Unobserved Performance of Hedge Funds

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Abstract

We investigate hedge fund firms' unobserved performance (*UP*), measured as the risk-adjusted return difference between a firm's reported gross return and portfolio return inferred from its disclosed long-equity holdings. Firms with high *UP* outperform those with low *UP* by 6.36% p.a. after accounting for typical hedge fund risk factors. *UP* better forecasts fund performance than other predictors. We find that *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. *UP* exhibits significant persistence but investors do not seem to use it for manager selection.

Keywords: Hedge fund skill, Confidential Holdings, Derivative Usage, Short Selling, Unobserved Performance

JEL Classification Numbers: G11, G23

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Disclosure Statement of Vikas Agarwal:

I declare that I have no relevant or material financial interests that relate to the current study. I do hold an unpaid position as a director on the board of the Southeastern Alternative Funds Association, a non-profit organization associated with alternative investments including hedge funds. I am also affiliated with the Centre of Financial Research in Cologne as a research fellow.

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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 to 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.

Two strands of academic literature have made some progress in this direction 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 a plethora of 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 quarterly basis.[2] In contrast to the returns-based approach, empirical evidence for 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 terms of 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

[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).

[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, 2018).

evidence of skill. These include having access to only quarterly snapshots, coverage of only large long 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 individual fund) level, and funds' intraquarter trading to prevent others from inferring their trading strategies and positions.

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 the mutual fund industry and combine the returns- and holdings-based approaches in the hedge fund context. The underlying intuition behind our investigation is as follows. When positive hedge fund alpha exists (as documented in the returns-based studies), but not observed in the disclosed long-equity positions, it must stem from the unobserved actions of hedge funds, i.e., actions that cannot be inferred from the fund firms' quarterly long-equity holdings. To capture this *unobserved* return component (*URC*), we combine data on *equity-oriented* hedge fund returns reported to commercial databases with data on long-equity positions of hedge fund firms disclosed in their 13F filings. Consistent with the limited evidence of skill in long-equity positions, we observe that the average nine-factor (seven factors in the Fung and Hsieh (2004) model augmented with the Fama and French (1993) book-to-market factor and the Carhart (1997) momentum factor) alpha of 0.295% per month (*t*-statistic of 3.09) for hedge fund firms in our sample is mostly driven by the fund firms' *URC* with an average alpha of 0.180% per month (*t*-statistic of 3.57). In comparison, fund firms' average alpha of their long-equity positions is 0.115% per month and statistically indistinguishable from zero (*t*-statistic of 1.59).

Unlike long-equity portfolio returns, hedge fund firms' reported returns are influenced by their exposure to non-equity classes. For this reason, we only focus on equity-oriented hedge

funds in this study. Nonetheless, we still adjust for the known risk factors that can influence hedge fund returns to isolate managerial skill. Specifically, we construct a new measure of skill, unobserved performance (or *UP*), which is the risk-adjusted difference between hedge fund firms' reported returns and hypothetical buy-and-hold returns from long-equity positions of 663 fund firms over the period from 1994 to 2017.[3]

As a first step to understand the sources of managerial skill, we investigate which fund firm characteristics are associated with high *UP*. If *UP* indeed captures skill, it should be persistent, and the characteristics associated with it should predict better fund performance. We find strong evidence in favor of *UP* being persistent and reflecting managerial skill. Specifically, younger and to a certain extent smaller fund firms show high *UP*, consistent with these firms being more nimble and less likely to suffer from capacity constraints compared to larger ones, and therefore perform better (Aggarwal and Jorion, 2010). *UP* is positively related to measures of managerial incentives (manager's pay-performance sensitivity or delta) and managerial discretion (proxied by a fund firm's lockup period). Finally, *UP* is positively related with a fund's R^2 and strategy distinctiveness (SDI) measures indicating that high *UP* managers are more active, less exposed to standard risk factors, and follow investment strategies that are distinct from their peers. These two measures have been shown to be associated with better fund performance (see Titman and Tiu, 2011; Sun, Wang, and Zheng, 2012).

In our main analysis, we then 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* and performance in the next quarter shows that firms with high *UP* perform significantly better than their peers. The spread in average returns of fund firms in top and bottom quintiles of *UP* is statistically

[3] 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).

significant 0.44% per month for raw returns and 0.53% per month for nine-factor alphas. Interestingly, *UP* predicts future fund firm performance significantly better than either past fund firm performance (future return spread of 0.23%) or past performance derived from long-equity positions (future return spread of 0.18%). This suggests that aggregating information from reported returns and long-equity positions can help reduce any noise associated with each of them. As individual funds do not disclose equity positions, our analysis is conducted at the hedge fund firm level, which makes it difficult to attribute this finding to individual funds. Therefore, we repeat our analysis on firms that only offer one fund and find virtually identical results, suggesting a clear link between an individual fund's *UP* and its future performance.

Furthermore, the *UP* performance spread is not driven by the exposure to other asset classes (such as emerging market and European equities, government and corporate bonds, commodities, real estate, and private equity) nor can it be explained by differences in the exposure to alternative risk factors like liquidity risk (Pástor and Stambaugh, 2003), betting-against-beta (Frazzini and Pedersen, 2014), macroeonomic uncertainty (Bali, Brown, and Caglayan, 2014), investor sentiment (Baker and Wurgler, 2006), correlation risk (Buraschi, Kosowski, and Trojani, 2014), and tail risk (Agarwal, Ruenzi, and Weigert, 2017) that have been shown to contribute to hedge fund performance.

Predictability of *UP* for future fund returns is also not subsumed by other fund firm characteristics and continues to hold when we control for a fund firm's past return, size, age, volatility, manager delta, management and incentive fees, minimum investment, lockup and redemption periods, offshore location, leverage usage, high-watermark, and hurdle rate. We also show that the impact of *UP* is not subsumed by other hedge fund skill measures – R^2 (Titman and Tiu, 2011) and strategy distinctiveness (Sun, Wang, and Zheng, 2012). Moreover, *UP* outperforms these two measures in a horserace when predicting future fund performance.

The impact of *UP* on future fund performance is also stable over time (i.e., it holds for the periods from 1996 to 2007 and 2008 to 2017) and across different states of the world (high vs. low economic growth / market returns / market volatility) and extends up to two years in the future. We also show that the documented outperformance of high *UP* fund firms survives a host of additional robustness checks. These include the use of different multifactor models to adjust for hedge fund risks, use of different performance measures (Sharpe ratio, Treynor ratio, and the manipulation-proof performance measure of Goetzmann, Ingersoll, Spiegel, and Welch, 2007), application of an alternative estimation horizon for *UP*, computation of *UP* based on transaction-cost adjusted net-of-fee returns, restricting our analysis to only long-short equity funds, or funds with similar leverage, and correcting for various biases such as return smoothing (Getmansky, Lo, and Makarov, 2004), backfill (Jorion and Schwarz, 2019), and delisting (Hodder, Jackwerth, and Kolokolova, 2014).

In the next step of our analysis, 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, we conjecture that *UP* could be related to active intraquarter trading of long-equity positions and the associated transaction costs. Frequent trading is shown to be potentially performance-enhancing in mutual funds (e.g., Puckett and Yan, 2011; Pástor, Stambaugh, and Taylor, 2017). Hedge funds are generally considered to be even more active investors that trade dynamically and change their investments more frequently in response to market conditions (Chen and Liang, 2007; Cao et al., 2013; Patton and Ramadorai, 2013). Consistent with this conjecture, we document that hedge fund firms with high portfolio turnover indeed exhibit high *UP*, regardless of whether we infer turnover from disclosed long-equity positions in funds' 13F filings or estimate turnover from actual transactions of hedge fund firms in the Abel Noser database. Controlling for the amount of

trading activity, we also find a negative relation between *UP* and transaction costs, suggesting that funds that trade more efficiently exhibit higher *UP*, i.e., *UP* also captures trading skills.

Second, *UP* is likely to be associated with a fund firm's derivative usage. Hedge funds are known to display nonlinear return profiles similar to writing out-of-the-money put options on the equity market (Agarwal and Naik, 2004; Jurek and Stafford, 2015). Moreover, Aragon and Martin (2012), based on a small sample of 250 hedge fund firms, show that hedge fund's option positions are associated with abnormal future returns and reduce portfolio risk. We test the link between derivatives usage and *UP* in our much broader sample of all hedge funds that file 13F by analyzing their long call and put option positions in the 13F filings. Our results reveal that a fund firm's *UP* is positively related to trading strategies involving long put options (but not call options) which can help funds enhance performance by mitigating downside risk.

Third, we examine if *UP* is associated with hedge funds' engagement in short-selling strategies which are shown to be profitable (Jones, Reed, and Waller, 2016; Jank and Smajlbegovic, 2017). To measure short-selling activity, we compute short-sale equity transactions for a sample of hedge funds that report detailed transaction data to the Abel Noser database. We find that funds with higher *UP* pursue short-selling strategies more actively.

Fourth, we investigate the relation between *UP* and a fund firm's confidential holdings. Firms can conceal certain positions and reveal them with a delay after the request of confidential treatment is either denied by the SEC or has expired (which typically occurs after one year). Agarwal, Jiang, Tang, and Yang (2013) and Aragon, Hertzel, and Shi (2013) show that hedge funds trade confidentially on information-sensitive events to reduce price impact and benefit from private information. As a result, confidential holdings exhibit superior future performance. We show that fund firms with a larger value of confidential holdings also have higher *UP*, indicating that a firm's unobserved performance can partly be explained by its long-equity positions disclosed with a delay.

In the final step of our analysis, we analyze investor response to *UP*. Interestingly, we do *not* find evidence of fund investors yet recognizing *UP* as a skill measure, and do *not* observe that more capital is allocated to funds with high *UP*. Instead, they seem to chase past fund performance. We attribute this finding to significant efforts associated with the construction of the *UP* measure and investors' limited ability to understand different components of managerial skill captured by this measure.

Our paper makes several contributions to the literature. First, we propose a new hedge fund performance metric, *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 returns and outperforms predictions by either returns-based performance measures or holdings-based performance measures. Second, our paper uncovers different sources of managerial skill in the hedge fund industry by showing that *UP* is driven by fund firms' intraquarter long and short equity trades, use of derivatives, and delayed disclosure of long-equity positions. Consequently, our *UP* measure also 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 much more restricted in such investment strategies. Particularly, while mutual funds predominantly use long-only buy-and-hold investment strategies, hedge funds are relatively less constrained and frequently use short selling, derivatives, and more dynamic trading strategies. Consequently, while the primary focus of our study is to offer a new measure to predict hedge fund performance, we also contribute to the literature by using this measure to analyze different sources of managerial skill in hedge funds.

The structure of the paper is as follows. Section 2 describes the data, introduces the concept of unobserved performance (*UP*), and sheds light on the relation between funds' characteristics and *UP*. Section 3 presents our main results on the relation between *UP* and the

cross section of future fund returns. In Section 4, we examine trading channels that are likely to influence *UP* while Section 5 investigates investors' response to *UP*. Section 6 concludes.

2. Data and Unobserved Hedge Fund Performance

2.1 Data

We obtain the data for this study from four distinct sources. The first source is the "Union Hedge Fund Database", which contains self-reported 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. As our second source, 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, all extracted from the 13F filings. Finally, we retrieve data from Abel Noser, a proprietary broker that tracks actual long and short transactions of institutional investors.

The Union Hedge Fund Database includes data for a total of 39,938 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

the first 24 months of a fund's return series to mitigate the backfill bias.[4] 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 a total value of $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 reported *Net Fund Firm Return* and *Equity Portfolio (PF) Return*. Since funds only report their net-of-fee returns to commercial databases, we estimate their gross-of-fee returns following the procedure in Agarwal, Daniel, and Naik (2009) and value-weight returns across all funds in a *firm* to compute the *Gross Fund Firm Return* in excess of the risk-free rate. Using the 13F long-equity positions of a firm, we compute the *Equity PF Return* as the value-weighted returns of these positions in excess of the risk-free rate.[5]

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 return series of monthly observations.[6] We eliminate all pairs of firms in which there are fewer than 24 overlapping periods of data from 13F and Union datasets. To ascertain the style of a hedge

[4] In a robustness check included later in Section 3.4, we find that our results hold when we apply the alternative method of Jorion and Schwarz (2019) to infer a fund's listing date when it is not available.
[5] 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 4.4).
[6] 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.

fund firm, we use the style in which its funds have invested most of their assets.[7] As we concentrate on equity-oriented firms, we only include firms that employ an "Emerging Markets", "Event Driven", "Equity Long", "Equity Long-Short", or "Equity Market Neutral" investment style, i.e., have invested most of their assets in equity-oriented strategies. We end up with 663 hedge fund firms managing 2,314 distinct funds during the period from 1994 to 2017.

Additionally, 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. Moreover, 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 663 firms that appear both in the Union Hedge Fund Database and in the 13F Thomson Reuters Ownership database, 316 firms report at least one long option position, and 174 firms file at least one confidential position.

