CFR Working Paper NO. 20-07

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This Version: August 2023

Abstract

We investigate hedge fund firms' unobserved performance (*UP*), measured as the risk-adjusted return difference between a firm's reported gross return and its portfolio return inferred from its disclosed long-equity holdings. Firms with high *UP* outperform those with low *UP* by 6.36% p.a. on a risk-adjusted basis. *UP* is negatively associated with a firm's trading costs and positively associated with intraquarter trading in equity positions, derivatives usage, short selling, and confidential holdings. We show that limited investor attention can delay investors' response to *UP* and lead to longer-lived predictability of fund firm performance.

Keywords: Hedge fund skills, Unobserved Performance, Hedge fund flows, Diseconomies of Scale, Performance Predictability

JEL Classification Numbers: G11, G23

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1. Introduction

Despite the growing importance of hedge funds in financial markets, there is still limited understanding about identifying skilled hedge fund managers and the sources of their skill that can help reliably predict their future performance. Hedge funds' lax regulation, opaque structure, and limited disclosure makes this task challenging, if not impossible. We introduce a new skill measure for hedge funds that strongly predicts future hedge fund performance and is a better predictor than other measures suggested in the literature. We also provide evidence on the role of limited investor attention and eventual learning that can result in delayed investor reaction and prolonged persistence in fund performance when there is limited transparency and significant complexity in investment strategies (as is the case for hedge funds). Our results are consistent with the equilibrium process portrayed in the theoretical framework of Berk and Green (2004) but with sluggish investor reaction to signals of fund manager's ability.

Two strands of academic literature have made some progress with respect to hedge fund performance prediction through the use of two distinctive approaches. The first strand pursues a returns-based methodology to investigate the relation between hedge funds' reported returns to different risk factors.[1] One of the main findings from this literature is that hedge fund performance can be explained by exposures to different risks, but that the average fund manager seems to be skilled enough to deliver a positive and significant net-of-fee alpha. The second strand of literature takes a different route and investigates the performance of portfolio holdings of hedge funds. Due to limited disclosure requirements, researchers can only analyze funds' long equity positions disclosed to the Securities and Exchange Commission (SEC) on a

[1] An incomplete list of papers that document the different risks explaining hedge fund performance include nonlinear risk (Agarwal and Naik, 2004; Fung and Hsieh, 2004), correlation risk (Buraschi, Kosowski, and Trojani, 2014), liquidity risk (Aragon, 2007; Sadka, 2010; Teo, 2011), macroeconomic uncertainty (Bali, Brown, and Caglayan, 2014), volatility risk (Bondarenko, 2004; Agarwal, Bakshi, and Huij, 2009; Agarwal, Arisoy, and Naik, 2017), rare disaster concerns (Gao, Gao, and Song, 2018), and tail risk (Agarwal, Ruenzi, and Weigert, 2017). For more details, see also the survey by Agarwal, Mullally, and Naik (2015).

quarterly basis.[2] In contrast to the returns-based approach, empirical evidence on skill in hedge funds using the holdings-based methodology has been relatively scarce. For example, Griffin and Xu (2009) document that hedge funds are no more skilled than mutual funds in security selection and returns of disclosed long-equity portfolios of funds do not significantly outperform the market return after fees. Several limitations of holdings data can potentially explain this scant evidence of skill. These include having access to only quarterly snapshots of long but not short positions, coverage of only large equity positions (more than 10,000 shares or more than $200,000 in market capitalization) some of which may be driven by hedging motives rather than information (Jiao, Massa, and Zhang, 2016; Chen, Da, and Huang, 2019), potential distortion of disclosed portfolios, disclosure only at the hedge fund firm but not at the individual fund level, and funds' intraquarter trading.

Our paper addresses these *prima facie* conflicting findings on the existence of managerial skill in the hedge fund industry and drivers of such skill. For this purpose, we propose to use a similar measure as introduced by Kacperczyk, Sialm, and Zheng (2008) for mutual funds and combine the returns- and holdings-based approaches to evaluate hedge funds. The underlying intuition behind our investigation is as follows. When the returns-based approach shows positive alpha (but the disclosed long-equity positions do not), it should stem from the unobserved actions of hedge funds, i.e., actions that cannot be inferred from the fund firms' quarterly long-equity holdings.

Unlike long-equity portfolio returns, hedge fund firms' reported returns are influenced by their exposure to non-equity classes. Therefore, we focus on *equity-oriented* fund firms in this study.[3] To capture the unobserved return component (*URC*), we combine data on fund returns reported to commercial databases with data on long-equity positions of hedge fund

[2] There are few notable exceptions that investigate disclosed derivative positions of hedge funds (Aragon and Martin, 2012; Aragon, Martin, and Shi, 2019; Joenväärä, Kauppila, and Tolonen, 2022).
[3] The main results of the paper are robust when we relax this restriction and include non-equity oriented hedge fund firms that disclose long-equity positions to the SEC.

firms disclosed in their 13F filings. Consistent with the limited evidence of skill in long-equity positions, we observe that the average alpha of 0.35% per month (*t*-statistic of 3.88) for hedge fund firms in our sample is mostly driven by the fund firms' *URC* with an average alpha of 0.22% per month (*t*-statistic of 6.29).[4] Fund firms' average alpha of their long-equity positions is smaller (0.13% per month) and statistically indistinguishable from zero (*t*-statistic of 1.61). We estimate alphas from a nine-factor model, which is the Fung and Hsieh (2004) seven-factor model augmented with book-to-market and momentum factors.

We next adjust for known risk factors that can influence hedge fund returns to construct our measure of unobserved performance (*UP*). This measure is the *risk-adjusted* difference between fund firms' reported gross returns and hypothetical buy-and-hold returns from long-equity positions of 698 fund firms from 1994 to 2017.[5] We investigate whether a hedge fund firm's *UP* is able to predict future performance and whether it does so better than known drivers of hedge fund performance. Our results from univariate portfolio sorts of fund firms' *UP* in month *t* and future alphas measured in month *t*+3 show that firms with high *UP* outperform their peers with low *UP* by 0.53% per month. Interestingly, *UP* predicts future fund firm performance significantly better than either past reported gross fund firm performance (future alpha spread of 0.26%) or past performance derived from long-equity positions (future alpha spread of 0.07%). We also examine whether the relation between UP and future fund firm performance varies with the correlation between reported fund firm returns and long-equity portfolio returns. We find the predictability of UP to be strongest for fund firms in the lowest quintile of correlation but it also exists for the other correlation quintiles.

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[4] Our estimate of an average hedge fund firm alpha of 0.35% per month is in line with previous literature. Yang, Havranek, Irsova, and Novak (2023) investigate the magnitude of hedge fund alphas from 74 studies published between 2001 and 2021 and find that most of the monthly alpha estimates fall within a relatively narrow range of 30 to 40 basis points per month.

[5] Based on this definition of *UP*, we compare reported *gross* alphas (i.e., fund performance *before* fees) with *gross* alphas of buy-and-hold long-equity positions before transaction costs. An alternative *UP* measure can be constructed using net-of-fee fund returns and transaction-cost adjusted net returns of a buy-and-hold strategy with long-equity positions. All our main results hold with this alternative measure (see Section 3.4 for more details).

The spread in alphas of funds sorted on *UP* is not explained by differences in the exposure to alternative risk factors that have been shown to contribute to hedge fund performance and is not driven by the exposure to other asset classes. The predictability of *UP* for future fund performance is also not subsumed by other fund firm characteristics and continues to hold when we control for a fund firm's past reported performance, size, age, volatility, manager delta, management and incentive fees, minimum investment, lockup and redemption periods, offshore location, leverage usage, high-watermark, hurdle rate, as well as other skill measures, such as R^2 (Titman and Tiu, 2011) and strategy distinctiveness (Sun, Wang, and Zheng, 2012). Notably *UP* outperforms these two measures in predicting future fund firm performance. The predictive power of *UP* for future performance is stable over time and across different states of the world (high vs. low economic growth, market returns, or market volatility). These results suggest that investors can benefit from aggregating information from reported returns and long-equity positions to forecast fund performance.

As individual funds do not disclose equity positions, our analysis is conducted at the hedge fund firm level, which raises the question whether our findings can be extended to individual funds. Also, it is not clear whether investors can implement a profitable trading strategy using *UP* as they face several practical constraints, such as restrictions on capital withdrawal in the form of lockup and redemption periods, portfolio concentration considerations, and delays in disclosure. To evaluate the performance of a real-life trading strategy using *UP*, we focus on single-fund firms, i.e., firms that only offer one fund, and consider a non-overlapping holding period of 12 months. We also relax other restrictions by excluding funds with a lockup and restriction period (sum of redemption and notice periods) of more than 12 months, focusing only on the long side of the strategy, and implementing the procedure suggested by Avramov, Barras, and Kosowski (2013) to mimic a realistic trading strategy. Even after accounting for these real-world frictions, investors can still profit substantially from a trading strategy based on *UP*.

We probe further into the nature of hedge funds' trading strategies that can help them enhance *UP*. While the opaqueness of the industry makes it challenging to provide definitive answers here, we are still able to shed light on four potential trading channels that contribute to *UP*. First, *UP* is positively related to active intraquarter trading of long-equity positions and the associated transaction costs. We find a negative relation between *UP* and transaction costs, suggesting that funds that trade more efficiently exhibit higher *UP*, i.e., *UP* captures trading skills. Second, our results show a positive relation between *UP* and the use of put options but an insignificant relation for the use of call options, consistent with funds enhancing performance by mitigating downside risk. Third, funds with higher *UP* short sell more actively. Fourth, more frequent use of confidential holdings is associated with higher *UP*.

Finally, we investigate whether investors use *UP* for manager selection and how investor flows affect the performance predictability of *UP*. If *UP* is a measure of manager skill, it should predict hedge fund performance, everything else equal. However, Berk and Green (2004) show that skilled fund managers' ability to generate abnormal performance is hampered by investor inflows, which – combined with diseconomies of scale among hedge funds (e.g., Teo, 2009, Getmansky, 2012, and Yin, 2016) – should lead to zero future net alphas in equilibrium. Such an equilibrium would emerge quickly if investor flows immediately and fully react to signals of skill, eroding any persistence in a fund's abnormal performance. However, if this is not the case and investor reaction is sluggish, e.g., because it is difficult for investors to parse information about skill due to limited disclosure and complexity of investment strategies, we would expect some degree of persistent predictability in future performance of skilled managers. Consistent with this idea, we find predictive power of *UP* for up to three years in the future, suggesting that investor reaction to *UP* is at best slow moving.

We investigate this *delayed equilibrium mechanism* in three steps. First, we analyze how investors react to different skill signals and find that they direct their money to fund firms with high past year's reported gross fund firm performance, but *not* to those with high *UP*. We conjecture that investors are either not aware of the predictive power of *UP* or unable to compute the measure due to substantial data requirements (i.e., data from commercial databases *and* detailed 13F holdings must be combined) and involved statistical analyses. Hence, investors quickly react to past reported fund firm performance by allocating money over the next year. In contrast, investor reaction to *UP* is more muted but gradually evolves over subsequent years as *UP* predicts future performance which then eventually leads to future investor flows. Second, we examine how this flow dynamics affects future fund firm performance over longer horizons. Consistent with Berk and Green (2004), predictability of future fund firm performance based on past reported (and easily observable) performance disappears after one year because of quick investor reaction. For *UP*, performance predictability is more long lived and persistent up to three years into the future because of delayed investor reaction. Third, we investigate why fund firms with high *UP* exhibit deterioration in future performance after receiving investor inflows. Our results reveal that, after large investor inflows, high *UP* fund firms reduce intraquarter trading as well as their use of put options, short-selling activities, and confidential holdings, suggesting that these trading channels are not easily scalable which eventually leads to diseconomies of scale. In light of earlier findings that these channels drive *UP*, it is intuitive that the predictive power of *UP* for fund firm performance finally deteriorates over time.

To provide additional evidence for the delayed equilibrium mechanism we portray, we also analyze the impact of how much *investor attention* a fund firms attracts. To proxy for investor attention, we use the number of downloads for a fund firm's 13F portfolio holdings to classify fund firms into high or low attention firms. If our hypothesized equilibrium mechanism is correct, we should observe that for low attention fund firms, (i) investor flows react least to *UP* and (ii) *UP* performance predictability is particularly high. This is exactly what we find.

Our paper makes several contributions to the literature. First, we propose a new performance metric for hedge funds, *UP*, which combines information from both equity-oriented hedge fund returns reported to commercial databases and long-equity positions disclosed to the SEC. We show that this measure strongly predicts the cross-section of future fund firm returns and outperforms predictions by either returns-based performance measures or holdings-based performance measures. Second, we uncover different sources of managerial skill in hedge funds by showing that *UP* is driven by fund firms' intraquarter equity trades, use of derivatives, short selling, and delayed disclosure of long-equity positions. Consequently, our *UP* measure captures managerial skills that are distinct from those inferred from the return gap measure of Kacperczyk, Sialm, and Zheng (2008) for mutual funds, which are more restricted in their use of such investment strategies. Third, we provide novel evidence on the relation between manager skill, performance predictability, and investor flows, and how this relation varies with investor attention. We show that investors' limited attention and ability to parse managerial skill can lead to delayed response and longer-lived predictability of fund performance. Moreover, we shed light on the dissipation of performance persistence due to managers' inability to scale up the unobservable actions that contribute to their superior performance.

The structure of the paper is as follows. Section 2 describes the data and introduces the concept of unobserved performance, *UP*. Section 3 presents evidence on the predictive ability of *UP* for future fund performance. Section 4 examines trading channels that contribute to *UP*. Section 5 lays out the framework to understand the relation between *UP*, investor flows, and performance predictability in equilibrium. Section 6 concludes.

2. Data and Unobserved Hedge Fund Performance

2.1 Data

We obtain the data for this study from five distinct sources. The first source is the "Union Hedge Fund Database", which contains monthly net-of-fee returns of hedge funds as well as a snapshot of fund characteristics. We create this union data by merging hedge fund data from four different commercial databases, namely Eurekahedge, Hedge Fund Research (HFR), Morningstar, and Lipper TASS. Second, we employ the 13F long-equity holdings database from Thomson Reuters. The third data source is the SEC's EDGAR (Electronic Data Gathering, Analysis, and Retrieval) database. It consists of a fund firm's long positions in call and put options as well as long-equity positions that are disclosed with a delay (i.e., confidential holdings), all extracted from the 13F filings. Fourth, we use the EDGAR log file data containing information on downloads of investment firms' 13F filings.[6] Finally, we retrieve data on long and short transactions of institutional investors from Abel Noser.

The Union Hedge Fund Database includes data for a total of 39,933 funds from 1994 to 2017. It is important to construct a comprehensive database because 71% of all funds only report to a single database (e.g., Lipper TASS has only 19% unique funds). We display the overlap between the four databases in Figure IA.1 in the Internet Appendix. We use multiple standard filters for our sample selection. First, we start our sample period in 1994, the year in which commercial hedge fund databases started to track defunct funds. Second, we require a fund to have at least 24 monthly return observations. Third, we exclude funds denoted in a currency other than US dollars. Fourth, following Agarwal, Arisoy, and Naik (2017), we eliminate

[6] We thank Sean Cao, Kai Du, Baozhong Yang, and Liang Zhang for sharing this data. See Cao et al. (2021) for more details on 13F downloads.

the first 24 months of a fund's return series to mitigate the backfill bias.[7] This filtering process leaves us with a sample of 12,424 hedge funds from January 1994 to December 2017.

The 13F Thomson Reuters Ownership database consists of quarterly long-equity positions of 8,705 institutional investors during the period from 1980 (when Thomson Reuters data starts) to 2017. This database does not separately categorize hedge fund firms. Therefore, we follow Agarwal, Fos, and Jiang (2013) and identify hedge fund firms manually. We end up with a sample of 2,512 unique hedge fund firms among the 13F filing institutions holding \$3.25 trillion of long-equity positions in 2017.

We merge the hedge fund firms from the 13F database with the firms listed in the Union Hedge Fund Database. Following Agarwal, Fos, and Jiang (2013) and Agarwal, Ruenzi, and Weigert (2017), we match firms by name allowing for minor variations. For each firm i in month t, we compute the *Net Fund Firm Return* as the AUM-weighted average of its underlying funds' net-of-fee returns in excess of the risk-free rate. Similarly, we compute the *Equity PF Return* as the value-weighted returns of the long-equity positions in excess of the risk-free rate.[8] We are able to match 95.02% of firms' 13F long-equity positions to CRSP stock returns.

Since 13F positions are reported only on a quarterly basis, we use a firm i's long-equity positions in month t to compute the *Equity PF Return* over months t+1 to t+3 to obtain a monthly return series.[9] We eliminate all pairs of firms in which there are fewer than 24 overlapping periods of data from the 13F and Union datasets. To ascertain the style of a hedge fund firm, we use the style in which its funds have invested most of their assets. In line with our focus on equity-oriented firms in this study, we only include firms that employ an

[7] In robustness checks included in Section 3.4, we find that our results hold when we eliminate the first 12 (instead of 24) monthly return observations and when we apply the alternative method of Jorion and Schwarz (2019) to infer a fund's listing date when it is not available.

[8] In calculating long-equity portfolio returns, we do *not* include confidential holdings that are disclosed later in 13F amendments, and therefore are not publicly observable at the time of quarterly disclosure (see Section 4).

[9] As an example, we use the disclosed 13F positions of a firm at the end of December 2011 to compute the *Equity PF Return* for the months from January 2012 to March 2012. To compute the *Equity PF Return* for the months from April 2012 to June 2012, we use the disclosed positions at the end of March 2012, and so on. Within-quarter weights are adjusted for price changes of the underlying stocks.

"Emerging Markets", "Event Driven", "Equity Long", "Equity Long-Short", or "Equity Market Neutral" styles. We end up with 698 fund firms managing 2,409 distinct funds.

For some of our analyses in Section 4, we merge our sample with quarterly 13F filings of long option positions and confidential holdings of firms in the period from April 1999 (when electronic filings become available) to December 2017 obtained from the SEC EDGAR database. The 13F filing institutions need to report long option positions on 13F securities and indicate whether the options are calls or puts and the underlying securities. As stated earlier, institutions can request confidential treatment from the SEC for certain holdings to delay disclosure. Following Agarwal, Jiang, Tang, and Yang (2013), we extract confidential holdings from 13F amendments. Of the 698 firms that appear both in the Union Hedge Fund Database and in the 13F Thomson Reuters Ownership database, 344 firms report at least one long option position, and 176 firms file at least one confidential position. To proxy for investor attention for fund firms in Section 5, we use SEC EDGAR log file data which contains information on downloads of fund firms' 13F filings between 2003 and 2017. We can identify downloads for 584 fund firms. Mean (median) number of downloads per firm and year is 4,611 (671).

Finally, for estimating the intraquarter portfolio turnover, computing actual short sales of hedge fund firms and computing a proxy for transaction costs, we use proprietary data from the brokerage firm, Abel Noser (i.e., Abel Noser Data). Abel Noser provides actual transaction data for different investment management firms and plan sponsors with identifying manager information between January 1999 and September 2011. We follow Jame (2018) to manually merge this data with the Union Hedge Fund Database and the 13F data based on fund firm names. We can merge 27 hedge fund firms through this process.[10] Following Busse, Chordia,

[10] Jame (2018) identifies 70 hedge fund firms with at least one equity-oriented hedge fund in the Abel Noser database (see Section 2 of his study) of which 27 firms appear both in the Union and 13F databases.

Jiang, and Tang (2021), we calculate transaction costs for trades reported in the Abel Noser data as the sum of monthly implicit trading costs, commissions, and tax plus fees.

2.2 Unobserved Performance

To capture a fund firm's *Unobserved Performance* (*UP*), we first define its *Unobserved Return Component* (*URC*) and then adjust it by commonly used risk factors for hedge funds to isolate managerial skill. Formally, for each firm i in month t, we first define the unobserved return component as the difference between a firm's reported gross-of-fee return *(Gross Fund Firm Return)* and its long-equity portfolio return *(Equity PF Return)*,

$$URC_{i,t} = Gross\ Fund\ Firm\ Return_{\ i,t} - Equity\ PF\ Return_{\ i,t}\ . \tag{1}$$

Since funds only report the *Net Fund Firm Return* to commercial databases, we estimate their gross-of-fee returns following the procedure in Agarwal, Daniel, and Naik (2009). The main idea of this procedure is to impute gross-of-fee returns as the sum of net-of-fee returns and the asset-based management fee if no incentive fee is paid out. In case the hedge fund manager is entitled to an incentive fee, gross-of-fee returns are computed as the sum of net-of-fee returns, asset-based management fee, and incentive fee estimated from an algorithm that considers the hurdle rate and high watermark provisions, if any.[11]

We report the descriptive statistics of firms' reported gross and net excess returns, long-equity portfolio excess returns, unobserved return components, and characteristics in Table 1, Panel A. We calculate statistics by averaging over the monthly cross-sectional statistics across all firms during our sample period.

