected hedge fund flows are statistically unrelated to hedge fund ETF investment for the full sample of all hedge funds, and for all subgroupings of transient, quasi-indexers, and dedicated hedge funds. But more interestingly, hedge funds that invest in ETFs in ways consistent with managing unexpected flow have alphas that are higher on average. And hedge funds investments in ETFs not related to capital flows are associated with lower alphas on average, which reflects an agency cost explanation for some hedge fund ETF investment.

Our paper is related to a large literature on hedge fund investment strategies (e.g., Fung and Hsieh, 2001; Fung et al., 2008; Getmansky, 2012; Kosowski et al., 2007), but a small literature on hedge fund investment in ETFs. To the best of our knowledge, the only other paper to examine hedge fund investments in ETFs is a concurrent paper by Sun and Teo (2022).[4] Sun and Teo (2022) show that performance is worse among hedge funds that invest in ETFs. Our findings are consistent. Our paper approaches the issues of hedge fund investment in ETFs with different data. We examine for the first time how capital flows are related to hedge fund ETF investment and the associated performance implications.

This paper is organized as follows. The hypotheses are explained and summarized in section 2. Section 3 introduces the data. Section 4 describes the empirical methods for our tests, presents the empirical evidence, and provides a discussion of limitations and future research. The last section concludes.

[4] At the time of preparing our paper, no other paper had examined ETFs. Sun and Teo (2022) was posted on SSRN in February 2022 at the same time of finalizing our paper, and hence referenced here upon finalizing this draft.

2. Hypotheses

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.

An academic researcher estimating predicted versus unexpected flow for each hedge fund manager 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 on 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 in ways consistent with that depicted in Figure 1.

Fund managers that receive 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. An advantage of hedge funds investing 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 first prediction as follows, and as depicted in Figure 2.

Hypothesis 1: *Unexpected flows will give rise to more hedge fund ETF investment, while expected hedge fund flows will be unrelated to ETF investment.*

An alternative explanation for hedge fund ETF investment involves agency problems. Hedge funds are normally active investors (e.g., Brav et al., 2008, 2015; Klein and Zur, 2009). But some hedge funds may simply be passive investors, even though they charge active 2/20 fees. Some hedge funds with obtuse strategies may not disclose these ETF investment strategies to their investors, or market them as their long-term investment strategy. An explanation for hedge fund investment in ETFs that are unrelated to past flows is simply agency costs of delegated portfolio management, as indicated in Figure 2.

[Figures 1 and 2 About Here]

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; Agrawal 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.

Hypothesis 2: *Positive changes in ETF investment alongside unexpected [expected] flows will enhance [diminish] future hedge fund alpha.*

All hedge fund investment in ETFs may at first glance appear unusual and associated with agency problems and lower returns. But here, we suggest that there are possibly valid reasons for short term unexpected flow management that could give rise to more hedge fund investment that should not dimmish returns. We test these propositions for the first time with a large dataset described in the next section.

3. Data

3.1. Sources and Data Description

The data examined here were derived 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).[5]To avoid delisting bias, we keep hedge fund managers in the sample until the point that the manager begins to report mutual fund ownership

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

information. Our sample list contains 609 Hedge Fund managers, and a total of 2,353 funds covered for a period of 1998-2018.[6]

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. We compute the quarterly returns and flows, at the manager level. We control for strategy and managers' regional investment focus using the same approach[7]. To avoid potential data errors, particularly originating from the fact that not all the funds pertained by the manager report assets under management to the HFR dataset, we remove hedge fund firms for which the ratio of the 13F assets to the AUM from HFR exceeds ten (Ben-David, Franzoni, and Moussawi, 2009). Additionally, to ensure that results are not driven by firms with insignificant holdings, we exclude managers with less than USD 1 million in total asset value reported on the 13F filings. These two filter processes dropped about 10% of the observations.

To examine the 13-F 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 13-F dataset[8]. We obtain ETFs characteristics from the CRSP Mutual Fund dataset and Bloomberg. We identify

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[6]We restrict our sample to this period for two reasons. First, ETFs transactions among Hedge Funds are scarce before this period. The quarter ending on 30-Jun-1998 is the first quarter we identify at least 10 Hedge Fund managers reporting ETFs on their 13-F filings. Second, the last annual update on Brian Bushee's institutional investors' classification is from 2018.

[7] 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.

[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.

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. 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 contains ETFs with an annual expense ratio as low as 0.05%, like the Vanguard Total Bond Market ETF(Ticker: BND), and an ETF with an annual expense ratio of 1.85%, the highest in our sample – from the ETF Star Buy-Write (Ticker: VEGA)

Finally, we measure Hedge Fund manager investment horizon using Bushee's (Bushee, 1998) classification provided on Brian Bushee's website.

3.2. Summary Statistics

Table 1 shows the summary statistics for the main variables in the full sample. Variables are defined in the Appendix A1. On average, ETFs represent 4% of the total quarterly portfolio reported. In Appendix A2 we present the summary statistics for the subsamples of transient, quasi-indexer, and dedicated managers.. The ETF weights relative to AUM are the lowest in the subsample of dedicated investors at 0.004 (or 0.4% of total portfolio) on average, compared to 0.037 (3.7%) and 0.047 (4.7%) for transient and quasi-indexer funds, respectively. Figure 3 shows that the percentage of hedge funds that hold ETFs has significantly increased over time such that more than 50% of quasi-indexer and transient funds hold ETFs as at 2018, and weights in ETFs are over 6% for transient and quasi-indexer funds as at 2018. Transient hedge fund CAPM and 7-

[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.

factor alphas are higher than that for quasi-indexer funds. Dedicated investors have the lowest average alphas in the sample, which to a notable degree is attributable to the global financial crisis (Figure 4).

[Table 1 About Here]

[Figures 3 and 4 About Here]

4. Empirical Evidence

4.1. Methods

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. 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.

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 13-F 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:

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

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' 13-F filings.

We calculate expected and unexpected flows by using the methodology of Fung, Hsieh, Naik, and Ramadorai (2008).[10] Quarterly flow is regressed on lagged quarterly flows and lagged quarterly returns in a method described as follows:

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

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 utilize a Newey and West (1987) covariance matrix using four quarterly lags to account for any possible autocorrelation and heteroskedasticity in the residuals. To account for unobserved factors at manager level, Eq.(2) is estimated for each manager.[11] The unexpected flows are then the regression residuals, while the expected flows are the predicted values. Standard errors are clustered at the fund manager level and year (Petersen, 2009).

[Figure 5]

4.2. 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. We do not use

[10] We considered Agrawal 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.

[11] We use the stata command asreg for each hedge fund manager. Baseline results if the residuals are obtained without the asreg option.

measures of unexpected flow in this section. Unexpected flow measures are introduced below in subsection 4.4.

Table 2 presents the most popular ETF among Hedge Fund managers in our dataset. ETFs are ranked by the total AUM between 1998 and 2018. The most popular ETF in our data is the SPDR S&P 500 ETF (ticker:SPY) that tracks the S&P 500 index. The list of popular ETFs by year is presented in the Appendix A3.

Table 3 reports the Poisson regressions of the percentage invested in ETF relative to AUM. The Poisson regressions have the advantage of modelling the fact that a large number of funds that have small weights in ETFs, and a small number of funds that have high weights in ETFs. The data indicate that in model (1), that being a transient or quasi-indexer investor increases the expected weights in ETFs compared to dedicated investors, the comparison category in model (1). This effect is statistically significant at the 5% level. The data also indicates that managers with higher management fee and with fund of funds are more likely to invest in ETFs. By contrast, larger hedge fund managers, measured by total AUM, managers with more diversity of stocks, and managers with more AUM in offshore vehicles, are less likely to invest in ETFs. More interestingly, Model (1) presents evidence that Advance Notice and Lock-up period are negatively associated with ETF investments. Both components are tools used by funds' managers to mitigate the influence of unexpected flows, which is consistent with the notion that unexpected flows impact the investments in ETFs in hedge funds.

In Table 3 we use investors' portfolio turnover as an alternative measure of managers' investment horizon (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.

[Table 3 About Here]

Appendix A4 presents regressions similar to Table 2 with the difference that logistic regressions are used to assess the probability of ETF investment. Such as in the Model (1) of Table 2, dedicated investor is the comparison group. The data indicate that transient investors are the group of more likely to have a high level of ETF investment (as defined in the Appendix A1) in model (1), and this effect is significant at the 1% level.

4.3. Performance Consequences of Hedge Fund Investment in ETFs

In this section, we investigate the impact of investments in ETFs on performance. As in section 4.2, we do not consider unexpected flow measures; instead, we use those measures in subsection 4.4 below. In this subsection, we first compare within each hedge fund manager, the performance of its ETF holdings and its Non-ETF holdings. The within-fund comparison approach allows us to control for hedge fund managers' characteristics and investments skills (Feng et al. 2022). Table 4 presents the univariate results for the within-fund analysis. On average, quarter returns of ETFs are more than 0.93% lower than those of non-ETF stocks for the full sample of all hedge funds. There are similar differences for all subgroupings of hedge funds. The differences are statistically significant for most subgroupings of hedge funds with the sole exception of group of dedicated investors.

Table 5 presents OLS regression of the performance. We include manager fixed effects in all the models that allow us to capture the effect of changes of weights of managers' aggregated portfolio investments in ETFs on performance. Consistent with the results presented in the univariate analysis, the data indicate that investments in ETFs, measured by Weight ETF, negatively impacts funds' CAPM alpha, 7-factor alphas, and raw returns. In general, this evidence provides some support for the idea that hedge funds can perform worse when the invest in ETFs and that ETF ownership is akin to an agency problem in general.

