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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 fund firm's reported return and hypothetical portfolio return derived from its disclosed long equity holdings. Fund firms with high *UP* outperform those with low *UP* by 7.2% p.a. after accounting for typical hedge fund risk factors. In a horse-race, *UP* better forecasts fund performance than other predictors. We find that *UP* is positively associated with a fund firm's intraquarter trading in equity positions, derivatives usage, short selling, and confidential holdings. *UP* exhibits significant persistence but investors do not yet 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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Abstract

We investigate hedge fund firms' unobserved performance (*UP*), measured as the risk-adjusted return difference between a fund firm's reported return and hypothetical portfolio return derived from its disclosed long equity holdings. Fund firms with high *UP* outperform those with low *UP* by 7.2% p.a. after accounting for typical hedge fund risk factors. In a horse-race, *UP* better forecasts fund performance than other predictors. We find that *UP* is positively associated with a fund firm's intraquarter trading in equity positions, derivatives usage, short selling, and confidential holdings. *UP* exhibits significant persistence but investors do not yet use it for manager selection.

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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 different risk factors, 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 equity portfolios of funds significantly outperform the market return

[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).

after fees. Several limitations of holdings data can potentially explain this lack of 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 motivated 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 hedge fund) level, and intraquarter trading by managers 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 combining the returns- and holdings-based approaches. The underlying intuition behind our investigation is as follows. When positive hedge fund alpha is existent (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 are not disclosed in the fund firms' quarterly long equity holdings or cannot be inferred from such holdings. To capture this *unobserved* return component (*URC*), we combine data on the hedge fund returns reported to commercial databases with data on the long-equity positions of hedge fund firms disclosed in their 13F filings. Consistent with the limited evidence of skill in disclosed long equity positions, we observe that the average risk-adjusted performance or alpha of 0.256% per month (*t*-statistic of 2.74) for the hedge fund firms in our sample is almost entirely driven by the fund firms' *URC* with an average alpha of 0.211% per month (*t*-statistic of 3.48). In comparison, the fund firms' average alpha of their disclosed equity positions is 0.046% per month and statistically indistinguishable from zero (*t*-statistic of 0.69).

Unlike long equity portfolio returns, hedge fund firms' reported returns are influenced by their exposure to non-equity classes. We therefore adjust for the known risk factors that 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 net returns and hypothetical buy-and-hold returns from long equity portfolio positions (after accounting for the estimated transaction costs associated with trading over the quarter) over the period from 1994 to 2017.[3]

To further understand the sources of managerial skill, we next investigate which fund firm characteristics are associated with high *UP*. If *UP* indeed captures skill, characteristics associated with it should predict better fund performance. We find strong evidence in favor of *UP* reflecting managerial skill. Specifically, we find that smaller fund firms show high *UP*, consistent with the notion that these fund firms are more nimble and less likely to suffer from capacity constraints compared to larger fund firms, and therefore perform better (Aggarwal and Jorion, 2010). In addition, *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), both of which predict better future fund performance (Agarwal, Daniel, and Naik, 2009). Finally, we uncover a strong relation between *UP* and a fund's R^2 and strategy distinctiveness (SDI) measures indicating that high *UP* managers are more active, less exposed to standard or conventional risk factors, and follow investment strategies that are distinct from their peers. These characteristics have been shown to be associated with better fund performance (see Titman and Tiu, 2011; Sun, Wang, and Zheng, 2012).

Following these findings indicative of *UP* being a skill measure, we further probe into the nature of hedge funds' trading strategies that can help them enhance *UP*. While the opaqueness of the industry makes it extremely challenging to provide definitive answers here,

[3] Based on this definition of *UP*, we compare the reported *net* alphas of hedge fund firms with the transaction cost-adjusted *net* alphas of a hypothetical long equity strategy based on the disclosed long positions. We construct *UP* in this way to take the perspective of an investor who seeks to evaluate hedge fund manager skill based on the given information in the databases. An alternative *UP* measure could be constructed by comparing the reported *gross* alphas of hedge fund firms (i.e., hedge fund performance *before* fees) with the transaction cost-adjusted *net* alphas of the disclosed portfolio positions. All our main results of the paper hold when we apply this alternative measure in the empirical analysis (see, e.g., Section 5.4 and the corresponding Table 13 of the paper).

we are still able to examine four potential trading channels in the paper. First, *UP* could be related to active intraquarter trading of long-equity positions. Such frequent trading is shown to be potentially performance-enhancing in mutual funds (e.g., Puckett and Yan, 2011; Pástor, Stambaugh, and Taylor, 2017). In contrast to mutual funds, hedge funds are more active traders 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). We use two different proxies to measure intraquarter trading by hedge fund firms. First, assuming that a fund firm that trades more frequently over the quarter is also likely to engage in more intraquarter trading, we use the changes in a fund firm's disclosed long-equity portfolio from quarter *t* to quarter *t+1* as a proxy for intraquarter trading. Second, we use the actual equity transactions of hedge fund firms identified in the Abel Noser database (see Jame, 2018, for details) to compute the intraquarter portfolio turnover.[4] Using both measures, we document that fund firms with high portfolio turnover exhibit high *UP*.

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 mechanical out-of-the-money put option writing strategies to the equity market (Agarwal and Naik, 2004; Jurek and Stafford, 2015). Moreover, hedge fund's option positions deliver abnormal future returns and reduce portfolio risk (Aragon and Martin, 2012). We test this conjecture by analyzing the sensitivity of fund firms to the Agarwal and Naik (2004) call and put option factors as well as actual disclosures of long call and put option holdings in the 13F filings. Our results reveal that a fund firm's *UP* is positively related to trading strategies involving long put options which can potentially help funds enhance performance through superior risk management.

Third, we examine if *UP* is associated with hedge funds' engagement in short-selling strategies which are shown to be highly profitable on average (see Jones, Reed, and Waller,

[4] We thank Russell Jame for sharing information about the hedge fund firms included in the Abel Noser database.

2016; Jank and Smajlbegovic, 2017). As in the case of intraquarter trading, we use two different proxies to measure short-selling activity by hedge fund firms. First, we compute a fund firm's sensitivity to an aggregate short interest index (Rapach, Ringgenberg, and Zhou, 2016) and relate this sensitivity to *UP*. Second, we compute the actual short-sale equity transactions for a sample of hedge fund firms that disclose long equity positions to the SEC and detailed transaction data of all trades to the Abel Noser database. We find that the higher a fund firm's sensitivity to short interest and the higher a fund firm's number and underlying value of actual short positions, the higher is the fund firm's *UP*. This suggests that hedge funds with higher *UP* measure profit from the use of short selling strategies.

Fourth, we investigate the relation between *UP* and a fund firm's trading confidentially. Fund firms can conceal certain portfolio positions that need to be revealed 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. As a result, confidential holdings exhibit superior future performance. We show that fund firms that disclose a large value of confidential holdings also display high *UP*. Hence, we provide empirical evidence that a fund firm's unobserved performance can partly be explained by its non-publicly disclosed portfolio positions.

Finally, we find that all the four described aspects of hedge funds' trading strategies – intraquarter trading, derivatives usage, short selling, and confidential trading – are jointly associated with higher *UP*. As these features of hedge fund trading are suggestive of better future fund performance, we investigate whether a hedge fund firm's *UP* is able to predict future 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 difference in average returns of fund firms in top and bottom quintiles of

UP amounts to statistically significant 0.51% per month for raw returns and 0.62% per month for the alpha from the nine-factor model (Fung and Hsieh (2004)'s seven-factor model augmented by the Fama and French (1993) book-to-market factor, *HML*, and the Carhart (1997) momentum factor, *UMD*). Interestingly, *UP* predicts future fund firm performance significantly better than either past fund firm performance (future risk-adjusted return spread of 0.44%) or past performance derived from long equity positions (future risk-adjusted return spread of 0.04%) individually. 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 be explained by differences in the exposure to other alternative risk factors like liquidity risk (Pástor and Stambaugh, 2003), betting-against-beta (Frazzini and Pedersen, 2014), macroeconomic uncertainty (Bali, Brown, and Caglayan, 2014), investor sentiment (Baker and Wurgler, 2006), correlation risk (Buraschi, Kosowski, and Trojani, 2014), tail risk (Agarwal, Ruenzi, and Weigert, 2017), and volatility of aggregate volatility risk (Agarwal, Arisoy, and Naik, 2017).