Finally, for estimating the intraquarter portfolio turnover, computing actual short sales of hedge fund firms and computing a proxy for transaction costs, we also 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 of commercial hedge fund databases and the 13F data based on fund firm names. We are able to successfully merge 24 hedge fund firms through this process.[8] Following Busse, Chordia, Jiang, and Tang (2021), we calculate transaction costs for

[7] For example, a firm is classified as *Long-Short Equity* if most of its assets are in *Long-Short Equity* funds.
[8] 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 24 firms appear both in the Union and 13F databases.

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 equity portfolio return *(Equity PF Return)*,

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

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. All variables are defined in Table IA.1 of the Internet Appendix.

[Insert Table 1 around here]

Our results indicate that, on average, the hypothetical *Equity PF Return* of hedge fund firms exceeds the reported *Gross Fund Firm Return* by 0.13% 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 equal-weighted average of *Gross Fund Firm Returns*, *Equity PF Returns*, and *Unobserved Return Components* 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., 10.60% in October 2008 (one month after the bankruptcy of Lehman Brothers and the beginning of a worldwide recession), 7.80% in August 1998 (Asian Financial Crisis with the collapse of Long Term Capital Management), and 7.20% in September 2001 (burst of the dotcom bubble), suggesting that unobserved actions of hedge fund firms are particularly valuable and informative during crisis periods. To the contrary, the lowest observations in the *Aggregate Unobserved Return Component* occur in October 2011 (–8.01%), April 2009 (−7.06%), and April 2001 (−6.51%), 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* (0.295%, *t*-statistic of 3.09) is much higher than that for the *Aggregate Equity PF Return* (0.115%, *t*-statistic of 1.59). Hence, alpha of hedge funds seems to largely stem from their unobserved actions (0.180%, *t*-statistic of 3.57).

As evident from the results in Panel B of Table 1, *URC* is significantly related to several risk factors. Therefore, to isolate manager skill, we adjust for these risk factors to construct our main measure of the empirical analysis, a fund firm's *Unobserved Performance* (*UP*). It is defined as the difference between a fund firm's performance based on its reported gross return

series (*Gross Fund Firm Performance)* and a fund firm's performance based on 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:

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

with

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

and

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

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

with $X \in \{Fund\ Firm, Equity\ PF\}$.

Therefore, *UP* reflects the performance of a hedge fund firm's unobserved components that are not captured by the performance inferred from its disclosed long-equity portfolio positions. Risk-adjusted performance of firms with high *UP* strongly deviates from that of their disclosed long-equity portfolio suggesting superior skill while firms with low *UP* exhibit risk-adjusted performance similar to that of their long-equity portfolio. A negative *UP* measure would indicate that the unobserved performance components for a firm are associated with worse performance compared to the buy-and-hold performance of their disclosed equity holdings. That is, 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).[9] However, unlike mutual funds, hedge

[9] 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 use this setting to infer changes in mutual fund trading costs, and Agarwal, Gay, and Ling (2014) who apply it to measure window dressing in mutual funds.

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, in terms of 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. Average *Gross Fund Firm Performance* is 0.28% per month across all fund firms and months in the sample, whereas *Equity PF Performance* and *UP* averages are 0.10% and 0.18%, respectively. Hence, as in Panel B of Table 1, we observe that even after adjusting for standard hedge fund risk factors, fund firms' performance is largely driven by their unobserved performance component. While the median *UP* is positive (0.16%), the 25th percentile is clearly negative (−1.11%), showing that there is a significant fraction of firms whose unobserved actions lead to performance worse than the buy-and-hold performance inferred from their disclosed long-equity holdings.

Panel C of Table 1 also reports the descriptive statistics of *UP* for different equity-oriented hedge fund styles. Perhaps not suprisingly, *UP* is smallest (value of 0.03%) for the Equity Long style, which is likely to be closest to mutual funds' buy-and-hold strategy, and is the highest for the Equity Market Neutral style (value of 0.25%) that actively hedges out most of their equity market exposure, and therefore short selling and derivatives usage likely contributing to the *UP* measure as we show later in the paper.

Table IA.2 in the Internet Appendix reports the correlations between *UP* as well as *Gross Fund Firm Performance*, *Equity PF Performance*, and other fund firm characteristics. As expected, based on the way we construct the *UP* measure, we find it to be positively correlated with *Fund Firm Performance* (+0.55), and negatively correlated to *Equity PF Performance* (−0.54). In addition, *UP* has a positive relation with the manager's delta, lockup

period, and use of leverage. Interestingly, correlations of *UP* with other existing hedge fund skill measures (high SDI and low R^2) are small, suggesting that *UP* captures distinctive aspects of managerial skill.

2.3 Unobserved Performance and Fund Characteristics

Results from Panel C in Table 1 indicate that superior performance of hedge fund firms is primarily driven by *UP*. To better understand the sources of this outperformance, we now examine the firm characteristics associated with high *UP*. For this purpose, we estimate the following regression of *UP* of a firm *i* in month *t+1* on different firm characteristics measured in month *t* using the Fama and MacBeth (1973) methodology:

$$UP_{i,t+1} = \alpha + \beta X_{i,t} + \varepsilon_{i,t+1} \tag{5}$$

where $UP_{i,t+1}$ denotes fund firm *i*'s *UP* in month *t+1*, and $X_{i,t}$ is a vector of fund firm characteristics. To adjust the standard errors for potential serial correlation, we again use the Newey and West (1987) adjustment with 36 lags. Table 2 reports the results.

[Insert Table 2 here]

In Column (1), we only include lagged *UP*. We observe pronounced persistence in *UP*, as indicated by the positive and highly significant (*t*-statistic of 13.78) coefficient estimate of 0.166 on last year's *UP*. In Column (2), we additionally include time-varying fund firm characteristics such as the past monthly gross return, fund firm size, age, standard deviation, and manager delta. Column (3) investigates the association between *UP* and (mostly) time-invariant characteristics, such as a firm's management and incentive fees, minimum investment amount, lockup and restriction periods, as well as indicator variables that equal one if the firm is an offshore firm, employs leverage, has a high-water mark and a hurdle rate.[10] In Column

[10] We determine the value of these indicators based on the characteristics of the firm's largest fund. For example, leverage of a fund firm *i* takes the value of one if its largest hedge fund uses leverage, and zero otherwise.

(4), we pool the time-varying and time-invariant variables, and in Column (5), we also add the two alternative skill measures, R^2 measure of Titman and Tiu (2011), and the strategy distinctiveness (SDI) measure of Sun, Wang, and Zheng (2012).

We observe the following patterns. First, young and small fund firms tend to display higher *UP*, consistent with their greater nimbleness and fewer capacity constraints. Second, firms with high *UP* are positively associated with measures of managerial incentives (i.e., incentive fee and delta). Therefore, better incentivized managers tend to show higher *UP*, i.e., add value over the buy-and-hold returns inferred from long-equity holdings. Third, high *UP* firms show greater managerial discretion (i.e., longer lockup period), which enables them to perform better through trading in illiquid securities and avoiding fire sales associated with investor redemptions. Finally, firms with high *UP* show a low R^2 from the nine-factor model and a higher SDI. This finding suggests that high *UP* firms do not seek a strong factor exposure and differentiate themselves from their peers. These traits reflect managers' confidence in their ability to generate superior performance through active and unique investment strategies.

To summarize, we document that the *UP* measure is related to several distinct firm characteristics that are associated with better performance. Hence, we will carefully control for these characteristics in our subsequent analysis of *UP*'s ability to predict future performance.

3. *UP* and Future Hedge Fund Returns

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 firm returns, we relate the *UP* measure in month *t* to firm returns and alphas in month

t+3. We leave out three months to account for the effect of serial correlation in hedge fund returns (see Getmansky, Lo, and Makarov, 2004). Later we consider predictability of *UP* for longer periods up to four years, which also allows for a practical implementation of the predictive strategy after accounting for typical lockup and redemption restrictions.[11]

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 Table 3 Panel A. For comparison, we report future excess returns of firms sorted on *Gross Fund Firm Performance* and *Equity PF Performance* in month *t* in Columns (2) and (3), respectively.

[Insert Table 3 around here]

Column (1) shows a strong positive relation between *UP* and future average returns. Hedge fund firms in the portfolio with the lowest (highest) *UP* earn future returns of 0.37% (0.81%) in excess of the risk-free rate. Moreover, future returns increase monotonically over the *UP* quintiles. The return spread between portfolios 5 and 1 is 0.44% per month, significant at the 1% level with a *t*-statistic of 2.64. 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 less economically and statistically significant monthly values of 0.23% (*t*-statistic of 1.65) and 0.18% (*t*-statistic of 1.71). Finally, in Columns 4 and 5, we also 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 at least significant at the 5% 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*. One potential explanation for better predictability

[11] We obtain similar results when we unsmooth hedge fund returns using the methodology in Getmansky, Lo, and Makarov (2004) or evaluate future firm returns in month *t+1* or *t+2* (see analyses in Section 3.3 and Section 3.4).

of *UP* is that combining information from both reported returns and long-equity portfolios helps reduce the noise associated with individual measures. We acknowledge that even though it is not feasible to short hedge funds, this analysis 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 0.11% and 0.19% per month.

Panel B of Table 3 reports the results when we adjust future firm returns for standard hedge fund risks in the augmented 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 −0.17% per month, whereas those with the highest *UP* earn a significant future average alpha of 0.36% per month (see Column 1). The spread between average alphas of portfolios 5 and 1 is 0.53% per month, significant at the 1% level with a *t*-statistic of 3.14. Therefore, the return spread between firms with high and low *UP* amounts to 6.36% per annum even after adjusting for exposures to risk factors. 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 (0.33% in Column 2) or *Equity PF* returns (0.17% 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 (0.20%, *t*-stat = 3.50; see Column 4) or firms sorted on *Equity PF* alphas (0.36%, *t*-stat = 2.62; see Column 5).

Our results hitherto are based on hedge fund firm performance, which makes it difficult to assign it to an individual fund if the firm offers multiple funds. Therefore, we repeat the analysis for 391 firms that only offer a single fund. Panel C shows that our findings for single-fund firms are qualitatively and quantitatively very similar to those for all firms in our sample.

Can the return spread based on *UP* be explained by additional hedge fund risk factors or funds' exposure to other asset classes despite our focus on only equity-oriented funds in this study? We address this question in Table 4 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).

[Insert Table 4 around here]

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: Pástor and Stambaugh (2003) traded liquidity factor; Frazzini and Pedersen (2014) betting-against-beta factor; Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor; Baker and Wurgler (2006) investor sentiment factor; Buraschi, Kosowski, and Trojani (2014) correlation risk factor; and Agarwal, Ruenzi, and Weigert (2017) tail risk factor. In Column (9), we simultaneously 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 0.46% to 0.69% per month.

Panel B of Table 4 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.[12] Statistical and economic significance of the return spread based on *UP* remain unchanged.

[12] 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. Consequently, we exclude the private equity risk factor in Column (9) where we use monthly returns of all other risk factors.

To summarize, we find that a hedge fund firm's unobserved performance (*UP*) is a strong predictor for the cross section of future average returns of firms. In particular, *UP* is superior in predicting future firm returns compared to either *Gross Fund Firm Performance* or *Equity PF Performance*. Moreover, the return spread based on *UP* is neither subsumed by additional risk factors nor explained by firms' investments in other asset classes.

3.2 Bivariate Portfolio Sorts

The return spread based on *UP* could be potentially driven by its core building blocks, *Gross Fund Firm Performance* and *Equity PF Performance*. In line with this idea, we find (as noted in Panel D of Table 1) that the correlations between *UP* and *Fund Firm Performance* (+0.55), and between *UP* and *Equity PF Performance* (−0.54) are high in absolute values. To distentangle the return spread based on *UP* from the two performance variables, we perform portfolio double sorts based on (i) *Gross Fund Firm Performance* and *UP*, as well as (ii) *Equity PF Performance* and *UP*. Table 5 reports the results.

[Insert Table 5 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 taking place 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 0.26% per month, significant at the 5% level. The last row in Panel A shows similar results for nine-factor alphas.