Table 5 also reports interaction terms between flow and ETF weights which is are positive and statistically significant in the models where CAPM alpha and 7-factor alpha are the dependent variable. The economic significance for the full sample is such that for a one standard deviation increase in flow, combined with an one standard deviation increase in ETF weight causes an increase in CAPM and 7-factor alpha by 0.18% and 0.17%,[12] respectively. Overall, the data presented in Table 5 present evidence that, when accompanied by capital flows, investments in ETFs reduces the negative impact of capital flows on funds' performance.

[Table 5 About Here]

Table 6 shows OLS regressions similar to those in Table 6 but with subsamples of the data by fund type using the Bushee (1998, 2001) classifications for transitory, quasi-indexer, and dedicated investors. The data indicate that investments in ETF, combined with capital flows, impacts positively alphas for transitory and quasi-indexer managers; however, this effect is only statistically significant at the 5% level for quasi-indexer funds.

[Table 6 About Here]

4.4. Expected and Unexpected flows and investments in ETFs

In this section, we test hypothesis that unexpected flows increase hedge fund ETF investments, while expected flows are unrelated to ETF investments. To measure hedge fund investments in ETFs in each quarter, we calculate the quarterly changes in ETF stocks under

[12] The calculation is 21.97*0.123 multiplied by the coefficients.

management less 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 the ETF holdings relative to total equity valued held by the manager. The data indicate that unexpected flow is significantly positively related to ETF investment in the full sample and in the sample excluding managers that do not invest in ETFs. In the subsample considering only hedge fund managers that invest in ETFs, the economic significance is such that a 1-standard deviation increase in unexpected flow causes a 61.5% increase in ETF investment relative to the average quarter investment in ETF in the sample, as presented in the model (6) with calendar-quarter and manager fixed effect .[13] However, the data also indicate in model (8) that non-ETF investment goes up as well with unexpected flow, with an economic significance that is slightly higher at 62.7% to the average level of non-ETF investment in the sample. This evidence is consistent with Hypothesis 1.

Table 8 shows OLS regressions similar to those in Table 7 but with subsamples of the data by fund type using the Bushee (1998, 2001). The data consistently indicate that unexpected flow increases ETF investment for transitory and quasi-indexer funds, and this effect is significant at the 10% level for transitory investors and at the 5% level for quasi-indexer funds.

[Table 7 About Here]

[Table 8 About Here]

[13] The calculation is 0.015 * 11.28/0.275

In Tables 7 and 8, expected flow is associated with significant changes in non-ETF investment, and these effects are significant at the 1% level. However, and importantly, expected flow is not significantly associated with ETF investment in any of the specifications in Tables 7 and 8. Interestingly, the marginal effect of expected flows on Non-ETF investment is more pronounced than the effect of unexpected flow. For example, in Table 7, a 1-standard deviation increase in expected flow gives rise to a 3.23% increase in Non-ETF investment in model (4).[14] By further contract, a 1-standard deviation increase unexpected flow gives rise to a 2.14% increase in non-ETF investments.[15]

In Appendix A5, we consider differences in unexpected inflows versus outflows. The data indicate that unexpected inflows are more often associated more ETF investment, while outflows unexpected are unrelated to ETF investment.

In sum, the data indicate in Tables 7 and 8 and Appendix A5 that unexpected flow is a significant determinant of hedge fund ETF investment. The data further indicate that expected flow has no significant effect hedge fund ETF investment; or if there is a significant effect, then it is not statistically significant and substantially less economically significant compared to the economic significance of unexpected flow on ETF investment. Overall, the evidence is consistent with Hypothesis 1.

Table 9 provides regression evidence of the impact of unexpected flow alongside ETF ownership on hedge fund alphas and raw returns. The data indicate that unexpected flows by themselves do not impact hedge fund alphas or raw returns in any of the econometric specifications

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[14] The calculation is 0.331*9.76.

[15] The calculation is 0.189*11.28.

or subsamples in the data. The data also indicate that ETF weight relative to equity portfolio has a negative impact on fund performance; however, the impact is only statistically significant at 5% level for raw return dependent variable.

[Table 9 About Here]

Table 9 also reports interaction terms between unexpected flow and ETF weights which are positive and statistically significant at the 5% level for all the regressions in the full sample and all of the regressions the full sample excluding non-ETF managers. The effect is statistically significant at the 10% level for 7-factor alpha and at 5% level for and raw return in the full sample. The effect is also significant at the 5% level for the subsample of dedicated investors in the raw return regression. Overall, the data are consistent with Hypothesis 2 insofar as alpha is higher when hedge funds invest in ETFs in ways consistent with managing unexpected flows. By contrast, the data indicate that the interaction term between expected flow and changes in ETF weights are not statistically significant in any specification.

Table 10 OLS regressions are similar to that in Table 9 albeit with subgroups of the data based on different investor types. The data indicate that the effect of investments in ETF alongside unexpected flow is more pronounced in the group of quasi-indexer hedge fund managers. The interaction term of unexpected flow on Weight ETF is positive and statistically significant at the 5% level for quasi-indexer investors with the 7-factor alpha and raw return as the dependent variable. These results suggest that quasi-indexers use ETFs to effectively manage unexpected flows and improve returns.

[Table 10 About Here]

4.4. Approaches in Related Papers, Limitations and Future Research

There are some differences 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.[16] 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, we examine ETF weights and how they interact with non-ETF weights. Moreover, we investigate the role of investments in ETFs of investments with different investment horizons, using Bushee's investors' classification (Bushee, 1998) and investment turnover (Gaspar et al. 2005).

As with any empirical paper, there are limitations to our approach, which in turn gives rise to future research opportunities. Perhaps most importantly, 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.

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

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[16] 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.

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 research (Joenväärä et al., 2021). Another potential limitation on our analysis derives from the dataset we use to obtain hedge fund historical ownership. The Refinitiv 13-F data does not provide shorting activities and derivatives, two popular investment instruments among hedge funds (Aragon and Spence Martin, 2012). Further research with additional hedge fund datasets could add insights into our analyses here.

5. Conclusions

This paper presented evidence that hedge funds often invest in ETFs. In recent years, quasi-indexer hedge funds and transitory hedge fund reported portfolios comprise 7% and 6% in ETFs, respectively. The data examined are consistent with two primary reasons for ETF investment: (1) to manage unexpected flow, and (2) agency problems. The data indicate that quasi-indexer investors (Bushee, 1998, 2001) are much more likely to use ETFs to manage unexpected flows, while transient investors also use ETFs to manage unexpected flows but to a much smaller degree.

We further examined the performance consequences of hedge fund ETF investment. Overall, for all hedge funds, alphas and raw returns are lower among hedge funds that invest in ETFs. The data do indicate hedge fund performance differences associated with ETF investment when one isolates the purpose of the ETF investment. Specifically, hedge funds that invest in ETFs in ways consistent with managing unexpected flows have higher alphas. We do not observe any other context in which losses from ETF investments are mitigated. As such, the data are consistent with the view that ETF investment by hedge funds is an agency problem of delegated portfolio management except when ETFs are used to manage unexpected flow.

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.

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Table 1

Summary statistics – Full Sample – Quarterly Observations

	N	Mean	Std. Dev.	Median	p25	p75
Weight Non ETF Stocks	15271	.96	.123	1	.987	1
Weight ETF	15271	.04	.123	0	0	.013
Weight Block Holdings	15271	.062	.14	0	0	.049
Weight ADR	15271	.102	.122	.07	.03	.132
Raw Return	15044	1.596	7.252	1.735	-1.472	5.01
CAPM Alpha	14829	.344	5.511	.322	-2.305	2.869
HF7 Alpha	14829	.467	6.37	.425	-2.553	3.22
Raw Return Non-ETF stocks	15263	2.633	12.039	3.314	-2.703	8.92
Raw Return ETFs	6745	1.336	10.829	2.188	-2.974	6.646
Transient	15271	.661	.473	1	0	1
Quasi-Indexer	15271	.31	.462	0	0	1
Dedicated	15271	.029	.168	0	0	0
Turnover	15271	.214	.149	.183	.092	.309
Turnover Non-ETF stocks	15263	.216	.159	.182	.09	.306
Turnover ETFs	6385	.123	.204	.015	0	.156
Active Share	15222	.902	.126	.951	.867	.988
Flow Total	15271	1.76	21.969	.02	-3.74	4.164
Expected Flow	13252	.645	9.766	-.104	-3.581	4.048
Unexpected Flow	13252	-.047	11.276	-.098	-4.272	3.44
Ln Asset	15271	6.125	1.507	5.918	4.997	7.127
# Securities Filling	15271	157.599	234.639	64	30	175
Income Fee (%)	15140	17.705	5.488	20	19.934	20
Management Fee (%)	15156	1.356	.413	1.5	1	1.5
Offshore	15271	.315	.39	.065	0	.643
Advance Notice (days)	15212	45.056	23.588	45	30	60
Lockup Period (months)	15226	5.846	7.035	2.248	0	12
Age (Years)	15271	8.534	5.283	7.608	4.491	11.51
Min Investments ($Thous)	15248	1781.572	2634.011	1000	539.283	1077.996
# of Funds per Manager	15271	2.479	2.091	2	1	3
Fund of Fund Dummy	15271	.044	.206	0	0	0

This table summarizes the statistics for the sample of 531 hedge fund managers from 1998 to 2018. All the metrics are computed at an aggregated manager level using the weighed-assets averages according to the quarterly asset under management of each fund reported by the manager in the HFR dataset.