Predictability of *UP* for future fund returns is not subsumed by other fund firm characteristics and holds 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 alternative, recently developed skill measures, such as the fund firm's R^2 (Titman and Tiu, 2011) and strategy distinctiveness (Sun, Wang, and Zheng, 2012). Moreover, *UP* beats those two measures in a horserace when predicting future cross-sectional hedge 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)), observed both in periods of high and low market returns as well as high and low market volatility, and extends up to 12 months in the future. We also show that the documented outperformance of high *UP* fund firms also survives a battery 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* using gross-of-fee returns, restricting our analysis to only long-short equity funds, single funds in a firm, TASS 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).

If *UP* captures different dimensions of managerial skill, it should be persistent. Our empirical results suggest that this is indeed the case. However, 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. This finding is most likely attributable to significant efforts associated with the construction of the *UP* measure and identification of different components of managerial skill that we uncover in this study.

Our paper makes several contributions to the literature. First, we derive a new performance metric, *UP*, which combines information from both hedge fund returns reported to commercial databases and long equity positions disclosed to the SEC. We show that this new measure predicts the cross-section of future hedge 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 unobserved performance of hedge funds is driven by fund firms' intraquarter long and short equity trades, use of derivatives, and delayed disclosure of long positions (i.e., confidential trading), all of which positively predict future fund performance. In that sense, our *UP* measure is also capturing different aspects of managerial skills than the return gap measure of Kacperczyk, Sialm, and Zheng (2008) for mutual funds. While mutual funds predominantly use long-only buy-and-hold investment strategies, hedge funds are relatively less constrained in their investment strategies which involve short selling, derivatives, and more dynamic trading strategies. Moreover, in contrast to the return gap measure, we risk-adjust a hedge fund firm's unobserved component to control for exposure to non-equity asset classes. As a result, the focus of our study is not only to introduce a new measure for hedge fund firm performance prediction, but to use this measure to identify the different sources of managerial skills in hedge funds.

The structure of the paper is as follows. Section 2 describes the data and introduces the concept of unobserved performance (*UP*). Section 3 sheds light on the relation between funds' characteristics and *UP*. In Section 4, we examine trading channels that are likely to influence *UP*. Section 5 presents empirical results on the relation between *UP* and the cross section of future hedge fund returns. Section 6 examines persistence in *UP* and investors' response to *UP*. Section 7 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 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 (formerly the CDA/Spectrum database). 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 (referred to as "confidential" by Agarwal, Jiang, Tang, and Yang, 2013), all extracted from the 13F filings. Finally, we retrive data from Abel Noser, a proprietary broker that tracks actual trading 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 use this merging procedure to obtain 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 A.1 in the 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 hedge 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 Kosowski, Naik, and Teo (2007), we eliminate the first 12 months of a fund's return series to mitigate the backfill bias.[5] This filtering process leaves us with a sample of 14,188 hedge funds in the sample period 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 classify 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 institutions by name allowing for minor variations. We compute for

[5] In a robustness check, we test the stability of our results when we apply the alternative method of Jorion and Schwarz (2019) to infer a hedge fund's listing date when it is not available. Our results are unaffected.

each hedge fund firm i in month t the reported *Fund Firm Return* and *Equity Portfolio (PF) Return*. Since hedge funds, and not firms, report their returns to commercial databases, we compute the reported *Fund Firm Return* as the value-weighted excess returns of all the funds in a firm. Using the 13F long equity positions, we compute the *Equity PF Return* as the value-weighted excess returns of the firm's disclosed equity positions after subtracting its hypothetical execution costs.[6] To compute a fund firm i's transaction costs in month t, we follow Wermers (2000) and Kacperczyk, Sialm, and Zheng (2008) who estimate execution costs according to a fitted regression approach separately for the costs of buying and selling stocks.[7] We consider *Equity PF Returns* net of costs because reported *Fund Firm Returns* are also net of trading costs.

Since 13F positions are reported only on a quarterly basis, we use a firm i's 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.[8] We eliminate all pairs in which there are fewer than 24 overlapping periods of data from both data sources. Furthermore, since we are interested in hedge funds with substantial long equity exposure, we exclude fund firms with a majority of CTA or Dedicated Short Bias funds. We end up with 915 hedge fund firms managing 3,568 distinct funds during the period from 1994 to 2017.

Additionally, for some empirical investigations in Section 4.2 and Section 4.4, we merge our sample with quarterly 13F filings of long option positions and confidential holdings of hedge fund 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

[6] In calculating equity portfolio returns, we do not include confidential holdings that are disclosed in later amendments, which are not publicly observable at the time of quarterly disclosure (see Section 4.4).
[7] For the detailed regression equations for the costs of buying and selling stocks, see the Appendix in Kacperczyk, Sialm, and Zheng (2008). Main determinants of the costs of buying and selling a stock include its trade size, market capitalization, price, and a binary variable that takes a value of one depending on whether the stock trades on the NASDAQ exchange or not.
[8] As an example, we use the disclosed 13F positions of a firm i 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.

to report holdings of long option positions on individual 13F securities and provide information on whether the options are calls or puts and the underlying securities. Moreover, 13F filing institutions can request confidential treatment from the SEC for certain holdings to delay disclosure. If a request is denied, or after the approval period of confidentiality expires, the filers must reveal these holdings by filing "amendments" to their original Form 13F. Following Agarwal, Jiang, Tang, and Yang, (2013), we refer to these amendments as confidential filings. Out of the 915 hedge fund firms that appear both in the Union Hedge Fund Database and in the 13F Thomson Reuters Ownership database, 475 fund firms file at least one long option position and 298 fund firms file at least one confidential position.

Finally, for estimating the intraquarter portfolio turnover and computing actual short sales of hedge fund firms, we also use proprietary data from the brokerage firm Abel Noser (i.e., Abel Noser Data). Abel Noser provides actual trading transaction data for different investment management firms and plan sponsors with identifying manager information for the time period from January 1999 to 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 obtain successful merges on 26 hedge fund firms through this process.[9]

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 fund firm i in month t, we first define the unobserved return component as the difference between a fund firm's reported return and its equity portfolio return,

[9] Jame (2018) identifies 70 hedge fund firms with at least one equity-oriented hedge fund in Abel Noser database (see Section 2) of which only 26 firms both appear in commercial hedge fund databases and file 13Fs.

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

We report the descriptive statistics of fund firms' reported excess returns, portfolio excess returns, unobserved return components, and characteristics in Panel A of Table 1. We calculate statistics over all fund firms and months in our sample period. All variables are defined in Table A.1 of the Appendix.

[Insert Table 1 around here]

Our results indicate that, on average, the hypothetical *Equity PF Return* of hedge fund firms exceeds the reported *Fund Firm Return* by 0.20% per month, i.e., *URC* is negative. We also investigate the time-series variation in the different return components of hedge fund firms. To do so, we compute a fund firm's *Aggregate Reported Return*, *Aggregate Equity PF Return*, and *Aggregate Unobserved Return Component* as the monthly equal-weighted average of *Aggregate Returns*, *Equity PF Returns*, and *Unobserved Return Components* across all fund firms. Panel A of Figure 1 displays the time-series of monthly *Aggregate Reported Returns* and *Aggregate Equity Portfolio Returns* while Panel B displays it for the *Aggregate Unobserved Return Component*.

[Insert Figure 1 around here]

Visual inspection shows that the time-series of *Aggregate Equity PF Returns* is more volatile than the time-series of *Aggregate Reported Returns*. We find that the highest spikes in the A*ggregate Unobserved Return Component* coincide with periods of financial downturns, i.e., in October 2008 (one month after the bankruptcy of Lehman Brothers and the beginning of a worldwide recession, value of 11.63%), August 1998 (Asian Financial Crisis with the collapse of Long Term Capital Management, value of 9.12%), and September 2001 (burst of the dotcom bubble, value of 8.06%), 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 (–8.91), April 2009 (−8.23%), and April 2001 (−6.98%), 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 *Aggregate Reported Returns*, *Aggregate Equity PF Returns*, and *Aggregate Unobserved Return Components* measured in month *t* 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*), also measured in month *t*. Standard errors are adjusted for serial correlation using the Newey and West (1987) correction over 36 lags. Results are shown in Panel B of Table 1.