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 with significant (at the 5% level or better) return spreads. The average *UP* spread after controlling for *Equity PF Performance* amounts to 0.44% per month, significant at the 5% level. When we evaluate differences in nine-factor alphas, we again obtain similar results (average monthly spread of 0.49% significant at the 1% level).[13]

Third, we investigate the effect of *UP* on future fund performance when we explicitly control for alternative manager skill measures, namely the R^2 and SDI measures in double sorts. In Panel A of Table 6, we present double sorts based on R^2 and *UP*, where we first sort hedge fund firms into quintiles according to their R^2 in reverse order, from high to low, since funds with low R^2 have been shown to have greater managerial skill, and then – within each R^2 quintile – based on *UP*. We observe a positive return spread between the highest and lowest *UP* quintile within each R^2 quintile and the spread is significant in four of five cases. The average spread amounts to 0.38% per month. Similar results are obtained based on 9-factor alphas with the average monthly spread equal to 0.34%. In Panel B, we repeat the same exercise for SDI and *UP*. The average return spread (alpha spread) between the highest and lowest *UP* quintile across SDI quintiles is 0.37% (0.36%) per month. These findings show that the spread in fund performance based on *UP* is not explained by either of the alternative skill measures.[14]

Finally, in Panel C, we analyze whether *UP* has stronger predictive power for future fund performance than 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 3 for comparison), R^2, and SDI. Consistent with Titman and Tiu (2011) and Sun,

[13] These findings hold when we perform independent (instead of dependent) portfolio double sorts based on either *Gross Fund Firm Performance* and *UP*, or on *Equity PF Performance* and *UP* (see Table IA.3 in the Internet Appendix).

[14] This finding also holds when we perform independent portfolio double sorts (see Table IA.4 in the Internet Appendix).

Wang, and Zheng (2012), both R^2 and SDI predict future fund performance. However, we observe that *UP* is a stronger predictor than either R^2 or SDI, i.e., the return spread of 0.44% per month between high *UP* firms and low *UP* firms is more than twice of spreads based on R^2 (0.20% per month) or SDI (0.21% per month). Moreover, in Columns (4) and (5) we compute the difference between the return spreads from sorts on *UP* and R^2 and from sorts on *UP* and SDI, respectively. Differences are significant at least at the 10% level based on raw returns (0.24% and 0.23%, respectively) and 9-factor alphas (0.20% and 0.28%, respectively).

[Insert Table 6 around here]

In summary, we find that the alpha spread based on *UP* can neither be explained by fund firm differences in *Gross Fund Firm Performance* and *Equity PF Performance* nor by differences in previously identified manager skill measures. These findings highlight that *UP* is a distinct and powerful skill measure that can strongly predict future fund performance after aggregating information from reported performance and disclosed long-equity positions.

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:

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

where $r_{i,t+3}$ denotes fund firm *i*'s reported 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 (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 measure and SDI.

[Insert Table 7 around here]

Panel A of Table 7 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 in all specifications. Depending on the specification, the coefficient estimates of *UP* range from 0.032 to 0.042 when we use future returns as the dependent variable and is 0.026 in Column (6) with future alpha as the dependent variable.

In Columns (1) to (8) of Panel B in Table 7, 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 positive and negative economic growth (i.e., positive or negative change in the Chicago Fed National Activity Index, CFNAI) 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 in periods of high and low market volatility as well as in the subperiods from 1996−2007 and 2008−2017. These findings suggest that *UP* is a robust skill measure that can be used by fund investors in different market conditions.

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 invest 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 portfolio holdings of hedge fund firms are not immediately observable to investors as regulation allows for a disclosure delay of 45 days after quarter ends. Therefore, investors may not be able to rebalance their fund portfolios within a quarter. Panel C reports the results of regressions of future fund firm alphas in month *t+3* (baseline scenario), *t+1*, and *t+2* in Columns (1) to (3).

In Columns (4) to (7), it reports the results for cumulative returns for two, three, six, and twelve months after portfolio formation. Again, we use a specification identical to Column (6) of Panel A, but only report the coefficient estimate of *UP* for brevity. We find that *UP* can significantly predict future fund firm returns up to twelve months into the future. Moreover, this effect is significant in all cases at the 5% level or better. This suggests that it is practically feasible for investors to use the *UP* measure to select hedge fund firms that are likely to perform well in the future, after accounting for capital withdrawal restrictions and disclosure delays.

In Columns (8) to (13), we split up the long-term period after portfolio formation into the months 4-6, 7-9, 10-12, 13-24, 25-36, and 37-48 to better understand the longer-term predictive power of *UP* for future fund performance. We find the strongest impact during the first year, but there is still a significant though weaker impact even in the second year after portfolio formation, which then fades out in the third year after portfolio formation. Finally, in Panel D, we document similar findings for single-fund hedge fund firms, which again suggests that fund investors can use *UP* in practice to select and invest in individual funds.

3.4 Robustness Checks

To examine the stability of our results regarding the relation between *UP* and future fund firm performance, we conduct a battery of robustness checks. Specifically, we (i) estimate *UP* using the seven risk factors in the Fung and Hsieh (2004) model or the four risk factors in the Carhart (1997) model, or average *UP* over the past 36 months; (ii) 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); (iii) estimate *UP* with a 24-month rolling window and compute *UP* 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), (iv) restrict our sample to

only long-short equity funds, 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 the returns of fund firms, control for backfill 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.

[Insert Table 8 around here]

Panel A in Table 8 reports the results from univariate portfolio sorts (as in Panel B of Table 3, 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 7) of future fund firm alphas in month *t+1* on *UP* and different fund firm characteristics measured in month *t* using the same robustness checks as above. We only report the coefficient estimate for *UP*. The other control variables are included in the regressions but are suppressed in the table for brevity. For the ease of comparison, we report the baseline results from Column (1) in Panel B of Table 3 and Column (6) in Panel A of Table 7. Across all robustness checks, we continue to find a positive and statistically significant effect of *UP* on future fund firm performance.

4. *UP* and Different Trading Channels

After having established that *UP* is a strong predictor of future hedge fund performance, we now investigate four potential trading features of hedge funds that might influence a fund firm's *UP*. Section 4.1 examines whether *UP* is related to intraquarter trading of long-equity positions, while Section 4.2 investigates the association between *UP* and fund firms' derivatives usage. In Section 4.3, we relate fund firms' *UP* with their short-selling activities. Finally, we analyze the link between *UP* and fund firms' confidential holdings in Section 4.4.

4.1 Active Trading in Long-Equity Positions

Hedge fund firms in our sample disclose long-equity positions to the SEC on a quarterly frequency. However, firms' intraquarter transactions, i.e., buys and sells that take place within a quarter, are not revealed to the public. However, any gains or losses from intraquarter trading should be reflected in firms' reported returns even though they will be excluded from the buy-and-hold return inferred from long-equity positions. Therefore, our *UP* measure that captures the wedge between these two returns should be naturally related to fund's interim trading.

Several academic studies investigate the relation between active trading and performance. While the link is shown to be significantly negative for individual investors (see Barber and Odean, 2000), mixed performance results have been documented for institutional investors (such as mutual funds and hedge funds). 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. Moreover, using a large proprietary database of institutional trades, Puckett and Yan (2011) find strong evidence that institutions earn significant abnormal returns on their interim trades within the quarter over which they disclose their equity positions. At the same time, active trading leads to higher transaction costs, which should reduce hedge fund firm returns and eventually *UP*.

Panel A in Table 9 examines the relation between *UP* and two proxies each for (i) interim trading by firms and (ii) transaction costs generated by 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*.[15] The underlying premise behind this proxy (which is a lower bound for the actual trading activity) is that firms that trade more over a quarter are also more likely to engage in intraquarter trading. Following DeMiguel, Utrera, Nogales, and Uppal (2017), we estimate a firm's trading costs associated with these trades 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 24 hedge funds 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 and divide it by the fund firm's total equity portfolio market capitalization in month *t*-1. Following Busse, Chordia, Jiang, and Tang (2020), 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 9 here]

Columns (1) and (2) show the results for the first proxy for interim trading and transaction costs with and without control variables, respectively. In Column (1), we find that the coefficient estimate of *Portfolio Turnover* is 1.045 and significant at the 1% level. In Column (2), we expand our model to control for different portfolio characteristics. Specifically, we add a fund firm's number of different stock positions, the portfolio's Herfindahl index (as a measure of portfolio concentration), size, beta, illiquidity (measured by the Amihud (2002) ratio), and book-to-market ratio in month *t* to our model. All control variables are based on disclosed holdings. Our results reveal that the relation between *UP* and *Portfolio Turnover* remains positive (coefficient = 1.663) and highly significant. Based on this estimate, a one standard deviation increase in portfolio turnover implies a higher annualized *UP* of 1.86% per month. The last two columns of Table 9 present the results with the second proxy for interim trading

[15] Our measure takes account of the total of stocks *purchased and sold* by the fund firm in month *t*. Our results between *Portfolio Turnover* and *UP* (as reported in Panel A of Table 9) are very similar when we compute the turnover measure based on pure buying or pure selling transactions.

(based on actual trading of hedge fund firms in the Abel Noser database). We continue to observe a positive and significant relation between *UP* and intraquarter trading in the same month. The coefficients on *Transaction-based Portfolio Turnover* are 0.823 (*t*-stat = 1.77) and 1.436 (*t*-stat = 2.67) in Columns (3) and (4). Estimates in Column (4) imply an annualized change in *UP* of 2.25% for a one standard deviation change in portfolio turnover from transactions reported in the Abel Noser database. Across all specifications, we find a significantly negative impact of transaction cost estimates on *UP*, which is expected as higher transaction costs should reduce reported returns of hedge fund firms.

4.2. Derivatives Usage

Hedge funds are known to employ derivatives in their trading strategies. Agarwal and Naik (2004) show that a large number of equity-oriented hedge fund strategies exhibit payoffs resembling a short position in a put option on the market index, and Agarwal, Ruenzi, and Weigert (2017) document that hedge fund's tail risk is largely driven by dynamic trading strategies that mimic the return of selling out-of-the money put options. Using detailed disclosures of equity option positions of 250 hedge fund advisors, Aragon and Martin (2012) find that option positions predict both volatility and returns on the underlying stocks, and that a quarterly tracking portfolio of stocks based on publicly observable option holdings earns abnormal returns of 1.55% per quarter. 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 measure derivatives usage by hedge fund firms, we use long call and put option holdings data from the 13F filings in the SEC EDGAR database during the sample period from April 1999 to December 2017. We find that during this period, 47.7% of firms in our sample (i.e., 316 of 663 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 hedge fund firm *i* in month *t*, (i) the *Number of different stocks on which fund firms hold call (put) positions*, (ii) the *Equivalent number of equity shares underlying call (put) positions* (in millions), and (iii) the *Equivalent value of equity shares underlying call (put) positions* (in $ millions).[16] To mitigate the effect of outliers, we winsorize (ii) and (iii) at the 1% level. The average number of different stocks with call (put) positions is 4.59 (4.54), the average number of equity shares underlying the put (call) positions is 2.05 (1.75) million, and the average value of equity shares underlying the put (call) positions is $78.40 ($72.80) million.

We regress *UP* of hedge fund firm *i* in month *t* on the *Number of different stocks on which fund firms hold call (put) positions*, as well as the natural logarithms of one plus the *Equivalent number of equity shares underlying the call (put) positions* and the *Equivalent value of equity shares underlying the call (put) positions* in month *t* using the Newey and West (1987) adjustment with 36 lags.[17] We display the results in Table 10.

[Insert Table 10 here]

In Columns (1), (3), and (5), *UP* is regressed on the number of different call and put options, the number of shares underlying these call and put options, and the value of shares underlying these call and put options, respectively. We observe that all explanatory variables that are related to put options significantly increase a fund firm's *UP*, whereas we do not find a significant impact of variables related to call options. In Columns (2), (4), and (6), we include additional controls for portfolio characteristics. We again observe significantly positive relations between *UP* and a fund's use of put options, which are also economically significant.

[16] To illustrate these measures, 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, (i) the number of stocks on which call options are held is 2 and the number of stocks on which put options are held is 1, (ii) the equivalent number of equity shares underlying the call options is 15,000 and the equivalent number of equity shares underlying the put options is 20,000, and (iii) the equivalent value of equity shares underlying the call options is $350,000 and that for put options is $800,000.
[17] We logarithmically transform *Equivalent number of equity shares underlying the call and put positions* and *Equivalent value of equity shares underlying the call and put positions* to reduce the skewness of the variables.

For example, a one standard deviation increase in the *Number of put options* (*Value of shares underlying the put options*) enhances a fund firm's annualized *UP* by 1.39% (1.41%).

Overall, these results provide evidence that derivatives usage by firms, in particular, long positions in put options, is an important channel that affects a firm's *UP*. These results are in line with the literature that documents superior risk management skills of hedge funds in tail risk strategies (see Agarwal, Ruenzi, and Weigert, 2017) and merger arbitrage strategies (see Cao, Goldie, Liang, and Petrasek, 2018), where put options are used to manage downside risk.

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 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 (2017), and Beschwitz, Lunghi, and Schmidt (2017)). 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 24 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 each day.[18] For firm *i* in month *t*, we compute (i) the *Number of different stocks on which firms hold short positions*, (ii) the *Maximum daily number of equity shares underlying the short positions*, and (iii) the *Maximum daily value of equity shares*

[18] 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.

underlying the short positions. To mitigate the effect of outliers, we winsorize the *Maximum daily number* and *Maximum daily value of equity shares* at the 1% level. The average number of different stocks with short positions is 233, and the maximum daily *number* and *value* of equity shares underlying the short positions is 6.48 million and $112.09 million, respectively.