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: SPDR Gold Shares	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..141%	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

Note: Information provided at Permno Level. Some ETFs have changed their CUSIPs and Names over the last years (i.e. PowerShares QQQ fund – a very popular ETF that tracks Nasdaq-100 Index, became Invesco QQQ in 2018). This list presents the last name associated with each Permno.

Table 3
Poisson Regression Weight ETF as Dependent Variable

	(1) **%ETF**	(2) **%ETF**
Transitory Investor	2.187***	
	(2.603)	
Quasi-Indexer	1.892**	
	(2.242)	
Turnover		1.689***
		(5.402)
Active Shares	-4.6***	-4.835***
	(-11.813)	(-12.307)
$Avg\_Flow_{t,t-5}$	.001	.001
	(.113)	(.228)
Ln_Assets	-.12***	-.146***
	(-3.744)	(-4.542)
Ln_Number_Securities	-.443***	-.466***
	(-8.313)	(-8.634)
Income Fee (%)	-.01	-.012
	(-1.298)	(-1.572)
Management Fee (%)	.289**	.238*
	(2.347)	(1.943)
Offshore	-.294**	-.303**
	(-2.173)	(-2.245)
Advance Notice	-.009***	-.008***
	(-3.783)	(-3.484)
Lockup Period	-.054***	-.055***
	(-6.203)	(-6.296)
Age	-.011	-.009
	(-1.281)	(-1.072)
Ln_Minimum_Investment	.088*	.085*
	(1.863)	(1.81)
Number of Funds	-.019	-.012
	(-.688)	(-.448)
Fund of Fund Dummy	1.282***	1.317***
	(7.414)	(7.69)
_cons	-3.941	-1.757
	(-.577)	(-.259)
Observations	13974	13974
Pseudo R^2	.13	.131
Year FE	Yes	Yes

This table presents the results of a Poisson regression of the determinants of the quarterly weight managers' total portfolio invested in ETFs. Coefficients are reported in terms of Poisson regression coefficients. The dependent Weight 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 A1. Column (1) presents the results when the investment horizon is measured by Bushee's classification (Bushee 1998). Comparison category is Dedicated HFs. Columns (2) present the results when the investment horizon is measured by portfolio turnover (Carhart,1997; Gaspar et al. 2005). Dummy variables are included for the observation year. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table 4
Within-fund NON_ETF versus ETF performance: Value-weighted quarterly performance

Type of HF Manager	N	Non_ETF Return	ETF Return	Diff	St Err	t value
Full Sample	6737	2.26	1.33	1.14	.13	8.832***
High-ETF	3680	2.43	1.20	1.11	.166	6.684***
Low-ETF	3057	2.54	1.50	1.18	.204	5.814***
Transient	4474	2.59	1.22	1.23	.162	7.603***
Quasi-Indexer	2171	2.64	1.55	.94	.219	4.284***
Dedicated	92	3.41	2.02	1.78	1.133	1.572

This table summarizes the return differences between the hedge fund portfolio of Non-ETF stocks (common stocks and ADRs) and portfolio of ETF stocks. High-ETF is the group of Hedge Fund managers above the median proportion of portfolio invested in ETFs. Low-ETF is group of Hedge Fund managers with investments in ETFs and below the median proportion of portfolio invested in ETFs over four quarters periods. Transient, Quasi-indexer, and Dedicated hedge fund manager are classified based on Bushee's (1998) classification. ***, **, and * denote 1%, 5% and 10% statistical significance, respectively

Table 5
OLS Regression – Performance measured by CAPM Alpha, FH-7 Factor Alpha, and Raw returns are dependent variable.

Dependent Variable	Full Sample			Excluding Non-ETF Managers		
	CAPM $Alpha_{t+1}$	FH-7 $Alpha_{t+1}$	Raw $Return_{t1+}$	CAPM $Alpha_{t+1}$	FH-7 $Alpha_{t+1}$	Raw $Return_{t1+}$
	(1)	(2)	(3)	(4)	(5)	(6)
Weight Etf_t	-1.171*	-1.229*	-2.078***	-1.283*	-1.554**	-2.468***
	(-1.801)	(-1.705)	(-2.595)	(-1.81)	(-1.964)	(-2.849)
$Flow_t$	-.002	.001	-.002	-.004	-.003	-.002
	(-.593)	(.216)	(-.697)	(-1.096)	(-.794)	(-.476)
Weight Etf*Flow	.063**	.06*	.072**	.061**	.063**	.066**
	(2.076)	(1.825)	(2.292)	(2.015)	(1.97)	(2.067)
$Turnover_t$	.056	-.162	1.096*	-.372	-.614	.917
	(.104)	(-.252)	(1.751)	(-.558)	(-.788)	(1.143)
Active $Shares_t$	-1.623	.409	-.773	-2.838*	-1.274	-2.999*
	(-1.253)	(.262)	(-.482)	(-1.908)	(-.708)	(-1.668)
Ln_$Assets_t$	-.838***	-.792***	-1.047***	-.822***	-.746***	-1.114***
	(-10.583)	(-8.629)	(-11.141)	(-8.676)	(-6.571)	(-9.615)
Ln_Number_$Securities_t$	-.058	.165	-.05	-.092	.02	-.094
	(-.442)	(1.047)	(-.333)	(-.574)	(.105)	(-.506)
Income Fee_t	.033	.031	-.03	.026	.021	-.015
	(1.088)	(.91)	(-.778)	(.792)	(.53)	(-.339)
Management Fee_t	.014	.311	-.254	-.183	-.052	-.748
	(.034)	(.654)	(-.497)	(-.322)	(-.081)	(-1.071)
$Offshore_t$	.324	-.276	-.151	.371	.037	-.354
	(.715)	(-.541)	(-.287)	(.673)	(.057)	(-.534)
Advance $Notice_t$	.009	.002	.009	-.002	-.001	-.005
	(.989)	(.188)	(.859)	(-.149)	(-.05)	(-.348)
Lockup $Period_t$	.003	.009	.008	-.018	.017	-.056
	(.142)	(.312)	(.263)	(-.414)	(.324)	(-.979)
Age_t	-.09***	-.098***	-.08***	-.118***	-.108***	-.127***
	(-3.338)	(-3.188)	(-2.588)	(-3.465)	(-2.894)	(-2.946)
Ln_Min_Investment	.373**	.286	.228	.196	.313	.207
	(2.101)	(1.394)	(1.141)	(1.031)	(1.272)	(.795)
Ln_Number_Funds	.082*	.06	.144***	.045	.001	.101
	(1.852)	(1.074)	(2.645)	(.828)	(.012)	(1.497)
Fund of Funds	.12	.692	-.628	.091	.691	-.783
	(.168)	(.897)	(-.706)	(.113)	(.962)	(-.916)
Alphas/$Returns_{t-1}$	2.32*	.987	.048	1.255	-.762	-2.228
	(1.781)	(.57)	(.038)	(.674)	(-.31)	(-1.237)
_cons	2.878	-.931	8.262**	8.722**	2.852	16.015***
	(.887)	(-.249)	(2.138)	(2.424)	(.676)	(3.456)
Observations	14415	14415	14666	8102	8102	8239
R-squared	.181	.137	.398	.223	.187	.424
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter 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 for 1998-2018 for the full sample. All other explanatory variables are defined in Appendix Table 1. To compute the quarterly alphas, we use the 24 months prior to the quarter observation to compute factor loadings. We obtain the alphas for each month and compound their values to compute the quarterly alphas. 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 calendar-quarter fixed effect. Standard errors are clustered at the manager level and year. Robust t-statistics errors are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table 6
OLS Regression – Performance measured by CAPM Alpha, FH-7 Factor Alpha, and Raw returns are dependent variable.

	Transient HFs			Quasi-Indexers HFs			Dedicated HFs		
Dependent Variable	**CAPM Alpha$_{t+1}$**	**FH-7 Alpha$_{t+1}$**	**Raw Return$_{t1+}$**	**CAPM Alpha$_{t+1}$**	**FH-7 Alpha$_{t+1}$**	**Raw Return$_{t1+}$**	**CAPM Alpha$_{t+1}$**	**FH-7 Alpha$_{t+1}$**	**Raw Return$_{t1+}$**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Weight Etf$_t$	-1.186*	-1.123	-1.951**	-.135	-.945	-1.774	-32.102*	-36.127*	3.227
	(-1.658)	(-1.399)	(-2.257)	(-.078)	(-.482)	(-.904)	(-1.707)	(-1.938)	(.11)
Flow$_t$	.001	.004	-.002	-.008	-.009	-.006	.045	.034	.055*
	(.171)	(1.028)	(-.486)	(-1.639)	(-1.54)	(-.843)	(1.58)	(1.111)	(1.918)
Weight Etf*Flow	.057	.053	.063	.064**	.069**	.077*	-1.039	-.443	3.324
	(1.29)	(1.138)	(1.364)	(2.442)	(2.031)	(1.944)	(-.508)	(-.247)	(1.125)
Other Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9468	9468	9639	4531	4531	4603	414	9468	9468
R-squared	.18	.154	.356	.212	.139	.51	.467	.18	.154
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	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 for 1998-2018 for the full sample. To compute the quarterly alphas, we use the 24 months prior to the quarter observation to compute factor loadings. We obtain the alphas for each month and compound their values to compute the quarterly alphas. To measure unexpected and expected flow, we rely on the methodology presented by Fung et al. (2008). All the regressions reported in this table include the control variables used in the previous tables. All other explanatory variables are defined in Appendix Table 1. Columns (1)-(3) presents the results of the transient investors sample according to the Bushee (1998) investor classification. Columns (4)-(6) report the results of the quasi-indexers investor's sample. Columns (7)-(9) report the results of the dedicated investor's sample. We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset.We use the calendar-quarter fixed effect. Standard errors are clustered at the manager level and year. Robust standard t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table 7
OLS Regression – Unexpected and Expected flows and changes on ETFs holdings