Compared to the results of average raw returns, we find that – when accounting for hedge fund risk factors – the alpha for *Aggregate Reported Returns* (0.256% per month, *t*-statistic of 2.74) is substantially higher than the alpha for *Aggregate Equity PF* returns (0.046% per month, *t*-statistic of 0.69). Hence, our results reveal that overall hedge fund firm alpha seems to (almost) entirely stem from the fund firms' unobserved actions (0.211% per month, *t*-statistic of 3.48). Furthermore, we find that the *Aggregate Unobserved Return Component* has significant negative loadings on the S&P 500 market factor, the small-minus-big *SCMLC* factor, and the *PTFSBD* (trend-following in bonds) factor, while loadings on the *BD10RET* (term spread) and *UMD* (momentum) factors are significantly positive.

Based on this first set of findings, we now define 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 return series (*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:

$$UP_{i,t} = Fund\ Firm\ Performance_{i,t} - Equity\ PF\ Performance_{i,t}\ . \tag{2}$$

with

$$X\ Performance_{i,t} = X\ Return_{i,t} - X\ Return_{i,t,expected} \tag{3}$$

and

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

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

(4)

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

Therefore, *UP* captures 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. Fund firms with high *UP* strongly deviate from their disclosed long equity risk-adjusted portfolio returns while risk-adjusted reported returns of fund firms with low *UP* are similar to their equity portfolio counterpart. Our *UP* measure is related to the return gap measure in Kacperczyk, Sialm, and Zheng (2008).[10] However, unlike mutual funds, hedge funds use dynamic trading strategies often involving derivatives, short selling, and leverage. Therefore, the *UP* measure 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 positions that are not immediately disclosed in their 13F filings. In the next section, we will provide a detailed analysis of these constitutents of the *UP* measure.

[10] Other papers 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.

We report summary statistics of *Fund Firm Performance*, *Equity PF Performance*, and *Unobserved Performance* (*UP*) in Panel C of Table 1. Average *Fund Firm Performance* is 0.20% per month across all fund firms and months in the sample, whereas *Equity PF Performance* and *UP* averages are 0.01% and 0.19%, respectively. Hence, as in Panel B, we observe that, after adjusting for standard hedge fund risk factors, fund firms' performance almost entirely comes from their unobserved performance component. *UP* is fairly constant across different hedge fund firm styles.[11] Perhaps not suprisingly, *UP* is smallest (value of 0.06%) for the Equity Long style, and is among the highest for the Equity Market Neutral style (value of 0.28%) that hedge out most of the equity market exposure. The style with the highest number of different fund firms is Long-Short Equity (525 fund firms). It displays an average *UP* of 0.16% per month, a number that is very close to the average *UP* of the overall sample.

Correlations between *UP* as well as *Fund Firm Performance*, *Equity PF Performance*, and other fund firm characteristics are reported in Panel D of Table 1. As expected, based on the way we construct the *UP* measure, we find it to be positively correlated with *Fund Firm Performance* (+0.52), and negatively correlated to *Equity PF Performance* (−0.60). In addition, our results reveal that *UP* has a positive relation with the manager's delta, lockup period, leverage usage, and a fund firm's strategy distinctiveness index. It reveals a negative relation with a fund firm's R^2 from the augmented Fung and Hsieh (2004) nine-factor model. We will formally analyze and discuss the relation between *UP* and these fund firm characteristics in the next section

3. UP and Fund Characteristics

[11] We classify a hedge fund firm's strategy according to the asset under management (AUM) of its individual funds. For example, a firm is classified as *Long-Short Equity* if most of its AUM is in *Long-Short Equity* funds.

Results from Panel C in Table 1 indicate that the outperformance of hedge fund firms is virtually entirely driven by its *UP*. To better understand the sources of this outperformance, we now examine the fund firm characteristics associated with high *UP*. For this purpose, we estimate the following regression of *UP* of hedge fund firm *i* in month *t+1* on different fund 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 include time-varying fund firm characteristics such as the past monthly return, fund firm size, age, standard deviation, and manager delta. We define all variables in Table A.1 of the Appendix. Column (2) investigates the association between *UP* and time-invariant characteristics, such as a fund firm's management and incentive fees, minimum investment amount, lockup and restriction periods, as well as indicator variables that equal one if the fund firm is an offshore fund firm, employs leverage, has a high-water mark and a hurdle rate.[12] In column (3), we pool the time-varying and time-invariant variables, and in column (4), we also add the R^2 measure of Titman and Tiu (2011), and the strategy distinctiveness (SDI) measure of Sun, Wang, and Zheng (2012).

Through columns (1) to (4), we observe the following patterns. First, small fund firms typically display high *UP*. This finding is in line with the previous hedge fund literature (see e.g., Aggarwal and Jorion, 2010) who find that small funds are more nimble and face less

[12] We determine the values of these indicator variables 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.

capacity constraints compared to large funds. Second, fund firms with high *UP* are positively associated with measures of managerial incentives (i.e., manager delta), management fee, and minimum investment. Therefore, better incentivized managers tend to invest outside the disclosed long equity holdings and show higher *UP*. Third, our results reveal that high *UP* fund firms display high managerial discretion, i.e., longer lockup period. Finally, we uncover that fund firms with high *UP* show a low R^2 from the nine-factor model and a higher strategy distinctiveness index. This finding is also intuitive in the sense that high *UP* fund firm managers do not seek a strong factor exposure and differentate themselves from their peers. These traits reflect managers' confidence in their abilities to generate superior performance through active and unique investment strategies.

To summarize, we document that the positive, abnormal *UP* return spread is not random and can be traced back to several distinct fund firm characteristics, most of which are associated with better performance. Hence, these findings indicate that *UP* is likely to reflect managerial skill. In the following section, we dig deeper and examine the trading channels that are correlated with a fund firm's *UP* to uncover the drivers of managerial skill in hedge funds.

4. *UP* and Different Trading Channels

We investigate four potential trading channels 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 engagements in short-selling activities. Finally, we analyze the link between *UP* and fund firms' confidential trading in Section 4.4.

4.1 Active Trading in Long Equity Positions

The hedge fund firms in our sample disclose long equity positions to the SEC on a quarterly frequency. However, fund firms' intraquarter transactions, i.e., buys and sells that take place within a quarter, are not revealed to the public. Based on our definition of the *UP* measure (as the risk-adjusted difference between a fund firm's reported return and the return of its disclosed quarterly equity holdings), there is potentially a significant link between a fund firm's *UP* and interim trading engagement.

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.

Panel A of Table 3 investigates the relation between *UP* and two proxies for interim trading by fund firms in our sample. Our first proxy 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*.[13] The underlying premise behind this proxy is that fund firms that trade more over a quarter are also more likely to engage in intraquarter trading. Our second proxy for interim trading is estimated based on actual transactions of 26 hedge fund firms identified in the Abel Noser database as in Jame (2018) in the time period from January 1999

[13] 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 3) are very similar when we compute the turnover measure based on pure buying or pure selling transactions.

to 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.

[Insert Table 3 here]

Columns (1) and (2) show the results for the first proxy. We find that the coefficient estimate of *Portfolio Turnover* is 0.632 and statistically 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 = 0.651) and highly significant. Based on this estimate, a one standard increase in portfolio turnover implies a higher annualized *UP* of 1.44% per month. The last two columns of Table 3 present the results with the second proxy (based on actual trading turnover). We continue to observe a positive and statistically significant relation between *UP* and intraquarter trading in the prior month. The coefficients on *Transaction-based Portfolio Turnover* are 0.198 (*t*-stat = 2.78) and 0.330 (*t*-stat = 2.66) in columns (3) and (4). Multivariate specification in (4) implies an annualized change in *UP* of 2.04% for a one standard deviation change in portfolio turnover from transactions reported in the Abel Noser database.