We regress *UP* of firm *i* in month *t* on our three proxies for short-selling activity in month *t* using the Newey and West (1987) adjustment with 36 lags. Table 11 reports the results.

[Insert Table 11 here]

We observe a significant relation between *UP* and our three proxies for short-selling activity in all cases regardless of whether we control for other portfolio characteristics. Our results are also economically meaningful: A one standard deviation increase in the number of *Different short positions* (the *Number of equity shares underlying the short positions*, the *Value of equity shares underlying the short positions*) is associated with a higher annualized *UP* of 1.60% (1.68%, 2.04%) based on the specifications with all controls. In summary, these findings suggest that short-selling activities are an important channel that influences a firm's *UP*.

4.4. Confidential Holdings

Another channel that influences a fund firm's *UP* could be their requested confidential treatment of certain long-equity positions. If the request is denied or after the approval period of confidentiality expires, filers must reveal these holdings by filing "amendments" to their original Form 13F. However, these amendments are not included in the Thomson Reuters 13F data and therefore 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 them 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 confidential holdings data from 13F filings in the SEC EDGAR database in the sample period from April 1999 to December 2017. During this time period, 26.2% of firms in our sample (i.e., 174 of 663 firms) file at least one confidential position. In the same way as for derivative holdings, we apply the convention that 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*, (i) the *Number of different confidential positions*, (ii) the *Equivalent number of equity shares underlying these positions* (in millions), and (iii) the *Equivalent value of equity shares underlying these positions* (in $ millions). To mitigate the influence of outliers, the *Number* and *Value of equity shares* are winsorized at the 1% level. In our sample, the average *Number of confidential positions* is 1.90, the *Number of equity shares underlying these positions* is 1.06 million, and the *Value of equity shares underlying the confidential positions* is $41.30 million.

We regress *UP* of hedge fund firm *i* in month *t* on the *Number of different confidential positions*, natural logarithms of (i) one plus the *Equivalent number of equity shares underlying these positions*, and (ii) one plus the *Equivalent value of equity shares underlying these positions* in month *t* using the Newey and West (1987) adjustment with 36 lags.

[Insert Table 12 here]

Regardless of whether we control for other portfolio characteristics, Table 12 indicates a significantly positive relation between *UP* and confidential holdings. This relation is also economically meaningful. For example, a one standard deviation rise in the equivalent *Number* (*Value*) *of equity shares underlying the confidential positions* increases a firm's annualized *UP* by 1.54% (1.14%) based on the specifications with all controls. These findings suggest that confidential holdings are an important channel that influences a firm's *UP*. Moreover, our

results are consistent with the findings of Agarwal, Jiang, Tang, and Yang (2013) and Aragon, Hertzel, and Shi (2013), who show that confidential holdings earn abnormal future returns.

Overall, these findings show certain 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 and a limited time frame, while *UP* measure not only jointly captures the effect of all these channels, but also of other unobserved actions of funds that drive performance.[19]

5. Investor Response to *UP*

As shown in Section 3, *UP* strongly predicts future fund firm performance. Thus, a natural follow-up question is whether hedge fund investors take into account *UP* when making their investment decisions. Following prior literature that documents hedge fund investors chasing past performance (Agarwal, Daniel, and Naik, 2004; Fung et al., 2008; Baquero and Verbeek, 2009; Liang et al., 2019), we regress fund firm flows in year *t+1* on *UP*, *Fund Firm Performance*, and *Equity PF Performance* in year *t*.[20] Table 13 presents the findings.

[Insert Table 13 here]

In Column (1), we only include *UP* and a host of fund characteristics. We find no impact of *UP* on future flows. In contrast, Columns (2) and (3) show that *Gross Fund Firm Performance* as well as *Equity PF Performance* have a significantly positive impact on future flows. Column (4) reports the results when we include all three performance variables simultaneously. Here, we observe that the coefficient of *Gross Fund Firm Performance* remains positive and significant (coeff. = 1.820; *t*-stat = 5.26), while *Equity PF Performance* has no significant impact on flows. In contrast to Column (1), the impact of *UP* is now even

[19] Note that it is not empirically feasible to simultaneously examine all trading channels as their intersection results in 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 used above. Hence, *UP* reflects the skills of funds across their sparsely observed trading features as well as other unobservable skill traits.

[20] Following prior studies (e.g., Agarwal, Green, and Ren, 2018), we investigate fund flows at annual frequency as AUM are either stale or missing at monthly or quarterly frequency. We winsorize fund flows at the 1% level.

significantly negative, which might in part be driven by the significant correlations between the three measures (see Panel D in Table 1). Taken together, these findings suggest that investors mainly rely on reported fund performance to allocate their capital. Their failure to account for the informative content of *UP* could be attributable to the significant effort necessary to construct the *UP* measure. Moreover, the lack of significant investor response to *UP* is likely to reduce the effects of capacity constraints (Naik, Ramadorai, and Stromqvist, 2007; Getmansky, 2012; Ramadorai, 2013) and diseconomies of scale (see Berk and Green, 2004, and Glode and Green, 2011) and explain performance persistence of firms with high *UP*.

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 highly persistent and strongly predicts future fund 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, engagement in short-selling, and confidential holdings are positively related with *UP* and contribute to superior fund performance of high *UP* funds. However, investors do not seem to yet use it to identify superior hedge fund managers.

Our findings show that hedge fund investors could benefit from long-equity positions, as it allows them to compute *UP* and make more informed investment decisions. However, benefits of such disclosure need to be weighed against potential costs such as front running by other market participants.

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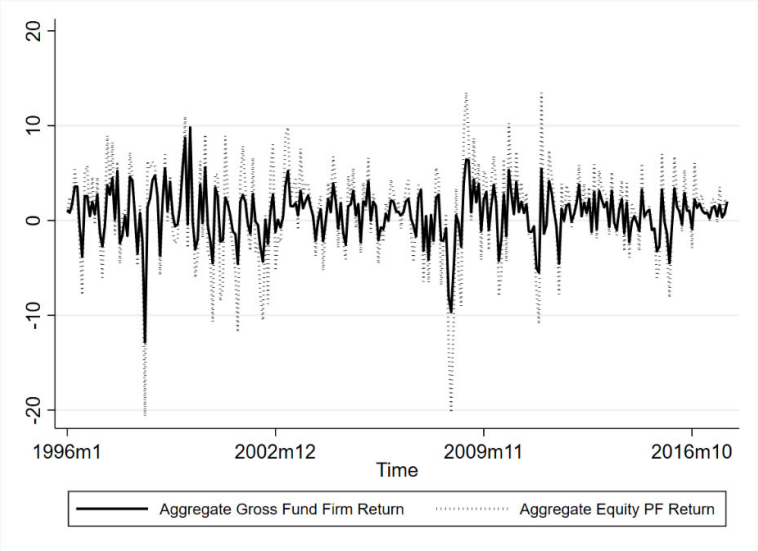
Figure 1: Aggregate Gross Fund Firm Return, Aggregate Equity Portfolio Return, and Aggregate *URC*

Panel A displays the evolution of the *Aggregate Gross Fund Firm Return* and *Aggregate Equity PF Return*. Panel B displays the evolution of the *Aggregate Unobserved Return Component* (*URC).* 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 1994 to December 2017.

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



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

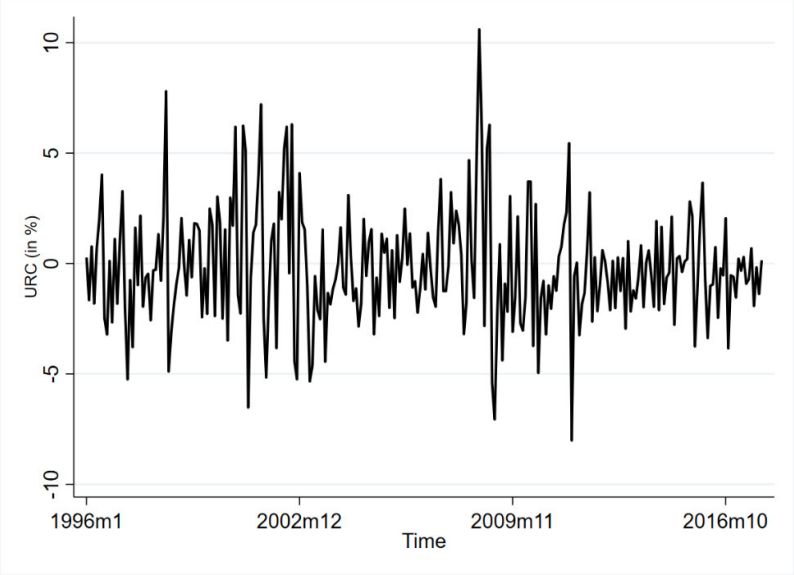


Table 1: Descriptive Statistics

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. 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*). 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	0.58%	–1.32%	0.59%	2.54%	4.76
Net Fund Firm Return	0.49%	–1.21%	0.53%	2.28%	4.35
Equity Portfolio Return	0.71%	–2.40%	1.06%	4.13%	6.36
Unobserved Return Component (URC)	–0.17%	–2.55%	–0.31%	1.94%	5.13
Size	5.23	4.26	5.30	6.32	1.58
Age (in months)	95.43	53.00	83.00	125.0	57.55
Standard Deviation	3.55	1.95	2.95	4.50	2.38
Delta (in $100 thousands)	3.75	0.42	1.43	4.03	6.14
Management Fee (in %)	1.35	1.00	1.42	1.50	0.37
Incentive Fee (in %)	18.25	19.00	20.00	20.00	4.51
Min Investment (in $100 thousands)	14.16	5.00	10.00	10.00	23.22
Lockup Period (in years)	0.48	0.00	0.38	1.00	0.51
Restriction Period (in years)	0.38	0.25	0.33	0.42	0.25
Offshore	0.37	0.00	0.33	0.67	0.38
Leverage	0.76	1.00	1.00	1.00	0.43
HWM	0.85	0.83	1.00	1.00	0.29
Hurdle Rate	0.18	0.00	0.00	0.33	0.33
R^2	0.63	0.48	0.64	0.77	0.19
SDI	0.41	0.21	0.32	0.53	0.28

Panel B: Aggregate *URC* and Risk Factors

	(1) Aggregate Gross Fund Firm Return	(2) Aggregate Equity PF Return	(3) Aggregate URC
S&P	0.444***	0.999***	–0.555***
	(15.77)	(42.14)	(–28.24)
SCMLC	0.301***	0.498***	–0.197***
	(7.50)	(17.51)	(–7.39)
BD10RET	–0.019	–0.033	0.014
	(–0.40)	(–0.84)	(0.84)
BAAMTSY	0.187***	0.162***	0.025
	(4.67)	(4.63)	(1.06)
PTFSBD	–0.017***	–0.005	–0.011***
	(–4.51)	(–1.43)	(–3.43)
PTFSFX	0.008***	0.005*	0.004*
	(3.32)	(1.70)	(1.85)
PTFSCOM	–0.008	–0.003	–0.005*
	(–1.58)	(–0.58)	(–1.94)
HML	–0.089**	–0.100**	0.011
	(–2.40)	(–2.56)	(0.74)
UMD	0.051**	–0.008	0.058***
	(2.19)	(–0.40)	(6.92)
Constant	0.295***	0.115	0.180***
	(3.09)	(1.59)	(3.57)
Observations	264	264	264
Adjusted R^2	0.850	0.966	0.941

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	663	0.28%	–0.97%	0.25%	1.48%	2.49
Equity PF Performance	663	0.10%	–1.01%	0.07%	1.22%	2.46
Unobserved Performance (UP)	663	0.18%	–1.11%	0.16%	1.43%	2.52

***UP* for HF Strategy**	**Number of Fund Firms**	**Mean**	**25%**	**Median**	**75%**	**StdDev**
Emerging Markets	11	0.20%	–1.22%	0.18%	1.51%	2.71
Event Driven	101	0.18%	–1.21%	0.16%	1.59%	2.75
Equity Long	29	0.03%	–1.23%	0.02%	1.30%	2.68
Equity Long–Short	500	0.18%	–1.11%	0.15%	1.42%	2.49
Equity Market Neutral	22	0.25%	–0.69%	0.22%	1.33%	2.05