	Full Sample				Excluding Non-ETF Managers			
Dependent Variable	Change ETF Holdings$_t$		Change Non-ETF Holdings$_t$		Change ETF Holdings$_t$		Change Non-ETF Holdings$_t$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unexpected Flow	.007**	.009***	.196***	.189***	.012**	.015***	.149***	.137***
	(2.336)	(2.847)	(7.516)	(7.55)	(2.37)	(2.851)	(4.843)	(4.637)
Expected Flow	.003	.004	.304***	.331***	.004	.006	.261***	.313***
	(.681)	(.746)	(9.915)	(10.181)	(.528)	(.679)	(6.836)	(7.668)
Controls								
Weight Etf	12.963***	29.781***	-4.835***	-22.257***	13.832***	32.974***	-4.291**	-20.045***
	(9.752)	(14.139)	(-2.636)	(-4.678)	(9.928)	(15.385)	(-2.179)	(-3.954)
Turnover	.211	.327	-12.381***	-46.643***	.45	1.06	-8.709***	-48.008***
	(.567)	(.453)	(-6.963)	(-10.769)	(.752)	(.834)	(-3.672)	(-8.046)
Active Shares	2.842***	4.511**	4.785**	-.344	3.981***	5.597**	6.815**	7.436
	(4.854)	(2.494)	(2.08)	(-.043)	(5.092)	(2.329)	(2.483)	(.773)
Ln_Assets	.062*	.093	.37**	-.684*	.092*	.139	.647***	-.402
	(1.944)	(1.473)	(2.05)	(-1.676)	(1.825)	(1.303)	(3.035)	(-.788)
Ln_Number_Securities	.157***	.482***	.209	8.471***	.355***	.93***	.264	9.884***
	(3.673)	(2.917)	(.674)	(9.084)	(4.338)	(3.413)	(.587)	(8.423)
Income Fee	.014	-.108***	.233***	.158	.012	-.157***	.236***	.303
	(1.322)	(-2.732)	(4.992)	(1.062)	(.811)	(-2.722)	(4.132)	(1.627)
Management Fee	-.34***	.485	1.403**	-5.775*	-.551***	.386	.625	-6.582
	(-2.689)	(.885)	(2.126)	(-1.946)	(-2.681)	(.392)	(.768)	(-1.58)
Offshore	.189*	.471	1.397*	.068	.388*	1.417**	.868	.375
	(1.726)	(1.427)	(1.901)	(.027)	(1.958)	(2.345)	(.901)	(.104)
Advance Notice	.001	.005	-.021	0.000	.002	.004	-.013	-.156**
	(.59)	(.634)	(-1.562)	(.005)	(.374)	(.24)	(-.551)	(-2.082)
Lockup Period	.016***	.009	-.049	-.164	.034***	.073*	-.028	.059
	(3.807)	(.652)	(-1.386)	(-1.081)	(3.753)	(1.812)	(-.577)	(.242)
Age	-.015**	-.042*	-.195***	.109	-.021*	-.048	-.213***	-.028
	(-2.159)	(-1.86)	(-4.482)	(.695)	(-1.776)	(-1.169)	(-3.966)	(-.131)
Ln_Min_Investment	-.067	.075	.309	.919	-.13*	.322	-.136	.533
	(-1.415)	(.402)	(1.1)	(1.012)	(-1.715)	(.978)	(-.372)	(.457)
Ln_Number_Funds	.007	-.036	-.104	-.051	.006	-.053	-.245	-.142

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(.398)	(-1.15)	(-.784)	(-.219)	(.248)	(-1.062)	(-1.571)	(-.488)
Fund of Funds	1.364***	1.696	5.417*	8.689*	1.787***	1.985	4.654	8.617
	(3.04)	(1.507)	(1.813)	(1.825)	(3.023)	(1.424)	(1.275)	(1.57)
_cons	-5.61***	-9.464**	-15.605***	-45.492**	-7.422***	-17.282***	-11.574	-42.682**
	(-4.453)	(-2.231)	(-2.62)	(-2.462)	(-4.349)	(-2.697)	(-1.517)	(-1.964)
Observations	13089	13089	13089	13089	7684	7679	7684	7679
R-squared	.095	.205	.04	.14	.098	.224	.032	.158
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	No	Yes	No	Yes	No	Yes	No	Yes
Quarter 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). 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 (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 calendar-quarter fixed effect. Standard errors are clustered at the manager level and year. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table 8

OLS Regression – Unexpected and Expected flows and changes on ETFs holdings

	Transient HFs		Quasi-Indexers HFs		Dedicated HFs	
Dependent variable	**Change ETF Holdings$_t$**	**Change Non-ETF Holdings$_t$**	**Change ETF Holdings$_t$**	**Change Non-ETF Holdings$_t$**	**Change ETF Holdings$_t$**	**Change Non-ETF Holdings$_t$**
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Flow	.008*	.236***	.007*	.127***	-.001	-.156
	(1.923)	(7.337)	(1.83)	(3.09)	(-.143)	(-.708)
Expected Flow	.005	.439***	-.002	.132***	.006	.172
	(.888)	(10.837)	(-.336)	(2.612)	(.72)	(.882)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8535	8535	4198	4198	350	350
R-squared	.232	.155	.134	.14	.393	.279
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter 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). All other explanatory variables are defined in Appendix Table 1. Columns (1)-(2) presents the results of the transient investors sample according to the Bushee (1998) investor classification. Columns (3)-(4) report the results of the quasi-indexers investor's sample. Columns (5)-(6) report the results of the dedicated investor's sample. We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset. We use the calendar-quarter fixed effect. Standard errors are clustered at the manager level and year. Robust standard t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table 9
OLS Regression – Expected and Non-Expected Flows Performance measured by CAPM Alpha, FH-7 Factor Alpha, and Raw returns are dependent variable.

	Full Sample			Excluding Non-ETF managers		
	CAPM Alpha$_{t+1}$ (1)	**FH-7 Alpha$_{t+1}$** (2)	**Raw Return$_{t1+}$** (3)	**CAPM Alpha$_{t+1}$** (4)	**FH-7 Alpha$_{t+1}$** (5)	**Raw Return$_{t1+}$** (6)
Unexpected Flow$_t$	.0005	.0003	-.0002	-.0001	-.0039	.0009
	(.1191)	(.0658)	(-.049)	(-.0162)	(-.6732)	(.1622)
Expected Flow$_t$	-.0071	-.0014	-.0073	-.0122*	-.0025	-.013
	(-1.2137)	(-.2013)	(-1.0428)	(-1.7316)	(-.2831)	(-1.3806)
Weight Etf$_t$	-.7877	-1.1106	-1.7519**	-.8728	-1.3291	-2.1765**
	(-1.0996)	(-1.3973)	(-1.9689)	(-1.1206)	(-1.5498)	(-2.2984)
Unexpected Flow$_t$* Weight Etf$_t$	.089	.1229**	.123**	.0837	.1238**	.1125**
	(1.6351)	(2.2575)	(2.1806)	(1.5059)	(2.2685)	(1.9712)
Expected Flow$_t$*Weight Etf$_t$	.0402	.0195	.0252	.0401	.0058	.0273
	(.9081)	(.4114)	(.5167)	(.8736)	(.1214)	(.5493)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12892	12892	12928	7542	7542	7570
R-squared	.176	.136	.4026	.214	.1805	.4298
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter 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 1998-2018 for the full sample. 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 A1. 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 calendar-quarter fixed effect. Standard errors are clustered at the manager and year level and year. Robust t-statistics errors are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Table 10

OLS Regression – Expected and Non-Expected Flows Performance measured by CAPM Alpha, FH-7 Factor Alpha, and Raw returns are dependent variable.