[Insert Table 1 around here]

[11] Our findings are not sensitive to the use of algorithm in Agarwal, Daniel, and Naik (2009). We obtain similar results either using an independent algorithm from Ben-David, Birru, and Rossi (2020) or using net returns to compute *UP* (see Section 3.4). We thank Alberto Rossi for sharing his algorithm to compute gross-of-fee returns.

Our results indicate that, on average, the hypothetical *Equity PF Return* of hedge fund firms exceeds the reported *Gross Fund Firm Return* by 0.10% per month, i.e., *URC* is negative. We also investigate the time-series variation in the different return components. To do so, we compute the *Aggregate Gross Fund Firm Return*, *Aggregate Equity PF Return*, and *Aggregate Unobserved Return Component* as the monthly equally-weighted average of the respective individual measures across all firms. Panel A of Figure 1 plots the monthly time-series of *Aggregate Gross Fund Firm Return* and *Aggregate Equity PF Return* while Panel B shows it for the *Aggregate Unobserved Return Component*.

[Insert Figure 1 around here]

Visual inspection shows that the time-series of the *Aggregate Equity PF Return* is more volatile than the time-series of the *Aggregate Gross Fund Firm Return*. We find that the highest spikes in the A*ggregate Unobserved Return Component* coincide with periods of financial downturns, i.e., 11.48% in October 2008 (one month after the bankruptcy of Lehman Brothers and the beginning of a worldwide recession), 9.07% in August 1998 (Asian Financial Crisis with the collapse of Long Term Capital Management), and 8.12% in September 2001 (burst of the dotcom bubble), suggesting that unobserved actions of hedge funds are particularly valuable and informative during crisis periods. In contrast, the lowest values for the *Aggregate Unobserved Return Component* are in October 2011 (–8.89%), April 2009 (−7.83%), and April 2001 (−7.47%), periods characterized by high equity market returns.

To determine the components of hedge fund returns that are associated with superior risk-adjusted performance, we estimate time-series regressions of the *Aggregate Gross Fund Firm Return*, the *Aggregate Equity PF Return*, and the *Aggregate Unobserved Return Component* on the risk factors in Fung and Hsieh (2004)'s seven-factor model (i.e., *S&P*, *SCMLC*, *BD10RET*, *BAAMTSY*, *PTFSBD*, *PTFSFX*, and *PTFSCOM*) augmented by the Fama and French (1993) book-to-market factor (*HML*) and the Carhart (1997) momentum factor

(*UMD*). We adjust the standard errors for serial correlation using the Newey and West (1987) correction over 36 lags. Panel B of Table 1 shows that the monthly alpha for the *Aggregate Gross Fund Firm Return* (0.35%, *t*-statistic of 3.88) is much higher than that for the *Aggregate Equity PF Return* (0.13%, *t*-statistic of 1.61). Therefore, the alpha of hedge funds seems to largely stem from their unobserved actions (0.22%, *t*-statistic of 6.29).

Panel B of Table 1 shows that *URC* is significantly related to several risk factors. Therefore, to isolate manager skill, we adjust for these factors to construct our main measure, *Unobserved Performance* (*UP*). It is defined as the difference between the abnormal performance associated with a fund firm's gross returns (*Gross Fund Firm Performance)* and the abnormal performance associated with its long equity portfolio (*Equity PF Performance*). We adjust both these performance measures for the nine risk factors mentioned above. In each case, we apply a rolling window of 36 months for the estimation of factor loadings. Formally, for each fund firm *i* in month *t*, we define:

$$UP_{i,t} = Gross\ Fund\ Firm\ Performance_{i,t} - Equity\ PF\ Performance_{i,t}\ . \qquad (2)$$

For $X \in \{Fund\ Firm, Equity\ PF\}$,

$$X\ Performance_{i,t} = X\ Return_{i,t} - X\ Return_{i,t,expected} \qquad (3)$$

with

$$X\ Return_{i,t,expected} = \hat{\beta}_{1,i,t} S\&P_t + \hat{\beta}_{2,i.,t} SCMLC_t + \hat{\beta}_{3,i,t} BD10RET_t + \hat{\beta}_{4,i,t} BAAMTSY$$

$$\hat{\beta}_{5,i,t} PTFSBD_t + \hat{\beta}_{6,i,t} PTFSFX_t + \hat{\beta}_{7,i,t} PTFSCOM_t + \hat{\beta}_{8,i,t} HML_t + \hat{\beta}_{9,i,t} UMD_t \qquad (4)$$

Therefore, *UP* reflects the performance of a fund firm's unobserved actions that are not captured by the performance inferred from its disclosed long-equity portfolio positions. Risk-adjusted performance of high *UP* firms strongly deviates from that of their disclosed long-equity portfolio suggesting superior skill while low *UP* firms exhibit performance similar to that of their long-equity portfolio. A negative *UP* measure indicates that the unobserved actions a firm are associated with worse performance compared to the buy-and-hold performance of their disclosed equity holdings, i.e., managers' active trading decisions destroy value.

As mentioned before, our *UP* measure is closely related to the return gap measure proposed by Kacperczyk, Sialm, and Zheng (2008).[12] However, unlike mutual funds, hedge funds use dynamic trading strategies often involving derivatives, short selling, and leverage. Therefore, *UP* not only captures the intraquarter trading as in the case of mutual funds but also reflects the distinctive nature of hedge funds' investment strategies, which involve the use of derivatives and short selling as well as long-equity positions disclosed with a delay. In Section 4, we explore these unique trading features of hedge funds that contribute to the *UP* measure.

We report summary statistics of *Gross Fund Firm Performance*, *Equity PF Performance*, and *Unobserved Performance* (*UP*) in Panel C of Table 1. As before, we calculate statistics by first averaging over the monthly cross-section and then over the time-series over our sample period. Average *Gross Fund Firm Performance* is 0.44% per month across all fund firms and months in the sample, whereas *Equity PF Performance* and *UP* averages are 0.13% and 0.31%, respectively.[13] As in Panel B of Table 1, we observe that after adjusting for standard hedge fund risk factors, fund firms' performance is largely driven by their unobserved performance component. Panel C of Table 1 also reports the descriptive statistics of *UP* for different equity-oriented fund styles. Perhaps not suprisingly, *UP* is smallest (value of 0.15%) for the Emerging Markets / Equity Long style, which follow long-only buy-and-hold strategies similar to mutual funds. *UP* is the highest for the Equity Market Neutral

[12] Other studies that work with the intersection of reported mutual fund returns and hypothetical returns inferred from disclosed long positions include Bollen and Busse (2006) who study mutual fund trading costs, and Agarwal, Gay, and Ling (2014) who examine window dressing in mutual funds.

[13] Note that while average *URC* is negative (−0.10%), firms' average *UP* value is positive (0.31%). This change is due to risk adjustment. *URC* has strong negative exposures to the market factor and the size factor.

funds (value of 0.41%) that hedge out most of their equity market exposure, and therefore short selling and derivatives use are likely to contribute to a higher *UP* measure as we show later.[14]

Table IA.1 in the Internet Appendix reports the correlations between *UP* and other variables. As expected, based on the way we construct the *UP* measure, we find it to be positively correlated with *Fund Firm Performance* (+0.53), and negatively correlated to *Equity PF Performance* (−0.60). In addition, in Table IA.2 of the Internet Appendix we examine the relation between *UP* in month *t+1* and different firm characteristics measured in month *t* using the Fama and MacBeth (1973) methodology. Our results reveal that past *UP*, *Gross Fund Firm Performance,* managerial incentive measures (such a manager delta and high-water mark) as well as discretion (proxied by the length of a fund's lockup period) are positive predictors of *UP*. Moreover, firms with high *UP* show a low R^2 from the nine-factor model (Titman and Tiu, 2011) as well as a high strategy distinctiveness (SDI, Sun, Wang, and Zheng, 2012), consistent with managers' ability to generate superior performance through active and unique investment strategies. We carefully control for these characteristics in our subsequent analysis of *UP*'s ability to predict future fund performance.

3. *UP* and Future Hedge Fund Performance

In this section, we analyze whether *UP* reflects managerial skill and therefore reliably predicts future net-of-fee performance. All applied measures to evaluate fund performance (i.e., excess returns and alphas) are computed net-of-fees unless stated otherwise.

3.1 Univariate Portfolio Sorts

To assess the predictive power of differences in a fund firm's *UP* on the cross section of future hedge fund firm returns, we relate *UP* in month *t* to firm returns and alphas in month

[14] As both the Emerging Markets and the Equity Long styles are represented by very few fund firms, we pool them together in one category to mitigate the effect of outliers on the descriptive statistics.

t+3. We leave out two months to ensure that investors can observe the long equity holdings which are disclosed with a delay of up to 45 days. We begin our investigation with univariate sorts. For each month t, we sort firms into quintiles based on the *UP* measure. We then compute equally-weighted monthly average excess returns of these quintile portfolios in month t+3, and report them in Column (1) of Panel A in Table 2.

[Insert Table 2 around here]

Hedge fund firms in the portfolio with the lowest (highest) *UP* earn future returns of 0.28% (0.75%) in excess of the risk-free rate. Moreover, future returns increase monotonically across the *UP* quintiles. The return spread between portfolios 5 and 1 is 0.47% per month, significant at the 1% level with a t-statistic of 4.17. We compare these findings with portfolio sorts based on *Gross Fund Firm Performance* (Column 2) and *Equity PF Performance* (Column 3) and show that the respective spreads between portfolios 5 and 1 amount to clearly less economically and statistically significant monthly values of 0.17% (t-statistic of 1.67) and 0.09% (t-statistic of 0.95).[15] Finally, in Columns 4 and 5, we document that the 5−1 differences in returns between forecasts based on *UP* and *Gross Fund Performance* and based on *UP* and *Equity PF Performance* are significant at the 1% level. These findings suggest that *UP* is a better predictor of future firm returns in the cross section compared to both *Gross Fund Firm Performance* and *Equity PF Performance*. Despite the constraint to short hedge funds, this analysis still demonstrates the superior predictability of the *UP* measure relative to returns-based or holdings-based performance measures. That is, funds in the highest *UP* quintile significantly outperform funds in the highest *Gross Fund Firm Performance* and *Equity PF Performance* quintiles by 0.17% (t-statistic of 4.11) and 0.25% (t-statistic of 3.68) per month.

[15] A potential interpretation of the results in columns (1) and (3) is that a hedge fund's skill that specifically relates to its unobserved performance persists across time to a greater extent than its stock-picking ability. We examine the persistence of *UP* together with investor response in more detail in Section 5.

Panel B of Table 2 reports the results when we adjust future firm returns for standard hedge fund risks in the nine-factor model. We continue to find that *UP* is clearly superior in predicting future risk-adjusted returns (or alphas) in comparison to either *Gross Fund Firm Performance* or *Equity PF Performance*. Hedge fund firms in the portfolio with the lowest *UP* earn an insignificant future average alpha of −0.12% per month, whereas those with the highest *UP* earn a significant future average alpha of 0.41% per month (see Column 1). The spread between average alphas of portfolios 5 and 1 is 0.53% per month (6.36% per annum), significant at the 1% level with a *t*-statistic of 4.52. This effect is much larger than the alpha spreads between the best and worst performance quintiles sorted on alphas estimated from reported *Gross Fund Firm* returns (0.26% in Column 2) or *Equity PF* returns (0.07% in Column 3). Moreover, the difference in the alpha spreads of firms sorted on *UP* is significantly larger than those of firms sorted on either reported *Gross Fund Firm* alphas (0.27%, *t*-stat = 3.46; see Column 4) or firms sorted on *Equity PF* alphas (0.46%, *t*-stat = 3.38; see Column 5).

Can the return spread based on *UP* be explained by additional hedge fund risk factors or funds' exposure to other asset classes? We address this question in Table IA.3 of the Internet Appendix by regressing the high minus low (5 − 1) *UP* return spread on additional risk factors (Panel A) and the returns from other asset classes (Panel B). To allow for the ease of comparison, in Column (1) of Panel A, we report the results of the nine-factor model as our baseline specification. In Column (2), we replace the nine-factor model by the 5-factor model from Fama and French (2015). In subsequent columns, we extend the nine-factor model from Column (1) to include: the Pástor and Stambaugh (2003) traded liquidity factor; the Frazzini and Pedersen (2014) betting-against-beta factor; the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor; the Baker and Wurgler (2006) investor sentiment factor; the Buraschi, Kosowski, and Trojani (2014) correlation risk factor; and the Agarwal, Ruenzi, and Weigert (2017) tail risk factor. In Column (9), we control for all risk factors together. Our results indicate a significantly positive alpha for the high minus low $(5 - 1)$ *UP* return spread in each case ranging from 0.52% to 0.63% per month.

Panel B of Table 3 investigates whether the return spread based on *UP* is due to hedge funds' exposure to other asset classes. Columns (2) through (8) extend our baseline specification by adding returns of the MSCI Emerging Market index, the MSCI European Market index, the Barclays US Government Bond index, the Barclays US Corporate Investment Grade Bond index, the S&P GSCI Commodities index, the FTSE NAREIT US Real Estate index, and the US Private Equity index from Cambridge Associates, respectively. Column (9) controls for funds' exposure to all these asset classes simultaneously.[16] Statistical and economic significance of the return spread based on *UP* remain unchanged.

We plot the cumulative returns from pursuing the *UP*-based investment strategy in Figure 2. To do so, we assume an initial investment of $1 at the beginning of 1997 and apply monthly rebalancing without accounting for trading costs.

[Insert Figure 2 around here]

Panel A of Figure 2 displays how one dollar invested in different *UP* portfolios grows over time on a risk-adjusted basis. The top *UP* portfolio outperforms the other portfolios by a wide margin by the end of our sample period. In Panel B, we compare the performance of the hypothetical $(5 - 1)$ *UP* spread to the $(5 - 1)$ spread portfolios based on *Gross Fund Firm Performance* and *Equity PF Performance.* At the end of our sample period in 2017, the final wealth of the investor amounts to $3.10 when pursuing the *UP* strategy and is substantially higher than the $1.47 and $1.22, respectively, from competing strategies.

[16] The US Private Equity index is only available at a quarterly frequency. Hence, Column (8) report the results of a time-series regression of the *UP* return spread on the *quarterly* returns of respective risk factors. We exclude the private equity risk factor in Column (9) where we use monthly returns of all other risk factors.

3.2 Bivariate Portfolio Sorts

The return spread based on *UP* could potentially be driven by its core building blocks, *Gross Fund Firm Performance* and *Equity PF Performance*. In line with this idea, we find (as shown in Table IA.1 in the Internet Appendix) that the correlations between *UP* and *Fund Firm Performance* (+0.53), and between *UP* and *Equity PF Performance* (−0.60) are high in absolute values. To distentangle the return spread based on *UP* from the two performance variables, we double sort portfolios on (i) *Gross Fund Firm Performance* and *UP*, as well as (ii) *Equity PF Performance* and *UP*. Table 3 reports the results.

[Insert Table 3 around here]

We first conduct *dependent* portfolio double sorts based on *Gross Fund Firm Performance* and *UP*. For this purpose, we form quintile portfolios sorted on *Gross Fund Firm Performance*. Then, within each *Gross Fund Firm Performance* quintile, we sort firms into five portfolios based on *UP* (both sorts in month *t*). We report the equally-weighted average returns of the 25 *Gross Fund Firm Performance* × *UP* portfolios in Panel A. Firms with high *UP* have higher returns than firms with low *UP* in all *Gross Fund Firm Performance* quintiles. Moreover, return spreads between *UP* 5 and *UP* 1 portfolios are statistically significant in four out of five quintiles. The average spread in returns between high *UP* and low *UP* firms after controlling for *Gross Fund Firm Performance* is 0.39% per month, significant at the 1% level. The last row in Panel A shows similar results for nine-factor alphas (i.e., spread of 0.45%).

Second, we conduct dependent portfolio double sorts based on *Equity PF Performance* and *UP* using the same methodology. We observe that high *UP* firms outperform low *UP* firms in all *Equity PF Performance* quintiles. Again, the spread is statistically significant in four out of five quintiles. The average *UP* return (nine-factor alpha) spread after controlling for *Equity PF Performance* is 0.51% (0.54%) per month and significant at the 1% level.[17]

Third, we examine whether the return spread based on *UP* is related to the correlation between *Gross Fund Firm Return* and *Equity PF Return*. In contrast to mutual funds, where the average time-series correlation between both return series is close to one, hedge funds show a much lower average of 0.50. In addition, there is considerable variability in the correlation (i.e., the interquartile range is from 0.31 to 0.76) because of several undisclosed aspects of trading strategies that include confidential holdings, derivatives, and short positions. For each fund firm *i* in month *t*, we estimate the correlation *(Corr)* between the two return series using a rolling window of 36 months. We then double sort (dependent) based on *Corr* and *UP* using the same methodology as above. Results in Panel C reveal that *Corr* cannot explain the spreads based on *UP*: high *UP* firms outperform low *UP* firms in all *Corr* quintile portfolios, both using raw and risk-adjusted returns.

Fourth, we investigate the effect of *UP* on future fund performance when we explicitly control for alternative manager skill measures, R^2 and SDI. In Panel A of Table 4, we double sort fund firms based on R^2 and *UP*, first into quintiles according to their R^2 in reverse order, from high to low, since funds with low R^2 have been shown to exhibit greater managerial skill, and then within each R^2 quintile, sort on *UP*. We observe positive return and alpha spreads between the highest and lowest *UP* quintile within each R^2 quintile and these spreads are significant in four of five cases. The average return (alpha) spread is 0.48% (0.52%) per month.

[Insert Table 4 around here]

In Panel B, we repeat the same exercise for SDI and *UP*. In all cases, we find significantly positive return and alpha spreads between the highest and lowest *UP* quintile

[17] These findings generally hold when we perform independent (instead of dependent) portfolio double sorts based on either *Gross Fund Firm Performance* and *UP*, *Equity PF Performance* and *UP*, or *Corr* and *UP* (see Table IA.4 in the Internet Appendix).

within each SDI quintile. The average return (alpha) spread across SDI quintiles is 0.50% (0.53%) per month. These findings show that the spread in fund firm performance based on *UP* cannot be explained by either of the alternative skill measures.[18]

Finally, in Panel C, we analyze whether *UP* has stronger predictive power for future performance compared to either R^2 or SDI. In the first three columns, we show 5-1 quintile return and alpha spreads from univariate sorts on *UP* (repeated from Column (1) in Panels A and B from Table 2 for comparison), R^2, and SDI. Consistent with Titman and Tiu (2011) and Sun, Wang, and Zheng (2012), R^2 and SDI predict future fund performance. However, *UP* is a stronger predictor than either R^2 or SDI. In Columns (4) and (5) we compute the difference between the spreads from sorts on *UP* and R^2 and from sorts on *UP* and SDI, respectively. Differences are significant at the 1% level based on raw returns (0.38% and 0.40%, respectively) and at 10% level or better based on 9-factor alphas (0.32% and 0.29%, respectively), showing that *UP* predicts performance significantly better than R^2 and SDI.

3.3 Multivariate Evidence

We next estimate Fama and MacBeth (1973) regressions of future firm returns in month t+3 on *UP* and firm characteristics in month t to control for their effect on fund performance:

$$r_{i,t+3} = \alpha + \beta_1 UP_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t+3}, \tag{8}$$

where $r_{i,t+3}$ denotes fund firm i's reported net return in month t+3, $UP_{i,t}$ is the fund firm's *unobserved performance*, and $X_{i,t}$ is a vector of fund firm characteristics. We use the Newey and West (1987) adjustment with 36 lags to adjust standard errors for potential serial correlation. In terms of firm characteristics, we include a firm's past return, size, age, volatility, manager delta, management and incentive fees, minimum investment, lockup and restriction

[18] These findings hold with independent portfolio double sorts (see Table IA.5 in the Internet Appendix).

(i.e., sum of redemption and notice) periods, indicator variables for a fund firm's offshore location, leverage usage, high-watermark, hurdle rate, as well as a firm's R^2 and SDI measure.

[Insert Table 5 around here]

Panel A of Table 5 shows that even after simultaneously controlling for a host of fund firm characteristics, the impact of *UP* on future fund firm performance is positive and statistically significant at the 1% level in all specifications. Depending on the specification, the coefficient estimates of *UP* range from 0.041 to 0.065 when we use future returns as the dependent variable and is 0.025 in Column (6) with future alpha as the dependent variable.

In Columns (1) to (8) of Panel B in Table 5, we examine the predictive power of *UP* on future alphas in different states of the world and across different time periods. We use the specification identical to the one in Column (6) of Panel A, but only report the coefficient estimates of *UP* for brevity. We find that the impact of *UP* on future fund firm alphas is positive and statistically significant during periods of both high and low economic growth (compared to the median GDP growth rate from 1997 to 2017), as well as positive and negative market returns in excess of the riskfree rate. Further, predictive ability of *UP* for future fund firm alphas is strong both in periods of high and low market volatility as well as in the subperiods from 1996−2008 and 2009−2017. These findings suggest that *UP* is a robust skill measure that predicts fund firm performance in different market conditions.