Table 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 return, 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	0.166***	0.156***		0.160***	0.162***
	(13.78)	(13.07)		(12.67)	(12.98)
Gross Fund Firm		0.010		0.008	0.007
Return		(1.08)		(0.81)	(0.68)
Size		–0.026*		–0.024	–0.017
		(–1.90)		(–1.48)	(–0.97)
Age (·100)		–0.146***		–0.154***	–0.153***
		(–2.97)		(–3.99)	(–3.61)
Standard Deviation		–0.027*		–0.028**	–0.023*
		(–1.81)		(–2.07)	(–1.78)
Delta		0.013***		0.014*	0.016*
		(2.76)		(1.82)	(1.71)
Management Fee			0.0204	–0.0266	–0.0505
			(0.34)	(–0.47)	(–0.83)
Incentive Fee			0.010***	0.003	0.001
			(3.49)	(0.69)	(0.28)
Minimum			0.007	–0.131	–0.168
Investment (·100)			(0.06)	(–0.84)	(–1.01)
Lockup Period			0.096*	0.054*	0.050*
			(1.76)	(1.71)	(1.75)
Restriction Period			–0.071	0.003	0.019
			(–0.72)	(0.04)	(0.25)
Offshore			–0.004	–0.006	–0.008
			(–0.12)	(–1.10)	(–0.74)
Leverage			0.009	0.012	0.021
			(0.17)	(0.23)	(0.33)
HWM			0.076	0.029	0.021
			(1.48)	(0.57)	(0.39)
Hurdle Rate			–0.097	–0.071	–0.067
			(–1.46)	(–1.55)	(–1.46)
R^2					–0.172*
					(–1.88)
SDI					0.162**
					(2.17)
Constant	0.181***	0.495***	–0.062	0.467**	0.518***
	(3.82)	(5.29)	(–0.65)	(2.45)	(3.07)
Observations	39,383	39,338	38,183	37480	37480
Adjusted R^2	0.054	0.114	0.078	0.189	0.209

Table 3: *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. Panel C repeats the sorts from Panel B, but we restrict our sample to hedge fund firms with only one fund in the analysis. 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 Perf.	(5) UP – Equity PF Performance
1 (Lowest)	0.37%**	0.47%***	0.44%***	–0.10%*	–0.07%
	(2.46)	(3.19)	(3.66)	(–1.74)	(–1.38)
2	0.40%**	0.43%***	0.44%***	–0.03%	–0.04%
	(2.46)	(3.23)	(4.15)	(–0.31)	(–0.45)
3	0.55%***	0.50%***	0.52%***	0.05%	0.03%
	(3.53)	(3.70)	(4.40)	(0.98)	(0.43)
4	0.60%***	0.54%***	0.55%***	0.06%	0.05%
	(4.50)	(4.71)	(4.81)	(0.38)	(0.93)
5 (Highest)	0.81%***	0.70%***	0.62%***	0.11%**	0.19%*
	(4.61)	(4.13)	(4.50)	(2.36)	(1.75)
5-1	0.44%***	0.23%*	0.18%*	0.21%***	0.26%**
	(2.64)	(1.65)	(1.71)	(3.47)	(2.09)

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 Perf.	(5) UP – Equity PF Performance
1 (Lowest)	–0.17%	–0.08%	–0.02%	–0.09%*	–0.15%**
	(–1.13)	(–0.44)	(–0.14)	(–1.85)	(–2.37)
2	–0.04%	–0.01%	0.09%	–0.03%	–0.13%
	(–0.64)	(–0.09)	(0.40)	(–0.24)	(–1.21)
3	0.13%*	0.10%	0.10%	0.03%	0.03%
	(1.68)	(1.29)	(0.73)	(0.48)	(0.65)
4	0.18%***	0.19%**	0.13%	–0.01%	0.05%
	(2.79)	(2.05)	(1.13)	(–0.02)	(1.14)
5 (Highest)	0.36%**	0.25%**	0.15%	0.11%**	0.21%**
	(2.47)	(2.04)	(1.56)	(2.21)	(2.54)
5-1	0.53%***	0.33%**	0.17%	0.20%***	0.36%***
	(3.14)	(2.31)	(1.59)	(3.50)	(2.62)

Panel C: Alphas: Hedge Fund Firms with only one Fund (in *t+3)*

Portfolio	(1) UP	(2) Gross Fund Firm Performance	(3) Equity PF Performance	(4) UP – Gross Fund Firm Perf.	(5) UP – Equity PF Performance
1 (Lowest)	–0.12%	–0.05%	0.09%	–0.07%	–0.21%*
	(–0.99)	(–1.08)	(0.70)	(–1.09)	(–1.83)
2	–0.02%	0.03%	0.08%	-0.05%	–0.10%
	(–0.12)	(–0.08)	(0.43)	(–0.71)	(–0.70)
3	0.19%	0.13%	0.12%	0.06%	0.07%
	(1.60)	(0.99)	(0.59)	(1.24)	(0.83)
4	0.21%	0.26%	0.10%	-0.05%	0.11%
	(1.48)	(1.45)	(1.05)	(-0.77)	(1.06)
5 (Highest)	0.41%**	0.26%	0.25%	0.15%	0.16%*
	(2.30)	(1.55)	(1.43)	(1.63)	(1.80)
5-1	0.53%***	0.31%**	0.16%	0.22%**	0.37%**
	(2.67)	(2.03)	(1.54)	(2.13)	(2.57)

Table 4: *UP* and Future Returns: Univariate Portfolio Sorts with Additional Factors

In this table, we regress the return of a portfolio consisting of fund firms in portfolio 1 with the lowest *UP* subtracted from the returns of the fund firms in portfolio 5 with the highest *UP*, 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	–0.032	–0.094***	–0.033	–0.067***	–0.029	–0.020	–0.047*	–0.074	–0.096*
	(–1.42)	(–3.19)	(–1.58)	(–3.48)	(–1.40)	(–0.75)	(–1.82)	(–1.41)	(–1.66)
SCMLC	0.035	–0.027	0.034	0.005	0.033	0.051	0.053	0.037	–0.022
	(0.59)	(–0.55)	(0.58)	(0.09)	(0.55)	(0.85)	(0.89)	(0.55)	(–0.31)
BD10RET	–0.029		–0.020	–0.022	–0.031	–0.041	–0.049	–0.052	–0.000
	(–0.55)		(–0.37)	(–0.35)	(–0.59)	(–0.62)	(–0.81)	(–0.87)	(–0.01)
BAAMTSY	–0.116*		–0.124*	–0.046	–0.123*	–0.160**	–0.193**	–0.191***	–0.126**
	(–1.66)		(–1.70)	(–0.77)	(–1.84)	(–2.10)	(–2.49)	(–2.97)	(–2.17)
PTFSBD	0.013		0.013	0.010	0.014	0.019	0.018*	0.016	0.015
	(1.48)		(1.48)	(1.28)	(1.51)	(1.62)	(1.93)	(1.64)	(1.41)
PTFSFX	0.003		0.003	0.005	0.003	–0.002	–0.002	–0.003	0.002
	(0.52)		(0.53)	(0.77)	(0.50)	(–0.45)	(–0.44)	(–0.59)	(0.41)
PTFSCOM	0.001		0.002	–0.002	0.002	0.012**	0.008*	0.009**	0.007
	(0.24)		(0.25)	(–0.24)	(0.29)	(2.42)	(1.96)	(2.09)	(1.05)
HML	–0.069**	–0.042	–0.068**	0.008	–0.068**	–0.086***	–0.068**	–0.047	0.049
	(–2.40)	(–1.15)	(–2.21)	(0.23)	(–2.26)	(–2.82)	(–2.43)	(–1.28)	(1.49)
UMD	0.0057		0.003	0.044*	0.008	–0.003	–0.002	0.011	0.023
	(0.19)		(0.10)	(1.74)	(0.25)	(–0.09)	(–0.07)	(0.30)	(0.84)
RMW		–0.125***							–0.126**
		(–3.14)							(–2.18)
CMA		0.029							0.009
		(0.69)							(0.32)
PS Liqui			0.021						0.070**
			(0.92)						(2.26)
BAB				–0.127***					–0.117*
				(–2.89)					(–1.83)
Macro					0.026				0.036
					(1.13)				(1.24)
Senti						0.002			0.002
						(1.37)			(1.45)
Corr							–0.024		–0.033**
							(–1.42)		(–2.14)
Tailrisk								0.076	–0.039
								(1.50)	(–0.47)
Constant	0.535***	0.537***	0.524***	0.593***	0.532***	0.685***	0.483***	0.609***	0.455***
	(3.14)	(3.19)	(3.14)	(3.90)	(3.13)	(4.16)	(3.34)	(3.23)	(4.62)
Observations	249	249	249	249	249	165	189	189	165
Adjusted R^2	0.110	0.094	0.112	0.184	0.112	0.146	0.152	0.141	0.276

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	–0.032	–0.031	–0.033	–0.031	–0.033	–0.033	0.024	0.063	0.018
	(–1.42)	(–0.70)	(–1.45)	(–1.42)	(–1.36)	(–1.45)	(0.66)	(0.95)	(0.31)
SCMLC	0.035	0.035	0.034	0.035	0.034	0.034	0.078	–0.087	0.076
	(0.59)	(0.54)	(0.58)	(0.59)	(0.58)	(0.58)	(1.07)	(–0.73)	(0.97)
BD10RET	–0.029	–0.029	–0.032	–0.030	–0.030	–0.032	0.028	–0.174	0.021
	(–0.55)	(–0.54)	(–0.61)	(–0.57)	(–0.56)	(–0.61)	(0.48)	(–1.60)	(0.35)
BAAMTSY	–0.116*	–0.116*	–0.116*	–0.116*	–0.114	–0.116*	–0.070	–0.099	–0.072
	(–1.66)	(–1.96)	(–1.66)	(–1.66)	(–1.61)	(–1.66)	(–1.31)	(–1.04)	(–1.59)
PTFSBD	0.013	0.013	0.014	0.013	0.013	0.014	0.013	0.028	0.013
	(1.48)	(1.57)	(1.49)	(1.40)	(1.46)	(1.49)	(1.41)	(1.47)	(1.49)
PTFSFX	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.009	0.003
	(0.52)	(0.53)	(0.49)	(0.52)	(0.52)	(0.49)	(0.47)	(0.91)	(0.42)
PTFSCOM	0.001	0.001	0.001	0.002	0.002	0.001	0.002	–0.001	0.002
	(0.24)	(0.24)	(0.22)	(0.31)	(0.31)	(0.22)	(0.22)	(–1.42)	(0.23)
HML	–0.069**	–0.069**	–0.071**	–0.067**	–0.070**	–0.071**	–0.022	–0.032	–0.023
	(–2.40)	(–2.07)	(–2.34)	(–2.17)	(–2.51)	(–2.34)	(–0.65)	(–1.21)	(–0.71)
UMD	0.006	0.006	0.005	0.005	0.006	0.005	–0.000	–0.006	–0.001
	(0.19)	(0.19)	(0.17)	(0.19)	(0.20)	(0.17)	(–0.02)	(–0.13)	(–0.04)
EM Equity		–0.000							0.004
		(–0.01)							(0.17)
Europe Equity			0.005						0.009
			(0.46)						(0.73)
Gov Bond				0.058					0.017
				(0.93)					(0.23)
Corp Bond					0.033				0.011
					(0.65)				(0.20)
Commodity						0.005			0.004
						(0.46)			(0.36)
Real Estate							–0.082**		–0.083**
							(–2.23)		(–2.19)
Private Equity								–0.177*	
								(–1.91)	
Constant	0.535***	0.535***	0.538***	0.521***	0.525***	0.538***	0.522***	2.140***	0.521***
	(3.14)	(3.22)	(3.09)	(2.93)	(2.99)	(3.09)	(3.13)	(3.48)	(2.95)
Observations	249	249	249	249	249	249	249	83	249
Adjusted R^2	0.110	0.110	0.111	0.112	0.111	0.110	0.145	0.216	0.147

Table 5: Bivariate Dependent Portfolio Sorts

This table reports the results of dependent bivariate portfolio sorts based on *UP* and *Gross Fund Firm Performance* and based on *UP* and *Equity PF Performance*. 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 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, within each quintile, 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 *Equity PF Performance* 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	0.42%***	0.24%**	0.42%***	0.45%***	0.67%***	0.44%***
UP 2	0.26%**	0.25%**	0.37%***	0.60%***	0.57%***	0.41%***
UP 3	0.47%***	0.42%***	0.40%***	0.61%***	0.65%***	0.51%***
UP 4	0.53%***	0.54%***	0.57%***	0.86%***	0.82%***	0.67%***
UP 5	0.77%***	0.52%***	0.67%***	0.72%***	0.83%***	0.70%***
UP 5 - UP 1	0.35%**	0.28%**	0.25%**	0.27%**	0.16%	0.26%**
	(2.22)	(2.09)	(2.31)	(2.21)	(1.25)	(2.02)
FH-9-Factor	0.37%**	0.27%	0.27%*	0.34%***	0.19%	0.29%**
alphas (5 – 1)	(2.23)	(1.37)	(1.85)	(2.92)	(1.62)	(2.00)