	Transient HFs			Quasi-Indexers HFs			Dedicated HFs		
Dependent Variable	**CAPM $Alpha_{t+1}$**	**FH-7 $Alpha_{t+1}$**	**Raw $Return_{t1+}$**	**CAPM $Alpha_{t+1}$**	**FH-7 $Alpha_{t+1}$**	**Raw $Return_{t1+}$**	**CAPM $Alpha_{t+1}$**	**FH-7 $Alpha_{t+1}$**	**Raw $Return_{t1+}$**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unexpected $Flow_t$	.0025	.0034	.0013	-.0029	-.0065	-.0012	.0846	.0708	.0572
	(.5144)	(.5834)	(.244)	(-.4195)	(-.7722)	(-.1496)	(1.5047)	(1.4531)	(.7996)
Expected $Flow_t$	-.002	.0052	-.0109	-.0273***	-.0225*	-.0124	.0581	.0046	.1018*
	(-.281)	(.6278)	(-1.3872)	(-2.7263)	(-1.7518)	(-.9332)	(1.424)	(.0818)	(1.9414)
Weight Etf_t	-.7913	-.9905	-1.595*	.437	-.5312	-1.2444	-12.2346	-26.2979	-6.5218
	(-1.007)	(-1.12)	(-1.6676)	(.2242)	(-.2545)	(-.5432)	(-.5568)	(-1.28)	(-.2359)
Unexpected $Flow_t$* Weight Etf_t	.0876	.1195	.0935	.0861	.1343**	.1429**	5.3963	10.6578	14.3254
	(1.0744)	(1.4199)	(1.0709)	(1.447)	(2.5668)	(1.9908)	(.5474)	(1.3283)	(1.498)
Expected $Flow_t$*Weight Etf_t	.0204	-.011	.024	.0767	.0766	.0296	4.4277	2.9137	2.0733
	(.3005)	(-.1399)	(.3143)	(1.5154)	(1.3326)	(.4714)	(1.0346)	(.7589)	(.5688)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8388	8388	8418	4152	4152	4158	346	346	346
R-squared	.1712	.1493	.3596	.2213	.1505	.5149	.439	.4206	.6423
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	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 1998-2018 for the full sample. 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 A1. Columns (1)-(3) presents the results of the transient investors sample according to the Bushee (1998) investor classification. Columns (4)-(6) report the results of the quasi-indexers investor's sample. Columns (7)-(9) report the results of the dedicated investor's sample. We control for strategy using strategy assets under management at the manager level in each quarter based on the HRF dataset. We use the calendar-quarter fixed effect. Standard errors are clustered at the manager level and year. Robust standard t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Appendix A1: Definitions of Variables

Variable	Source	Definition
Weight Non- ETF 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
Weight ETF	Refinitiv-13F, CRSP, and CRSP Mutual Fund databases	Weight of managers' aggregated portfolio invested in ETFs (CRSP code 73). Quarterly observation
Weight Block Holding	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 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	Refinitiv-13F	The group above the median proportion of portfolio invested in ETFs over four quarters periods
Raw Return	HFR	Asset-weighted quarterly raw return at the manager-level.
FH-7Alpha	HFR and David Hsieh website	Quarterly 7-factor alpha (Fung and Hsieh, 2004), using 24 months to compute the factor loadings; alpha is computed using the 3 months in each quarter.
CAPM Alpha	HFR and Kenneth French's website	Quarterly Capital Asset Pricing Model Alpha, using 24 months to compute factor loadings; alpha is computed using the 3 months in each quarter
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 Hedfe Fund manager is classified as dedicated institutional investor
Turnover	Refinitiv-13F	Manager quarterly turnover rate (more details on Gaspar et al. 2005,2012).
Transient	Brian Bushee's web page	Percentage ownership of transient institutional investors (Bushee 1998,2001).
Flow	HFR	Asset-Weight aggregated quarterly flows.
Change Non-ETF 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).
Change ETF 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.
# of securities Filling	Refinitiv-13F and CRSP	The total number of different securities held by the manager in each quarter – Common stocks, ADRs and ETFs.
Income Fee	HFR	The asset-weighted carried interest performance fee in percentage for management compensation.
Management Fee	HFR	The asset-weighted fixed fee in percentage for management compensation
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 (days)	HFR	The date minus the funds' inception day
Minimum Investment	HFR	Funds' minimum investment required.
# of funds per manager	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.

Appendix A2
Summary Statistics – Type of Institutional Investor – Quarterly Observations

	N	Mean	Std. Dev.	Median	p25	p75
Panel A. Transitory HFs						
Weight Non ETF Stocks	10100	.963	.114	1	.984	1
Weight ETF	10100	.037	.114	0	0	.016
Weight Block Holdings	10100	.038	.092	0	0	.026
Weight ADR	10100	.108	.12	.077	.035	.141
Raw Return	9938	1.493	6.725	1.653	-1.387	4.667
CAPM Alpha	9797	.512	5.372	.48	-2.059	2.929
HF7 Alpha	9797	.628	6.257	.524	-2.315	3.328
Raw Return Non-ETF stocks	10092	2.595	12.252	3.32	-2.867	9.017
Raw Return ETFs	4482	1.218	11.274	2.136	-3.702	6.996
Transient	10100	1	0	1	1	1
Quasi-Indexer	10100	0	0	0	0	0
Dedicated	10100	0	0	0	0	0
Turnover	10100	.273	.142	.251	.164	.375
Turnover Non-ETF stocks	10092	.276	.156	.248	.162	.371
Turnover ETFs	4258	.154	.229	.021	0	.242
Active Share	10055	.914	.099	.952	.877	.985
Flow Total	10100	1.215	18.263	-.03	-4.265	4.264
Expected Flow	8693	.26	9.757	-.304	-4.107	4.052
Unexpected Flow	8693	-.032	11.131	-.095	-4.615	3.749
Ln Asset	10100	6.029	1.496	5.876	4.9	7.018
# Securities Filling	10100	159.418	229.003	66	32	187.5
Income Fee (%)	9980	18.281	4.907	20	20	20
Management Fee (%)	9996	1.408	.415	1.5	1	1.657
Offshore	10100	.374	.4	.207	0	.753
Advance Notice (days)	10057	44.657	23.34	45	30	60
Lockup Period (months)	10074	5.339	6.091	1.546	0	12
Age (Years)	10100	8.261	5.059	7.381	4.354	11.252
Min Investments ($Thous)	10088	1826.704	2523.726	1000	806.486	1689.427
# of Funds per Manager	10100	2.722	2.236	2	1	3
Fund of Fund Dummy	10100	.025	.157	0	0	0
Panel B. Quasi-Indexer HFs						
Weight Non ETF Stocks	4729	.953	.143	1	.989	1
Weight ETF	4729	.047	.143	0	0	.011
Weight Block Holdings	4729	.071	.132	0	0	.082
Weight ADR	4729	.094	.127	.058	.025	.112
Raw Return	4673	1.777	8.036	1.888	-1.612	5.687
CAPM Alpha	4606	.047	5.611	.063	-2.741	2.74
HF7 Alpha	4606	.196	6.416	.241	-2.939	2.912
Raw Return Non-ETF stocks	4729	2.641	10.909	3.241	-2.074	8.527
Raw Return ETFs	2171	1.552	9.857	2.223	-2	6.038
Transient	4729	0	0	0	0	0
Quasi-Indexer	4729	1	0	1	1	1

Dedicated	4729	0	0	0	0	0
Turnover	4729	.099	.075	.082	.046	.13
Turnover Non-ETF stocks	4729	.098	.079	.082	.045	.13
Turnover ETFs	2041	.057	.107	.012	0	.066
Active Share	4725	.87	.167	.93	.815	.99
Flow Total	4729	2.756	23.518	.158	-2.587	3.973
Expected Flow	4204	1.532	9.783	.292	-2.584	4.153
Unexpected Flow	4204	-.083	11.782	-.166	-3.777	2.901
Ln Asset	4729	6.274	1.489	5.941	5.165	7.349
# Securities Filling	4729	164.79	253.541	67	28	175
Income Fee (%)	4718	16.52	6.414	20	15	20
Management Fee (%)	4718	1.238	.385	1.075	1	1.5
Offshore	4729	.188	.331	0	0	.228
Advance Notice (days)	4713	45.422	23.317	45	30	60
Lockup Period (months)	4710	6.729	8.309	4.017	0	12
Age (Years)	4729	9.211	5.653	8.197	4.891	12.504
Min Investments ($Thous)	4718	1582.3	2786.4	1000	500	1000
# of Funds per Manager	4729	2.002	1.72	1	1	2
Fund of Fund Dummy	4729	.089	.284	0	0	0
Panel C. Transitory HFs						
Weight Non ETF Stocks	442	.996	.016	1	1	1
Weight ETF	442	.004	.016	0	0	0
Weight Block Holdings	442	.522	.273	.567	.304	.742
Weight ADR	442	.071	.1	.033	.001	.104
Raw Return	433	2.024	9.577	2.295	-2.05	7.106
CAPM Alpha	426	-.313	7.169	-.138	-3.786	3.134
HF7 Alpha	426	-.302	8.081	-.182	-4.313	4.11
Raw Return Non-ETF stocks	442	3.418	17.461	3.91	-5.34	10.873
Raw Return ETFs	92	2.027	10.615	2.897	-.783	7.844
Transient	442	0	0	0	0	0
Quasi-Indexer	442	0	0	0	0	0
Dedicated	442	1	0	1	1	1
Turnover	442	.099	.092	.065	.027	.136
Turnover Non-ETF stocks	442	.095	.095	.065	.027	.136
Turnover ETFs	86	.138	.233	0	0	.234
Active Share	442	.99	.015	.997	.981	1
Flow Total	442	3.584	55.884	-.016	-3.604	3.741
Expected Flow	355	-.419	9.074	-.738	-3.525	2.823
Unexpected Flow	355	.006	8.277	0	-2.367	2.849
Ln Asset	442	6.708	1.692	6.605	5.369	7.787
# Securities Filling	442	39.095	38.8	22	12	56
Income Fee (%)	442	17.339	5.134	20	15.06	20
Management Fee (%)	442	1.442	.392	1.5	1.058	1.96
Offshore	442	.324	.406	0	0	.678
Advance Notice (days)	442	50.233	30.469	45	30	74.731
Lockup Period (months)	442	8.001	10.236	0	0	12
Age (Years)	442	7.54	5.48	6.198	3.609	9.81
Min Investments	442	2878.58	3076.913	1000	500	5000

($Thous)						
# of Funds per Manager	442	2.016	1.083	2	1	2
Fund of Fund Dummy	442	0	0	0	0	0

This table summarizes the statistics for the sample of 531 hedge fund managers from 1998 to 2018. All the metrics are computed at an aggregated manager level using the weighed-assets averages according to the quarterly asset under management of each fund reported by the manager in the HFR dataset. Panel A reports statistics for managers considered transient according to Bushee's (1998) classification. Panel B reports the statistics for managers considered quasi-indexers. Panel C reports the statistics for the dedicated managers. All the variables are winsorized at the 1% and 99% levels.