3.4 Robustness Checks

To examine the stability of our results regarding the relation between *UP* and future fund firm performance, we conduct a host of robustness checks. Specifically, we (i) estimate *UP* with a 24-month rolling window, use the seven factors in the Fung and Hsieh (2004) model or the four factors in the Carhart (1997) model for risk adjustment, or average *UP* over the past 36 months; (ii) compute *UP* with an alternative estimate of gross fund firm returns following Ben-David, Birru, and Rossi (2020) or as the difference between a fund firm's performance based on its reported net-of-fee return series and a firm's performance based on its transaction-cost adjusted long-equity portfolio (see Section 4.1 for our computation method of transaction costs); (iii) use alternative performance metrics that include the Sharpe ratio, the Treynor ratio, the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measure (MPPM, with a risk aversion parameter of three), and the value-added measure of Berk and van Binsbergen (2015); (iv) include also non-equity related fund firms in the sample, restrict our sample to only long-short equity fund firms or funds listed in the TASS database, exclude the smallest (bottom 20%) funds to allow for feasibility of investment, and restrict our sample to funds with similar long-only leverage (long-equity portfolio relative to funds' assets being 120% or less) to mitigate the effect of leverage; and (v) use the Getmansky, Lo, and Makarov (2004) methodology to unsmooth fund returns, control for backfill bias when we delete the first 12 monthly observations of a fund (instead of 24 months) and infer the bias as in Jorion and Schwarz (2019), and assign a delisting return of –1.61% as in Hodder, Jackwerth, and Kolokolova (2014) to funds that leave the database.[19]

[Insert Table 6 around here]

Panel A in Table 6 reports the results from univariate portfolio sorts (as in Panel B of Table 2, Column 1), using each of these robustness checks. We only report spreads in the nine-factor alphas of the high minus low (5 – 1) *UP* portfolios. Panel B reports the results of Fama and MacBeth (1973) regressions (as in Column (6) of Panel A in Table 5) of future fund firm alphas in month t+3 on *UP* and different fund firm characteristics measured in month t.[20] For brevity, we only report the coefficient estimate for *UP* and suppress the coefficients of other

[19] In our baseline setting, we require a fund to have at least 24 monthly return observations to be included in the dataset. We also check whether our results are stable when we require a fund to exist for only 12 months (and estimate *UP* based on a minimum of 12 observations or 36 months (instead of 24 months). Results of univariate portfolio sorts are reported in Table IA.6 of the Internet Appendix and are robust to the baseline result.

[20] For robustness checks (8), (9), (10), and (11) of Table 6 we use Sharpe Ratios, Treynor Ratios, MPMMs, and Value-Added measures instead of the respective alphas as the dependent variable.

control variables included in the regressions. Across all robustness checks, we continue to find that *UP* strongly predicts future fund performance.

Finally, we provide a comparison of the predictive power of *UP* between hedge funds and mutual funds. For this purpose, we follow Kacperczyk, Sialm, and Zheng (2005) and repeat our analysis for mutual funds during our sample period from 1997 to 2017. We retrieve data on open-end US domestic equity funds in CRSP Mutual Fund Database for which CDA/Spectrum holdings data is complete. Our filtered sample consists of a total of 2,705 funds with an average 1,432 funds each year.[21] For ease of comparison, we also report the baseline results from Column (1) in Panel B of Table 2 and Column (6) in Panel A of Table 5.[22] Our findings reveal that the performance spread is statistically positive, but economically smaller than for hedge funds. These results confirm the fact that hedge funds are less restricted in their asset allocation and investment strategies compared to mutual funds. Consequently, unobserved actions of hedge funds are more diverse and informative about future performance.

3.5 Practical Implementation

Sections 3.1 to 3.4 document that *UP* strongly predicts hedge fund firm performance. However, it is not clear whether investors can implement a profitable investment strategy using *UP* after incorporating real-world trading constraints, an issue we examine in this section. Since a typical investor is unlikely to invest in all funds belonging to a firm, we start our investigation by looking at the performance impact of *UP* for hedge fund firms with only one fund (there exist 407 single-fund entities in our sample of 698 fund firms).

[Insert Table 7 around here]

[21] Note that in the case of mutual funds, the empirical analysis can be performed at the fund level where detailed holdings data is available. To compute *UP*, we risk-adjust the *URC* using the Carhart (1997) four-factor model.
[22] For mutual funds, we use past return, size, age, volatility, and management fee, and R^2 as control variables in the Fama and MacBeth (1973) regressions.

In Panel A of Table 7, we conduct univariate portfolio sorts on *UP* measured at month *t* and evaluate fund performance in month *t*+3. Column (2) shows that---compared to the baseline specification in Column (1) for *all* firms---there is greater dispersion in spreads: top *UP* funds outperform the bottom *UP* funds by 0.67% per month (*t*-statistic of 4.17) for raw returns and by 0.76% per month (*t*-statistic of 4.38) for alphas. This is an intuitive because we consider only single-fund firms here and therefore there is less diversification across a firm's funds. In Columns (3) and (4), we use an alternative approach to conduct our analysis at the fund level instead of the fund firm level, but accounting for all fund firms (both single- and multi-fund firms) in our sample. Specifically, we assign *UP* estimates obtained at the firm level to each individual fund of a firm (i.e., observations are at the individual fund level and all funds of a firm receive the same *UP* measure). We continue to observe economically and statistically significant performance spreads for *UP* when we consider an equally-weighted (Column 3) or value-weighted (i.e., weighted by a fund's AUM, Column 4) portfolio sorting scheme.

Until now, we have investigated the ability of *UP* in month *t* to predict future fund firm returns and alphas in month *t*+3. A natural question is whether predictive power of *UP* extends to longer horizons. This question is particularly important for two reasons to investors who aim to benefit from investing in high *UP* firms. First, a majority of hedge fund firms in our sample employ lockup and restriction periods that can sometimes be more than one year. Second, long-equity positions of hedge fund firms are not immediately observable to investors as regulation allows for a disclosure delay of up to 45 days after quarter ends. Therefore, investors may not be able to rebalance their fund portfolios within a quarter.

Panel B reports the results of univariate portfolio sorts based on *UP*, measured at time *t*, and longer-term portfolio returns, i.e., holding horizons of 3 months (i.e., from *t*+1 to *t*+3), 6 months (i.e., from *t*+1 to *t*+6), 12 months (i.e., from *t*+1 to *t*+12), 18 months (i.e., from *t*+1 to *t*+18), and 24 months (i.e., from *t*+1 to *t*+24). All portfolio sorts are performed with non-overlapping data which reduces transaction costs of rebalancing hedge fund portfolios and alleviates concerns regarding trading restrictions.[23] Our results reveal that *UP* has predictive power for hedge fund firm performance up to two years into the future. For example, the risk-adjusted return spread for the 24-month period for the sample of all fund firms amounts to 5.67% (*t*-statistic of 2.77), while it amounts to 6.32% (*t*-statistic of 2.93) for single-fund firms.

Finally, we follow Avramov, Barras, and Kosowski (2013) to impose various real-world constraints which might impede the implementation of a trading strategy based on *UP* in practice. To do so, we first simulate the strategy using a rebalancing frequency of 12 months but exclude all fund firms with a lockup and restriction period of more than 12 months from our sample. Second, we limit the minimum and maximum number of funds in a portfolio to 25 and 75, respectively. Third, we set up a threshold each month restricting the maximum investment by a typical fund of hedge fund (FOF) to 10% of each underlying hedge fund's AUM. This ensures that the FOF does not end up being too dominant an investor in any hedge fund. Even after accounting for these real-world frictions, we observe that high *UP* firms outperform low *UP* firms by a risk-adjusted return of 4.23% p.a. (*t*-statistic of 4.68) for the entire sample and 3.45% p.a. (*t*-statistic of 2.63) for the subsample of single-fund firms (see last column of Table 7, Panel C).

As it is not possible to short hedge funds, investors can only allocate money to hedge fund firms with the highest *UP* but cannot short sell funds with the lowest *UP*. Accounting for this limitation and again applying a rebalancing frequency of 12 months with the same real-world constraints imposed as in Panel C, we find that the annual alpha for the top quintile *UP* portfolio for all fund firms is 3.69% (*t*-statistic of 4.54) and 2.91% (*t*-statistic of 3.65) for the

[23] As an example, for the 12-month frequency, we hold portfolios constant between January and December in year t before rebalancing it to a new portfolio starting in January of year $t+1$.

single-fund firms, suggesting that investors can still profit by only investing in the long leg of the investment strategy.

4. *UP* and Different Trading Channels

After having established that *UP* is a strong and practically implementable predictor of future hedge fund performance, we next investigate four trading features of hedge funds that can influence a fund firm's *UP*: intraquarter trading of long-equity positions, derivatives use, short-selling activities, and confidential holdings.

4.1 Active Trading in Long-Equity Positions

Hedge fund firms disclose long-equity positions to the SEC at a quarterly frequency but their intraquarter transactions are not revealed to the public. However, any gains or losses from intraquarter trading will be reflected in firms' reported returns even though they will be excluded from the buy-and-hold returns inferred from long-equity positions. Therefore, our *UP* measure that captures the wedge between the reported and inferred returns should naturally be related to funds' interim trading, although how this relation affects the predictability of *UP* for future fund performance is not obvious. Several academic studies investigate the relation between active trading and performance. While Bennett, Sias, and Starks (2003), Cai and Zheng (2004), and Yan and Zhang (2009) find conflicting results on whether institutional trading predicts future stock returns, Chen, Jegadeesh, and Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), and Alexander, Cici, and Gibson (2007) observe that the stocks that mutual funds purchase earn significantly higher returns than the stocks they sell. Using a proprietary database of institutional trades, Puckett and Yan (2011) find that institutions earn significant abnormal returns on their interim trades. At the same time, active trading leads to higher transaction costs, which should reduce hedge fund returns and eventually *UP*.

Columns (1) and (2) of Table 8 examine the relation between *UP* at month *t* and two proxies each for (i) interim trades by firms and (ii) transaction costs incurred for these trades. Our first proxy for interim trading is a fund firm *i*'s *Portfolio Turnover* in month *t* defined as the total of its stock purchases and sales (computed based on changes in quarterly disclosed holdings) in month *t*, divided by its total equity portfolio market capitalization in month *t*-1. The underlying premise behind this proxy (which is a lower bound for the actual trading activity) is that firms that change their positions more between disclosure dates are also more likely to engage in intraquarter trading. Following DeMiguel, Utrera, Nogales, and Uppal (2017), we also compute a proxy for a firm's trading costs in month *t* by applying proportional transaction costs to changes in equity portfolio. Our second proxy for interim trading is estimated from actual transactions of 27 hedge fund firms identified in the Abel Noser database as in Jame (2018) between January 1999 and September 2011. Over each month, we sum the daily buys and sells of a fund firm in month *t* and divide it by the fund firm's total equity portfolio market capitalization in month *t*-1. Following Busse, Chordia, Jiang, and Tang (2021), we compute a firm's total trading costs using transaction-level data as the sum of monthly implicit trading costs, commissions, and tax plus fees.

[Insert Table 8 here]

Column (1) shows the results for the first proxy for interim trading and transaction costs taking account of control variables at the hedge fund firm portfolio level.[24] We find that the relation between *UP* and *Portfolio Turnover* is significantly positive, whereas the relation between *UP* and *Trading Costs* is significantly negative. A one standard deviation change in *Portfolio Turnover* (*Trading Costs)* is associated with an annualized change in *UP* of 1.99% (−1.24%). Column (2) confirms our results for the smaller sample with actual hedge fund transactions.

[24] These controls include a fund firm's number of different stock positions, the portfolio's Herfindahl index (measure of portfolio concentration), size, standard deviation of returns, illiquidity (measured by the Amihud (2002) ratio), and the book-to-market ratio. All control variables are based on the fund firm's disclosed holdings.

4.2. Derivatives Usage

Hedge funds are known to employ derivatives in their trading strategies (e.g., Agarwal and Naik, 2004, Aragon and Martin,2012, and Agarwal, Ruenzi, and Weigert, 2017). Since profits and losses from derivatives trading will be reflected in fund firms' returns but not in their long-equity portfolio performance, we conjecture that derivatives holdings of hedge funds should also influence the *UP* measure.

To capture derivatives usage by fund firms, we use long call and put option holdings data from the 13F filings in the SEC EDGAR database from April 1999 to December 2017. We find that 49.3% of firms in our sample (i.e., 344 of 698 firms) file at least one long option position. To merge fund firms that disclose their derivative positions quarterly with monthly *UP* estimates, we again apply the convention that disclosed positions in month *t* are carried forward for the subsequent months *t*+1 to *t*+3. We then compute for fund firm *i* in month *t*, the *Equivalent value of equity shares underlying call poitions* and the *Equivalent value of equity shares underlying put positions* (in $ millions).[25] To mitigate the effect of outliers, we winsorize these measures at the 1% level. The average value of equity shares for the call positions is $112.38 million and the corresponding value for put positions is $104.96 million.

We regress *UP* of hedge fund firm *i* in month *t* on the natural logarithms of one plus the *Equivalent value of equity shares underlying the call positions* and one plus the *Equivalent value of equity shares underlying the put options* in month *t* using the Newey and West (1987) adjustment with 36 lags accounting for portfolio-level controls. We display the results in Columns (3) and (4) of Table 8. We observe that use of put options, but not call options, significantly increases a fund firm's *UP*. A one standard deviation increase in the put options measure enhances a fund firm's annualized *UP* by 1.94%.

[25] To illustrate this measure, consider the following example: a fund firm holds call options on 10,000 shares of stock A that trades at $20 and 5,000 shares of stock B that trades at $30. It holds put options on 20,000 shares of stock C that trades at $40. In this case, the equivalent value of equity shares underlying the call options is $350,000 and that for put options is $800,000.

4.3. Short Selling

Short selling is a quintessential component of arbitrage strategies used by hedge funds. It should therefore influence the reported returns of hedge fund firms but is excluded from the buy-and-hold returns imputed from long-equity positions. Therefore, short selling activity should be positively related to *UP*. Recent studies observe that short-selling strategies yield abnormal profits on average (e.g., Jones, Reed, and Waller, 2016, Jank and Smajlbegovic, 2021, Beschwitz, Lunghi, and Schmidt, 2022, and Busse, Ding, Jiang, and Wu, 2023). Hence, the return spread in *UP*-sorted fund portfolios that we document earlier can be related to the profitability of short positions.

We examine the relation between *UP* and short-selling activity. Our proxy for short-selling activity are short-sale transactions for a sample of 27 fund firms that disclose long-equity positions to the SEC and detailed transaction data to Abel Noser between January 1999 and September 2011. We follow Choi, Park, Pearson, and Sandy (2016) to identify short positions for firm *i* for each stock and each day.[26] For firm *i* in month *t*, we compute a proxy for short-selling activity, the *Maximum daily value of equity shares underlying the short positions*. To mitigate the effect of outliers, we winsorize this measure at the 1% level. The average short selling activity in our sample is $91.64 million which corresponds to 11.3% of the fund firm's average reported assets under management of $810.12 million. We regress *UP* of firm *i* in month *t* on the proxy for short-selling activity in month *t* using the Newey and West (1987) adjustment with 36 lags and portfolio-level control variables. Column (5) of Table 8 shows a significant relation between *UP* and short-selling activity with meaningful economic magnitude: a one standard deviation increase in short selling activity is associated with a higher annualized *UP* of 2.52%.

[26] For details of the procedure, see Section 2 in Choi, Park, Pearson, and Sandy (2016). Starting with a fund firm *i*'s long positions disclosed to the SEC in quarter *t*, over the next three months, they add/subtract the firm's daily transactions with respect to holding *j* on a daily basis and classify a negative position in stock *j* as a short sale.

4.4. Confidential Holdings

Another channel that influences a fund firm's *UP* could be their requested confidential treatment of certain long-equity positions. However, these requests made through 13F amendments are not included in the Thomson Reuters 13F data and therefore are not included in our imputed equity portfolio return of fund firms. Prior studies by Agarwal, Jiang, Tang, and Yang (2013) and Aragon, Hertzel, and Shi (2013) find that stocks in confidential filings are disproportionally associated with information-sensitive events and greater information asymmetry, as well as characteristics that make hedge funds more susceptible to front-running. Furthermore, confidential holdings allow hedge funds to reduce price impact and earn significantly positive abnormal returns over the confidential period. Hence, we conjecture that fund firms that report more confidential holdings have higher *UP*.

We retrieve the confidential holdings from 13F filings in the SEC EDGAR database from April 1999 to December 2017. During this time period, 25.2% of hedge funds in our sample (i.e., 176 of 698 firms) file at least one confidential position. Disclosed positions in month t are carried forward for the subsequent months, t+1 to t+3. We compute for firm i in month t, the *Equivalent value of equity shares underlying these positions* (in $ millions). To mitigate the effect of outliers, we winsorize this variable at the 1% level. The average value of confidential positions is $45.98 million. We regress *UP* of firm i in month t on the natural logarithm of one plus the *Equivalent value of equity shares underlying these positions* in month t using the Newey and West (1987) adjustment with 36 lags and portfolio-level controls. Results in Column (6) of Table 8 reveal a positive and significant relation between confidential holdings and *UP*. This result is also economically meaningful. A one standard deviation increase in the value of confidential positions increases a firm's annualized *UP* by 1.84%, suggesting that confidential holdings are an important channel that influences a firm's *UP*.

Overall, these findings show different trading channels that contribute to *UP*. However, these channels can only be measured with some noise or are often only available for a small sample of funds over a limited time, while the *UP* measure not only jointly captures the effect of all these channels, but also of other unobserved actions of funds that drive performance.[27]

5. Investor Response to *UP*

Our previous results show that *UP* is a measure of manager skill which strongly predicts future fund firm performance. This result gives rise to questions such as whether investors realize the value of *UP* for manager selection and how fund flows affect the performance predictability of *UP* in equilibrium. We attempt to address these questions in this section.

Generally, a measure of manager skill should predict hedge fund performance, everything else equal. However, as shown by Berk and Green (2004), managers' ability to generate abnormal performance is hampered by investor flows, which combined with diseconomies of scale should lead to zero future net alphas in equilibrium. If investor flows react immediately and fully to signals of skill, one should observe no performance predictability. However, if investor reaction is delayed, one can observe longer-lived persistent predictability of future performance. We provide evidence consistent with such a delayed equilibrium mechanism. Our analysis proceeds in three steps: First, we analyze whether and how investors respond to *UP* as well as other skill signals and what role investor attention plays in this context. We show that investor reaction is sluggish. Second, we show that *UP* predicts longer-term performance better than other skill measures to which investors react more rapidly, particularly for funds with low investor attention. Third, we provide evidence on the limited

[27] Note that it is not empirically feasible to simultaneously examine all trading channels as their intersection results in a very small sample size. This further highlights the utility of our *UP* measure, which is available for many more funds than for those we have information on the trading channel proxies. Hence, *UP* reflects the skills of funds across their sparsely observed trading features as well as other unobservable skill traits.

scalability of the trading channels that contribute to *UP*, which eventually explains the dissipation in the predictive power of *UP* in the long run.

5.1 Investor Response to Performance Measures

As shown in prior literature (Agarwal, Daniel, and Naik, 2004; Fung et al., 2008; Baquero and Verbeek, 2009; Liang et al., 2019), investors direct money to best performing funds. We first examine which performance metric they apply to make their decision. To this end, we regress fund firm flows in year *t*+1 on *UP*, *Gross Fund Firm Performance*, and *Equity PF Performance* in year *t* controlling for fund firm characteristics as in Table 5, Panel A. [28]

[Insert Table 9 here]

In Columns (1) and (2) of Table 9, we include *Gross Fund Firm Performance* and *Equity PF Performance*, respectively, as performance measures in the regressions, but leave out *UP*. Both performance measures have a positive and significant influence on investor flows in the next year. In Column (3) we add both performance measures together and find that only *Gross Fund Firm Performance* has a significant impact on future flows, while *Equity PF Performance* loses its statistical significance. Thus, the positive effect of *Equity PF Performance* is only driven by its positive correlation with *Gross Fund Firm Performance* (see Table IA.1 in the Internet Appendix). Column (4) reports the results when we include *Gross Fund Firm Performance* and *UP* jointly in the regressions. The coefficient on *Gross Fund Firm Performance* in Column (4) remains positive and significant (coefficient = 0.457; *t*-statistic = 3.69), while *UP* does not show any significant association with future flows.[29] Investors seem to rely mainly on reported

[28] Following prior studies (e.g., Agarwal, Green, and Ren, 2018), we examine fund flows at the annual frequency as AUMs can be stale or missing at the monthly or quarterly frequency. We compute a fund firm *i*'s flow in year *t* as $Flow_{i,t} = \left(\frac{AUM_{i,t}}{AUM_{i,t-1}}\right) - (1 + r_{i,t})$, where *AUM* denotes a fund firm's assets uder management and *r* denotes a fund firm's net-of-fee return in excess of the risk-free rate. We winsorize fund flows at the 1% level.

[29] We find similar results when we include *Equity PF Performance* and *UP* in a model. The coefficient on *Equity PF Performance* is positive and significant, whereas the coefficient on *UP* is insignificant. We cannot include all three variables due to multicollinearity.

performance to allocate their capital, while *UP*, despite its superior predictive power for future performance, is not considered by most investors. We hypothesize that (i) many investors are not aware about the predictive power of *UP*, or (ii) this behavior is related to the significant effort necessary to construct the *UP* measure.