4.2. Derivatives

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) show that a main part of hedge fund's tail risk is 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 hedge fund advisors to the SEC, 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 hedge fund option holdings earns abnormal returns of 1.55% per quarter. We therefore hypothesize that derivatives holdings of hedge funds should also influence the *UP* measure. Consequently, we investigate the relation between derivatives exposure and *UP*.

To do so, we determine fund firms' exposures to the Agarwal and Naik (2004) out-of-the money (OTM) call option and put option factors. These factors are constructed by computing the return of a strategy that involves buying OTM call and put options on the S&P Composite index with two months to maturity at the beginning of each month and selling them at the beginning of the next month. We estimate fund firm *i*'s univariate exposures to the OTM call and put option factors using a rolling window of 36 monthly returns. In the second step, we estimate the following Fama and MacBeth (1973) regressions at the individual fund firm level of *UP* in month *t+1* on the OTM call and put option factor sensitivities in month *t*:

$$UP_{i,t+1} = \alpha + \lambda_1 \hat{\beta}_{OTMCall,t} + \lambda_2 \hat{\beta}_{OTMPut,t} + \varepsilon_{i,t+1} \tag{6}$$

To adjust the standard errors for serial correlation, we use the Newey and West (1987) adjustment with 36 lags. Since we perform a two-step estimation procedure, we correct the standard errors for the errors-in-variables problem using the Shanken (1992) correction. Panel A of Table 4 reports the results.

[Insert Table 4 here]

In column (1), we regress *UP* on the sensitivity of the OTM-call option factor and do not find a significant relation. Column (2) investigates the link between *UP* and a fund firm's sensitivity to the OTM-put option factor. We find a significantly positive relation between *UP* and β_{OTMPut} with a coefficient estimate of 9.898 and a *t*-statistic of 2.65. In economic terms, this implies an annualized increase in *UP* of 1.68% for a one standard deviation increase in β_{OTMPut}. In columns (3) and (4), we replace a fund firm's sensitivities to the OTM call option and put option factors with the corresponding sensitivities to the at-the-money (ATM) call option and put option factors. Our results are similar to those in the first two columns. We observe (i) no significant relation between *UP* and the call option factor, but a (ii) significant positive relation between *UP* and a fund firm's exposure to put options. Finally, in the last two columns of Panel A of Table 4, we include the OTM and ATM put option factor, respectively, and control for a host of portfolio characteristics as in Table 3. Our results continue to exhibit a positive association between fund firms' sensitivity to the put option factor and *UP*.

In addition to investigating the relation between *UP* and fund firms' sensitivities to aggregate option returns, we also examine actual disclosed option data from hedge fund firms. For this purpose, 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, 51.9% of firms (i.e., 475 of 915 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).[14] To mitigate the influence of outliers, we winsorize the *Number* and *Value of equity shares* at the 1% level. We observe that the average *Number of different stocks on which call (put) positions* are held is 5.88 (5.63),

[14] To illustrate these measures, we provide 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. Then, (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 the equivalent value of equity shares underlying the put options is \$800,000.

the *Number of equity shares underlying the put (call) positions* is 2.15 (2.09) million, and the *Value of equity shares underlying the put (call) positions* is \$85.50 (\$98.60) million.

We regress *UP* of hedge fund firm *i* in month *t+1* 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.[15] We display the results in Panel B of Table 4.

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. Consistent with our findings in Panel A, we observe that all explanatory variables that are related to put options significantly increase a fund firm's *UP*, whereas we do not find any significant impact of the call options. In columns (2), (4), and (6), we estimate a multivariate regression of *UP* on all explanatory variables after controlling for portfolio characteristics. We continue to observe significantly positive relations between *UP* and the (i) *Number of different stocks on which fund firms hold put positions*, (ii) *Number of equity shares underlying the put positions*, and (iii) *Equivalent value of equity shares underlying put positions*. These results are also economically significant. For example, we find that 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 1.68% (1.20%).

Overall, these results provide evidence that derivatives usage of hedge fund firms, in particular, long put option usage, is an important channel that affects a fund firm's *UP*. These results are in line with previous findings of the literature that document superior risk

[15] 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 and make them conform more closely to the normal distribution.

management skills of hedge fund managers in tail risk strategies (see Agarwal, Ruenzi, and Weigert, 2017) and merger arbitrage strategies (see Cao, Goldie, Liang, and Petrasek, 2018).

4.3. Short-Selling

Recent academic literature observes that short-selling strategies yield abnormal profits on average. Jones, Reed, and Waller (2016) find that large short positions in the European Union earn statistically significant 90-day cumulative abnormal returns of 5.23% and seem to be informed. Jank and Smajlbegovic (2017) document that hedge funds, those that predominantly short sell in financial markets, earn an annualized Fama-French risk-adjusted return of 5.5% on their disclosed short positions. The profitability of short positions is also confirmed by Beschwitz, Lunghi, and Schmidt (2017) when evaluating detailed hedge fund transaction data. Hence, it is possible that *UP* is connected to a fund firm's short-selling activities and that a part of the return spread in *UP*-sorted fund portfolios is related to the profitability of short positions.

We investigate the relation between *UP* and short-selling activity during our sample period from 1994 to 2017 using two proxies. Our first proxy is a fund firm's *i* exposure to the relative changes in the aggregate short interest index of Rapach, Ringgenberg, and Zhou (2016).[16] The aggregate short index is constructed as a monthly time series by calculating the equally-weighted average of short interest (as a percentage of shares outstanding) available in Compustat across all publicly listed stocks on the US exchanges. We estimate fund firm *i*'s univariate exposure to the changes in the aggregate short interest index using a rolling window of 36 monthly returns. Our second proxy is based on actual short-sale transactions for a sample of 26 hedge fund firms that disclose long equity positions to the SEC and detailed transaction data of all trades to the Abel Noser database the time period from January 1999 to September 2011. We follow the procedure of Choi, Park, Pearson, and Sandy (2016) to compute actual

[16] Data for this index (and additional subindices) is obtained from the webpage of Matthew Ringgenberg.

short positions for hedge fund firm *i* for each stock each day.[17] We then compute for hedge fund firm *i* in month *t*, (i) the *Number of different stocks on which fund 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 underlying the short positions*. To mitigate the influence of outliers, we winsorize the *Maximum daily number* and *Maximum daily value of equity shares* at the 1% level. We observe that the average number of different stocks on which short positions are held is 187, the maximum daily number of equity shares underlying the short positions is 3.90 million, and the maximum daily value of equity shares underlying the short positions is $91.20 million.

We regress *UP* of hedge fund firm *i* in month *t+1* on the aggregate short interest sensitivity in month *t*, as well as the *Number of different short positions*, the *Number of equity shares underlying the short positions*, and the *Value of equity shares underlying the short positions* using the Newey and West (1987) adjustment with 36 lags. To correct for the the errors-in-variables problem in a two-step estimation procedure when estimating the aggregate short interest sensitivity, we use the Shanken (1992) correction. Table 5 reports the results.

[Insert Table 5 here]

Column (1) shows the results of the univariate regression of *UP* in month *t+1* on a fund firm's sensitivity to the aggregate short interest index. We find a coefficient estimate of 0.912 which is statistically significant at the 1% level. Hence, fund firms that show a high sensitivity to the aggregate short index (i.e., are likely to invest in short positions) have a high *UP*. In terms of economic significance, we find that a one standard deviation increase in $\beta_{ShortInteest}$ leads to an average annualized *UP* increase of 2.04%. In column (2), we add different portfolio

[17] For the detailed computational procedure, see Section 2 in Choi, Park, Pearson, and Sandy (2016). The general approach is to start with fund firm *i*'s long positions disclosed to the SEC in quarter *t*. Based on these disclosures, over the next three months, one adds/subtracts the daily transactions of the fund firm with respect to holding *j* on a daily basis and classifies a negative position in stock *j* as a short sale.

characteristics to our model, namely 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 (as in column (2) in Panel A of Table 3). Our results reveal that the association between *UP* and $\beta_{ShortInterest}$ is robust and remains highly significant even after controlling for other portfolio characteristics.