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%***	0.22%**	0.23%**	0.43%***	0.55%***	0.37%***
UP 2	0.50%***	0.25%**	0.27%***	0.35%**	0.39%***	0.35%***
UP 3	0.61%***	0.37%***	0.41%***	0.64%***	0.66%***	0.54%***
UP 4	0.47%***	0.65%***	0.85%***	0.72%***	0.82%***	0.70%***
UP 5	0.50%***	0.78%***	1.01%***	0.95%***	0.81%***	0.81%***
UP 5 - UP 1	0.08%**	0.56%***	0.78%***	0.51%***	0.26%**	0.44%**
	(0.31)	(2.84)	(3.42)	(2.97)	(2.16)	(2.34)
FH-9-Factor	0.11%	0.69%***	0.80%***	0.55%***	0.32%*	0.49%***
alphas (5 – 1)	(0.50)	(3.62)	(4.02)	(3.97)	(1.86)	(2.79)

Table 6: Bivariate 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 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, we sort hedge 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 dependent bivariate portfolio sorts based on SDI and *UP*. First, we form quintile portfolios based on SDI in month *t*. Then, 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*. 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 hedge 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. We also report the "5-1" difference in monthly average alphas in the last row of panels. 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	0.12%*	0.56%***	0.51%***	0.37%**	0.28%*	0.37%***
UP 2	0.34%**	0.58%***	0.50%***	0.29%**	0.40%***	0.42%***
UP 3	0.56%***	0.67%***	0.49%***	0.44%***	0.49%***	0.53%***
UP 4	0.50%***	0.90%***	0.57%***	0.60%***	0.59%***	0.63%***
UP 5	0.69%***	0.93%***	0.67%***	0.67%***	0.77%***	0.75%***
UP 5 – UP 1	0.57%***	0.37%*	0.17%	0.30%**	0.48%**	0.38%**
	(3.63)	(1.94)	(1.12)	(2.20)	(2.41)	(2.26)
FH-9-Factor	0.47%***	0.22%	0.18%	0.46%***	0.39%**	0.34%**
alphas (5 – 1)	(3.49)	(1.58)	(1.29)	(3.19)	(2.43)	(2.40)

Panel B: SDI and *UP*

	SDI 1	SDI 2	SDI 3	SDI 4	SDI 5	Average
UP 1	0.26%**	0.47%***	0.35%***	0.52%***	0.36%**	0.39%***
UP 2	0.24%*	0.35%***	0.50%***	0.49%***	0.45%***	0.41%***
UP 3	0.48%***	0.73%***	0.43%***	0.31%**	0.51%***	0.49%***
UP 4	0.60%***	0.62%***	0.71%***	0.72%***	0.50%***	0.63%***
UP 5	0.65%***	0.67%***	1.09%***	0.72%***	0.68%***	0.76%***
UP 5 – UP 1	0.39%**	0.20%	0.74%***	0.20%	0.33%**	0.37%**
	(2.04)	(1.20)	(3.60)	(0.88)	(2.52)	(2.05)
FH-9-Factor	0.36%**	0.27%	0.66%***	0.15%	0.36%**	0.36%**
alphas (5 – 1)	(2.28)	(1.15)	(3.94)	(1.03)	(2.06)	(2.09)

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)	0.37%**	0.41%***	0.40%**	−0.04%	−0.03%
	(2.46)	(3.01)	(2.59)	(−0.21)	(−0.09)
2	0.40%**	0.55%***	0.52%***	−0.15%	−0.11%
	(2.46)	(3.17)	(3.56)	(−1.34)	(−1.42)
3	0.55%***	0.55%***	0.61%***	0.00%	−0.06%
	(3.53)	(3.45)	(4.10)	(0.01)	(−0.07)
4	0.60%***	0.60%***	0.56%***	0.00%	0.04%
	(4.50)	(4.78)	(4.36)	(0.08)	(0.13)
5 (Highest)	0.81%***	0.61%***	0.61%***	0.20%	0.20%
	(4.61)	(4.56)	(5.12)	(1.29)	(1.52)
5-1	0.44%***	0.20%	0.21%*	0.24%**	0.23%**
	(2.64)	(1.44)	(1.69)	(2.14)	(2.00)
FH-9-Factor	0.53%***	0.33%**	0.25%**	0.20%*	0.28%**
alphas (5 – 1)	(3.14)	(2.37)	(2.23)	(1.87)	(2.34)

Table 7: *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). 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 positive / negative economic growth, positive / negative excess market returns, high (low) market volatility, and in subsamples in the period from 1996–2007 and 2008–2017. 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 1996–2017. Panel C of this table reports the results of Fama and MacBeth (1973) regressions of different future returns on *UP* and different fund firm characteristics in month *t*. As fund firm characteristics, we use the same set of variables as in Column (6) of Panel A. As the dependent variable we use the *t+1* and *t+2* excess returns, as well as the 2-months, 3-months, 6-months, 12-months, 4-6 months, 7-9 months, and 10-12 months cumulative future excess returns. Panel D of this table repeats the specifications from Panel C, but we restrict our sample to hedge fund firms with only one fund in the analysis. 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: 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	0.042***	0.035***	0.038***	0.035**	0.032**	0.026***
	(3.55)	(3.04)	(2.88)	(3.26)	(2.54)	(3.28)
Gross Fund Firm Return		0.026		0.015	0.015	0.022**
		(1.23)		(0.87)	(1.04)	(1.99)
Size		–0.027		–0.068**	–0.059**	0.009
		(–1.12)		(–2.07)	(–2.07)	(0.62)
Age (·100)		–0.082		–0.202***	–0.174***	–0.103*
		(–1.64)		(–3.75)	(–5.07)	(–1.94)
Standard Deviation		0.078**		0.051**	0.047**	0.035*
		(2.52)		(2.26)	(2.10)	(1.77)
Delta		0.024***		0.038***	0.040**	0.011***
		(4.37)		(2.83)	(2.58)	(2.90)
Management Fee			–0.107	–0.118	–0.135	–0.079
			(–0.76)	(–0.86)	(–0.96)	(–0.82)
Incentive Fee (·100)			0.401	–1.062**	–0.943	–0.414
			(0.57)	(–1.97)	(–1.55)	(–0.74)
Minimum Investment (·100)			0.321*	0.227	0.105	0.029
			(1.77)	(1.01)	(0.41)	(0.18)
Lockup Period			–0.017	–0.021	–0.003	0.045
			(–0.33)	(–0.41)	(–0.06)	(0.98)
Restriction Period			0.097	0.243**	0.222**	0.075
			0.89)	(2.52)	(2.26)	(1.46)
Offshore			–0.247*	–0.226*	–0.219**	–0.099**
			(–1.86)	(–1.95)	(–2.19)	(–2.27)
Leverage			0.031	0.052	0.043	0.034
			(0.33)	(0.65)	(0.61)	(0.52)
HWM			–0.021	0.045	0.064	0.079
			(–0.22)	(0.50)	(0.66)	(1.00)
Hurdle Rate			–0.236	–0.291	–0.258	–0.105
			(–1.20)	(–1.46)	(–1.49)	(–1.47)
R^2					–0.094	–0.436***
					(–0.71)	(–4.97)
SDI					0.066	0.187***
					(0.35)	(2.87)
Constant	0.530***	0.397**	0.629***	1.041***	0.976***	0.598***
	(4.04)	(2.58)	(2.82)	(2.85)	(3.03)	(3.10)
Observations	39,701	39,655	37,804	37,770	37,770	36,104
Adjusted R^2	0.016	0.197	0.121	0.275	0.306	0.232

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

	(1) Econmic Growth > 0	(2) Economic Growth < 0	(3) MKTRF > 0	(4) MKTRF < 0	(5) High Market Volatility	(6) Low Market Volatility	(7) Subsample 1997 - 2006	(8) Subsample 2007 - 2017
UP	0.031**	0.032***	0.023**	0.031**	0.038**	0.022**	0.036**	0.029***
	(2.18)	(3.00)	(2.07)	(2.33)	(2.53)	(2.18)	(2.49)	(3.08)
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

Panel C: Alphas at Different Horizons

	(1) Fund Firm Return *t+3*	(2) Fund Firm Return *t+1*	(3) Fund Firm Return *t+2*	(4) Fund Firm Return Cumulative 2-months	(5) Fund Firm Return Cumulative 3-months	(6) Fund Firm Return Cumulative 6-months	(7) Fund Firm Return Cumulative 12-months
UP	0.026***	0.027***	0.017**	0.046***	0.080***	0.133***	0.227***
	(3.28)	(4.20)	(3.04)	(4.21)	(6.32)	(3.82)	(3.72)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.232	0.194	0.197	0.199	0.201	0.202	0.202

	(8) Fund Firm Return Cumulative 4-6 months	(9) Fund Firm Return Cumulative 7-9 months	(10) Fund Firm Return Cumulative 10-12 months	(11) Fund Firm Return Cumulative 13-24 months	(12) Fund Firm Return Cumulative 25-36 months	(13) Fund Firm Return Cumulative 37-48 months
UP	0.062***	0.063***	0.047**	0.117*	0.088	–0.037
	(2.66)	(3.10)	(2.27)	(1.90)	(1.47)	(–0.36)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.205	0.208	0.210	0.228	0.242	0.257

Panel D: Alphas at Different Horizons: Hedge Fund Firms with only one Fund

	(1) Fund Firm Return *t+3*	(2) Fund Firm Return *t+1*	(3) Fund Firm Return *t+2*	(4) Fund Firm Return Cumulative 2-months	(5) Fund Firm Return Cumulative 3-months	(6) Fund Firm Return Cumulative 6-months	(7) Fund Firm Return Cumulative 12-months
UP	0.030***	0.028***	0.014**	0.043***	0.079***	0.128***	0.217***
	(3.18)	(4.06)	(2.50)	(4.22)	(4.41)	(3.44)	(3.23)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.246	0.206	0.212	0.211	0.214	0.213	0.217

	(8) Fund Firm Return Cumulative 4-6 months	(9) Fund Firm Return Cumulative 7-9 months	(10) Fund Firm Return Cumulative 10-12 months	(11) Fund Firm Return Cumulative 13-24 months	(12) Fund Firm Return Cumulative 25-36 months	(13) Fund Firm Return Cumulative 37-48 months
UP	0.063**	0.064**	0.045**	0.142*	0.081	–0.011
	(2.55)	(2.49)	(2.04)	(1.76)	(1.34)	(–0.11)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.219	0.222	0.229	0.249	0.261	0.286

Table 8: *UP* and Hedge Fund Firm Performance: Robustness Checks

This table reports the results from robustness checks of the relation between *UP* of hedge fund firms in month *t* and their future performance in month *t+3*. We investigate the robustness if we estimate *UP* using the risk factors of the Fung and Hsieh (2004) seven-factor model in (2), estimate *UP* using the risk factors of the Carhart (1997) four-factor model in (3), average *UP* over the past 36 months and use it as independent variable in (4), apply the Sharpe ratio as performance measure in (5), apply the Treynor ratio as performance measure in (6), apply the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measure (MPPM) with a risk aversion parameter of three as our performance measure in (7), estimate *UP* using a rolling horizon of 24 months in (8), use net-of-fee returns instead of gross-of-fee returns in the estimation of *UP* in (9), restrict our sample to hedge fund firms with an equity long-short strategy in (10), exclude the 20% smallest hedge fund firms per month from our sample in (11), restrict our sample to hedge fund firms for which their long portfolio value of 13F equities deviates from their total AUM by less than 20% in percentage value in (12), use the Getmansky, Lo, and Makarov (2004) methodology to unsmooth hedge fund returns in (13), adjust for the backfill bias as illustrated in Jorion and Schwarz (2019) in (14), and assign a delisting return of –1.61% to those hedge funds that leave the database as in Hodder, Jackwerth, and Kolokolova (2014) in (15). Panel A displays the results of from the same univariate portfolio sorts as in Panel B of Table 3 (Column 1), risk-adjusted 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 7 (Column 6) of future nine-factor alphas in month *t+3* on *UP* and different fund firm characteristics measured in month *t*. 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. We only display the results of the relation between *UP* and future performance (control variables are included but suppressed in the table for brevity).