It is possible that some investors respond with a delay to *UP* if they do not pay attention to hedge fund holdings which are necessary to compute *UP*. We test this possibility by using the data on downloads of 13F filings from the SEC to proxy for investor attention. In Columns (5) and (6) of Table 10, we divide all fund firms each year based on the median download into high and low investor attention firms. Our results reveal that for fund firms with high investor attention, future investor flows do significantly respond to *UP* (column 5, coefficient = 0.326; *t*-statistic = 3.71). In contrast, column (6) shows that for fund firms with low investor attention, investors solely consider past reported fund performance, and not *UP* (coefficient = 0.053; *t*-statistic = 0.59), when making their capital allocation decisions.[30]

5.2 *UP* and Predictability of Long-Term Performance

According to the framework of Berk and Green (2004), inflows to funds should lead to diseconomies of scale and a quick decline of any abnormal performance (see also, Bollen and Busse, 2004, as well as Glode and Green, 2011). We test this prediction in this section. First, in Table 10, we check the relation between firm performance in year *t+1* as well as *UP*, *Gross Fund Firm Performance*, and *Equity PF Performance* in year *t*, again controlling for firm characteristics.

[Insert Table 10 here]

[30] Table IA.7 in the Internet Appendix supports our conclusions in bivariate portfolio sorts. Panel A finds that the *t*+1 spread in fund flows between fund firms with high *Gross Fund Firm Performance* and low *Gross Fund Firm Performance* is larger for low attention fund firms than for high attention firms. In contrast, Panel B shows that the *t*+1 spread in fund flows between fund firms with high *UP* and low *UP* is larger for high attention fund firms than for low attention firms.

In line with the short-term monthly results in Panel A of Table 5, we show in Columns (1) to (3) that *UP* and *Gross Fund Firm Performance* are significant predictors for one-year ahead fund firm performance, whereas *Equity PF Performance* does not pass significance at the 10% level. In Columns (4) and (5), we investigate the relation between future performance in year *t+1* as well as *Gross Fund Firm Performance* and *UP* in year *t* for fund firms with high and low investor attention separately. Consistent with the idea that inflows into high *UP* funds with high investor attention (but not into those with low investor attention) can lead to a deterioration of future performance, we find that the positive impact of *UP* is much more pronounced for firms with low investor attention. The coefficient estimate for *UP* for the low investor attention subsample is 0.169 and therefore nearly double the coefficient estimate of 0.098 for the high investor attention subsample.

In Figure 3, we analyze this pattern for longer-term performance persistence, i.e., we plot the coefficient estimates of *UP* and *Gross Fund Firm Performance* for future nine-factor alphas in the years *t*+2, *t*+3, and *t*+4.

[Insert Figure 3 here]

When considering all fund firms in our sample, we observe that *UP* has predictive power for fund firm performance up to year *t*+3, while the predictive power of *Gross Fund Firm Performance* quickly dissipates after year *t*+1 (Panel A). However, when comparing fund firms with high and low investor attention, *UP* is a persistent predictor of fund firm performance even up to four years in the future for funds with low investor attention (Panel C), while it only predicts performance for the following year for funds with high investor attention (Panel B). *UP* can therefore benefit investors in manager selection till performance deteriorates because of their flows and this benefit lasts much longer if investor attention is low.[31]

[31] Figure IA.2 in the Internet Appendix shows results from the predictability of *UP* for fund firm performance during years *t*+1, *t*+2, *t*+3, and *t*+4, when we split our sample into the different drivers of *UP* (i.e., firms with high vs. low portfolio turnover, put option usage, short-selling activity, and usage of confidential holdings). In line

5.3 Changes in Hedge Fund Firm Trading Channels after Investor Flows

Results in Sections 5.1 and 5.2 are consistent with investors directing flows in response to past performance and with inflows eventually---but in the case of low attention, high *UP* funds only slowly---leading to a drop in performance. In this section, we investigate *why* this is the case and how hedge funds' trading strategies may be affected by investor inflows. We do so by concentrating on trading channels that we have shown to influence *UP* in Section 4.

To investigate whether high *UP* firms change their trading behavior after large inflows, we regress each trading channel, measured in year t+1, on an indicator variable that takes a value of one if a firm is in the top quintile of investor inflows in a certain year as well as an interaction term between a fund firm's *UP* and the top quintile flow indicator in year t. Table 11 reports the results.

[Insert Table 11 here]

Our results reveal that high flows lead to higher trading costs and less activity in different trading channels that we found to contribute to a higher *UP* in Table 8. The interaction term in year t is also significantly negatively related to all trading channels identified to boost *UP*. In particular, we find a negative association between the interaction term as well as turnover, put option usage, short-selling activity, and confidential holdings usage, while there exists a positive association with transaction costs. Hence, our results reveal that more capital infusion makes it more challenging for fund managers to follow the very same trading strategies that are associated with higher *UP*. This effect is particularly pronounced for funds with high *UP*, as indicated by the significant interaction terms.

Overall, our findings show that the limited scalability of these strategies lead to diseconomies of scale that eventually lead to a weakening of the predictive power of *UP* for

with our main results, we observe that the magnitude of the performance from *UP* is higher for firms with high portfolio turnover, high put option usage, high short-selling activity, and high usage of confidential holdings.

future performance in the longer run. More capital makes fund managers trade in a way that lowers their *UP*, particularly so if high flows go together with high past *UP*. This makes future performance persistence due to *UP* disappear for these fund firms.

6. Conclusion

In this paper, we propose a new measure of hedge fund skill, unobserved performance (*UP*), defined as the risk-adjusted difference between a fund firm's reported return and the hypothetical portfolio returns derived from its long-equity holdings. Our results indicate that *UP* is persistent and strongly predicts future performance. High *UP* firms outperform low *UP* firms by 6.36% p.a. after accounting for standard hedge fund risk factors. *UP* predicts future firm performance better than either past gross firm performance or past performance derived from long-equity positions. *UP* also outperforms other predictors of fund performance (R^2 and SDI). We find that various trading channels such as intraquarter trading of equities, put option strategies, short selling, and confidential holdings are positively related with *UP* and contribute to superior performance of high *UP* funds. However, if funds face large inflows, they are not able to scale up these trading channels, leading to diseconomies of scale.

A trading strategy based on *UP* continues to deliver positive abnormal returns even after considering real-world trading restrictions and transaction costs. *UP* predicts fund performance for up to three years in the future. This relatively long-term predictive power can emerge because investors only react to *UP* with a significant delay, after observing realized performance. Investor reaction is stronger and quicker – and *UP* only predicts shorter-term performance – for hedge funds where holdings information is accessed more intensively by investors. Overall, our evidence draws a nuanced picture of the dynamics and interplay between skills, flows, and performance in the hedge fund industry and is broadly in line with a slow path to the equilibrium of active management laid out in Berk and Green (2004).

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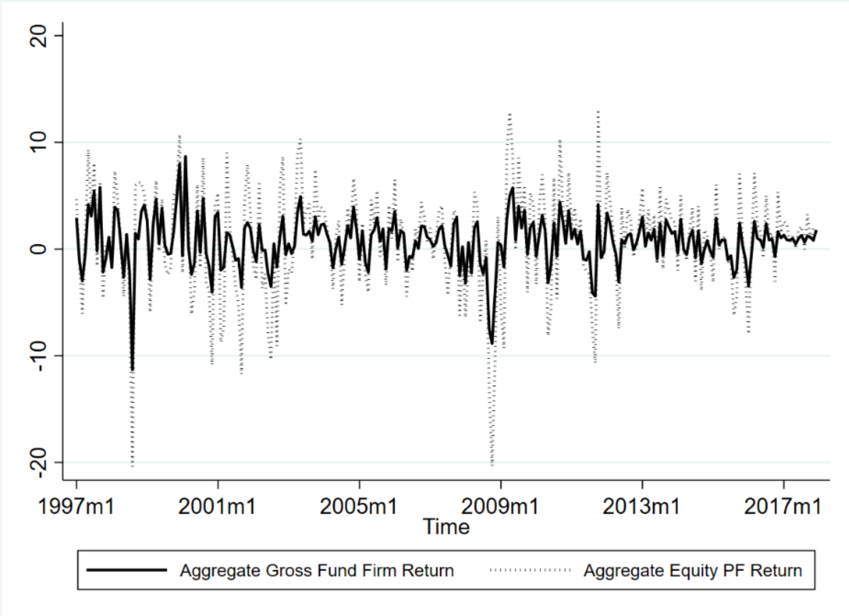
Figure 1: Aggregate Gross Fund Firm Return, Aggregate Equity Portfolio Return, and Aggregate *URC*

Panel A displays the evolution of the *Aggregate Gross Fund Firm Return* and *Aggregate Equity PF Return*. Panel B plots the *Aggregate Unobserved Return Component* (*URC)* over time. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017.

Panel A: Aggregate Gross Fund Firm Return and Aggregate Equity Portfolio Return



Panel B: Aggregate Unobserved Return Component (*URC*)

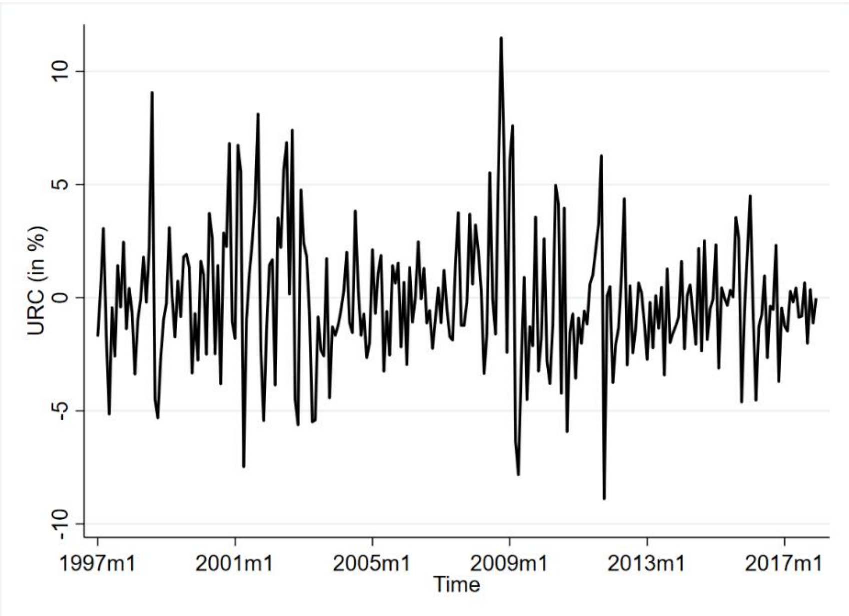
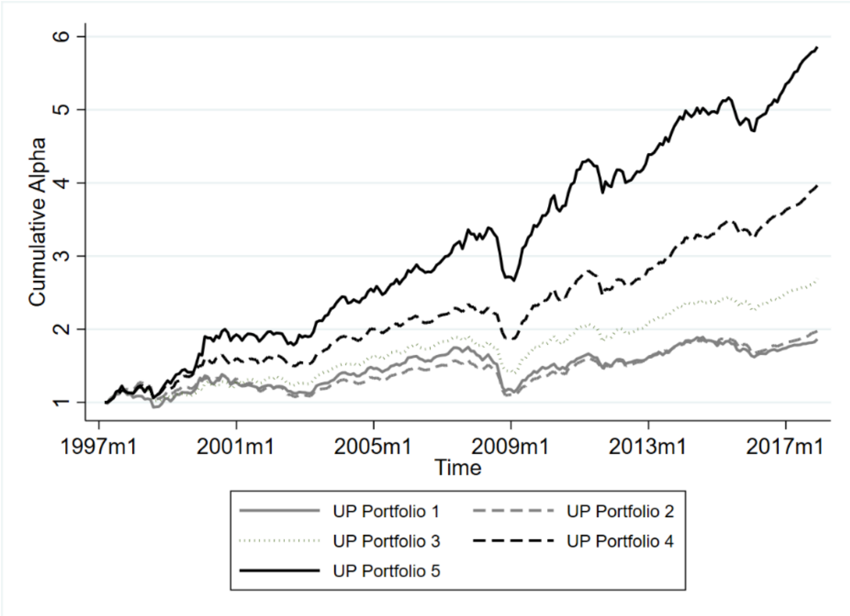


Figure 2: Cumulative Returns for Trading based on *UP*

Figure 2 displays cumulative returns from pursuing the *UP*-based trading strategy. We assume an initial investment of $1 at the beginning of 1997 and apply monthly rebalancing. Panel A shows how one dollar invested in the different quintile *UP* portfolios grows over time on a risk-adjusted basis. Panel B plots the performance of the (5 – 1) *UP* spread, as well as the spreads based on *Gross Fund Firm Performance* and *Equity PF Performance* over time. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017.

Panel A: *UP* Quintile Portfolios



Panel B: Spreads based on *UP*, *Gross Fund Firm Performance*, and *Equity PF Performance*

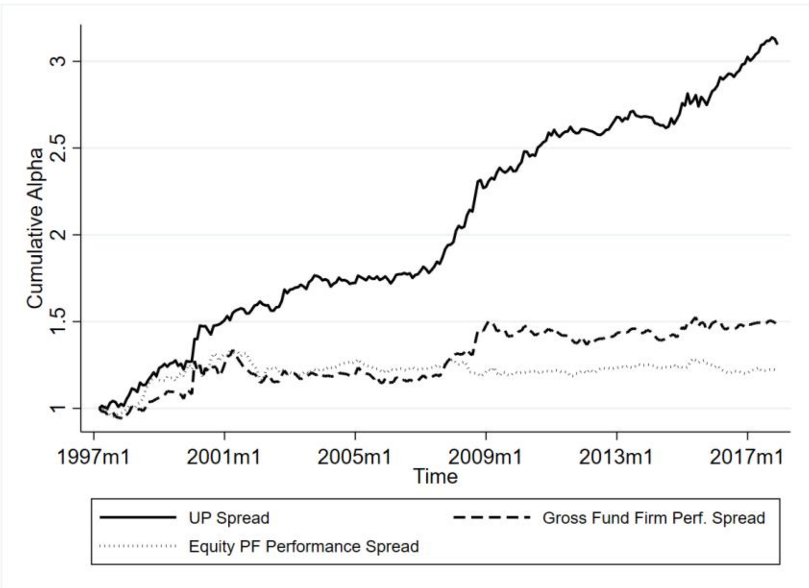
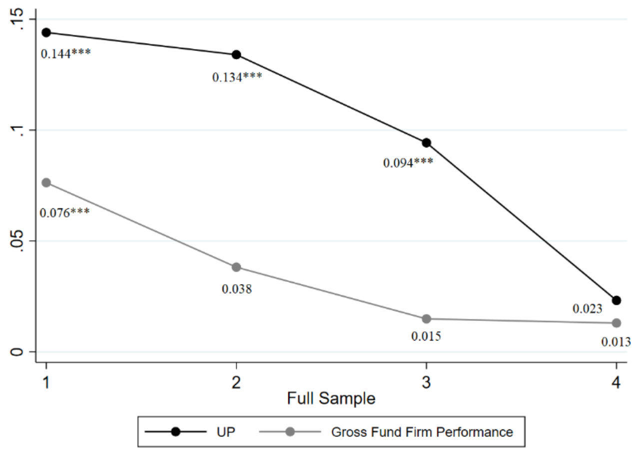


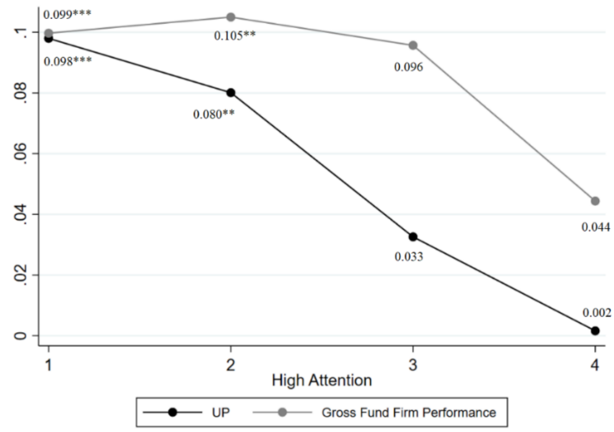
Figure 3: *Gross Fund Firm Performance* and *UP*: Long-Term Predictability

Figure 3 plots the results of of Fama and MacBeth (1973) regressions of a hedge fund firm *i*'s nine-factor alphas in years *t+1*, *t+2, t+3* and *t+4* on *Gross Fund Firm Performance, Equity PF Performance, UP,* and different fund firm characteristics in year *t*. We plot the coefficient estimates on *Gross Fund Firm Performance* and *UP* for the different years for the full sample (Panel A), high attention firms (Panel B) and low attention firms (Panel C).

Panel A: Full Sample



Panel B: High Attention Sample



Panel C: Low Attention Sample

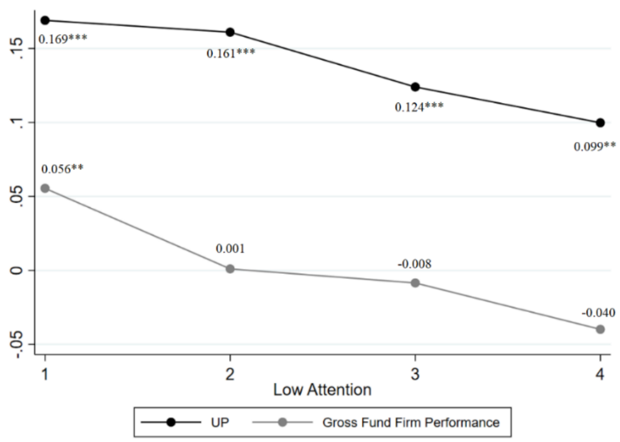


Table 1: Descriptive Statistics

Panel A of this table provides descriptive statistics for the main variables in our empirical study that include the monthly excess gross and net-of-fees fund firm returns (over the risk-free rate), the fund firm's excess portfolio return, the unobserved return component (*URC*), and different fund firm characteristics. Firm characteristics include *Size* (natural logarithm of a fund firm's AUM), *Age* (Age of a fund firm since its inception), *Standard Deviation* (standard deviation of a fund firm's reported returns over the past 36 months), *Delta* (pay-performance sensitivity computed as the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value; delta for a fund firm is computed as the AUM-weighted delta over all funds within a fund firm), *Management Fee* (annual hedge fund firm management fee; computed as the AUM-weighted management fee over all funds within a firm), *Incentive Fee* (annual hedge fund firm incentive fee; computed as the AUM-weighted incentive fee over all funds within a fund firm), *Min Investment* (fund firm's minimum investment amount; computed as the AUM-weighted minimum investment over all funds within a fund firm), *Lockup Period* (minimum amount of time that an investor is required to keep his money invested in the fund firm; computed as the AUM-weighted lockup period over all funds within a fund firm), *Restriction Period* (sum of firm's notice period and redemption period; computed as the AUM-weighted restriction period over all funds within a fund firm), *Offshore* (indicator variable that takes the value of one if the largest hedge fund in the fund firm is located outside of the USA and zero otherwise), *Leverage* (indicator variable that takes the value of one if the largest hedge fund in the fund firm uses leverage and zero otherwise), *HWM* (indicator variable that takes the value of one if the largest hedge fund in the fund firm uses a high-watermark and zero otherwise), *Hurdle Rate* (indicator variable that takes the value of one if the largest hedge fund in the fund firm uses a hurdle rate and zero otherwise), R^2 (Titman and Tiu (2011)'s R^2 measure of a fund firm using the nine-factor model estimated over the past 36 months), and *SDI* (Sun, Wang, and Zheng (2012)'s strategy distinctiveness index computed as one minus the correlation between a fund firm's return and the average return of the style group estimated based on the past 36 months), We calculate statistics by averaging over the monthly cross-sectional statistics across all firms during the sample period. Panel B reports the results of a time-series regression of aggregate reported returns, aggregate equity portfolio returns, and the aggregate *URC* on the risk factors of Fung and Hsieh (2004)'s seven-factor model (i.e., *S&P*, *SCMLC*, *BD10RET*, *BAAMTSY*, *PTFSBD*, *PTFSFX*, and *PTFSCOM*) augmented by the Fama and French (1993) book-to-market factor (*HML*) and the Carhart (1997) momentum factor (*UMD*). *S&P* is the monthly total return of the S&P 500 index, *SCMLC* is the size spread factor computed as the difference between the Russell 2000 index monthly return and the S&P 500 monthly return, *BD10RET* is the return on the bond market factor, computed from the monthly change in the 10-year treasury maturity yield, *BAAMTSY* is the monthly return of the credit spread factor computed from the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield, and *PTFSBD*, *PTFSFX*, and *PTFSCOM* are the monthly returns on the trend-following risk factors in bonds, currencies, and commodities, respectively. Panel C displays descriptive statistics for *Gross Fund Firm Performance*, *Equity PF Performance*, and unobserved performance (*UP*) of hedge fund firms. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long equity holdings to the SEC. The sample period is from January 1997 to December 2017.