In columns (3), (5), and (7), we examine the univariate relation between *UP* and the *Number of different short positions*, the *Number of equity shares underlying the short positions*, and the *Value of equity shares underlying the short positions*. We find that all variables have a significantly positive influence on *UP* in the univariate regressions. In columns (4), (6), and (8), a multivariate regression of *UP* on the three explanatory variables is estimated. In these specifications, we continue to observe significant relation between *UP* and our three proxies for short-selling activity. 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 1.92% (2.04%, 3.12%). In summary, these findings suggest that short-selling activities are an important channel that influences a fund firm's *UP*.

4.4. Confidential Holdings

Another potential channel that influences a fund firm's *UP* is request for confidential treatment of certain portfolio holdings. 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 shown in the Thomson Reuters 13F data and are not included in our imputed equity portfolio return of fund firms.

Confidential holdings of institutional investors (particularly hedge funds) have already been investigated in Agarwal, Jiang, Tang, and Yang (2013) and Aragon, Hertzel, and Shi (2013). Both studies find that stocks in these holdings are disproportionally associated with information-sensitive events and greater information asymmetry, as well as share characteristics that make them more susceptible to front-running. Furthermore, confidential holdings allow institutions to reduce price impact and earn significantly positive abnormal returns over the post-filing confidential period up to twelve months into the future. Hence, it is likely that fund firms that file a substantial number of confidential holdings have high *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, 32.6% of firms (i.e., 298 of 915 firms) file at least one confidential position. In the same way as for derivatives 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 hedge fund 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 2.63, the *Number of equity shares underlying these positions* is 1.16 million, and the *Value of equity shares underlying the confidential positions* is $36.30 million.

We regress *UP* of hedge fund firm *i* in month *t+1* 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. Table 6 reports the results.

[Insert Table 6 here]

In columns (1), (3), and (5), we look at the univariate relation between *UP* and the *Number of different confidential positions*, the *Equivalent number of equity shares underlying these positions*, and the *Equivalent value of equity shares underlying these positions*. Our results indicate that all variables significantly increase *UP* in the univariate regressions. In columns (2), (4), and (6), we estimate a multivariate regression of *UP* on the three explanatory variables. We continue to observe significant relation between *UP* and our three proxies for confidential treatment. Again, these findings are economically meaningful. For example, we find that a one standard deviation rise in the equivalent *Number* (*Value*) *of equity shares underlying the confidential positions* increases a fund firm's annualized *UP* by 2.52% (0.96%). These findings suggest that confidential holdings are an important channel that influences a fund 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 and therefore improve the future performance of hedge fund firms.

4.5. Combined evidence

So far, we have shown that a fund firm's intraquarter trading in equity positions, derivatives usage, short selling, and confidential holdings are all independently associated with higher *UP* measures. A natural question would be whether this evidence remains when we combine these different traits of hedge fund firms altogether. Therefore, we also examine the relation between *UP* and the four attributes of hedge funds' trading jointly.

[Insert Table 7 here]

To allow for a comparison with our previous findings in Tables 3 through 6, columns (1) to (4) in Table 7 present the results for each of the attributes individually. Columns (5) and (6) report the findings for all the attributes together with and without controlling for other portfolio characteristics, respectively. We continue to observe that interim trading, put option exposure, short selling activity, and confidential positions, all positively contribute to the UP measure of a fund firm. Moreover, the estimated slope coefficients on each of the attributes remain largely similar, suggesting that their economic impact on the UP measure is mostly independent of each other.

5. UP and Future Hedge Fund Returns

As mentioned earlier, the four attributes of hedge fund trading have been previously shown to be positively related to future fund performance. Therefore, *UP* should reflect managerial skill and reliably predict future fund performance, an issue we investigate in this section.

5.1 Univariate Portfolio Sorts

To assess the predictive power of differences in a fund firm's unobserved performance on the cross section of future fund firm returns, we relate the *UP* measure in month *t* to fund firm returns and alphas in month *t+3*. We leave out three months to account for the effect of serial autocorrelation in hedge fund returns (see Getmansky, Lo, and Makarov, 2004) and to allow for a practical implementation of the predictive strategy after accounting for lockup and redemption restrictions.[18]

We start our investigation by looking at univariate portfolio sorts. For each month *t*, we sort fund firms into quintile portfolios based on the *UP* measure in increasing order. We then compute equally weighted monthly average excess returns of these portfolios in month *t+3*. Panel A of Table 8 reports the results. We also show the results of univariate portfolio sorts based on *Fund Firm Performance* and *Equity PF Performance* for the sake of comparison. It is important to note here that we control for risk factors explaining both these performance measures, and use alphas instead of raw returns for the univariate sorts.

[Insert Table 8 around here]

Column (3) in Panel A shows that there is a strong positive relation between *UP* and future average returns. Hedge fund firms in the portfolio with the lowest (highest) *UP* earn

[18] We obtain very similar results when we unsmooth hedge fund returns using the methodology in Getmansky, Lo, and Makarov (2004) or evaluate future fund firm returns in month *t+1* or *t+2* (see our empirical analyses in Section 5.3 and Section 5.4).

future returns of 0.25% (0.76%) in excess of the risk-free rate. The return spread between portfolios 5 and 1 is 0.51% per month, which is statistically significant at the 1% level with a *t*-statistic of 3.46. We compare these findings with portfolio sorts based on *Fund Performance* (column 1) and *Equity PF Performance* (column 2) and show that the respective spreads between portfolios 5 and 1 amount to lower values of 0.34% (*t*-statistic of 2.26) and 0.07% (*t*-statistic of 0.92) per month. Finally, in columns 4 and 5, we also document that the 5−1 differences in returns between forecasts based on *UP* and *Fund Performance*, and based on *UP* and *Equity PF Performance* are also statistically significant at the 5% level. These findings suggest that *UP* is a better predictor of future hedge fund firm returns in the cross section compared to both *Fund Performance* and *Equity Portfolio Performance*. To further illiustrate this point, we display the cumulative returns of hypothetical trading strategies based on (i) *Fund Performance*, (ii) *Equity PF Performance*, and (iii) *UP* in Figure 2. For each strategy we go long (short) the quintile of hedge fund firms with the highest (lowest) realizations of the respective sorting criteria and apply monthly rebalancing without accounting for trading costs. We assume an investment of $100 at the beginning of 1997 (i.e., at the end of the first estimation of the performance metrics based on a horizon of 36 months).

[Insert Figure 2 around here]

Similar to the results of the univariate portfolio sorts in Panel A of Table 8, we observe that a trading strategy based on *UP* strongly outperforms the two competing strategies based on *Fund Performance* and *Equity PF Performance*. At the end of our sample period in 2017, the final wealth of the investor amounts to $348.63 when pursuing the *UP* strategy and is substantially higher than $220.26 and $117.52 from the two competing strategies.[19] We

[19] The weak performance of the hypothetical buy-and-hold strategy based on disclosed portfolio positions does not necessarily imply that hedge fund managers do not display skill on the long side. Moreover, as mentioned earlier, we believe that the disclosed positions suffer from several limitations (such as not capturing intraquarter trades, coverage of only large positions, and potential distortion of disclosed portfolios to prevent copycat investors from inferring trades) that significantly reduces their value to construct a profitable investment strategy.

acknowledge that even though it is not feasible to short hedge fund firms, this analysis nonetheless demonstrates the superior predictability of *UP* measure relative to returns-based or holdings-based performance measures. Furthermore, the strong outperformance of high *UP* fund firms can also be realized based on a long-only strategy.