Appendix A3

Popular ETFs among HF managers over the years

Rank\Year	2000	2001	2002	2003
1	SPDR S&P 500 Trust	SPDR S&P 500 Trust	SPDR S&P 500 Trust	SPDR S&P 500 Trust
2	Nasdaq-100 Trust	Nasdaq-100 Trust	Nasdaq-100 Trust	Nasdaq-100 Trust
3	SPDR S&P 400 MidCap	SPDR S&P 400 MidCap	SPDR S&P 400 MidCap	Diamonds Dow Jones Trust
4	Diamonds Dow Jones Trust	Diamonds Dow Jones Trust	Diamonds Dow Jones Trust	SPDR S&P 400 MidCap
5	iShares Core S&P 500 Index	iShares Core S&P 500 Index	iShares Core S&P 500 Index	Semconductor HOLDRS Trust
6	Biotech HOLDRS Trust	Semconductor HOLDRS Trust	Oil Service HOLDRs Trust	iShares Core S&P 500 Index
7	Semconductor HOLDRS Trust	Biotech HOLDRS Trust	iShares Russell 2000	Retail HOLDRS Trust
8	SPDR Technological Sector	iShares MSCI EAFE	C P HOLDRs ETF	iShares Russell 1000 Value
9	Internet HOLDRS Trust	Telecom HOLDRS	Biotech HOLDRS Trust	iShares MSCI Japan
10	iShares Russell 2000	iShares MidCap 400/Barra Growth	Retail HOLDRS Trust	C P HOLDRs ETF
Rank\Year	**2004**	**2005**	**2006**	2007
1	SPDR S&P 500 Trust	SPDR S&P 500 Trust	SPDR S&P 500 Trust	SPDR S&P 500 Trust
2	Nasdaq-100 Trust	SPDR S&P 400 MidCap	Oil Service HOLDRs Trust	PowerShares QQQ
3	SPDR S&P 400 MidCap	Nasdaq-100 Trust	iShares Russell 2000	SPDR S&P 400 MidCap
4	iShares Russell 2000	iShares Russell 2000	SPDR S&P 400 MidCap	iShares Russell 2000
5	Semconductor HOLDRS Trust	streetTRACKS Gold Shares	Nasdaq-100 Trust	iShares MSCI EM
6	iShares Russell 1000 Value	SPDR Energy Sector	iShares MSCI Japan	streetTRACKS Gold Shares
7	iShares MSCI EAFE	iShares MSCI EAFE	Invesco Euro Trust	iShares MSCI EAFE
8	Diamonds Dow Jones Trust	Oil Service HOLDRs Trust	streetTRACKS Gold Shares	iShares MSCI Japan
9	iShares MSCI Japan	iShares Russell 2000 Growth	iShares MSCI EAFE	Oil Service HOLDRs Trust
10	Oil Service HOLDRs Trust	Semconductor HOLDRS Trust	Invesco Euro Trust	iShares Lehman 20+ Treasury
Rank\Year	**2008**	**2009**	**2010**	**2011**
1	SPDR S&P 500 Trust	SPDR Gold Trust	SPDR Gold Trust	SPDR S&P 500 Trust
2	PowerShares QQQ	SPDR S&P 500 Trust	SPDR S&P 500 Trust	SPDR Gold Trust
3	SPDR Financial Sector	Market Vectors Gold Miners	iShares MSCI EM	Vanguard EM Index Funds
4	SPDR Gold Trust	iShares MSCI EM	Vanguard EM Index Funds	iShares MSCI EM
5	iShares Russell 2000	iShares FTSE/Xinhua China 25	SPDR MidCap 400	iShares MSCI EAFE
6	SPDR S&P 400 MidCap	iShares MSCI EAFE	iShares MSCI EAFE	VanEck Vectors Gold Miners

7	iShares MSCI EAFE	iShares Russell 2000	Market Vectors Gold Miners	SPDR MidCap 400
8	iShares MSCI EM	iShares GS Corp Bonds	iShares Russell 2000	iShares Russell 2000
9	iShares FTSE/Xinhua China 25	Oil Service HOLDRs Trust	PowerShares QQQ	iShares GS Corp Bonds
10	iShares Core S&P 500 Index	PowerShares QQQ	iShares GS Corp Bonds	iShres iBoxx HY Corp Bonds
Rank\Year	**2013**	**2014**	**2015**	**2016**
1	SPDR S&P 500 Trust	SPDR S&P 500 Trust	SPDR S&P 500 Trust	SPDR S&P 500 Trust
2	Vanguard EM Index Funds	Vanguard EM Index Funds	Vanguard EM Index Funds	Vanguard EM Index Funds
3	iShares MSCI EM	iShares MSCI EM	iShares MSCI EM	iShares MSCI EM
4	SPDR Gold Trust	SPDR Gold Trust	SPDR Gold Trust	SPDR Gold Trust
5	iShares MSCI EAFE	iShares MSCI EAFE	iShares MSCI EAFE	iShares MSCI EAFE
6	SPDR MidCap 400	SPDR MidCap 400	iShares Russell 2000	SPDR MidCap 400
7	iShares Russell 2000	iShares Russell 2000	SPDR MidCap 400	iShares Russell 2000
8	iShres iBoxx HY Corp Bonds	iShares GS Corp Bonds	iShares GS Corp Bonds	VanEck Vectors Gold Miners
9	VanEck Vectors Gold Miners	iShares Russell 1000 Value	iShares Russell 1000 Value	iShares Core S&P 500 Index
10	iShares GS Corp Bonds	SPDR Energy Sector	iShares iBoxx HY Corp Bonds	iShares GS Corp Bonds
Rank\Year	**2017**	**2018**		
1	SPDR S&P 500 Trust	SPDR S&P 500 Trust		
2	Vanguard EM Index Funds	Vanguard EM Index Funds		
3	iShares MSCI EM	SPDR Gold Trust		
4	iShares MSCI EAFE	iShares MSCI EAFE		
5	SPDR Gold Trust	iShares Core S&P 500 Index		
6	iShares Core MSCI EM	iShares MSCI EM		
7	iShares Russell 2000	iShares Russell 2000		
8	SPDR MidCap 400	iShares GS Corp Bonds		
9	iShares GS Corp Bonds	iShares Core MSCI EM		
10	iShares Core S&P 500 Index	SPDR MidCap 400		

Appendix A4
Logistic Regression – coefficients are reported in odd ratios

	High ETF	Low ETF	Non ETF
	(1)	(2)	(3)
Transitory Investor	5.64***	.571***	.59***
	(7.892)	(-4.4)	(-4.41)
Quasi-Indexer	2.798***	.916	.671***
	(4.627)	(-.67)	(-3.245)
Active Shares	.009***	22.954***	62.725***
	(-20.034)	(13.972)	(14.625)
Flow	.755	1.295	1.559**
	(-1.343)	(1.242)	(2.234)
Ln_Assets	1.00	.94***	1.011
	(-.006)	(-3.893)	(.713)
Ln_Number_Securities	.816***	2.111***	.679***
	(-8.393)	(29.908)	(-16.779)
Income Fee	.989***	.989***	1.032***
	(-2.737)	(-2.675)	(6.684)
Management Fee	1.316***	1.183***	.605***
	(4.753)	(2.942)	(-9.069)
Offshore	.95	1.174***	.887**
	(-.855)	(2.645)	(-2.088)
Advance Notice	.996***	.995***	1.006***
	(-3.648)	(-4.397)	(6.025)
Lockup Period	.965***	1.007**	1.024***
	(-9.97)	(2.158)	(8.039)
Age	1.029***	1.018***	.954***
	(6.728)	(4.191)	(-11.866)
Ln_Minimum_Investment	.918***	1.191***	.88***
	(-3.538)	(7.485)	(-5.331)
Number of Funds	.963***	1.098***	.954***
	(-3.342)	(8.549)	(-3.956)
Fund of Fund Dummy	1.77***	1.168	.382***
	(5.343)	(1.424)	(-7.289)
_cons	6.885**	0***	1.016
	(2.509)	(-16.629)	(.033)
Observations	13974	13974	13974
Pseudo R^2	.085	.111	.145
Year FE	Yes	Yes	Yes

This table presents the results of a Logistic regression of the determinants of the propensity of a hedge fund manager to utilize ETFs. The dependent variable is an indicator that takes the value of one of the Hedge Fund managers is in the High-ETF, Low-ETF, or Non-ETF user group. Comparison category is Dedicated HFs Coefficients are reported in Odds ratio. All other explanatory variables are defined in Appendix Table 1. Dummy variables are included for the observation year. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