Panel A: Portfolio Sorts

	(1) Baseline	(2) 7-Factor Model	(3) 4-Factor Model	(4) Average UP	(5) Sharpe Ratio	(6) Treynor Ratio	(7) MPMM RA=3	(8) 24-month Estimation
5-1 *UP*	0.53%***	0.55%***	0.54%***	0.58%***	0.45%***	0.42%***	0.35%**	0.50%***
	(3.14)	(3.45)	(3.21)	(3.67)	(3.28)	(3.20)	(2.34)	(3.02)

	(9) UP based on Net Returns	(10) Long-Short Equity	(11) Exclude Small Funds	(12) Funds with similar Leverage	(13) Return Smoothing	(14) Backfill Bias	(15) Delisting Return
5-1 *UP*	0.57%***	0.55%***	0.45%***	0.51%***	0.42%***	0.45%***	0.53%***
	(3.45)	(3.29)	(2.98)	(3.05)	(2.79)	(3.08)	(3.12)

Panel B: Fama-MacBeth Regressions

	(1) Baseline	(2) 7-Factor Model	(3) 4-Factor Model	(4) Average UP	(5) Sharpe Ratio	(6) Treynor Ratio	(7) MPMM RA=3	(8) 24-month Estimation
UP	0.026***	0.027***	0.027***	0.030***	0.010***	0.075***	0.017**	0.022***
	(3.28)	(3.56)	(3.39)	(4.24)	(3.12)	(2.98)	(2.10)	(3.18)

	(9) UP based on Net Returns	(10) Long-Short Equity	(11) Exclude Small Funds	(12) Funds with similar Leverage	(13) Return Smoothing	(14) Backfill Bias	(15) Delisting Return
UP	0.029***	0.027***	0.022***	0.027***	0.019**	0.022***	0.025***
	(3.79)	(2.74)	(2.77)	(2.89)	(2.44)	(2.71)	(3.21)

Table 9: *UP* and Interim Trading

This table reports the results of Fama and MacBeth (1973) regressions of *UP* in month *t* on portfolio turnover, trading costs and different portfolio characteristics in month *t*. In columns (1) and (2), 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 columns (3) and (4), 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. 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, beta, 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 for the tests in (1) and (2) 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 (3) and (4) 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) and (2) is from January 1997 to December 2017. The sample period in (3) and (4) 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.

	13F Data		Abel Noser Data	
	(1)	(2)	(3)	(4)
	UP	UP	UP	UP
	t	*t*	*t*	*t*
Portfolio Turnover	1.045***	1.663***		
(*13F based*)	(3.34)	(5.09)		
Trading Costs	–1.250*	–2.841***		
(*13F based*)	(–1.81)	(–3.28)		
Portfolio Turnover			0.823*	1.436***
(*Transaction-Based*)			(1.77)	(2.67)
Trading Costs			–4.322**	–4.607**
(*Transaction-Based*)			(–2.00)	(–2.18)
Number of Stocks		–0.003*		0.014
		(–1.82)		(1.29)
Herfindahl Index		1.545***		1.085
		(4.34)		(0.56)
Size (·100)		0.022**		–0.055
		(2.13)		(–0.88)
Beta		0.023		–0.076
		(1.60)		(–1.31)
Illiquidity		0.030**		–0.027
		(2.16)		(–0.25)
Book–To–Market		0.000		–0.012**
		(0.54)		(–2.54)
Constant	0.152***	–0.136*	0.157*	0.326
	(3.95)	(–1.69)	(1.77)	(0.79)
Observations	40,021	37,764	2,107	2,090
Adjusted R^2	0.030	0.097	0.153	0.678

Table 10: *UP* and Derivatives Usage

This table reports the results of Fama and MacBeth (1973) regressions of *UP* of hedge fund firm *i* in month *t* on hedge fund firm *i*'s long positions in call and put options in month *t*. We compute a hedge fund firm *i*'s number of different stocks on which call positions are held (*Number of Different Call Positions*), the number of different stocks on which put positions are held (*Number of Different Put positions*), the number of equity shares underlying the call positions (*Number of Equity Shares Underlying the Call Positions*, in millions), the number of equity shares underlying the put positions (*Number of Equity Shares Underlying the Put Positions*, in millions), the value of equity shares underlying the call positions (*Value of Equity Shares Underlying the Call Positions*, in millions of dollars), and the value of equity shares underlying the put positions (*Value of Equity Shares Underlying the Put Positions*, in millions of dollars). As control variables, we include a fund firm's number of different stock positions, the portfolio's Herfindahl index (as a measure of portfolio concentration), size, beta, 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 and derivatives to the SEC. The sample period for derivative positions is from April 1999 to December 2017. We use the Newey-West (1987) adjustment with 24 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*	(2) UP *t*	(3) UP *t*	(4) UP *t*	(5) UP *t*	(6) UP *t*
Number of Different Call Positions (·100)	–0.059 (–0.77)	–0.002 (–0.04)				
Number of Different Put Positions (·100)	0.235** (2.42)	0.295** (2.05)				
log (1+Number of Equity Shares Underlying the Call Positions) (·100)			–0.192 (–0.82)	–0.138 (–0.25)		
log (1+Number of Equity Shares Underlying the Put Positions) (·100)			0.989*** (5.62)	1.120*** (5.31)		
log (1+Value of Equity Shares Underlying the Call Positions) (·100)					–0.143 (–0.77)	–0.101 (–0.66)
log (1+Value of Equity Shares Underlying the Put Positions) (·100)					0.770*** (5.55)	0.864*** (5.27)
Control Variables	No	Yes	No	Yes	No	Yes
Constant	0.198*** (3.53)	–0.018 (–0.64)	0.154** (2.32)	–0.062 (–0.56)	0.154** (2.32)	–0.062 (–0.97)
Observations	40,139	37,853	40,139	37,853	40,139	37,853
Adjusted R^2	0.010	0.080	0.016	0.086	0.016	0.086

Table 11: *UP* and Short-Selling Activities

This table reports the results of Fama and MacBeth (1973) regressions of *UP* of hedge fund firm *i* in month *t* on a hedge fund firm's short-selling activities. Short-selling activity in month *t* is calculated in columns as the number of different short positions (*Number of Different Short Positions*), the maximum daily number of equity shares underlying the short positions (*Number of Equity Shares Underlying the Short Positions*, in millions), and 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. 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, beta, 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 for the tests in (3) and (4) 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 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 *t*	(2) UP *t*	(3) UP *t*	(4) UP *t*	(5) UP *t*	(6) UP *t*
Number of Different Short Positions (·100)	0.022** (2.08)	0.046*** (3.20)				
log (1+Number of Equity Shares Underlying the Short Positions)			0.039*** (6.33)	0.039*** (4.51)		
log (1+Value of Equity Shares Underlying the Short Positions)					0.033*** (6.39)	0.035*** (4.69)
Control Variables	No	Yes	No	Yes	No	Yes
Constant	0.087 (1.29)	0.158 (0.82)	–0.321*** (–3.48)	0.073 (0.19)	–0.326*** (–3.51)	0.066 (0.18)
Observations	2,107	2,090	2,107	2,090	2,107	2,090
Adjusted R^2	0.077	0.556	0.086	0.610	0.085	0.609

Table 12: *UP* and Confidential Holdings

This table reports the results of Fama and MacBeth (1973) regressions of *UP* of hedge fund firm *i* in month *t* on hedge fund firm *i*'s confidential 13F positions in month *t*. Confidential holdings are quarter-end equity holdings that are disclosed with a delay through amendments to Form 13F. We compute a hedge fund firm *i*'s number of different confidential holding stocks (*Number of Different Confidential Holdings*), the number of equity shares underlying the confidential holdings (*Number of Equity Shares Underlying the Confidential Holdings*, in millions), and the value of equity shares underlying the confidential holdings positions (*Value of Equity Shares Underlying the Confidential Holdings*, in millions of dollars). Our sample covers hedge fund firms from the Union Hedge Fund Database constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases who report 13F long equity holdings and confidential 13F filing amendments to the SEC. As control variables, we include a fund firm's number of different stock positions, the portfolio's Herfindahl index (as a measure of portfolio concentration), size, beta, 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 and confidential holdings to the SEC. The sample period for confidential holdings is from April 1999 to December 2017. We use the Newey-West (1987) adjustment with 24 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*	(2) UP *t*	(3) UP *t*	(4) UP *t*	(5) UP *t*	(6) UP *t*
Number of Different Confidential Holdings (·100)	0.374** (2.39)	0.388** (2.32)				
log (1+Number of Equity Shares Underlying the Confidential Holdings)			0.032*** (3.17)	0.028*** (2.70)		
log (1+Value of Equity Shares Underlying the Confidential Holdings)					0.028*** (3.19)	0.024*** (2.72)
Control Variables	No	Yes	No	Yes	No	Yes
Constant	0.214*** (3.57)	–0.001 (–0.01)	0.206*** (3.40)	–0.010 (–0.10)	0.207*** (3.40)	–0.011 (–0.11)
Observations	40,139	37,853	40,139	37,853	40,139	37,853
Adjusted R^2	0.007	0.078	0.009	0.079	0.008	0.079

Table 13: *UP* and Investor Flows

This table reports the results of Fama and MacBeth (1973) regressions of a hedge fund firm *i*'s flows in year *t+1* on *UP* in year *t* (Column 1), *Gross Fund Firm Performance* in year *t* (Column 2), *Equity PF Performance* in year *t* (Column 3), and all three variables simultaneously (Column 4). Controls for fund firm characteristics 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 (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 firm, employs leverage, has a high-water mark (HWM) and a hurdle rate, R^2 and *SDI* measures, all measured in year *t*. 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) Fund Firm Flow *t+1*	(2) Fund Firm Flow *t+1*	(3) Fund Firm Flow *t+1*	(4) Fund Firm Flow *t+1*
UP	0.210			–1.065***
	(1.40)			(–3.42)
Gross Fund Firm Performance		0.777***		1.820***
		(4.86)		(5.26)
Equity PF Performance			0.698**	–0.603
			(2.65)	(–1.33)
Size	–8.934***	–10.110***	–10.060***	–8.515***
	(–4.58)	(–5.61)	(–5.99)	(–5.12)
Age	–0.108***	–0.098***	–0.120***	–0.096***
	(–5.40)	(–4.27)	(–5.58)	(–3.87)
Standard Deviation	–2.101***	–2.080***	–1.997***	–1.351**
	(–3.97)	(–3.86)	(–3.32)	(–2.64)
Delta	0.970***	0.879**	1.167***	0.969**
	(2.89)	(2.73)	(3.46)	(2.85)
Management Fee	0.482	4.598	4.462	3.206
	(0.14)	(1.55)	(1.11)	(0.68)
Incentive Fee	–0.951**	–0.858*	–0.815*	–0.999**
	(–2.44)	(–1.89)	(–2.02)	(–2.45)
Minimum Investment	0.080	0.111	0.072	0.020
	(1.36)	(1.60)	(1.22)	(0.33)
Lockup Period	–0.226	–0.606	–0.121	–0.091
	(–0.10)	(–0.30)	(–0.06)	(–0.03)
Restriction Period	0.408	–2.760	–2.204	–0.587
	(0.10)	(–0.73)	(–0.82)	(–0.12)
Offshore	7.247	4.235	2.604	6.352
	(1.11)	(0.65)	(0.44)	(1.13)
Leverage	2.687	3.149	1.246	–0.107
	(1.06)	(1.24)	(0.41)	(–0.04)
HWM	5.112	2.756	3.938	4.826
	(1.38)	(0.58)	(0.86)	(1.24)
Hurdle Rate	8.321	5.751	6.619	10.750
	(1.09)	(0.78)	(0.84)	(1.24)
R^2	5.374	11.060	6.997	4.683
	(0.53)	(1.53)	(1.02)	(0.52)
SDI	3.468	2.759	5.473	1.572
	(0.59)	(0.49)	(0.99)	(0.28)
Constant	64.100***	61.742***	64.045***	57.706***
	(4.05)	(4.11)	(4.35)	(3.50)
Observations	3,230	3,230	3,230	3,230
Adjusted R^2	0.189	0.199	0.199	0.244

Internet Appendix

This Internet Appendix consists of an illustration of the composition of the Union Hedge Fund Database, definitions and data sourses of the main variables, and additional empirical results. We relate to these different figures and tables in the main paper.

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.

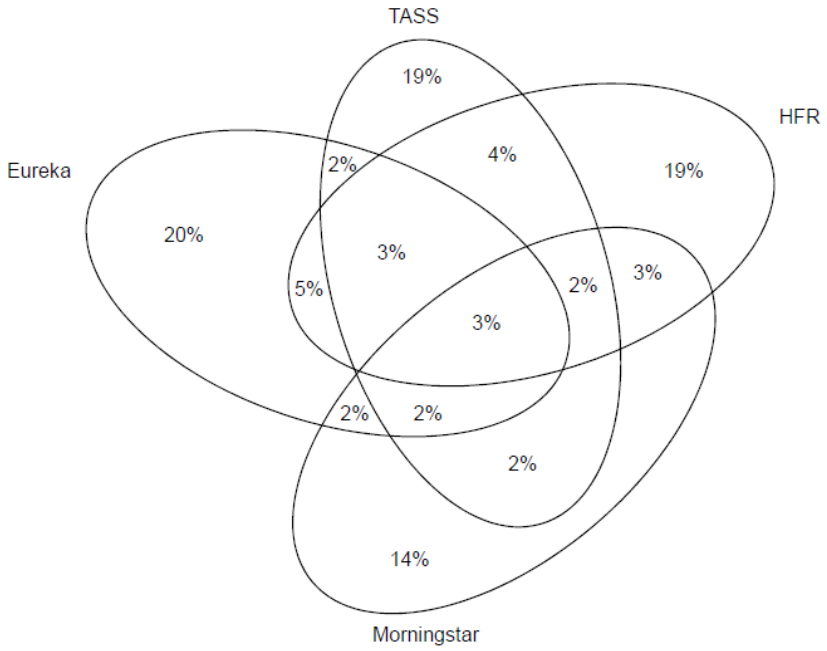


Table IA.1: Definitions and Data Sources of Main Variables

This table briefly defines the main variables used in the empirical analysis. The data sources are; (i) UNION: Union Hedge Fund Database constructed from combining the Eurekahedge, HFR, Morningstar, and Lipper TASS databases, (ii) KF: Kenneth French Data Library, (iii) THOMSON: 13F Thomson Reuter Ownership Database, (iv) DH: David A. Hsieh's webpage, (v) FRS: Data library of the Federal Reserve System, (vi) FED: Data library of the Federal Reserve Bank of St. Louis. (vii) Datastream. EST indicates that the variable is estimated or computed based on original variables from the respective data sources.