Panel B of Table 8 reports the results when we adjust future fund firm returns by the augmented nine-factor model. As before, we document that *UP* is superior in predicting future risk-adjusted returns (or alphas) in comparison to *Fund Performance* and *Equity PF Performance*. Hedge fund firms in the portfolio with the lowest *UP* earn future alphas of −0.17% per month, whereas fund firms in the portfolio with the highest *UP* earn future alphas of 0.45% per month. The spread between alphas of portfolios 5 and 1 is 0.62% per month, which is statistically significant at the 1% level with a *t*-statistic of 4.47. Therefore, the return spread between hedge fund firms with high *UP* and low *UP* amounts to 7.44% per annum even after adjusting for exposures to the traditional hedge fund risk factors, i.e., *S&P*, *SCMLC*, *BD10RET*, *BAAMTSY*, *PTFSBD, PTFSFX*, *PTFSCOM*, *HML*, and *UMD*. This effect is much larger than the alpha spreads between the best and worst performance quintiles based on reported *Fund Firm Alphas* (0.44% in column 1) or on Equity *PF* alphas (0.04% in column 2). Moreover, the difference in the alpha spreads of fund firms sorted on *UP* is significantly larger than those of fund firms sorted on either reported *Fund Firm Alphas* (0.18%, *t*-stat = 2.43; see column 4) or fund firms sorted on Equity PF Alphas (0.58%, *t*-stat = 3.86; see column 5).

Can the return spread based on *UP* be explained by additional hedge fund risk factors or funds' exposure to other asset classes? We address this question in Table 9, where we regress 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 9 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. We include the Pástor and Stambaugh (2003) traded liquidity factor to control for liquidity exposure of fund firms in column (2). Column (3) adds the Frazzini and Pedersen (2014) betting-against-beta factor to our model. In columns (4) to (8), we control for the exposures to the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, Baker and Wurgler (2006) investor sentiment factor, Buraschi, Kosowski, and Trojani (2014) correlation risk factor, Agarwal, Ruenzi, and Weigert (2017) tail risk factor, and Agarwal, Arisoy, and Naik (2017) volatility of aggregate volatility risk factor (*Vola*), respectively. Finally, in column (9), we simultaneously control for all the additional risk factors together. Our results indicate a significant positive alpha for the high minus low (5 − 1) *UP* return spread ranging from 0.58% to 0.72% per month.

Panel B of Table 8 investigates whether the return spread based on *UP* is due to hedge fund firms' exposure to other asset classes. After repeating our basic specification in column (1), we extend it 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 in columns (2) through (8). In column (9), we control for hedge funds' exposure to all these asset classes together.[20] Again, we find that the inclusion of these factors does not reduce the statistical and economic significance of the return spread based on *UP*.

To summarize, we find that a fund firm's unobserved performance (*UP*), computed as the difference between a *Fund Firm's Reported Performance and Equity PFPerformance*, is a strong predictor for the cross section of future average hedge fund firm returns. In particular,

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

UP is superior in predicting future fund firm returns compared to either a *Fund Firm's Reported Performance* or its *Equity PFportfolio Performance*. We also show that the return spread based on *UP* is neither subsumed by different hedge fund risk factors nor explained by fund firms' investments in emerging market and European equity markets, US government and corporate bonds, commodities, real estate, and private equity.

5.2 Bivariate Portfolio Sorts

The return spread based on *UP* could be potentially driven by its core building blocks, *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* (+0.52), and between *UP* and *Equity PF Performance* (−0.60) are high in absolute values. To distentangle the return spread based on *UP* from the two performance variables, we perform portfolio double sorts based on (i) *Fund Firm Performance* and *UP*, as well as (ii) *Equity PF Performance* and *UP*. Results are displayed in Table 10.

[Insert Table 10 around here]

We first conduct *dependent* portfolio double sorts based on *Fund Firm Performance* and *UP*. For this purpose, we form quintile portfolios sorted on *Fund Firm Performance*. Then, within each *Fund Firm Performance* quintile, we sort fund firms into five portfolios based on *UP* (both sorts taking place in month *t*). We report the equally weighted average returns of the 25 *Fund Firm Performance* × *UP* portfolios in Panel A. Our results reveal that fund firms with high *UP* have higher returns than fund firms with low *UP* in all *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 *Fund Firm Performance* amounts to 0.34% per month and is statistically significant at the 5% level. The last row in Panel A shows that we obtain similar results when we report nine-factor alphas instead of raw returns.

Second, we conduct dependent portfolio double sorts based on *Equity PF Performance* and *UP* using the same methodology. We observe that high *UP* fund firms outperform low *UP* fund firms in all *Equity PF Performance* quintiles with statistically significant return spreads in four out of five *Equity PF Performance* quintiles. The average *UP* spread after controlling for *Equity PF Performance* amounts to 0.58% per month and is statistically significant at the 1% level. When we evaluate differences in nine-factor alphas, we obtain similar results (average spread of 0.68% per month which is also statistically significant at the 1% level). [21]

Finally, we investigate the effect of *UP* on future hedge fund performance when we explicitly control for related manager skill measures, namely the R^2 measure of Titman and Tiu (2011) and the SDI measure of Sun, Wang, and Zheng (2012). Panels A and B of Table 11 show that the return spread based on *UP* is not explained by either of these measures. [22] Moreover, from Panel C, we observe that *UP* predicts future hedge fund performance better than R^2 and SDI, i.e., the spread between high *UP* fund firms and low *UP* fund firms is significantly more pronounced than the equivalent spreads based on R^2 and SDI.

[Insert Table 11 around here]

In summary, we find that the risk-adjusted return spread based on *UP* can neither be explained by fund firm differences in *Fund Firm Performance* and *Equity PF Performance* nor by differences in previously identified manager skill measures.

5.3 Multivariate Evidence

To simultanously control for several control variables when investigating the impact of *UP* on future fund firm returns, we estimate Fama and MacBeth (1973) regressions of future fund firm returns in month *t+3* on *UP* and fund firm characteristics in month *t*:

[21] This finding holds when we perform independent (instead of dependent) portfolio double sorts based on either *Fund Firm Performance* and *UP*, or on *Equity PF Performance* and *UP*. We report the results of these sorts in Table A.2 in the Appendix.
[22] Again, this finding is stable when we perform independent (instead of dependent) portfolio double sorts. We report the results of these sorts in Table A.3 in the Appendix.

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

where $r_{i,t+3}$ denotes fund firm *i*'s reported 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 fund firm characteristics, we include a fund 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 fund firm's R^2 measure and strategy distinctiveness. Panel A of Table 12 reports the results.

[Insert Table 12 around here]

Our results indicate that even after simultaneously controlling for various fund firm characteristics, the impact of *UP* on future fund firm returns and alphas is positive and statistically significant in all specifications. Depending on the specification, the coefficient estimates of *UP* range from 0.035 to 0.069 when we use future returns as the dependent variable, and is 0.022 in column (6) with future alpha as the dependent variable. Hence, considering a standard deviation of 2.47 for *UP* over our sample, a one standard deviation increase in *UP* is associated with an annualized increase in future fund firm returns (and alphas) between 0.64% and 2.04%.

In columns (1) to (6) of Panel B in Table 12, we examine the predictive power of *UP* on future alphas in different states of the world and across different time periods. We use the identical specification as in column (6) of Panel A, but only report the coefficient estimates of *UP* for the sake of brevity. We find that the impact is statistically significant during periods of both high and low market returns in excess of the riskfree rate (positive and negative, respectively). The alphas associated with *UP* are statistically significant in periods of high and low market volatility. Finally, our results indicate that the impact of *UP* on future fund firm alphas is strong in both subperiods from 1996−2007 and 2008−2017.

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 if and how the relation between *UP* and future performance alters when we use fund firm alphas in different months and how far in the future this relation persists. This question is particularly important to investors who aim to invest in high *UP* hedge fund firms: the majority of hedge fund firms in our sample employ lockup and restriction periods, and actual 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 can only construct and rebalance their portfolios with a delay. Panel C reports the results of regressions of future fund firm alphas in month *t+3* (baseline scenario), *t+1*, and *t+2*. In addition, 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. This suggests that investors can use the *UP* measure to select hedge fund firms that are likely to perform well in the future, even if long equity positions are disclosed with a delay.[23]

5.4 Robustness Checks

To confirm the results concerning *UP* and future fund firm performance, we conduct a battery of robustness checks: we examine the stability of our results by (i) estimating UP using the seven risk factors in the Fung and Hsieh (2004) model and the four risk factors in Carhart (1997) model, (ii) applying the Sharpe ratio, the Treynor ratio, the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measure (MPPM) with risk

[23] Note, however, that the performance of a potential trading strategy based on *UP* will suffer from substantial transaction costs which we do not take into account in this study.

aversion parameters of two and three as performance metrics, (iii) estimating *UP* with a 24-month rolling window and based on gross returns, (iv) restricting our sample to only long-short equity funds, single funds in a firm, TASS funds or funds with similar long-only leverage (long-equity portfolio relative to funds' assets being 120% or less), and (v), using the Getmansky, Lo, and Makarov (2004) methodology to unsmooth the returns of hedge fund firms, controlling for backfill bias as in Jorion and Schwarz (2019), and assigning a delisting return of −1.61% as in Hodder, Jackwerth, and Kolokolova (2014) to those hedge funds that leave the database.