Appendix A5
Unexpected Inflows and Outflows and Investments in ETFs

	Full Sample		Excluding Non-ETF Managers		High-ETF Managers	
Dependent Variable	**Change ETF Holdings$_t$**	**Change Non-ETF Holdings$_t$**	**Change ETF Holdings$_t$**	**Change Non-ETF Holdings$_t$**	**Change ETF Holdings$_t$**	**Change Non-ETF Holdings$_t$**
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Inflow	.012***	.131***	.019**	.073*	.048**	.082
	(2.635)	(3.617)	(2.394)	(1.736)	(2.299)	(.972)
Unexpected Outflow	.004	.286***	.009	.244***	.017	.233**
	(.504)	(6.036)	(.717)	(4.142)	(.598)	(2.181)
Expected Flows	.003	.345***	.005	.33***	.011	.297***
	(.578)	(10.336)	(.564)	(7.783)	(.618)	(4.643)
Controls?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13089	13089	7679	7679	3632	3632
R-squared	.205	.141	.225	.16	.261	.209
Strategy Control	Yes	Yes	Yes	Yes	Yes	Yes
Manager FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter 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). Unexpected Inflow is max(0,Unexpected_Flow). Unexpected Outflow is min(0,Unexpected_Flow). All the columns include the control variables defined in Appendix Table 1. Columns (1)-(2) present the results for the total sample. Columns (3)-(4) report the results of the sample excluding managers that did not invest in ETFs in the four-quarter previous the observation (Non-ETF) users. Columns (5)-(5) report the results of the sample of High-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 calendar-quarter fixed effect. Standard errors are clustered at the manager level. Robust t-statistics are reported in the parentheses ***p<0.01, **p<0.05, and *p<0.1, respectively

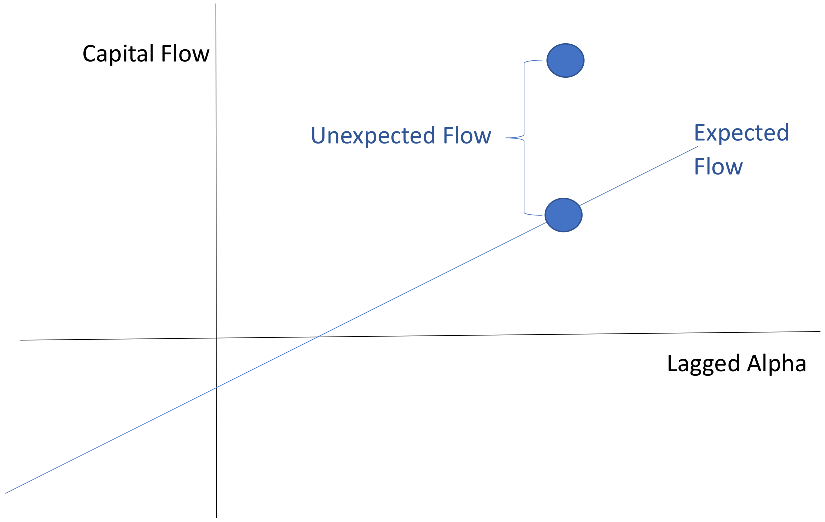


Figure 1. Unexpected Hedge Fund Flows
This figure presents a graphical depiction of unexpected hedge fund flows. Flows into and out of hedge funds depend on past performance (alpha, or another performance measure). The figure does not show possible nonlinearities in the flow-performance relation here, but these nonlinearities are checked in the empirical tests. In the figure there is a net positive shock to capital flows into the fund.

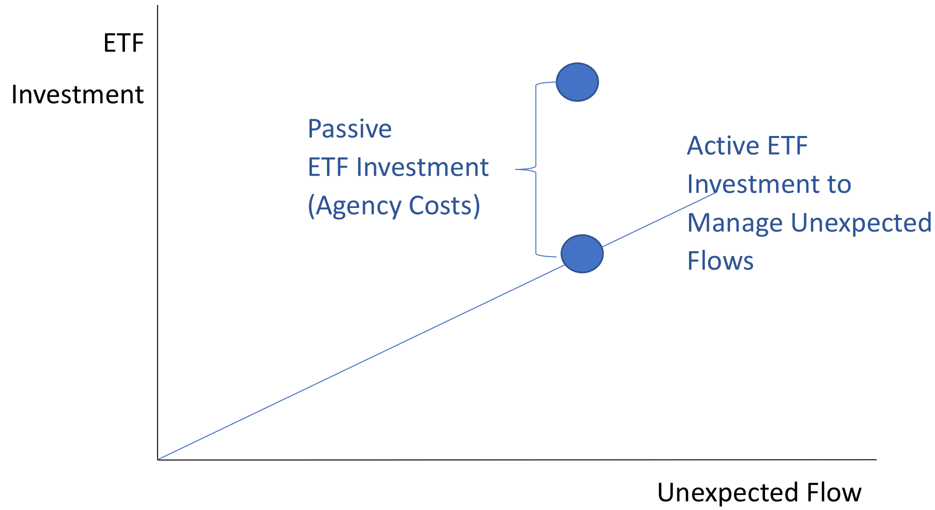
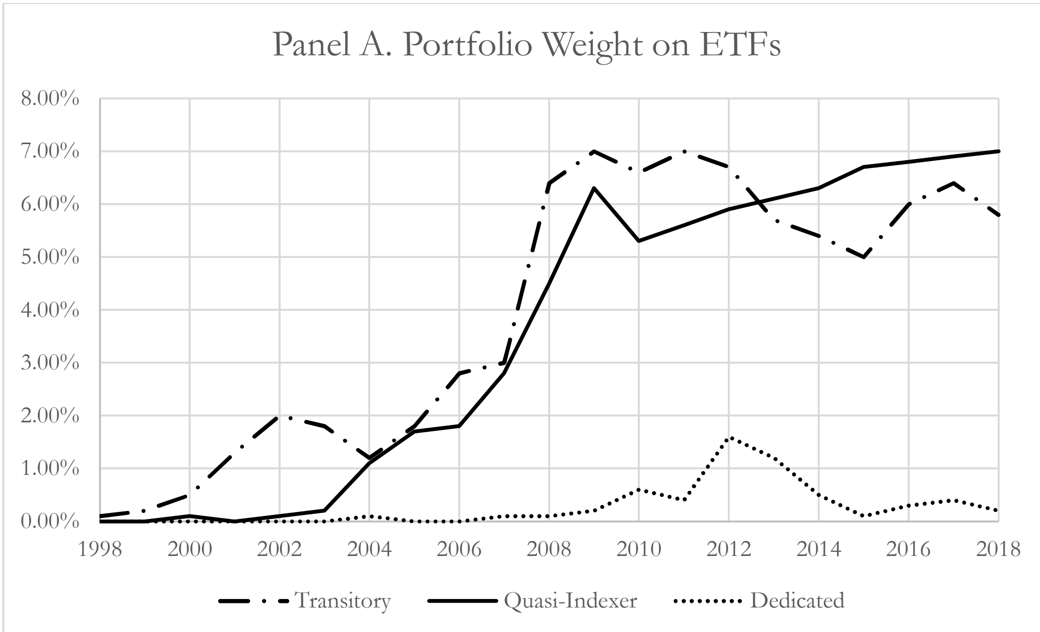


Figure 2. Active versus Passive Hedge Fund ETF Investment

This figure presents a graphical depiction of active hedge fund ETF investment to manage unexpected capital flows versus passive hedge fund ETF investment, which reflects an agency problem of delegated portfolio management.



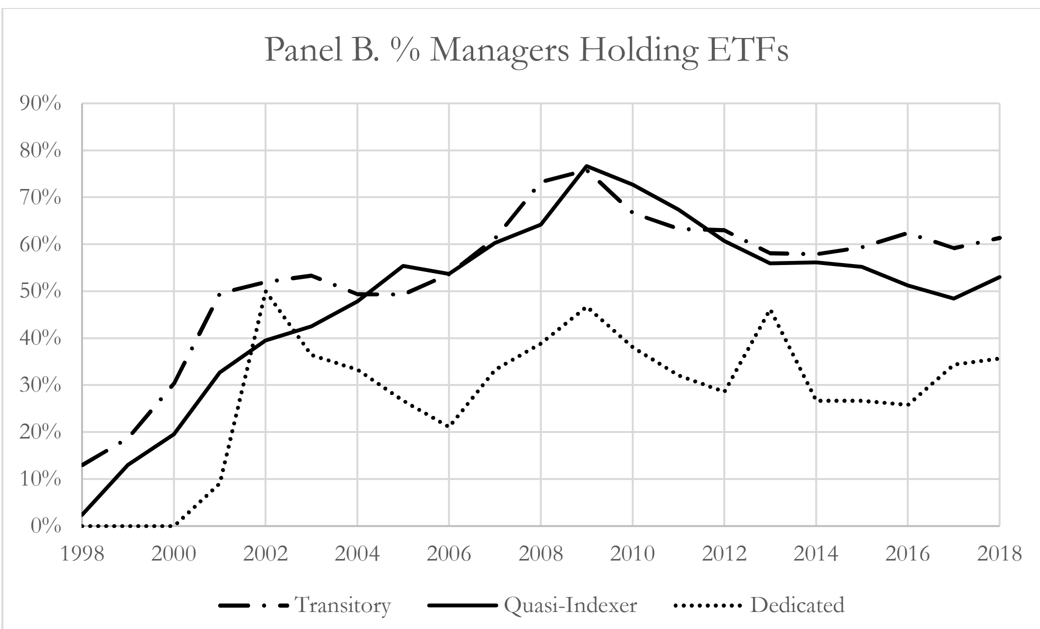


Figure 3. Panel A reports the time-series fraction of ETFs market capitalization as a percentage of the market capitalization of all the stocks reported by the Hedge Fund manager. Panel B reports the time series fraction of Hedge Fund managers that invest in ETFs.