Panel A: Returns and Fund Characteristics

Variable	Mean	25%	Median	75%	StdDev
Gross Fund Firm Return	0.68%	–0.63%	0.82%	1.97%	2.36
Net Fund Firm Return	0.45%	–0.83%	0.65%	1.76%	2.31
Equity Portfolio Return	0.78%	–2.03%	1.23%	4.06%	5.04
Unobserved Return Component (URC)	−0.10%	–1.84%	-0.46%	1.51%	2.98
Size (in $ million)	5.34	5.11	5.43	5.56	0.26
Age (in months)	105.48	88.72	96.11	124.58	21.23
Standard Deviation	3.66	2.77	3.32	4.58	1.03
Delta (in $100 thousands)	5.08	3.44	5.18	6.51	1.76
Management Fee (in %)	1.32	1.21	1.36	1.41	0.10
Incentive Fee (in %)	17.21	16.62	17.42	17.74	0.68
Min Investment (in $100 thousands)	17.32	16.61	17.64	18.35	1.49

Lockup Period (in years)	0.41	0.38	0.41	0.46	0.07
Restriction Period (in years)	0.38	0.35	0.39	0.41	0.04
Offshore	0.38	0.34	0.40	0.43	0.06
Leverage	0.60	0.58	0.60	0.61	0.02
HWM	0.80	0.77	0.82	0.85	0.05
Hurdle Rate	0.18	0.17	0.18	0.19	0.03
R^2	0.60	0.57	0.60	0.64	0.04
SDI	0.44	0.38	0.44	0.49	0.06

Panel B: Aggregate *URC* and Risk Factors

	(1) *Aggregate Gross Fund Firm Return*	(2) *Aggregate Equity PF Return*	(3) *Aggregate URC*
S&P	0.381***	0.995***	–0.615***
	(11.30)	(46.08)	(–24.13)
SCMLC	0.242***	0.462***	–0.219***
	(6.16)	(15.95)	(–9.36)
BD10RET	0.0187	−0.0244	0.0431*
	(0.38)	(−0.65)	(1.97)
BAAMTSY	0.203***	0.169***	0.0342
	(4.54)	(5.83)	(1.26)
PTFSBD	–0.0137***	–0.0066*	–0.0071*
	(–3.75)	(–1.72)	(–1.76)
PTFSFX	0.0096***	0.0068**	0.0028
	(4.07)	(2.44)	(1.26)
PTFSCOM	–0.0063	–0.0044	–0.0019
	(–1.38)	(–0.87)	(–0.93)
HML	–0.0931***	–0.104***	0.0106
	(–2.78)	(–3.29)	(1.03)
UMD	0.0479***	–0.0134	0.0613***
	(2.71)	(-0.75)	(5.18)
Constant	0.347***	0.129	0.218***
	(3.88)	(1.61)	(6.29)
Observations	252	252	252
Adjusted R^2	0.821	0.968	0.954

Panel C: *Gross Fund Firm Performance*, *Equity PF Performance* and *Unobserved Performance* (*UP*)

Variable	**Number of Fund Firms**	**Mean**	**25%**	**Median**	**75%**	**StdDev**
Gross Fund Firm Performance	698	0.44%	0.02%	0.41%	0.90%	0.67
Equity PF Performance	698	0.13%	–0.24%	0.11%	0.52%	0.62
Unobserved Performance (UP)	698	0.31%	–0.01%	0.30%	0.61%	0.49

***UP* for HF Strategy**	**Number of Fund Firms**	**Mean**	**25%**	**Median**	**75%**	**StdDev**
Emerging Markets / Equity Long	36	0.15%	–0.66%	0.20%	0.92%	1.60
Event Driven	114	0.26%	–0.21%	0.25%	0.68%	0.86
Equity Long–Short	516	0.32%	–0.02%	0.26%	0.60%	0.52
Equity Market Neutral	32	0.41%	–0.50%	0.38%	1.42%	1.64

Table 2: *UP* and Future Returns: Univariate Portfolio Sorts

This table reports the results from univariate portfolio sorts. Panel A reports the results from equally-weighted univariate portfolio sorts based on *UP*, *Gross Fund Firm Performance*, and *Equity PF Performance*, and the difference between *UP* and *Gross Fund Firm Performance* as well as the difference between *UP* and *Equity PF Performance* in month *t* and monthly excess returns in month *t*+3. In each month *t*, we sort all hedge funds into quintile portfolios based on the respective measure in increasing order. We then compute equally-weighted monthly average net-of-fee excess returns of these portfolios in month *t*+3. The column "5-1" reports the difference in monthly average excess returns with corresponding statistical significance. In Panel B, we repeat the univariate portfolio sorts in month *t* and estimate alphas in month *t*+3. We employ the Fung and Hsieh (2004) seven-factor model augmented with the book-to-market (HML) and momentum (UMD) factors. The row "5-1" reports the difference in monthly average alphas with corresponding statistical significance. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Excess Returns (in *t+3)*

Portfolio	(1) *UP*	(2) *Gross Fund Firm Performance*	(3) *Equity PF Performance*	(4) *UP – Gross Fund Firm Performance*	(5) *UP – Equity PF Performance*
1 (Lowest)	0.28%**	0.41%**	0.41%***	–0.13%**	–0.12%**
	(2.00)	(2.51)	(3.62)	(–2.48)	(–2.02)
2	0.30%**	0.41%***	0.40%***	–0.11%***	–0.10%**
	(2.14)	(3.52)	(3.34)	(–2.96)	(–2.51)
3	0.42%***	0.43%***	0.47%***	–0.01%	–0.04%
	(4.09)	(3.91)	(4.43)	(–0.16)	(–0.92)
4	0.58%***	0.51%***	0.54%***	0.07%*	0.04%
	(4.98)	(4.56)	(4.87)	(1.66)	(0.79)
5 (Highest)	0.75%***	0.58%***	0.50%***	0.17%***	0.25%***
	(5.03)	(3.93)	(3.34)	(4.11)	(3.68)
5-1	0.47%***	0.17%*	0.09%	0.30%***	0.37%***
	(4.17)	(1.67)	(0.95)	(4.76)	(3.67)

Panel B: Alphas from the nine-factor model (in *t+3)*

Portfolio	(1) *UP*	(2) *Gross Fund Firm Performance*	(3) *Equity PF Performance*	(4) *UP – Gross Fund Firm Performance*	(5) *UP – Equity PF Performance*
1 (Lowest)	–0.12%	–0.01%	0.08%	–0.11%	–0.20%***
	(–1.41)	(–0.12)	(0.82)	(–1.64)	(–2.73)
2	–0.05%	0.10%**	0.03%	–0.14%***	–0.08%*
	(–0.65)	(2.15)	(0.55)	(–4.36)	(–1.92)
3	0.13%	0.14%*	0.14%*	–0.01%	–0.02%
	(1.43)	(1.66)	(1.72)	(–0.19)	(–0.28)
4	0.28%***	0.21%***	0.22%**	0.07%	0.06%
	(3.17)	(2.63)	(2.35)	(1.59)	(0.98)
5 (Highest)	0.41%***	0.25%*	0.15%	0.17%***	0.26%***
	(2.78)	(1.86)	(1.45)	(5.06)	(3.19)
5-1	0.53%***	0.26%**	0.07%	0.27%***	0.46%***
	(4.52)	(2.57)	(0.65)	(3.46)	(3.38)

Table 3: Bivariate Dependent Portfolio Sorts

This table reports the results of dependent bivariate portfolio sorts based on *UP* and *Gross Fund Firm Performance*, based on *UP* and *Equity PF Performance*, as well as based on *UP* and *Corr*, defined as the 36-month rolling correlation between *Gross Fund Firm Return* and *Equity PF Return*. Panel A reports equally-weighted future average returns of 25 portfolios double sorted on *Gross Fund Performance* and *UP*. First, we form quintile portfolios based on *Fund Firm Performance* in month *t*. Then, within each quintile, we sort funds into quintile portfolios based on *UP* in month *t*. The last column shows the average of the future returns of the respective *UP* quintile portfolio across the *Gross Fund Firm Performance* quintiles in month *t*+3. Panel B reports equally-weighted future average returns of 25 portfolios double sorted on *Equity PF Performance* and *UP*. Panel C reports equally-weighted future average returns of 25 portfolios double sorted on *Corr* and *UP*. The row "UP 5 - UP 1" reports the difference in monthly average excess returns with corresponding statistical significance. We also provide the "5-1" difference in monthly average alphas. We employ the Fung and Hsieh (2004) seven-factor model augmented with the book-to-market (HML) and momentum (UMD) factors. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: *Gross Fund Firm Performance* and *UP*

	Gross Fund Firm Performance 1	Gross Fund Firm Performance 2	Gross Fund Firm Performance 3	Gross Fund Firm Performance 4	Gross Fund Firm Performance 5	Average
UP 1	0.17%*	0.33%***	0.32%**	0.22%*	0.30%***	0.27%***
UP 2	0.25%**	0.30%**	0.33%***	0.39%***	0.35%***	0.32%***
UP 3	0.44%***	0.48%***	0.45%***	0.65%***	0.71%***	0.54%***
UP 4	0.51%***	0.48%***	0.42%***	0.52%***	0.80%***	0.55%***
UP 5	0.45%***	0.49%***	0.60%***	0.79%***	0.95%***	0.66%***
UP 5 - *UP* 1	0.28%	0.16%**	0.28%***	0.57%***	0.65%***	0.39%***
	(1.53)	(2.15)	(3.08)	(3.17)	(3.92)	(2.77)
FH-9-Factor	0.52%***	0.06%	0.34%***	0.64%***	0.68%***	0.45%***
alphas (5 – 1)	(3.12)	(0.72)	(3.02)	(3.67)	(3.40)	(2.79)

Panel B: *Equity PF Performance* and *UP*

	Equity PF Performance 1	*Equity PF Performance* 2	*Equity PF Performance* 3	*Equity PF Performance* 4	*Equity PF Performance* 5	Average
UP 1	0.42%***	0.09%	0.18%*	0.29%*	0.30%**	0.26%**
UP 2	0.35%***	0.20%**	0.36%***	0.45%***	0.22%**	0.31%***
UP 3	0.45%***	0.31%***	0.43%***	0.34%***	0.62%***	0.43%***
UP 4	0.41%***	0.56%***	0.64%***	0.66%***	0.63%***	0.58%***
UP 5	0.52%***	0.90%***	0.79%***	0.99%***	0.64%***	0.77%***
UP 5 - UP 1	0.10%	0.81%***	0.61%***	0.70%***	0.34%***	0.51%***
	(0.88)	(3.87)	(4.25)	(3.47)	(2.69)	(3.03)
FH-9-Factor	0.23%**	0.80%***	0.70%***	0.67%***	0.30%*	0.54%***
alphas (5 – 1)	(1.99)	(4.54)	(4.64)	(2.91)	(1.84)	(3.18)

Panel C: *Corr* and *UP*

	Corr 1	Corr 2	Corr 3	Corr 4	Corr 5	Average
UP 1	0.02%	0.25%**	0.40%***	0.31%***	0.40%***	0.28%***
UP 2	0.31%***	0.39%***	0.49%***	0.35%***	0.60%***	0.43%***
UP 3	0.11%	0.31%***	0.47%***	0.42%***	0.48%***	0.36%***
UP 4	0.31%***	0.65%***	0.66%***	0.80%***	0.59%***	0.60%***
UP 5	0.62%***	0.76%***	0.64%***	0.88%***	0.89%***	0.76%***
UP 5 - *UP* 1	0.60%***	0.51%***	0.24%*	0.57%***	0.49%***	0.48%***
	(3.76)	(2.70)	(1.93)	(3.50)	(3.05)	(2.99)
FH-9-Factor	0.73%***	0.39%***	0.33%**	0.66%***	0.54%***	0.53%***
alphas (5 – 1)	(4.53)	(2.79)	(2.59)	(3.25)	(2.79)	(3.19)

Table 4: Portfolio Sorts - Alternative Skill Measures

This table reports the results of portfolio sorts based on *UP* and R^2 and based on *UP* and the strategy distinctiveness index (SDI). Panel A provides the results of dependent bivariate portfolio sorts based on R^2 (sorted in reverse order, from high to low, since low R^2 implies higher skill) and *UP*. First, we form quintile portfolios based on R^2 (sorted in reverse order, from high to low) in month *t*. Then, we sort funds into quintile portfolios based on *UP* in month *t*. The last column shows the average future return of the respective *UP* quintile portfolio across the R^2 quintiles in month *t*+3. Panel B provides dependent bivariate portfolio sorts based on SDI and *UP*. Panel C reports the results from equally-weighted univariate portfolio sorts based on *UP*, R^2 (sorted in reverse order, from high to low), and SDI. In each month *t*, we sort all funds into quintile portfolios based on the respective measure. We then compute equally-weighted monthly average net-of-fee excess returns of these portfolios in month *t*+3. The row "UP 5 - UP 1" reports the difference in monthly average excess returns with corresponding statistical significance. Last rows of panels report the "5-1" difference in monthly average nine-factor alphas. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Reverse Sorted R^2 and *UP*

	Reverse Sorted R^2 1	Reverse Sorted R^2 2	Reverse Sorted R^2 3	Reverse Sorted R^2 4	Reverse Sorted R^2 5	Average
UP 1	0.04%	0.00%	0.47%***	0.29%***	0.39%***	0.24%*
UP 2	0.38%***	0.38%***	0.55%***	0.33%***	0.57%***	0.44%***
UP 3	0.39%***	0.29%**	0.41%***	0.51%***	0.47%***	0.41%***
UP 4	0.42%***	0.39%***	0.72%***	0.69%***	0.54%***	0.55%***
UP 5	0.75%***	0.56%***	0.67%***	0.97%***	0.65%***	0.72%***
UP 5 – *UP* 1	0.72%***	0.57%***	0.20%	0.68%***	0.26%*	0.48%**
	(2.62)	(2.65)	(1.26)	(3.90)	(1.93)	(2.43)
FH-9-Factor	0.77%***	0.67%***	0.20%	0.68%***	0.27%*	0.52%**
alphas (5 – 1)	(3.12)	(3.12)	(1.26)	(3.58)	(1.62)	(2.54)

Panel B: SDI and *UP*

	SDI 1	SDI 2	SDI 3	SDI 4	SDI 5	Average
UP 1	0.42%***	0.37%***	0.18%*	0.04%	0.31%***	0.26%***
UP 2	0.43%***	0.29%**	0.41%***	0.26%**	0.44%***	0.37%***
UP 3	0.57%***	0.57%***	0.51%***	0.48%***	0.21%**	0.47%***
UP 4	0.51%***	0.46%***	0.64%***	0.60%***	0.54%***	0.55%***
UP 5	0.84%***	0.79%***	0.70%***	0.69%***	0.78%***	0.76%***
UP 5 – *UP* 1	0.42%**	0.43%**	0.52%***	0.65%***	0.47%**	0.50%**
	(2.32)	(2.34)	(2.76)	(2.64)	(2.38)	(2.49)
FH-9-Factor	0.25%	0.67%***	0.54%**	0.68%***	0.49%***	0.53%**
alphas (5 – 1)	(1.29)	(3.14)	(2.59)	(3.01)	(2.66)	(2.54)

Panel C: Excess Returns

Portfolio	(1) *UP*	(2) Reverse Sorted R^2	(3) SDI	(4) *UP* – Reverse Sorted R^2	(5) *UP* – SDI
1 (Lowest)	0.28%**	0.41%***	0.43%***	–0.13%	–0.15%
	(2.00)	(3.85)	(4.26)	(–1.37)	(–1.18)
2	0.30%**	0.26%***	0.44%***	0.04%	–0.14%
	(2.14)	(3.31)	(3.21)	(-–0.48)	(–1.07)
3	0.42%***	0.56%***	0.52%***	–0.14%	–0.10%
	(4.09)	(4.02)	(3.58)	(–1.63)	(–1.01)
4	0.58%***	0.52%***	0.45%***	0.06%	0.13%
	(4.98)	(3.27)	(3.05)	(0.86)	(1.40)
5 (Highest)	0.75%***	0.50%***	0.50%***	0.25%	0.25%*
	(5.03)	(3.53)	(3.67)	(1.46)	(1.70)
5-1	0.47%***	0.09%	0.07%	0.38%***	0.40%***
	(4.17)	(0.48)	(0.37)	(3.66)	(2.89)
FH-9-Factor	0.53%***	0.21%**	0.24%***	0.32%**	0.29%*
alphas (5 – 1)	(4.52)	(2.50)	(2.71)	(2.30)	(1.95)

Table 5: *UP* and Future Returns: Fama-Macbeth (1973) Regressions

Panel A of this table reports the results of Fama and MacBeth (1973) regressions of excess returns and nine-factor (the Fung and Hsieh (2004) seven-factor model augmented with the book-to-market (HML) and momentum (UMD) factors) alphas in month t+3 on *UP* and different fund firm characteristics in month t. As fund firm characteristics, we include a fund firm's monthly gross return, size, age, standard deviation (estimated over the previous 24 months), the delta of the incentive fee contract, a fund firm's management and incentive fee (in %), minimum investment amount (in $100 thousands), the length of a fund firm's lockup and restriction period (in years), indicator variables that equal one if the fund firm is an offshore fund, employs leverage, has a high-water mark and a hurdle rate, the R^2 measure of Titman and Tiu (2011), and the *SDI* measure of Sun, Wang, and Zheng (2012). We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. In Panel B, we report the results of Fama and MacBeth (1973) regressions of returns in month t+3 on *UP* and different fund firm characteristics (as in Column (6) of Panel A) during periods with high or low economic growth (compared to the median GDP growth rate from 1997 to 2017), positive or negative excess market returns, high (low) market volatility, and in subsamples in the period from 1996–2008 and 2009–2017. The respective states of the world are measured contemporaneous to returns (i.e., in month t+3). We compute market volatility as the standard deviation of the CRSP value-weighted market return over the past 36 months. We classify t as a high (low) market volatility period if the standard deviation is above (below) the median standard deviation over the whole sample period from 1997–2017. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017.

Panel A: Fama-Macbeth (1973) Regressions

	(1) Fund Firm Return *t+3*	(2) Fund Firm Return *t+3*	(3) Fund Firm Return *t+3*	(4) Fund Firm Return *t+3*	(5) Fund Firm Return *t+3*	(6) 9-Factor Alpha *t+3*
UP	0.0654***	0.0418***	0.0588***	0.0414***	0.0429***	0.0252***
	(4.37)	(3.55)	(4.61)	(2.79)	(2.80)	(4.25)
Gross Fund Firm Performance		–0.0150		–0.0269**	–0.0300**	0.0160**
		(–1.36)		(–2.19)	(–2.18)	(1.99)
Size		–0.0920**		–0.117**	–0.113**	–0.0414*
		(–2.17)		(–2.18)	(–2.16)	(–1.97)
Age (·100)		–0.0230		–0.122**	–0.158***	–0.0650*
		(–0.40)		(–2.47)	(–2.77)	(–1.78)
Standard Deviation		0.0525		0.0357	0.0284	–0.0471**
		(1.65)		(1.03)	(0.83)	(–2.04)
Delta		0.0219***		0.0288***	0.0283***	0.0129***
		(4.49)		(3.18)	(3.10)	(3.65)
Management Fee			–0.0997	–0.101*	–0.102*	–0.0666
			(–1.63)	(–1.75)	(–1.81)	(–1.02)
Incentive Fee			–0.00171	–0.0111	–0.00975	–0.00554
			(–0.22)	(–1.49)	(–1.21)	(–1.50)
Minimum Investment (·100)			0.185**	0.303**	0.231**	0.0775
			(2.07)	(2.22)	(2.07)	(1.04)
Lockup Period			0.0704*	0.0929**	0.0564	0.0769***
			(1.91)	(2.19)	(1.44)	(2.77)
Restriction Period			0.138	0.156*	0.164*	0.132**
			(1.49)	(1.87)	(1.92)	(2.30)
Offshore			–0.0821	–0.122	–0.109	–0.0405
			(–0.91)	(–1.30)	(–1.61)	(–0.88)
Leverage			0.115	0.0721	0.0506	–0.0116
			(1.10)	(0.79)	(0.60)	(–0.30)
HWM			0.132	0.109	0.108	0.119
			(0.86)	(1.07)	(1.08)	(1.48)
Hurdle Rate			–0.0669	–0.0875	–0.115	–0.122
			(–0.54)	(–0.65)	(–0.79)	(–1.50)
R^2					0.283	–0.256**
					(1.09)	(–2.44)
SDI					0.170	0.126
					(0.64)	(1.03)
Constant	0.444***	0.728**	0.352**	1.105**	0.880***	0.689**
	(3.78)	(2.48)	(2.00)	(2.37)	(2.61)	(2.07)
Observations	44,569	41,514	41,502	38,975	38,975	38,976
Adjusted R^2	0.018	0.178	0.119	0.271	0.307	0.223

Panel B: Alphas associated with UP in different states of the world

	(1) High Economic Growth	(2) Low Economic Growth	(3) MKTRF > 0	(4) MKTRF < 0	(5) High Market Volatility	(6) Low Market Volatility	(7) Subsample 1997 - 2008	(8) Subsample 2009 - 2017
UP	0.0210**	0.0321***	0.0210**	0.0318***	0.0302***	0.0207*	0.0216**	0.0300***
	(2.15)	(3.30)	(2.29)	(2.83)	(3.23)	(1.96)	(2.00)	(3.81)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.215	0.225	0.237	0.223	0.266	0.168	0.265	0.172

Table 6: *UP* and Hedge Fund Firm Performance: Robustness Checks

This table reports the results from robustness checks of the relation between *UP* of fund firms in month *t* and future firm performance in month *t*+3. We investigate the robustness if we estimate *UP* with a 24-month rolling window in (2), use the seven factors in the Fung and Hsieh (2004) model in (3), use the four factors in the Carhart (1997) model in (4), average *UP* over the past 36 months in (5), compute *UP* with an alternative estimate of gross fund firm returns following Ben-David, Birru, and Rossi (2020) in (6), compute *UP* as the difference between a fund firm's performance based on its reported net-of-fee returns and a firm's performance based on its transaction-cost adjusted long-equity portfolio in (7), use alternative performance metrics that include the Sharpe ratio in (8), the Treynor ratio in (9), the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measure (MPPM, with a risk aversion parameter of three) in (10), and the value-added measure of Berk and van Binsbergen (2015) in (11), also include non-equity fund firms in the sample in (12), restrict our sample to only long-short equity fund firms in (13) or funds listed in the TASS database in (14), exclude the smallest (bottom 20%) funds to allow for feasibility of investment in (15), restrict our sample to fund firms for which their long portfolio value of 13F equities deviates from their total AUM by less than 20% in percentage value in (16), use the Getmansky, Lo, and Makarov (2004) methodology to unsmooth hedge fund returns in (17), control for backfill bias when we delete the first 12 monthly observations of a fund (instead of 24 months) in (18) or infer the backfill bias as in Jorion and Schwarz (2019) in (19), and assign a delisting return of –1.61% to those funds that leave the database as in Hodder, Jackworth, and Kolokolova (2014) in (20). Panel A displays the results from the univariate portfolio sorts as in Panel B of Table 2 (Column 1), risk adjustment using the augmented Fung and Hsieh (2004) nine-factor model. Panel B reports the results of Fama and MacBeth (1973) regressions as in Panel A of Table 5 (Column 6) of future nine-factor alphas in month *t*+3 on *UP* and different fund firm characteristics measured in month *t*. (21) reports the relation between *UP* and mutual fund performance. To compute *UP*, *URC* is risk adjusted using the Carhart (1997) four-factor model. For mutual fund sample, past return, size, age, volatility, and management fee, and R^2 are used as controls in the Fama and MacBeth (1973) regressions. Newey-West (1987) adjustment with 36 lags is made to adjust the standard errors for serial correlation. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Only coefficients on *UP* are displayed (control variables are included but suppressed for brevity).