Panel A: Unobserved Performance, Returns, and Fund Characteristics

Variable Name	Description	Source
Net Fund Firm Return	Monthly excess return of a hedge fund firm, net-of-fees, computed as the AUM-weighted net excess return over all funds within a fund firm. As risk-free rate, the 1-month T-Bill rate is used.	UNION, KF, EST
Gross Fund Firm Return	Monthly excess return of a hedge fund firm, gross-of-fees, computed as the AUM-weighted gross excess return over all funds within a fund firm. We follow Agarwal, Daniel, and Naik (2009) to compute gross excess returns from net excess returns and other fund characteristics. As risk-free rate, the 1-month T-Bill rate is used.	UNION, KF, EST
Equity PF Return	Value-weighted excess return of a fund firm's disclosed equity holdings including transaction costs as detailed in Section 2.1. As risk-free rate, the 1-month T-Bill rate is used.	THOMSON, KF, EST
URC	Unobserved return gap, computed as the difference between a fund firm's gross return and the equity portfolio return as detailed in Section 2.2.	UNION, THOMSON, EST
Gross Fund Firm Performance	Risk-adjusted alpha of a fund firm's reported gross return series based on a nine-factor asset pricing model estimated over a time-period of 36 months.	UNION, KF, DH, EST
Equity PF Performance	Risk-adjusted alpha of a fund firm's equity portfolio return series based on a nine-factor asset pricing model estimated over a time-period of 36 months.	THOMSON, KF, DH, EST
UP	Unobserved performance, computed as the difference between a fund firm's gross performance and equity portfolio performance as detailed in Section 2.2.	UNION, THOMSON KF, DH, EST
Size	Natural logarithm of the hedge fund firm's asset under management (in $ million).	UNION
Age	The age of a hedge fund firm since its inception (in months).	UNION
Standard Deviation	Standard deviation of a hedge fund firm's reported returns over the past 36 months.	UNION, EST
Delta	Hedge fund manager's delta computed as the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value (in $100 thousands). Delta per hedge fund firm is computed as the AUM-weighted delta over all funds within a fund firm.	Agarwal, Daniel, and Naik (2009)
Management Fee	The annual hedge fund firm management fee (in percentage). Computed as the AUM-weighted management fee over all funds within a fund firm.	UNION

Incentive Fee	The annual hedge fund firm incentive fee (in percentage). Computed as the AUM-weighted incentive fee over all funds within a fund firm.	UNION
Min Investment	Hedge fund firm's minimum investment amount (in $100 thousands). Computed as the AUM-weighted minimum investment over all funds within a fund firm.	UNION
Lockup Period	The lockup period of a hedge fund firm, defined as the minimum amount of time that an investor is required to keep his money invested in the fund firm (in years). Computed as the AUM-weighted lockup period over all funds within a fund firm.	UNION
Restriction Period	The restriction period of a hedge fund firm, computed as the sum of its notice period and redemption period (in years). Computed as the AUM-weighted restriction period over all funds within a fund firm.	UNION
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.	UNION
Leverage	Indicator variable that takes the value of one if the largest hedge fund in the fund firm uses leverage and zero otherwise.	UNION
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.	UNION
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.	UNION
R^2	Titman and Tiu (2011)'s R^2 measure of a fund firm to the extendend Fung and Hiseh (2004) nine-factor model estimated based on the past 36 months.	UNION, EST
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.	UNION, EST

Panel B: Hedge Fund Risk Factors

Variable Name	Description	Source
S&P	The S&P 500 index monthly total return.	DH
SCMLC	The size spread factor, computed as the difference between the Russell 2000 index monthly return and the S&P 500 monthly return.	DH
BD10RET	The bond market factor, computed as the monthly change in the 10-year treasury maturity yield.	FRS
BAAMTSY	The credit spread factor, computed as the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield.	FRS
PTFSBD	Trend-following risk factor in bonds.	DH
PTFSFX	Trend-following risk factor in currencies.	DH
PTFSCOM	Trend-following risk factor in commodities.	DH
HML	Fama and French (1993) high-minus-low value factor.	KF
UMD	Carhart (1997) up-minus-down momentum factor.	KF

PS Liqui	The Pástor and Stambaugh (2003) traded liquidity risk factor.	Pástor and Stambaugh (2003)
BAB	The Frazzini and Pedersen (2014) betting-against-beta factor.	Frazzini and Pedersen (2014)
Macro	The Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor.	Bali, Brown, and Caglayan (2014)
Senti	The Baker and Wurgler (2004) investor sentiment factor.	Baker and Wurgler (2004)
Corr	The Buraschi, Kosowski, and Trojani (2014) correlation risk factor.	Buraschi, Kosowski, and Trojani (2014)
Tailrisk	The Agarwal, Ruenzi, and Weigert (2017) tail risk factor.	Agarwal, Ruenzi, and Weigert (2017)
RMW	The Fama and French (2015) robust-minus-weak profitability factor.	Fama and French (2015)
CMA	The Fama and French (2015) conservative-minus-aggressive investment factor.	Fama and French (2015)
EM Equity	The MSCI Emerging Market index monthly total return.	Datastream
European Equity	The MSCI Europe index monthly total return.	Datastream
Gov Bond	The monthly return of the Barclays US Goverment Bond index.	Datastream
Corp Bond	The monthly return of the Barclays US Corporate Investment Grade Bond index.	Datastream
Commodity	The monthly return of the S&P GSCI commodity index.	Datastream
Real Estate	The monthly return of the FTSE NAREIT index.	Datastream
Private Equity	The quarterly return of the Cambridge Associate private equity index.	Cambridge Associates

Table IA.2: Correlations

The table reports correlations between *UP*, gross fund firm performance, equity portfolio 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.	+0.55	+1.00																
Equity PF Performance	–0.54	+0.38	+1.00															
Size	+0.00	+0.02	+0.02	+1.00														
Age	–0.04	–0.05	–0.01	+0.11	+1.00													
Std. Dev.	+0.01	+0.01	+0.00	–0.16	–0.06	+1.00												
Delta	+0.02	+0.04	+0.02	+0.54	+0.18	–0.06	+1.00											
Mgmt. Fee	+0.00	+0.00	–0.01	+0.09	–0.14	–0.06	+0.14	+1.00										
Inc. Fee	+0.02	+0.03	+0.01	–0.01	–0.07	+0.02	+0.15	+0.21	+1.00									
Min Inv	+0.00	+0.01	+0.01	+0.23	–0.05	–0.07	+0.24	+0.05	–0.08	+1.00								
Lockup	+0.02	+0.02	+0.01	+0.04	–0.04	+0.04	+0.07	+0.04	+0.24	+0.05	+1.00							
Restriction	+0.00	+0.02	+0.02	+0.10	+0.06	+0.05	+0.16	+0.04	+0.24	+0.16	+0.33	+1.00						
Offshore	–0.00	–0.00	–0.01	+0.15	–0.07	–0.08	+0.09	+0.22	+0.03	–0.04	–0.19	–0.14	+1.00					
Leverage	+0.01	+0.01	+0.00	+0.13	–0.01	–0.03	+0.05	+0.11	+0.13	–0.06	+0.03	+0.01	+0.07	+1.00				
HWM	+0.01	+0.02	–0.00	+0.04	+0.00	–0.01	+0.13	+0.17	+0.53	–0.02	+0.23	+0.19	–0.03	+0.17	+1.00			
Hurdle Rate	–0.01	–0.01	–0.00	–0.09	+0.02	+0.01	–0.11	–0.11	+0.03	–0.09	+0.01	–0.05	–0.19	–0.00	+0.00	+1.00		
R^2	–0.04	–0.03	+0.01	+0.06	+0.15	+0.24	+0.00	–0.17	–0.12	–0.04	+0.00	+0.00	–0.16	–0.07	–0.04	+0.03	+1.00	
SDI	+0.04	+0.04	–0.00	–0.12	–0.13	–0.17	–0.08	+0.04	+0.04	+0.20	–0.02	+0.00	+0.00	+0.00	–0.04	+0.03	–0.64	+1.00

Table IA.3: Bivariate Independent Portfolio Sorts

This table reports the results of independent bivariate portfolio sorts based on *UP* and *Gross Fund Firm Performance* and based on *UP* and *Equity PF Performance*. Panel A reports equally weighted future average returns of 25 portfolios double sorted on *Gross Fund Firm Performance* and *UP*. First, we form quintile portfolios based on *Gross Fund Firm Performance* in month *t*. Then, independently, we sort hedge 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 *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 of the future return of the respective *UP* quintile portfolio across the *Equity PF Performance* 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 1994 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	0.28%*	0.34%**	0.39%***	0.45%***	0.48%***	0.39%***
UP 2	0.42%***	0.26%**	0.41%***	0.55%***	0.49%***	0.43%***
UP 3	0.65%***	0.43%***	0.41%***	0.49%***	0.80%***	0.56%***
UP 4	0.70%***	0.47%***	0.50%***	0.64%***	0.67%***	0.60%***
UP 5	0.72%***	0.40%***	0.75%***	0.80%***	0.92%***	0.72%***
UP 5 - UP 1	0.44%***	0.07%	0.36%**	0.35%**	0.44%**	0.33%**
	(2.70)	(0.79)	(2.26)	(2.37)	(2.30)	(2.08)
FH-9-Factor	0.43%***	0.25%	0.31%**	0.65%***	0.17%	0.36%**
alphas (5 – 1)	(2.70)	(1.48)	(1.97)	(3.37)	(1.39)	(2.18)

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	0.37%**	0.15%*	0.34%**	0.58%***	0.61%***	0.41%***
UP 2	0.30%**	0.36%***	0.38%***	0.47%***	0.48%***	0.40%***
UP 3	0.59%***	0.32%***	0.43%***	0.63%***	0.82%***	0.56%***
UP 4	0.48%***	0.53%***	0.68%***	0.73%***	0.88%***	0.66%***
UP 5	0.59%***	0.54%***	1.13%***	1.18%***	1.04%***	0.90%***
UP 5 - UP 1	0.22%	0.38%***	0.79%***	0.60%***	0.43%***	0.48%**
	(0.55)	(3.56)	(2.94)	(3.04)	(3.22)	(2.66)
FH-9-Factor	0.39%	0.57%***	0.63%***	0.64%***	0.38%*	0.52%***
alphas (5 – 1)	(1.63)	(3.85)	(3.55)	(3.25)	(1.73)	(2.80)

Table IA.4: 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	0.16*	0.53***	0.50***	0.33**	0.28**	0.36***
UP 2	0.34**	0.64***	0.48***	0.27*	0.32**	0.41***
UP 3	0.51***	0.77***	0.44***	0.32**	0.52***	0.51***
UP 4	0.65***	0.80***	0.59***	0.57***	0.51***	0.62***
UP 5	0.74***	0.94***	0.64***	0.67***	0.80***	0.76***
UP 5 - UP 1	0.58***	0.41**	0.15	0.34*	0.51***	0.40**
	(3.02)	(1.98)	(0.89)	(1.95)	(2.74)	(2.12)
FH-9-Factor	0.42**	0.53***	0.24	0.43**	0.45***	0.41**
alphas (5 – 1)	(2.07)	(2.74)	(1.43)	(2.26)	(2.75)	(2.12)

Panel B: SDI and *UP*

	SDI 1	SDI 2	SDI 3	SDI 4	SDI 5	Average
UP 1	0.28*	0.42***	0.37**	0.57***	0.27*	0.38***
UP 2	0.40***	0.55***	0.38***	0.31**	0.39***	0.41***
UP 3	0.46***	0.73***	0.62***	0.47***	0.49***	0.55***
UP 4	0.58***	0.57***	0.64***	0.63***	0.53***	0.59***
UP 5	0.56***	0.70***	1.04***	0.68***	0.93***	0.78***
UP 5 - UP 1	0.28**	0.28	0.67**	0.11	0.66**	0.40**
	(2.21)	(1.04)	(2.48)	(1.26)	(2.03)	(2.00)
FH-9-Factor	0.38**	0.30*	0.59***	0.06	0.57**	0.38**
alphas (5 – 1)	(2.28)	(1.88)	(3.72)	(0.27)	(2.21)	(2.21)