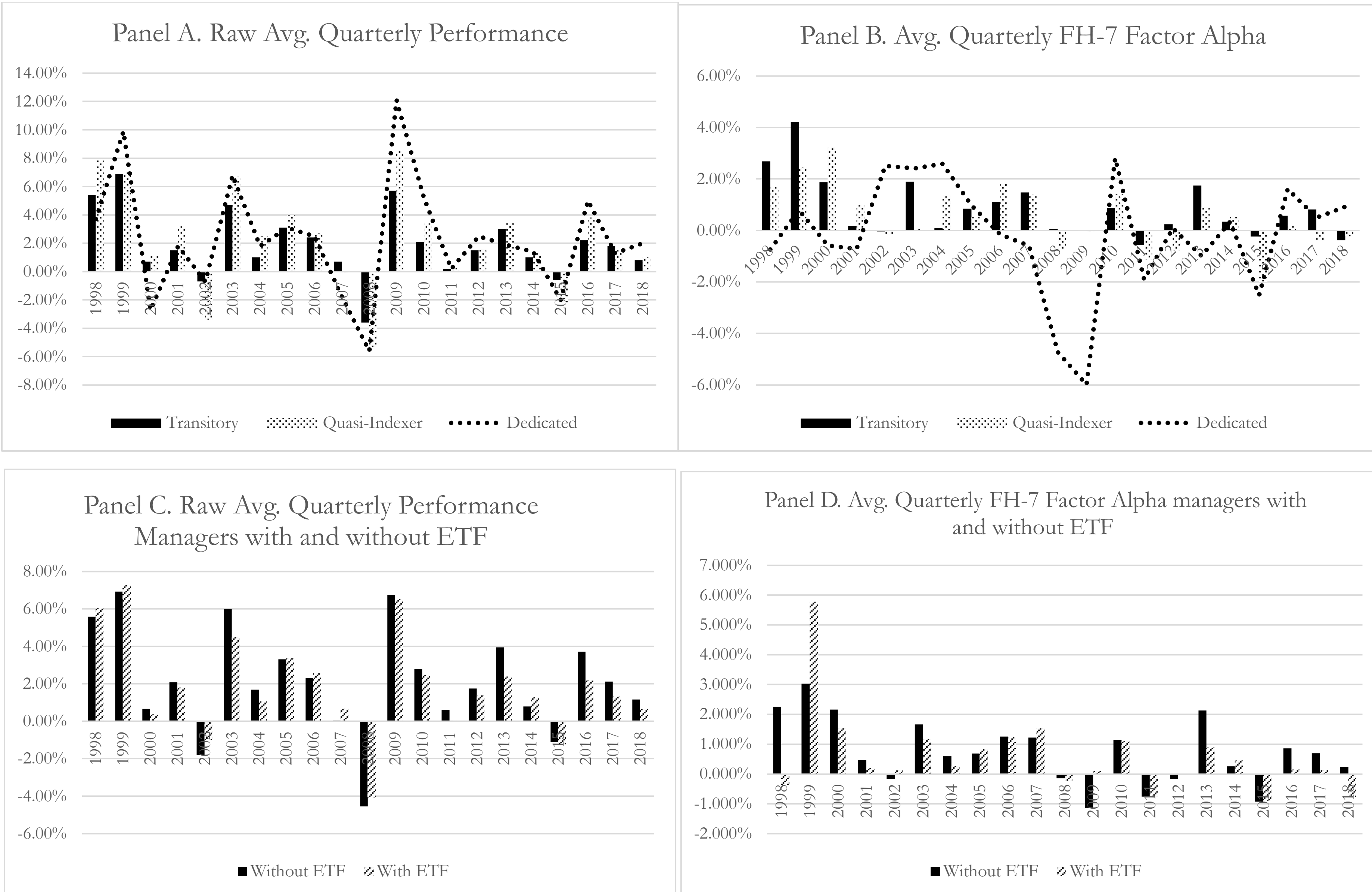
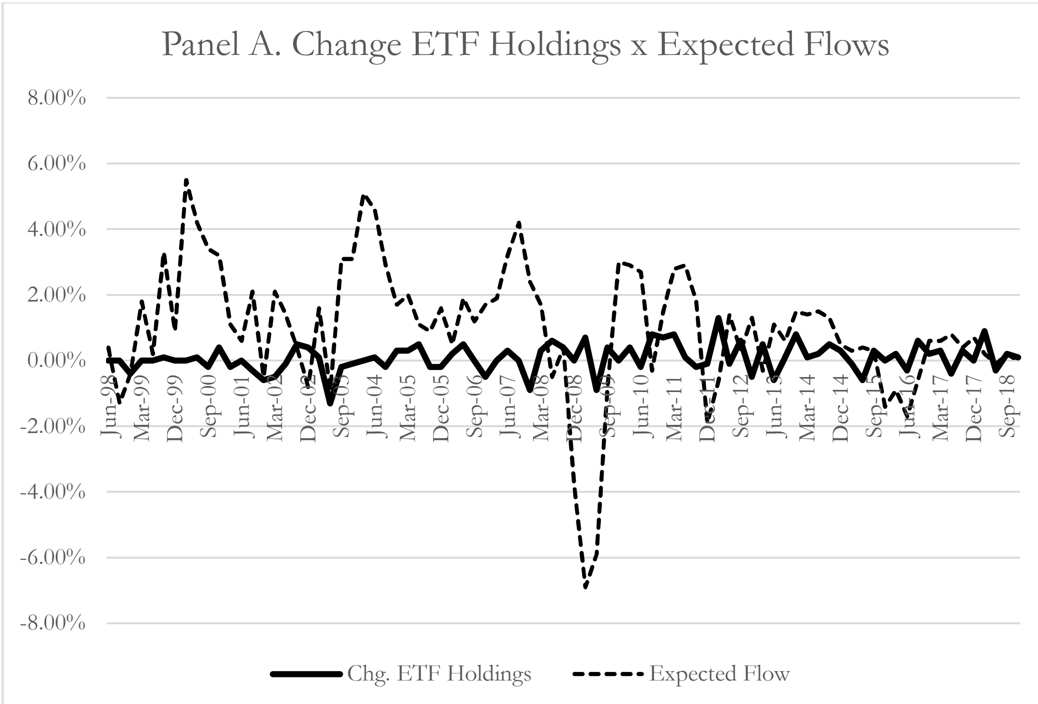


Figure 4 - This figure presents the cross-time quarterly performance of the Hedge Fund managers in our sample. Panel A presents the returns of the quarterly value-weighted Hedge Fund quarterly Raw returns. Panel B reports the quarterly Fung and Hsieh (2004) 7-factor alphas. We use the 24-months before each quarter to compute the factor loadings. Next, we compound the monthly alphas to compute the quarterly alphas. Panel C reports the quarterly raw returns for the managers with and without ETF reported on their 13-F quarterly filings. Panel D reports the quarterly 7-factor alphas for the managers with and without ETFs.



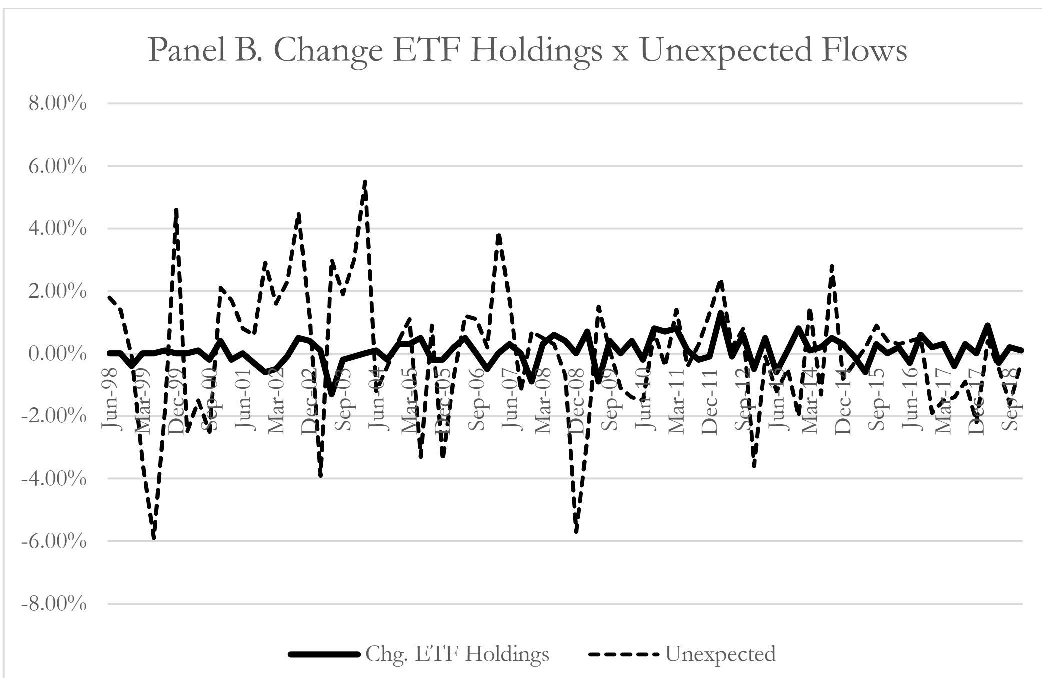


Figure 5. This figure shows relation between the Net Change of ETF holdings relative to the Hedge Fund equity portfolio value and the unexpected and expected flows. The quarterly flows are regressed on lagged quarterly flows and lagged quarterly returns. The expected flows are the predicted values, while the unexpected flows are the regression residuals. Panel A presents the relation between Change ETF holdings and expected flows. Panel C presents the relation between Change ETF holdings and unexpected flows.

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