Panel A: Portfolio Sorts

	(1) Baseline	(2) 24-month window	(3) 7-Factor Model	(4) 4-Factor Model	(5) Average *UP*	(6) Alternative Gross Returns	(7) Net Returns
5-1 *UP*	0.53%***	0.45%***	0.51%***	0.57%***	0.48%***	0.50%***	0.50%***
	(4.52)	(3.74)	(4.03)	(5.40)	(3.86)	(5.52)	(4.23)

	(8) Sharpe Ratio	(9) Treynor Ratio	(10) MPMM	(11) Value-Added	(12) All Fund Firms	(13) Long-Short Equity	(14) TASS
5-1 *UP*	0.099***	0.087***	0.340***	2.52***	0.52%***	0.59%***	0.38%***
	(5.60)	(3.17)	(3.06)	(4.50)	(4.74)	(4.87)	(3.94)

	(15) Exclude Smallest	(16) Similar Leverage	(17) Desmoothing	(18) Backfill 12 months	(19) Backfill Inferred	(20) Delisting	(21) Mutual Funds
5-1 *UP*	0.44%***	0.48%***	0.44%***	0.52%***	0.55%***	0.52%***	0.16%**
	(4.35)	(4.06)	(3.73)	(4.38)	(4.54)	(4.57)	(2.12)

Panel B: Fama-MacBeth Regressions

	(1) Baseline	(2) 24-month window	(3) 7-Factor Model	(4) 4-Factor Model	(5) Average *UP*	(6) Alternative Gross Returns	(7) Net Returns
UP	0.0252***	0.0158**	0.0244***	0.0183***	0.0220***	0.0211***	0.0231***
	(4.25)	(2.45)	(5.14)	(3.35)	(3.56)	(5.05)	(4.66)

	(8) Sharpe Ratio	(9) Treynor Ratio	(10) MPMM	(11) Value-Added	(12) All Fund Firms	(13) Long-Short Equity	(14) TASS
UP	0.0111***	0.0109***	0.0034*	0.126**	0.0195***	0.0223***	0.0115**
	(3.94)	(3.73)	(1.93)	(2.06)	(3.80)	(4.77)	(2.19)

	(15) Exclude Smallest	(16) Similar Leverage	(17) Desmoothing	(18) Backfill 12 months	(19) Backfill Inferred	(20) Delisting	(21) Mutual Funds
UP	0.0100***	0.0119***	0.0147***	0.0246***	0.0252***	0.0251***	0.0112**
	(2.78)	(2.69)	(2.96)	(4.12)	(4.30)	(4.25)	(2.34)

Table 7: Practical Trading Strategies: Univariate Portfolio Sorts

This table reports the results from univariate portfolio sorts. Panel A reports the results between *UP* at month *t* and monthly excess raw and risk-adjusted returns in month *t*+3. Column (2) reports equally-weighted sorts for fund firms with only one fund compared to the baseline specification with all fund firms in column (1). In columns (3) and (4), we assign *UP* estimates obtained at the firm level to each individual fund of a firm on an equally-weighted and value-weighted basis, respectively, and perform sorts at the fund level. In Panel B, we report the results of univariate equally -weighted portfolio sorts based on *UP* and longer-term returns, i.e., holding horizons of 3 months (i.e., from *t*+1 to *t*+3), 6 months (i.e., from *t*+1 to *t*+6), 12 months (i.e., from *t*+1 to *t*+12), 18 months (i.e., from *t*+1 to *t*+18), and 24 months (i.e., from *t*+1 to *t*+24). Panel C reports the results of univariate equally-weighted portfolio sorts between *UP* at month *t* and monthly excess raw and risk-adjusted returns in month *t*+3 with a non-overlapping holding horizon of 12 months. In columns (1) and (2), we exclude all fund firms with a lockup and restriction period of more than 12 months, respectively. In column (3) we limit the minimum and maximum number of funds in a portfolio to 25 and 75, respectively. In column (4), we set up a dynamic AUM cut-off so that investment in any given fund is not more than 10% of assets of a typical fund of hedge fund. In column (5), we implement the restrictions from (1) to (4) all together. The rows "5-1" and "FH-9-Factor alphas (5 – 1)" report differences in monthly average returns and alphas with corresponding statistical significance. We use the Newey-West (1987) adjustment to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Single -Fund Firms (in *t*+3*)*

Portfolio	(1) *UP* Baseline All Fund Firms	(2) *UP* Single-Fund Firms	(3) *UP* Fund-Level Equal-Weighted	(4) *UP* Fund-Level Value-Weighted
1 (Lowest)	0.28%**	0.15%	0.07%	0.16%
	(2.00)	(0.85)	(0.32)	(0.72)
2	0.30%**	0.12%	0.30%*	0.29%
	(2.14)	(0.55)	(1.94)	(1.58)
3	0.42%***	0.55%	0.42%***	0.26%
	(4.09)	(4.27)	(3.19)	(1.58)
4	0.58%***	0.61%	0.51%***	0.49%***
	(4.98)	(4.50)	(3.91)	(3.14)
5 (Highest)	0.75%***	0.82%	0.77%***	0.61%***
	(5.03)	(6.33)	(5.38)	(6.47)
5-1	0.47%***	0.67%***	0.70%***	0.45%**
	(4.17)	(4.17)	(2.96)	(2.51)
FH-9-Factor	0.53%***	0.76%***	0.78%***	0.49%**
alphas (5 – 1)	(4.52)	(4.38)	(3.47)	(2.27)

Panel B: Longer Return Performance Frequencies

All Fund Firms

Portfolio	*UP* 3 months *t*+1 to *t*+3	*UP* 6 months *t*+1 to *t+6*	*UP* 12 months *t*+1 to *t+12*	*UP* 18 months *t*+1 to *t+18*	*UP* 24 months *t*+1 to *t+24*
5-1	1.28%***	2.71%**	3.53%***	4.19%**	4.90%**
	(3.60)	(2.64)	(3.35)	(2.52)	(2.89)
FH-9-Factor	1.37%***	2.41%***	3.95%***	4.96%***	5.67%**
alphas (5 – 1)	(5.93)	(4.79)	(4.70)	(4.41)	(2.77)

Single-Fund Firms

Portfolio	*UP* 3 months *t*+1 to *t*+3	*UP* 6 months *t*+1 to *t+6*	*UP* 12 months *t*+1 to *t+12*	*UP* 18 months *t*+1 to *t+18*	*UP* 24 months *t*+1 to *t+24*
5-1	1.45%***	2.53%***	3.24%***	4.75%*	4.81%**
	(3.62)	(3.12)	(3.40)	(2.00)	(2.93)
FH-9-Factor	1.80%***	3.66%***	4.73%***	5.08%***	6.32%**
alphas (5 – 1)	(5.12)	(4.93)	(5.22)	(4.36)	(2.93)

Panel C: 12 Month Frequency with Real-World Trading Constraints

All Fund Firms

Portfolio	*UP* Baseline 12 months	*UP* Excluding Lockup Period > 12 months	*UP* Excluding Rest. Period > 12 months	*UP* 25 to 75 funds in a portfolio	*UP* Dynamic AUM Cutoff	*UP* All Constraints Together
5-1	3.53%***	3.89%***	4.05%***	3.19%***	3.20%***	3.90%***
	(3.35)	(4.27)	(4.51)	(2.94)	(3.39)	(3.37)
FH-9-Factor	3.95%***	3.97%***	4.30%***	3.97%***	3.85%***	4.23%***
alphas (5 – 1)	(4.70)	(4.60)	(4.91)	(4.62)	(4.61)	(4.68)
FH-9-Factor	3.97%***	3.59%%%	3.90%***	4.11%***	4.00%***	3.69%***
alpha PF 5	(4.80)	(4.67)	(4.67)	(4.25)	(5.00)	(4.54)

Single-Fund Firms

Portfolio	*UP* Baseline 12 months	*UP* Excluding Lockup Period > 12 months	*UP* Excluding Rest. Period > 12 months	*UP* 25 to 75 funds in a portfolio	*UP* Dynamic AUM Cutoff	*UP* All Constraints Together
5-1	3.24%***	2.68%***	2.97%***	2.95%***	3.00%**	3.25%***
	(3.40)	(2.93)	(3.84)	(3.01)	(2.84)	(3.42)
FH-9-Factor	4.73%***	3.84%**	4.46%***	4.71%***	4.29%***	3.45%**
alphas (5 – 1)	(5.22)	(2.98)	(4.09)	(5.03)	(4.80)	(2.63)
FH-9-Factor	4.15%***	3.33%**	3.88%***	3.74%***	4.24%***	2.91%***
alpha PF 5	(4.96)	(3.10)	(4.35)	(4.32)	(4.95)	(3.65)

Table 8: Trading Channels

This table reports the results of Fama and MacBeth (1973) regressions of *UP* in month *t* on measures of different trading activities and portfolio characteristics in month *t*. In column (1), portfolio turnover in month *t* is calculated as the total of a fund firm's stock purchases and sales (as indicated in the 13F Thomson Reuters Ownership database), divided by its total equity portfolio market capitalization in month *t-1*. We estimate a fund firm's trading costs in month *t* following DeMiguel, Utrera, Nogales, and Uppal (2017) by applying proportional transaction costs to equity portfolio changes. In column (2), portfolio turnover in month *t* is calculated as the total of a fund firm's actual stock purchases and sales (based on actual transactions as reported in the Abel Noser database), divided by its total equity portfolio market capitalization in month *t-1*. We compute a fund firm's total trading costs following Busse, Chordia, Jiang, and Tang (2020) using transaction level data as the sum of monthly implicit trading costs, commissions, and tax plus fees. In columns (3) and (4), we consider the value of equity shares underlying the call and put positions (*Value of Equity Shares Underlying the Call Positions*, *Value of Equity Shares Underlying the Put Positions* in millions of dollars). In column (5), we consider short-selling activities and compute the maximum daily value of equity shares underlying the short positions (*Value of Equity Shares Underlying the Short Positions*, in millions of dollars) – all based on actual transactions as reported in the Abel Noser database. In column (6), we consider the value of equity shares underlying the confidential holdings positions (*Value of Equity Shares Underlying the Confidential Holdings*, in millions of dollars). As control variables, we add a fund firm's number of different stock positions, the portfolio's Herfindahl index (as a measure of portfolio concentration), portfolio size (the average firm size in a hedge fund firm portfolio), portfolio standard deviation (the value-weighted standard deviation of stocks in a hedge fund firm portfolio), portfolio illiquidity (the value-weighted illiquidity of stocks in a hedge fund firm portfolio measured by the Amihud (2002) illiquidity ratio), and the portfolio book-to-market ratio (the value-weighted book-to-market value of stocks in a hedge fund firm portfolio), all measured in month *t*. Our sample for the tests in (1), (3), (4) and (5) is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long equity holdings to the SEC. Our sample for the tests in (2) and (6) is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database, firms that report 13F long equity holdings to the SEC, and firms that report trade data to Abel Noser. The sample period in (1), (3), (4) and (5) is from January 1997 to December 2017. The sample period in (2) and (6) for Abel Noser data is from January 1999 to September 2011. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) *UP* month *t*	(2) *UP* month *t*	(3) *UP* month *t*	(4) *UP* month *t*	(5) *UP* month *t*	(6) *UP* month *t*
Portfolio Turnover *(13F Based)*	0.0016*** (4.61)					
Trading Costs *(13F Based)*	–5.958*** (–3.11)					
Portfolio Turnover *(Transaction Based)*		0.0153*** (2.89)				
Trading Costs *(Transaction Based)*		–6.379** (–2.56)				
log (1+Value of Equity Shares Underlying the Call Positions)			–0.00130 (–0.50)			
log (1+Value of Equity Shares Underlying the Put Positions)				0.0235*** (4.59)		
log (1+Value of Equity Shares Underlying the Short Positions)					0.0365*** (2.77)	
log (1+Value of Equity Shares Underlying the Confidential Holdings)						0.0339*** (7.66)
Number of Stocks (·100)	–0.014*** (–4.77)	0.0033 (0.70)	–0.0096*** (–3.04)	–0.0167*** (–4.33)	–0.018*** (–5.31)	0.0009 (0.05)
Concentration of Stock Portfolio (·100)	0.669** (2.52)	0.224* (1.77)	0.848*** (3.32)	0.710*** (3.16)	0.657*** (2.87)	–0.177 (–1.08)
Portfolio Size	0.0194 (0.85)	0.373 (0.79)	0.0482** (2.58)	0.0459*** (2.96)	0.0476** (2.54)	0.219*** (3.21)
Portfolio Standard Deviation	–0.0137 (–1.00)	–0.0802 (–0.81)	–0.00166 (–0.13)	–0.00669 (–0.54)	0.000966 (0.08)	–0.0308 (–0.41)
Portfolio Illiquidity	0.128*** (3.42)	3.499 (1.19)	0.0681 (1.61)	0.0678 (1.61)	0.0527 (1.33)	0.829 (0.95)
Portfolio Book–to–Market	0.429*** (3.07)	–2.371 (–1.40)	0.339*** (3.73)	0.330*** (3.42)	0.366*** (3.95)	–0.536 (–0.74)
Constant	0.478 (1.02)	–3.605 (–0.47)	–0.690*** (–2.90)	–0.658*** (–3.44)	–3.175* (–1.87)	–0.728*** (–2.88)
Observations	45,152	2,113	44,422	44,422	2,627	45.614
Adjusted R^2	0.106	0.954	0.099	0.103	0.571	0.097

Table 9: Investor Response to Performance Measures

This table reports the results of Fama and MacBeth (1973) regressions of a hedge fund firm *i*'s flows in year *t+1* on *Gross Fund Firm Performance*, *Equity PF Performance*, *UP*, and different fund firm characteristics in year *t*. As fund firm characteristics, we include a fund firm's size, age, standard deviation, the delta of the incentive fee contract, a fund firm's management and incentive fee (in %), minimum investment amount, the length of a fund firm's lockup and restriction period (in years), indicator variables that equal one if the fund firm is an offshore fund, employs leverage, has a high–water mark and a hurdle rate, the R^2 measure of Titman and Tiu (2011), and the *SDI* measure of Sun, Wang, and Zheng (2012). In columns (5) and (6), we divide the sample according to the median of 13F filing downloads as a proxy for a fund firm's investor attention. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long–equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Firm Flows *t+1*	(2) Firm Flows *t+1*	(3) Firm Flows *t+1*	(4) Firm Flows *t+1*	(5) Firm Flows *t+1* High Attention	(6) Firm Flows *t+1* Low Attention
Gross Fund Firm Performance	0.516***		0.478***	0.457***	0.294	0.495***
	(4.87)		(3.91)	(3.69)	(1.39)	(6.10)
Equity PF Performance		0.305***	0.136			
		(3.42)	(1.67)			
UP				0.104	0.326***	0.0530
				(1.37)	(3.71)	(0.59)
Size	–6.464***	–5.735***	–6.093***	–6.282***	–6.080***	–4.535***
	(–5.43)	(–6.74)	(–6.44)	(–6.01)	(–3.45)	(–3.98)
Age	–0.0550**	–0.0602***	–0.0512***	–0.051***	–0.081***	–0.0509**
	(–2.71)	(–3.58)	(–3.09)	(–3.70)	(–3.75)	(–2.81)
Standard Deviation	–1.491***	–1.554***	–1.543***	–1.608***	–2.470*	–1.465*
	(–3.07)	(–4.14)	(–2.97)	(–3.10)	(–1.94)	(–2.09)
Delta	0.363	0.429*	0.410	0.415	0.333	0.278
	(1.45)	(1.99)	(1.71)	(1.67)	(0.93)	(1.47)
Management Fee	–2.083	–1.233	–1.445	–1.204	–2.100	0.457
	(–1.45)	(–0.70)	(–0.90)	(–0.73)	(–0.79)	(0.16)
Incentive Fee	–0.619***	–0.687***	–0.675***	–0.599***	–0.857***	–0.243
	(–4.08)	(–5.00)	(–5.09)	(–4.02)	(–3.58)	(–1.04)
Minimum Investment	0.0993***	0.0928***	0.0950***	0.0850***	0.103***	0.0516
	(3.28)	(3.48)	(3.25)	(3.25)	(5.87)	(1.51)
Lockup Period	0.520	0.924	0.343	–0.0300	–3.745	1.957
	(0.29)	(0.49)	(0.19)	(–0.02)	(–1.43)	(0.68)
Restriction Period	–1.796	–0.703	–1.671	–1.793	–0.729	–2.695
	(–0.66)	(–0.27)	(–0.65)	(–0.71)	(–0.17)	(–1.05)
Offshore	3.805	1.595	1.701	1.856	1.955	2.513
	(1.41)	(0.53)	(0.56)	(0.66)	(0.49)	(0.75)
Leverage	0.0301	–0.00228	–0.0754	–0.0420	0.00755	–0.0465
	(1.14)	(–0.02)	(–0.49)	(–0.33)	(0.88)	(–0.36)
HWM	1.407	2.929	2.899	2.435	1.980	3.316
	(0.30)	(0.58)	(0.58)	(0.48)	(0.25)	(0.68)
Hurdle Rate	2.154	0.198	1.263	1.986	0.526	0.909
	(0.90)	(0.06)	(0.35)	(0.49)	(0.13)	(0.23)
R^2	–3.072	–1.523	–2.467	–2.117	–13.27	7.347
	(–0.41)	(–0.15)	(–0.25)	(–0.20)	(–1.04)	(0.68)
SDI	–4.682	0.458	–2.125	–2.401	–14.53	–4.181
	(–0.85)	(0.05)	(–0.24)	(–0.25)	(–1.11)	(–0.44)
Constant	56.70***	50.92***	52.11***	52.13***	79.76***	26.98**
	(4.64)	(4.49)	(4.61)	(4.40)	(3.13)	(2.52)
Observations	3,289	3,003	3,003	3,003	1502	1501
Adjusted R^2	0.162	0.165	0.186	0.183	0.218	0.251