Panel A of Table 13 report the results from univariate portfolio sorts using each of these robustness checks.

[Insert Table 13 around here]

We only report returns of the high minus short (5 – 1) *UP* return spread portfolio, after adjusting for the risks captured by the nine-factor model. Panel B reports the results of Fama and MacBeth (1973) regressions (as in column (6) of Panel A in Table 11) 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*. 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 (3) in Panel B of Table 8 and column (6) in Panel A of Table 12. Across all robustness checks, we continue to find a positive and statistically significant effect of *UP* on future fund firm performance.

6. Persistence in *UP* and Investor Response to *UP*

Based on the evidence so far, *UP* is positively related to several hedge fund trading strategies, such as interim trading, derivatives usage, confidential holdings, and short selling activity. Moreover, *UP* strongly predicts future fund firm performance, which suggests that it reflects managerial skill. If *UP* indeed captures skill, it should be persistent. To test this conjecture, we estimate Fama and MacBeth (1973) regressions of *UP* in month *t*+1 on *UP* in month *t*. We repeat this analysis for both *Fund Firm Performance* and *Equity PF Performance*, and report the results in Panel A of Table 14.

[Insert Table 14 around here]

Results in columns (1) through (3) show that *UP* is more persistent (coeff. = 0.161; *t*-stat = 13.21) than *Fund Firm Performance* and *Equity PF Performance* (coeff. = 0.102, *t*-stat = 10.55; and coeff. = 0.054, *t*-stat = 5.35, respectively). Columns (4) and (5) report the findings from a comparison of AR(1) coefficients for *UP* relative to those for both *Fund Firm Performance* and *Equity PF Performance*. We find that the difference between the coefficient estimate on *UP* and the coefficient estimate on *Fund Firm Performance* amounts to 0.059 with a *t*-statistic of 4.92 (significant at the 1% level). The difference between the coefficient estimate on *UP* and the coefficient estimate on *Equity PF Performance* is even more pronounced and amounts to 0.107 with a *t*-statistic of 8.90, again significant at the 1% level. Hence, *UP* shows a higher degree of persistence than either *Fund Firm Performance* or *Equity PF Performance*.

A natural follow-up question is whether hedge fund investors are smart enough to consider and disentangle the three metrics of performance from one another. Following prior literature that documents hedge fund investors chasing 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*.[24] Panel B of Table 14 presents the findings. Concentrating on column (4), which shows the results of a regression of fund firm flows on all three performance variables simultaneously, we observe that *UP* and *Equity PF Performance* carry negative and insignificant coefficient estimates (i.e., the coefficient estimate of *UP* is –1.004 with a *t*-statistic of –1.30). In contrast,

[24] For this empirical analysis, we follow the standard in the literature (see, e.g., Agarwal, Green, and Ren, 2018) and shift to annual frequency when investigating fund flows as assets under management are either stale or missing at monthly or quarterly frequency. We winsorize fund flows on the 1% level.

the coefficient of *Fund Firm Performance* is positive and significant (coeff. = 1.811; *t*-stat = 4.23). Note that there is an insignificant relation between future flows and *UP* even in column (1) when we do not include the other two performance measures. Therefore, it is unlikely that correlations between the three performance measures make *UP* insignificant in column (4). Taken together, these findings suggest that investors mainly rely on *Reported Fund Firm Performance* of hedge funds to allocate their capital. The failure to consider the informative content of *UP* could perhaps be attributable to the significant effort necessary to construct the *UP* measure and the identification of different components of skill that we uncover in this study. Moreover, the failure to consider the informative content of *UP* by investors 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, i.e., well-performing fund firms obtain large inflows that can adversely affect their future performance) and lead to increased performance persistence of fund firms with high *UP*.

7. Conclusion

In this paper, we investigate unobserved performance (*UP*) of hedge funds. We define *UP* as the risk-adjusted difference between a fund firm's reported return and the hypothetical portfolio returns derived from its disclosed long equity holdings. We show that *UP* is not a random attribute of a fund firm, but is strongly associated with measures of managerial incentives, fund firm discretion, and manager skill. We find that various trading channels such as intraquarter trading of equities, put option strategies, engagement in short-selling, and confidential trading are positively related with *UP* and contribute to superior fund performance of high *UP* funds. We find that *UP* strongly predicts future fund performance. Fund firms with high *UP* outperform fund firms with low *UP* by 7.2% p.a. after accounting for standard hedge fund risk factors. This spread is robust to controls for fund firm characteristics in multivariate analysis. Interestingly, *UP* predicts future fund firm performance better that past fund firm performance or past performance derived from long equity positions. *UP* is highly persistent but investors do not seem to yet use it to identify superior fund managers.

Collectively, our study uncovers a new measure of managerial skill in hedge funds by combining returns-based and holdings-based performance measures. Such a measure can help investors better predict future fund performance and understand the sources behind such predictability.

Appendix

Figure A.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.

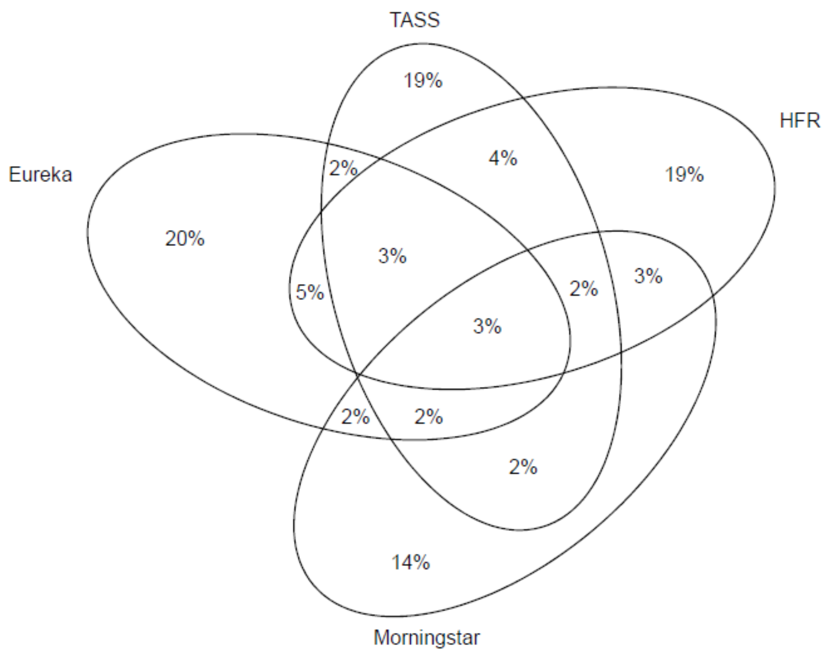

Table A.1: Definitions and Data Sources of Main Variables

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
Fund Firm Return	Monthly excess return of a hedge fund firm, computed as the AUM-weighted excess return over all funds within a fund firm. 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 return and the equity portfolio return as detailed in Section 2.2.	UNION, THOMSON, EST
Fund Firm Performance	Risk-adjusted alpha of a fund firm's reported 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 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)
Vola	The Agarwal, Arisoy, and Naik (2017) volatility of aggregate volatility factor.	FED
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 A.2: Bivariate Independent Portfolio Sorts

This table reports the results of independent bivariate portfolio sorts based on *UP* and *Fund Firm Performance* and based on *UP* and *Equity Portfolio Performance*. Panel A reports equally weighted future average returns of 25 portfolios double-sorted on *Fund Firm Performance* and *UP*. First, we form quintile portfolios based on *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 *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*. Our sample is the intersection of 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: Fund Firm Performance and *UP*