Table 10: Predictability of Fund Firm Performance

This table reports the results of Fama and MacBeth (1973) regressions of a hedge fund firm *i*'s nine-factor (the Fung and Hsieh (2004) seven-factor model augmented with the book-to-market (HML) and momentum (UMD) factors) alphas in year *t+1* on *Gross Fund Firm Performance, Equity PF Performance, UP,* and different fund firm characteristics in year *t*. As fund firm characteristics, we include a fund firm's size, age, standard deviation, the delta of the incentive fee contract, a fund firm's management and incentive fee (in %), minimum investment amount, the length of a fund firm's lockup and restriction period (in years), indicator variables that equal one if the fund firm is an offshore fund, employs leverage, has a high-water mark and a hurdle rate, the R^2 measure of Titman and Tiu (2011), and the *SDI* measure of Sun, Wang, and Zheng (2012). In columns (4) and (5), we divide the sample according to the median of 13F filing downloads as a proxy for a fund firm's investor attention. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Fund Firm Performance *t+1*	(2) Fund Firm Performance *t+1*	(3) Fund Firm Performance *t+1*	(4) Fund Firm Performance *t+1* High Attention	(5) Fund Firm Performance *t+1* Low Attention
Gross Fund Firm	0.171***		0.0763***	0.0997***	0.0555**
Performance	(11.23)		(3.91)	(3.40)	(2.20)
Equity PF		0.0476			
Performance		(1.74)			
UP			0.144***	0.0980***	0.169***
			(6.05)	(3.99)	(5.83)
Size	–0.0521	0.00452	0.00462	0.181	0.0300
	(–0.32)	(0.02)	(0.03)	(0.84)	(0.13)
Age	–0.00573	–0.00786	–0.00411	0.000415	–0.00671
	(–1.32)	(–1.11)	(–0.61)	(0.13)	(–0.91)
Standard Deviation	–0.326*	–0.405**	–0.432**	–0.641**	–0.422***
	(–1.89)	(–2.16)	(–2.68)	(–2.42)	(–3.18)
Delta	–0.0250	–0.0235	–0.0443	0.0281	–0.0805
	(–0.46)	(–0.37)	(–0.95)	(0.63)	(–1.66)
Management Fee	0.0293	0.311	0.179	0.917	0.457
	(0.06)	(0.40)	(0.27)	(1.50)	(0.60)
Incentive Fee	–0.0143	–0.0363	–0.0110	0.00795	–0.00460
	(–0.38)	(–0.65)	(–0.26)	(0.19)	(–0.09)
Minimum	0.0199	0.0259	0.0259	0.00901*	0.0172
Investment	(1.52)	(1.48)	(1.66)	(2.10)	(0.85)
Lockup Period	0.878**	1.041***	0.915**	1.178*	0.973**
	(2.62)	(3.15)	(2.86)	(1.98)	(2.17)
Restriction Period	1.018**	1.465**	1.158***	1.151**	1.796
	(2.48)	(2.37)	(3.28)	(2.19)	(1.41)
Offshore	–0.130	0.209	0.360	0.364	–0.144
	(–0.30)	(0.44)	(0.72)	(0.81)	(–0.19)
Leverage	–0.0640	–0.0799	–0.0733	–0.0002	–0.0721
	(–0.93)	(–0.98)	(–0.96)	(–0.15)	(–0.94)
HWM	0.625	1.012	0.440	–0.246	0.396
	(0.70)	(0.85)	(0.51)	(–0.62)	(0.35)
Hurdle Rate	–1.036	–1.473	–1.370*	–0.0149	–2.367***
	(–1.31)	(–1.59)	(–1.75)	(–0.03)	(–2.92)
R^2	–0.842	0.632	0.551	2.116	1.321
	(–0.36)	(0.31)	(0.20)	(1.00)	(0.45)
SDI	2.411	4.812***	3.692**	4.405**	3.463*
	(1.53)	(3.49)	(2.35)	(2.33)	(1.84)
Constant	1.619	–0.0481	–0.284	–4.220	–0.545
	(0.49)	(–0.01)	(–0.08)	(–1.48)	(–0.14)
Observations	3,289	3,003	3003	1502	1501
Adjusted R^2	0.201	0.199	0.249	0.276	0.332

Table 11: Changes in Hedge Fund Firm Trading after Investor Flows

This table reports the results of Fama and MacBeth (1973) regressions of a hedge fund firm *i*'s trading channel in year *t+1* on *UP*, a dummy variable that is one if the hedge fund firm is in the top quintile of investor flows in year *t*, an interaction term based on *UP* the high fund firm flows variable, and portfolio characteristics in year *t*. In column (1), we use portfokio turnover in year *t+1* as the dependent variable. In column (2), we use a fund firm's trading costs in year *t+1* following DeMiguel, Utrera, Nogales, and Uppal (2017) as the dependent variable. In column (3) we use the the value of equity shares underlying the put positions in year *t+1* as the dependent variable. In column (4), we use the value of equity shares underlying the confidential holdings positions in year *t+1* as the dependent variable. In column (5) we approximate for short-selling activities with the maximum daily value of equity shares underlying the short positions *t+1* as the dependent variable. As control variables, we add a fund firm's number of different stock positions, the portfolio's Herfindahl index (as a measure of portfolio concentration), size, standard deviation, illiquidity (measured by the Amihud (2002) ratio), and the book-to-market ratio in month *t* to our model. All control variables are based on the fund firm's disclosed holdings. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Portfolio Turnover (13F Based) *t+1*	(2) Trading Costs (13F Based) *t+1*	(3) Put Option Usage *t+1*	(4) Confidential Holdings Usage *t+1*	(5) Short–Selling Activity *t+1*
UP	–0.000817	0.0000119	0.0246***	0.0737***	–0.0122
	(–0.00)	(0.49)	(3.61)	(3.63)	(–0.21)
High Fund Firm	–32.89***	0.00324***	–5.978***	–0.417***	–8.504***
Flows	(–5.28)	(6.15)	(–11.47)	(–4.47)	(–3.64)
UP · High Fund	–0.923*	0.000273***	–0.320***	–0.0957***	–1.147*
Firm Flows	(–2.01)	(7.27)	(–8.73)	(–5.81)	(–1.91)
Number of Stocks	0.0162	0.00000242***	0.0000603	0.00163**	–0.00234
	(1.43)	(4.33)	(0.19)	(2.63)	(–1.38)
Concentration of	–0.664	–0.00011***	0.000974	0.0360***	–0.174
Stock Portfolio	(–1.72)	(–3.34)	(0.12)	(3.14)	(–1.06)
Portfolio Size	1.048	–0.00248***	–0.0383	–0.180**	0.296
	(0.57)	(–5.20)	(–0.69)	(–2.10)	(0.40)
Portfolio Standard	8.873***	0.002***	0.0637*	–0.077	0.167
Deviation	(4.63)	(3.90)	(1.93)	(–1.05)	(0.48)
Portfolio Illiquidity	–12.42**	0.008***	–0.059	0.910***	0.901
	(–2.50)	(7.35)	(–0.32)	(3.19)	(0.15)
Portfolio Book–to–	–15.76	0.00856**	–0.006	–1.229	–0.751
Market	(–1.20)	(2.50)	(–0.02)	(–1.58)	(–0.30)
Constant	91.04***	0.159***	13.00***	4.017**	15.00
	(3.49)	(24.07)	(13.98)	(2.42)	(1.16)
Observations	3,013	3,004	3,027	3,027	219
Adjusted R^2	0.159	0.464	0.581	0.134	0.219

Internet Appendix

Figure IA.1: Venn Diagram of the Union Hedge Fund Database

The Union Hedge Fund Database contains a sample of 39,938 hedge funds created by merging four commercial databases: Eureka, HFR, Morningstar, and Lipper TASS. This figure shows the percentage of funds covered by each database individually and by all possible combinations of multiple databases.

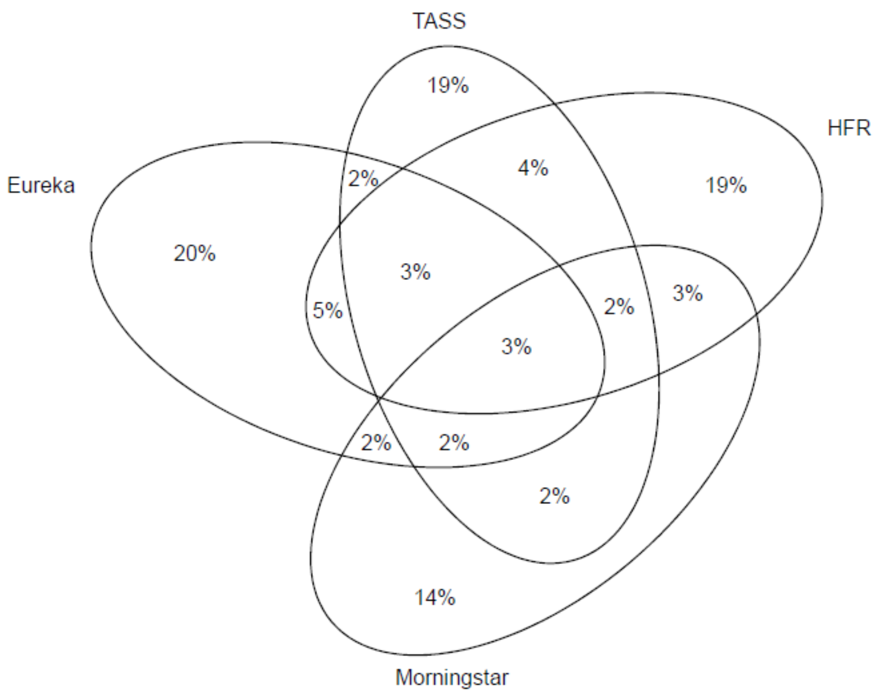
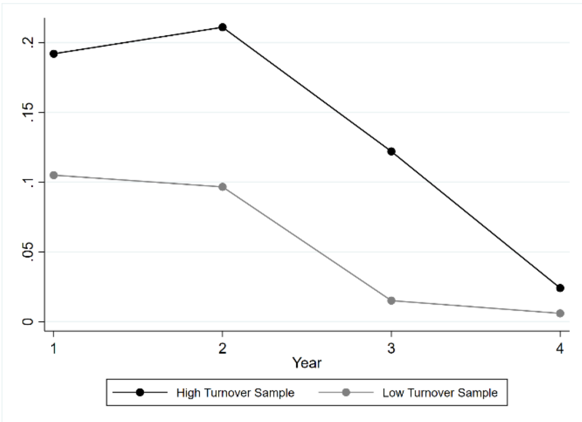


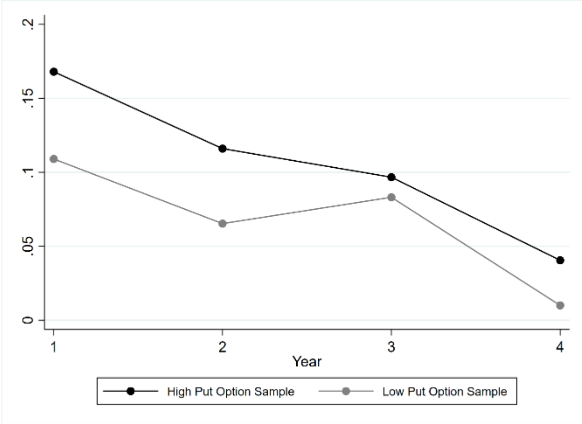
Figure IA.2: *Gross Fund Firm Performance* and *UP*: Long-Term Predictability for Different Subsamples

Figure IA.2 plots the results of of Fama and MacBeth (1973) regressions of a hedge fund firm *i*'s nine-factor alphas in years *t+1*, *t+2*, *t+3* and *t+4* on *Gross Fund Firm Performance, Equity PF Performance*, *UP*, and different fund firm characteristics in year *t*. We separate our sample into the different drivers of a fund firm's *UP*. In Panel A, we show the coefficient estimate of *UP* for the sample of firms with high vs. low *Portfolio Turnover*. The sample is divided according to the median value of *Portfolio Turnover* in each year. In Panel B, we show the coefficient estimate of *UP* for the sample of firms with high vs. low put option usage. The sample is dividing firms which file / do not file at least one put option in each year. In Panel C, we show the coefficient estimate of *UP* for the sample of firms with high vs. low short-selling activity. The sample is divided according to the median value of *Maximum daily value of equity shares underlying the short positions* in each year. In Panel D, we show the coefficient estimate of *UP* for the sample of firms with high vs. low usage of confidential holdings. The sample divides firms which file and do not file at least one confidential holding position in each year. Our sample for the tests in (1), (3), (4) and (5) is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long equity holdings to the SEC. Our sample for the tests in (2) and (6) is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database, firms that report 13F long equity holdings to the SEC, and firms that report trade data to Abel Noser. The sample period in (1), (3), (4) and (5) is from January 1997 to December 2017. The sample period in (2) and (6) for Abel Noser data is from January 1999 to September 2011. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

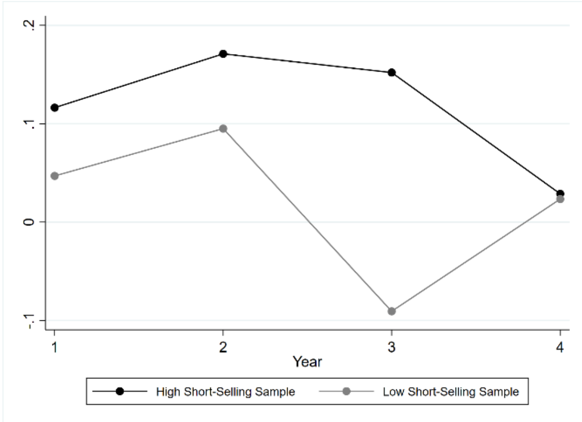
Panel A: High vs. Low Portfolio Turnover



Panel B: High vs. Low Put Option Usage



Panel C: High vs. Low Short-Selling Activity



Panel D: High vs. Low Usage of Confidential Holdings

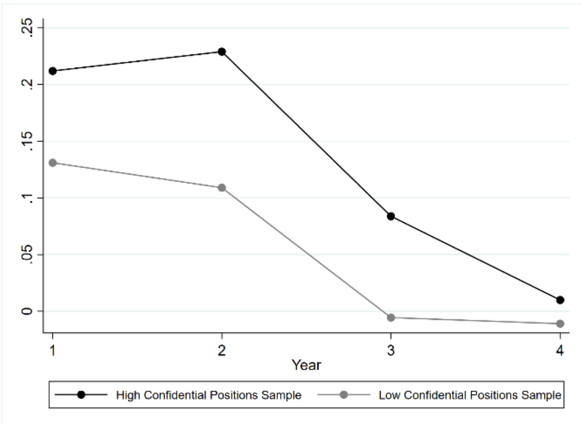


Table IA.1: Correlations

The table reports correlations between *UP*, *Gross Fund Firm Performance*, *Equity PF Performance*, and fund firm characteristics. Descriptive statistics are calculated over all hedge fund firms and months in our sample period. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long equity holdings to the SEC. The sample period is from January 1997 to December 2017.

	UP	*Gross FF Perf.*	*Equity PF Perf.*	Size	Age	Std Dev.	Delta	Mgmt Fee	Inc. Fee	Min Inv.	Lockup Period	Restr. Period	Offshore	Lev.	HWM	Hurdle Rate	R^2	SDI
UP	+1.00																	
Gross Fund Firm Perf.	+0.53	+1.00																
Equity PF Perf.	–0.60	+0.35	+1.00															
Size	+0.01	+0.01	+0.00	+1.00														
Age	–0.02	–0.04	–0.01	+0.19	+1.00													
Std. Dev.	–0.01	+0.01	+0.01	–0.22	–0.07	+1.00												
Delta	+0.04	+0.05	+0.00	+0.58	+0.22	–0.08	+1.00											
Mgmt. Fee	+0.03	+0.02	–0.01	+0.08	–0.05	–0.03	+0.18	+1.00										
Inc. Fee	+0.03	+0.04	+0.01	–0.05	–0.03	+0.10	+0.21	+0.29	+1.00									
Min Inv	+0.02	+0.01	–0.01	+0.31	+0.10	–0.08	+0.34	+0.06	-0.01	+1.00								
Lockup	+0.02	+0.02	+0.00	–0.02	–0.03	+0.06	+0.05	+0.04	+0.22	+0.00	+1.00							
Restriction	+0.00	+0.03	+0.02	+0.08	+0.07	+0.05	+0.11	+0.00	+0.18	+0.02	+0.26	+1.00						
Offshore	+0.00	–0.00	-0.01	+0.23	–0.06	–0.12	+0.21	+0.19	+0.03	+0.05	–0.14	-0.15	+1.00					
Leverage	+0.02	+0.02	+0.00	+0.02	–0.00	+0.05	+0.14	+0.16	+0.23	+0.05	+0.07	+0.03	+0.06	+1.00				
HWM	+0.02	+0.02	-0.01	+0.02	–0.00	+0.05	+0.13	+0.21	+0.57	–0.02	+0.22	+0.18	–0.05	+0.21	+1.00			
Hurdle Rate	–0.00	–0.01	–0.00	–0.09	+0.06	+0.00	–0.12	–0.10	+0.04	–0.06	+0.03	+0.02	–0.21	–0.04	+0.01	+1.00		
R^2	–0.03	–0.03	+0.01	+0.02	+0.14	+0.28	–0.01	–0.18	–0.10	–0.04	+0.03	+0.10	–0.17	–0.11	–0.02	+0.02	+1.00	
SDI	+0.04	+0.06	+0.01	–0.13	–0.19	–0.17	–0.07	+0.09	+0.10	+0.07	–0.06	–0.09	+0.04	+0.11	–0.00	+0.02	–0.67	+1.00

Table IA.2: Determinants of *UP*

This table reports the results of Fama and MacBeth (1973) regressions of *UP* in month *t+1* on *UP* in month *t* and fund firm characteristics in month *t*. For fund firm characteristics, we include a fund firm's monthly *Gross Fund Firm Performance*, size, age, standard deviation (estimated over the previous 36 months), the delta of the incentive fee contract, a fund firm's management and incentive fee (in %), minimum investment amount (in $100 thousands), the length of a fund firm's lockup and restriction period (in years), indicator variables that equal one if the fund firm is an offshore fund, employs leverage, has a high-water mark and a hurdle rate, the R^2 measure of Titman and Tiu (2011), and the *SDI* measure of Sun, Wang, and Zheng (2012). Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) UP *t+1*	(2) UP *t+1*	(3) UP *t+1*	(4) UP *t+1*	(5) UP *t+1*
UP	0.0587***	0.0414***		0.0405***	0.0377***
	(5.84)	(4.20)		(4.10)	(4.09)
Gross Fund Firm		0.0228**		0.0240***	0.0203***
Return		(2.39)		(3.02)	(2.82)
Size		–0.0381**		–0.0533**	–0.0336
		(–2.16)		(–2.53)	(–1.36)
Age (·100)		–0.114*		–0.133***	–0.0861*
		(–1.90)		(–2.88)	(–1.92)
Standard Deviation		0.0048		–0.0016	0.0292
		(0.28)		(–0.10)	(1.65)
Delta		0.0102**		0.0125***	0.0136***
		(2.36)		(4.23)	(3.44)
Management Fee			0.106***	0.120***	0.0634
			(2.61)	(3.69)	(1.56)
Incentive Fee			0.0003	–0.0049	-0.0092
			(0.05)	(–0.87)	(–1.60)
Minimum			0.080	0.080	0.0300
Investment (·100)			(0.60)	(0.95)	(0.36)
Lockup Period			0.0907**	0.0856*	0.101**
			(2.23)	(1.78)	(2.00)
Restriction Period			0.0858	0.0937	0.162
			(0.61)	(0.77)	(1.28)
Offshore			–0.0655	–0.0272	–0.0816*
			(–1.00)	(–0.53)	(–1.97)
Leverage			0.0724*	0.0426	–0.0320
			(1.95)	(1.14)	(–0.73)
HWM			0.156**	0.138**	0.154***
			(2.07)	(2.40)	(2.62)
Hurdle Rate			–0.0612	–0.0053	–0.0296
			(–1.18)	(–0.11)	(–0.54)
R^2					–0.568**
					(–2.54)
SDI					0.593***
					(6.69)
Constant	0.298***	0.558***	-0.0684	0.385**	0.370*
	(4.37)	(4.49)	(-0.56)	(2.47)	(1.92)
Observations	45,205	41,610	42,444	39,047	39,047
Adjusted R^2	0.027	0.088	0.085	0.174	0.198

Table IA.3: *UP* and Future Returns: Univariate Portfolio Sorts with Additional Factors

This table reports the results from regressions of the returns of a long-short portfolio, long in fund firms with highest *UP* (portfolio 5) and short in fund firms with lowest *UP* (portfolio 1), on returns of different risk factors and asset classes. As risk factors, we use in addition to the factors of the augmented Fung and Hsieh (2004) nine-factor model presented in the first column, the Fama and French (2015) profitability factor (*RMW)* and investment (CMA) factors, the Pástor and Stambaugh (2003) traded liquidity factor (*PS Liqui*), the Frazzini and Pedersen (2014) betting-against-beta factor (*BAB*), the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor (*Macro*), the Baker and Wurgler (2006) investor sentiment factor *(Senti)*, the Buraschi, Kosowski, and Trojani (2014) correlation risk factor (*Corr*), and the Agarwal, Ruenzi, and Weigert (2017) tail risk factor *(Tailrisk)*. For returns of different asset classes, we use the MSCI Emerging Market index (*EM Equity)*, the MSCI Europe Market index (*Europe Equity)*, the Barclays US Government Bond index (*Gov Bond)*, the Barclays US Corporate Investment Grade Bond index (*Corp Bond)*, the S&P GSCI Commodity index *(Commodity)*, the FTSE NAREIT US Real Estate index (*Real Estate)*, and the US Private Equity index *(Private Equity)* from Cambridge Associates. All data series are monthly except for the quarterly US Private Equity index. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Additional Risk Factors

	(1) 5 – 1 *UP*	(2) 5 – 1 *UP*	(3) 5 – 1 *UP*	(4) 5 – 1 *UP*	(5) 5 –1 *UP*	(6) 5 – 1 *UP*	(7) 5 – 1 *UP*	(8) 5 – 1 *UP*	(9) 5 – 1 *UP*
S&P	–0.005	–0.0534	–0.0041	–0.0307	–0.0019	0.0118	–0.0036	–0.0396	–0.0395
	(–0.14)	(–1.28)	(–0.11)	(–0.85)	(–0.05)	(0.30)	(–0.10)	(–0.57)	(–0.52)
SCMLC	0.0643	0.0174	0.0647	0.0428	0.0629	0.0611	0.0637	0.0487	–0.0044
	(1.26)	(0.41)	(1.24)	(0.89)	(1.20)	(0.97)	(1.05)	(0.71)	(–0.06)
BD10RET	–0.0634		–0.0676	–0.0589	–0.0662	–0.0706	–0.0682	–0.0668	–0.0584
	(–1.44)		(–1.35)	(–1.08)	(–1.45)	(–1.15)	(–1.20)	(–1.20)	(–0.83)
BAAMTSY	–0.0913*		–0.0875*	–0.0405	–0.0983*	–0.128**	–0.139***	–0.148***	–0.0931*
	(–1.75)		(–1.78)	(–0.94)	(–1.84)	(–2.32)	(–2.88)	(–2.94)	(–1.70)
PTFSBD	0.0064		0.0065	0.0042	0.0066	0.0069	0.0065	0.0047	0.0038
	(1.21)		(1.25)	(0.78)	(1.26)	(0.90)	(1.01)	(0.72)	(0.49)
PTFSFX	0.0066		0.0066	0.0077	0.0065	–0.0001	–0.0001	–0.0008	0.0028
	(0.94)		(0.93)	(1.14)	(0.92)	(–0.02)	(–0.03)	(–0.12)	(0.39)
PTFSCOM	–0.0011		–0.0011	–0.0034	–0.0008	0.0029	0.0018	0.0029	0.0003
	(–0.17)		(–0.17)	(–0.49)	(–0.12)	(0.27)	(0.21)	(0.31)	(0.02)
HML	–0.0500**	–0.0101	–0.0506**	0.0064	–0.0491**	–0.0605***	–0.0497**	–0.0300	0.0493
	(–2.39)	(–0.40)	(–2.38)	(0.20)	(–2.25)	(–2.79)	(–2.24)	(–0.97)	(1.29)
UMD	0.0043		0.0056	0.0317*	0.0069	0.0033	0.0025	0.0127	0.0289
	(0.20)		(0.26)	(1.81)	(0.28)	(0.15)	(0.12)	(0.47)	(1.39)
RMW		–0.112***							–0.116***
		(–3.04)							(–2.70)
CMA		0.0038							–0.0210
		(0.05)							(–0.22)
PS Liqui			–0.0107						0.0142
			(–0.33)						(0.27)
BAB				–0.0918***					–0.0709*
				(–3.17)					(–1.79)
Macro					0.0275				0.0442
					(0.98)				(0.99)
Senti						0.0011			0.0019
						(0.78)			(1.18)
Corr							–0.0103		–0.0153
							(–0.91)		(–1.15)
Tailrisk								0.0693	–0.0169
								(1.11)	(–0.22)
Constant	0.530***	0.532***	0.536***	0.573***	0.527***	0.629***	0.523***	0.561***	0.541***
	(4.52)	(4.22)	(4.16)	(6.26)	(4.65)	(4.33)	(3.34)	(4.09)	(2.93)
Observations	249	249	249	249	249	165	189	189	165
Adjusted R^2	0.071	0.063	0.071	0.112	0.072	0.067	0.067	0.070	0.130

Panel B: Other Asset Classes

	(1) 5 – 1 *UP*	(2) 5 – 1 *UP*	(3) 5 – 1 *UP*	(4) 5 – 1 *UP*	(5) 5 – 1 *UP*	(6) 5 – 1 *UP*	(7) 5 – 1 *UP*	(8) 5 – 1 *UP*	(9) 5 – 1 UP
S&P	–0.0050	–0.0081	0.0078	–0.0088	–0.0009	–0.0082	0.0280	0.0374	0.0375
	(–0.14)	(–0.16)	(0.15)	(–0.25)	(–0.02)	(–0.21)	(0.65)	(0.67)	(0.64)
SCMLC	0.0643	0.0632	0.0666	0.0627	0.0628	0.0622	0.0900*	–0.0450	0.0855
	(1.26)	(1.14)	(1.34)	(1.29)	(1.23)	(1.21)	(1.82)	(–0.79)	(1.64)
BD10RET	–0.0634	–0.0639	–0.0613	0.112	0.0342	–0.0621	–0.0300	–0.132***	0.178
	(–1.44)	(–1.40)	(–1.37)	(0.68)	(0.51)	(–1.47)	(–0.62)	(–2.84)	(0.99)
BAAMTSY	–0.0913*	–0.0927*	–0.0869	–0.0919	–0.0283	–0.0973*	–0.0638	–0.135	–0.0201
	(–1.75)	(–1.79)	(–1.65)	(–1.63)	(–0.86)	(–1.70)	(–1.29)	(–1.29)	(–0.60)
PTFSBD	0.0064	0.0065	0.0059	0.0064	0.0052	0.0064	0.0062	0.0168	0.0049
	(1.21)	(1.28)	(1.15)	(1.25)	(0.95)	(1.23)	(1.21)	(1.57)	(0.97)
PTFSFX	0.0066	0.0066	0.0068	0.0066	0.0076	0.0067	0.0064	0.0096	0.0074
	(0.94)	(0.93)	(0.96)	(0.95)	(1.13)	(0.95)	(0.91)	(0.95)	(1.10)
PTFSCOM	–0.0011	–0.0011	–0.0008	–0.0018	–0.0024	–0.0014	–0.0011	–0.0139	–0.0023
	(–0.17)	(–0.17)	(–0.13)	(–0.27)	(–0.37)	(–0.23)	(–0.16)	(–1.10)	(–0.34)
HML	–0.0500**	–0.0493**	–0.0493**	–0.0558**	–0.0549**	–0.0518***	–0.0220	–0.0342	–0.0307
	(–2.39)	(–2.04)	(–2.37)	(–2.43)	(–2.53)	(–2.63)	(–0.89)	(–1.35)	(–1.15)
UMD	0.0042	0.0046	0.0039	0.0021	0.0017	0.0025	0.00053	–0.0415	–0.0034
	(0.20)	(0.21)	(0.18)	(0.09)	(0.08)	(0.12)	(0.03)	(–1.44)	(–0.15)
EM Equity		0.0031							0.0068
		(0.14)							(0.26)
Europe Equity			–0.0133						–0.0217
			(–0.57)						(–0.76)
Gov Bond				–0.187					–0.145
				(–1.20)					(–0.91)
Corp Bond					–0.170*				–0.124
					(–1.81)				(–1.19)
Commodity						0.0103			0.0063
						(0.67)			(0.43)
Real Estate							–0.0488**		–0.0449*
							(–2.10)		(–1.93)
Private Equity								–0.0265	
								(–0.19)	
Constant	0.530***	0.531***	0.527***	0.539***	0.533***	0.535***	0.523***	1.599***	0.530***
	(4.52)	(4.58)	(4.45)	(4.66)	(4.53)	(4.48)	(4.55)	(5.47)	(4.52)
Observations	249	249	249	249	249	249	249	83	249
Adjusted R^2	0.071	0.071	0.072	0.072	0.078	0.081	0.073	0.144	0.098

Table IA.4: Bivariate Independent Portfolio Sorts

This table reports the results of *independent* bivariate portfolio sorts based on *UP* and *Gross Fund Firm Performance*, based on *UP* and *Equity PF Performance*, as well as based on *UP* and *Corr*, defined as the 36-month rolling correlation between *Gross Fund Firm Return* and *Equity PF Return*. Panel A reports equally-weighted future average returns of 25 portfolios double sorted on *Gross Fund Performance* and *UP*. First, we form quintile portfolios based on *Fund Firm Performance* in month *t*. Then, independently, we sort funds into quintile portfolios based on *UP* in month *t*. The last column shows the average future return of the respective *UP* quintile portfolio across the *Gross Fund Firm Performance* quintiles in month *t*+3. Panel B reports equally-weighted future average returns of 25 portfolios double sorted on *Equity PF Performance* and *UP*. First, we form quintile portfolios based on *Equity PF Performance* in month *t*. Then, independently, we sort funds into quintile portfolios based on *UP* in month *t*. The last column shows the average future return of the respective *UP* quintile portfolio across the *Equity PF Performance* quintiles in month *t*+3. Panel C reports equally-weighted future average returns of 25 portfolios double sorted on *Corr* and *UP*. First, we form quintile portfolios based on *Corr* in month *t*. Then, independently, we sort funds into quintile portfolios based on *UP* in month *t*. The last column shows the average future return of the respective *UP* quintile portfolio across the *Corr* quintiles in month *t*+3. The row "UP 5 - UP 1" reports the difference in monthly average excess returns with corresponding statistical significance. We also provide the "5-1" difference in monthly average alphas. We employ the Fung and Hsieh (2004) seven-factor model augmented with the book-to-market (HML) and momentum (UMD) factors. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: *Gross Fund Firm Performance* and *UP*

	Gross Fund Firm Performance 1	Gross Fund Firm Performance 2	Gross Fund Firm Performance 3	Gross Fund Firm Performance 4	Gross Fund Firm Performance 5	Average
UP 1	0.22%*	0.36%***	0.45%***	0.11%	0.35%***	0.30%***
UP 2	0.37%***	0.32%***	0.24%*	0.40%***	0.26%***	0.32%***
UP 3	0.63%***	0.34%***	0.40%***	0.41%***	0.22%*	0.40%***
UP 4	0.56%***	0.67%***	0.59%***	0.50%***	0.53%***	0.57%***
UP 5	0.62%***	0.51%***	0.54%***	0.80%***	0.82%***	0.66%***
UP 5 - UP 1	0.39%***	0.15%	0.09%	0.69%***	0.47%**	0.36%**
	(3.32)	(0.92)	(1.42)	(3.22)	(2.42)	(2.26)
FH-9-Factor	0.57%***	0.11%	0.25%*	0.69%***	0.53%**	0.43%**
alphas (5 – 1)	(3.13)	(0.70)	(1.90)	(3.42)	(2.29)	(2.29)

Panel B: *Equity PF Performance* and *UP*

	Equity PF Performance 1	Equity PF Performance 2	Equity PF Performance 3	Equity PF Performance 4	Equity PF Performance 5	Average
UP 1	0.31%***	0.18%*	0.14%*	0.35%***	0.27%***	0.25%**
UP 2	0.14%*	0.22%**	0.17%**	0.36%***	0.41%***	0.26%***
UP 3	0.47%***	0.14%**	0.50%***	0.54%***	0.77%***	0.49%***
UP 4	0.36%***	0.63%***	0.54%***	0.88%***	0.76%***	0.63%***
UP 5	0.50%***	0.76%***	0.85%***	0.86%***	0.91%***	0.78%***
UP 5 - UP 1	0.19%	0.58%***	0.71%***	0.51%***	0.64%**	0.53%***
	(1.05)	(4.03)	(3.81)	(3.65)	(2.34)	(2.98)
FH-9-Factor	0.35%**	0.65%***	0.81%***	0.51%**	0.39%*	0.54%***
alphas (5 – 1)	(2.26)	(4.44)	(5.04)	(2.46)	(1.66)	(3.17)

Panel C: ***Corr*** and ***UP***

	Corr 1	Corr 2	Corr 3	Corr 4	Corr 5	Average
UP 1	0.09%	0.29%**	0.42%***	0.22%*	0.63%***	0.33%***
UP 2	0.23%*	0.34%***	0.40%***	0.29%*	0.37%***	0.33%***
UP 3	0.14%*	0.45%***	0.40%***	0.59%***	0.73%***	0.46%***
UP 4	0.38%***	0.51%***	0.51%***	0.75%***	0.66%***	0.56%***
UP 5	0.60%***	0.77%***	0.79%***	0.88%***	0.80%***	0.77%***
UP 5 - UP 1	0.51%***	0.49%**	0.38%**	0.66%***	0.17%	0.44%**
	(3.81)	(2.44)	(2.51)	(3.08)	(1.27)	(2.62)
FH-9-Factor	0.59%***	0.39%**	0.42%***	0.71%***	0.46%*	0.51%***
alphas (5 – 1)	(4.06)	(2.40)	(3.50)	(2.72)	(1.70)	(2.88)

Table IA.5: Bivariate Independent Portfolio Sorts: Skill Measures

This table reports the results of portfolio sorts based on *UP*, R^2, and the strategy distinctiveness index (SDI). Panel A provides the results of independent bivariate portfolio sorts based on R^2 (sorted in reverse order, from high to low, since low R^2 implies higher managerial skill) and *UP*. First, we form quintile portfolios based on R^2 (sorted in reverse order, from high to low) in month *t*. Then, independently, we sort funds into quintile portfolios based on *UP* in month *t*. The last column shows the average of the future return of the respective *UP* quintile portfolio across the R^2 quintiles in month *t+3*. Panel B provides independent bivariate portfolio sorts based on SDI and *UP*. First, we form quintile portfolios based on SDI in month *t*. Then, independently, we sort funds into quintile portfolios based on *UP* in month *t*. The last column shows the average of the future return of the respective *UP* quintile portfolio across the SDI quintiles in month *t+3*. The row "UP 5 - UP 1" reports the difference in monthly average excess returns with corresponding statistical significance. We also provide the "5-1" difference in monthly average alphas. We employ the Fung and Hsieh (2004) seven-factor model augmented with the book-to-market (HML) and momentum (UMD) factors. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Reverse Sorted R^2 and *UP*

	Reverse Sorted R^2 1	Reverse Sorted R^2 2	Reverse Sorted R^2 3	Reverse Sorted R^2 4	Reverse Sorted R^2 5	Average
UP 1	0.10%	0.00%	0.40%***	0.23%**	0.36%***	0.21%**
UP 2	0.15%*	0.40%***	0.45%***	0.26%**	0.39%***	0.33%***
UP 3	0.37%***	0.21%*	0.33%***	0.54%***	0.68%***	0.42%***
UP 4	0.44%***	0.53%***	0.72%***	0.74%***	0.45%***	0.58%***
UP 5	0.73%***	0.57%***	0.69%***	1.03%***	0.69%***	0.74%***
UP 5 - UP 1	0.64%***	0.58%**	0.29%	0.80%***	0.33%***	0.53%***
	(3.10)	(2.33)	(1.58)	(2.61)	(3.66)	(2.66)
FH-9-Factor	0.68%***	0.65%***	0.25%*	0.80%**	0.39%**	0.55%**
alphas (5 – 1)	(3.30)	(2.82)	(1.74)	(2.48)	(2.33)	(2.53)

Panel B: SDI and *UP*

	SDI 1	SDI 2	SDI 3	SDI 4	SDI 5	Average
UP 1	0.45%***	0.39%***	0.19%*	0.03%*	0.26%***	0.26%***
UP 2	0.41%***	0.33%***	0.39%***	0.20%**	0.42%***	0.35%***
UP 3	0.58%***	0.40%***	0.45%***	0.56%***	0.21%**	0.44%***
UP 4	0.49%***	0.54%***	0.61%***	0.64%***	0.45%***	0.55%***
UP 5	0.89%***	0.76%***	0.71%***	0.76%***	0.81%***	0.79%***
UP 5 - UP 1	0.44%*	0.37%***	0.52%***	0.73%**	0.55%*	0.52%**
	(1.87)	(2.90)	(2.72)	(2.55)	(2.17)	(2.44)
FH-9-Factor	0.31%	0.63%***	0.58%**	0.58%***	0.59%**	0.54%**
alphas (5 – 1)	(1.29)	(3.07)	(2.39)	(2.90)	(2.43)	(2.42)

Table IA.6: Univariate Portfolio Sorts: Different Filters

This table reports the results from univariate portfolio sorts based on *UP* in month *t* and monthly excess returns in month *t*+3. In each month *t*, we sort all hedge funds into quintile portfolios based on *UP* in increasing order. We then compute equally-weighted monthly average net-of-fee excess returns of these portfolios in month *t*+3. The column "5-1" reports the difference in monthly average excess returns with corresponding statistical significance. The row "FH-9-Factor alphas (5 – 1)" reports the difference in monthly average alphas with corresponding statistical significance. Column (1) uses the baseline specification where we require a fund to have at least 24 monthly return observations. Column (2) reports the specification where we require a fund to have at least 12 monthly return observations (and estimate *UP* based on a minimum of 12 observations). Column (3) shows the specification where we require a fund to have at least 36 monthly return observations. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Portfolio	(1) Baseline: *UP* for funds with a minimum of 24 monthly return observations	(2) *UP* for funds with a minimum of 12 monthly return observations	(3) *UP* for funds with a minimum of 36 monthly return observations
1 (Lowest)	0.28%**	0.32%*	0.26%**
	(2.00)	(1.87)	(2.56)
2	0.30%**	0.35%**	0.32%***
	(2.14)	(2.21)	(2.88)
3	0.42%***	0.49%***	0.44%***
	(4.09)	(3.54)	(4.33)
4	0.58%***	0.61%***	0.55%***
	(4.98)	(3.87)	(5.24)
5 (Highest)	0.75%***	0.74%***	0.76%***
	(5.03)	(4.22)	(5.44)
5-1	0.47%***	0.42%***	0.50%***
	(4.17)	(4.01)	(4.42)
FH-9-Factor	0.53%***	0.47%***	0.56%***
alphas (5 – 1)	(4.52)	(4.22)	(4.66)

Table IA.7: Bivariate Dependent Portfolio Sorts based on Investor Attention, Performance, and Future Flows

This table reports the results of portfolio sorts based on investor attention, *Gross Fund Firm Performance*, and future flows as well as investor attention, *UP*, and future flows. In Panel A, we first form quintile portfolios based on investor attention in year *t*. Then, we sort fund firms into quintile portfolios based on *Gross Fund Firm Performance* in year *t*. We show average flows of the different fund firm portfolios in year *t*+1. In Panel B, we first form quintile portfolios based on investor attention in year *t*. Then, we sort fund firms into quintile portfolios based on *UP* in year *t*. We show average flows of the different fund firm portfolios in year *t*+1. We measure investor attention of a firm in year *t* according to the number of 13F filing downloads. The row "Flow 5 - Flow 1" reports the difference in annual average flows with corresponding statistical significance. Our sample is the intersection of equity-oriented hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long-equity holdings to the SEC. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for potential serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Investor Attention, *Gross Fund Firm Performance*, and Fund Flows

	Investor Attention 1	Investor Attention 2	Investor Attention 3	Investor Attention 4	Investor Attention 5	Average
GFFP 1	–2.32%	–5.32%*	–-6.87%*	–4.01%*	–3.14%	–4.33%*
GFFP 2	1.79%	–6.38%	–4.32%	–2.01%	1.16%	–1.95%
GFFP 3	8.57%*	–0.31%	1.59%	–1.46%	–0.47%	1.58%
GFFP 4	7.70%*	4.96%	1.10%	6.48%*	–2.08%	3.63%
GFFP 5	12.98%***	7.21%**	2.97%	5.45%*	5.81%*	6.88%**
Flows 5 -	15.30%***	12.53%**	9.84%*	9.46%**	8.95%	11.22%**
Flows 1	(3.30)	(2.54)	(1.86)	(2.43)	(1.54)	(2.33)

Panel B: Investor Attention, *UP*, and Fund Flows

	Investor Attention 1	Investor Attention 2	Investor Attention 3	Investor Attention 4	Investor Attention 5	Average
UP 1	1.82%	–4.84%**	–6.05%**	–6.28%**	–3.65%	–3.80%*
UP 2	–0.85%	–2.75%	1.21%	–0.77%	8.87%*	1.14%
UP 3	–0.98%	1.28%	1.98%	1.59%	–1.59%	0.46%
UP 4	2.19%	1.03%	–2.45%	3.71%	1.92%	1.28%
UP 5	4.74%*	2.46%	4.23%	4.55%*	11.62%***	5.52%*
Flows 5 -	2.92%	7.30%	10.28%***	10.83%***	15.26%***	9.32%**
Flows 1	(0.53)	(1.49)	(2.89)	(3.56)	(3.98)	(2.49)

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