	Fund Firm Performance 1	Fund Firm Performance 2	Fund Firm Performance 3	Fund Firm Performance 4	Fund Firm Performance 5	Average
UP 1	0.20%	0.34%	0.30%	0.37%	0.38%	0.32%
UP 2	0.47%	0.35%	0.37%	0.45%	0.21%	0.37%
UP 3	0.58%	0.30%	0.32%	0.42%	0.56%	0.44%
UP 4	0.49%	0.58%	0.63%	0.55%	0.41%	0.53%
UP 5	0.48%	0.56%	0.65%	0.67%	0.94%	0.66%
UP 5 - UP 1	0.28%	0.22%*	0.35%**	0.30%*	0.56%***	0.34%**
	(1.13)	(1.76)	(2.31)	(1.87)	(2.98)	(2.01)
FH-9-Factor	0.30%*	0.23%	0.44%***	0.21%	0.50%**	0.34%**
	(1.86)	(1.56)	(2.92)	(1.22)	(2.57)	(2.03)

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	0.50%	0.12%	0.09%	0.22%	0.40%	0.27%
UP 2	0.49%	0.24%	0.31%	0.31%	0.43%	0.35%
UP 3	0.29%	0.25%	0.29%	0.68%	0.79%	0.46%
UP 4	0.38%	0.48%	0.53%	0.80%	0.68%	0.58%
UP 5	0.56%	0.63%	1.15%	1.10%	1.11%	0.91%
UP 5 - UP 1	0.05%	0.51%***	1.05%***	0.88%***	0.71%***	0.64%***
	(0.04)	(4.18)	(3.91)	(5.35)	(3.43)	(3.38)
FH-9-Factor	0.09%	0.66%***	1.07%***	0.84%***	0.66%**	0.66%***
	(0.32)	(5.50)	(5.24)	(3.80)	(2.48)	(3.47)

Table A.3: 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 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 independent bivariate portfolio sorts based on SDI and *UP*. First, we form quintile portfolios based on SDI 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 SDI quintiles in month *t+3*. 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 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: 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	0.15%	0.20%	0.30%	0.34%	0.41%	0.28%
UP 2	0.18%	0.18%	0.34%	0.42%	0.51%	0.33%
UP 3	0.35%	0.32%	0.46%	0.48%	0.71%	0.46%
UP 4	0.34%	0.41%	0.57%	0.65%	0.76%	0.55%
UP 5	0.37%	0.42%	0.68%	0.72%	0.87%	0.61%
UP 5 - UP 1	0.22%	0.22%	0.38%**	0.38%**	0.46%***	0.33%**
	(1.34)	(1.29)	(2.31)	(2.54)	(3.79)	(2.25)
FH-9-Factor	0.25%	0.18%	0.46%***	0.39%**	0.45%***	0.35%**
	(1.45)	(1.21)	(3.01)	(2.43)	(3.54)	(2.33)

Panel B: SDI and *UP*

	SDI 1	SDI 2	SDI 3	SDI 4	SDI 5	Average
UP 1	0.14%	0.25%	0.36%	0.40%	0.41%	0.31%
UP 2	0.17%	0.25%	0.41%	0.54%	0.52%	0.38%
UP 3	0.18%	0.35%	0.56%	0.59%	0.64%	0.46%
UP 4	0.35%	0.41%	0.57%	0.62%	0.79%	0.55%
UP 5	0.49%	0.44%	0.64%	0.74%	0.80%	0.62%
UP 5 - UP 1	0.35%**	0.19%	0.28%*	0.34%**	0.39%***	0.31%**
	(2.55)	(1.34)	(1.78)	(2.45)	(3.01)	(2.23)
FH-9-Factor	0.31%**	0.22%	0.26%*	0.39%***	0.41%***	0.32%**
	(2.11)	(1.54)	(1.69)	(2.99)	(3.23)	(2.31)

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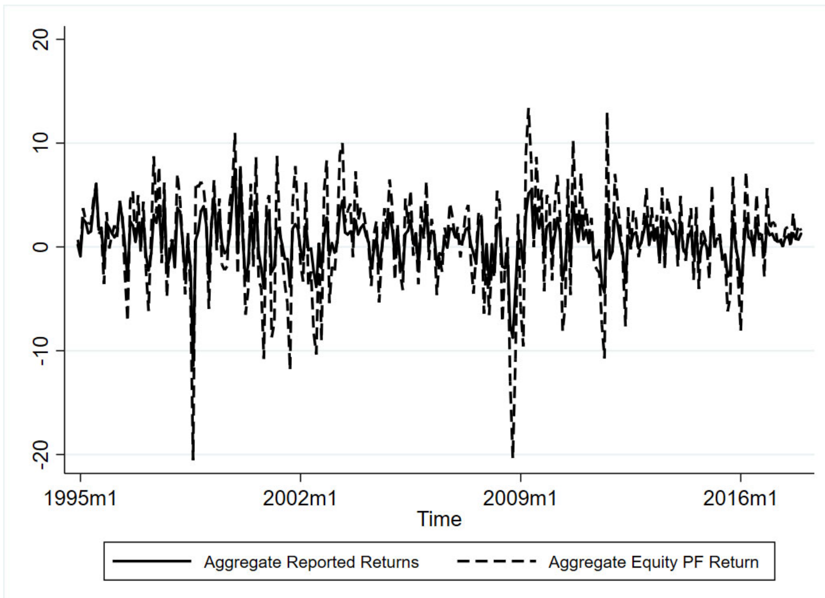
Figure 1: Aggregate Reported Returns, Aggregate Equity Portfolio Returns, and Aggregate *URC*

Panel A displays the evolution of the *Aggregate Reported Returns* and *Aggregate Equity PF returns*. Panel B displays the evolution of the aggregate unobserved return component (*URC*). 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 to the SEC. The sample period is from January 1994 to December 2017.

Panel A: Aggregate Reported Returns and Equity Portfolio Returns



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

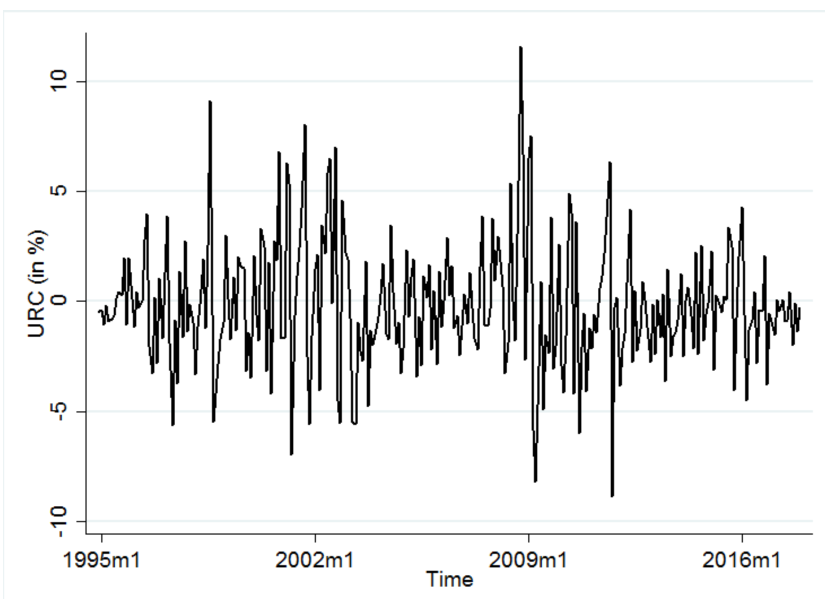


Figure 2: Cumulative Returns

This figure displays the temporal variation of the cumulative monthly returns for three hypothetical long-short investment strategies: (i) a trading strategy based on *Fund Firm Performance*, (ii) a trading strategy based on *Equity PF Performance*, and (iii) a trading strategy based on *UP*. For each strategy we go long the quintile of hedge fund firms with the highest realizations of the respective sorting criteria and go short the quintile with the lowest realizations and apply monthly rebalancing without accounting of trading costs. We assume an investment of $100 at the beginning of 1997 (i.e., at the end of the first estimation of the performance metrics). 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 to the SEC. The sample period is from January 1994 to December 2017.

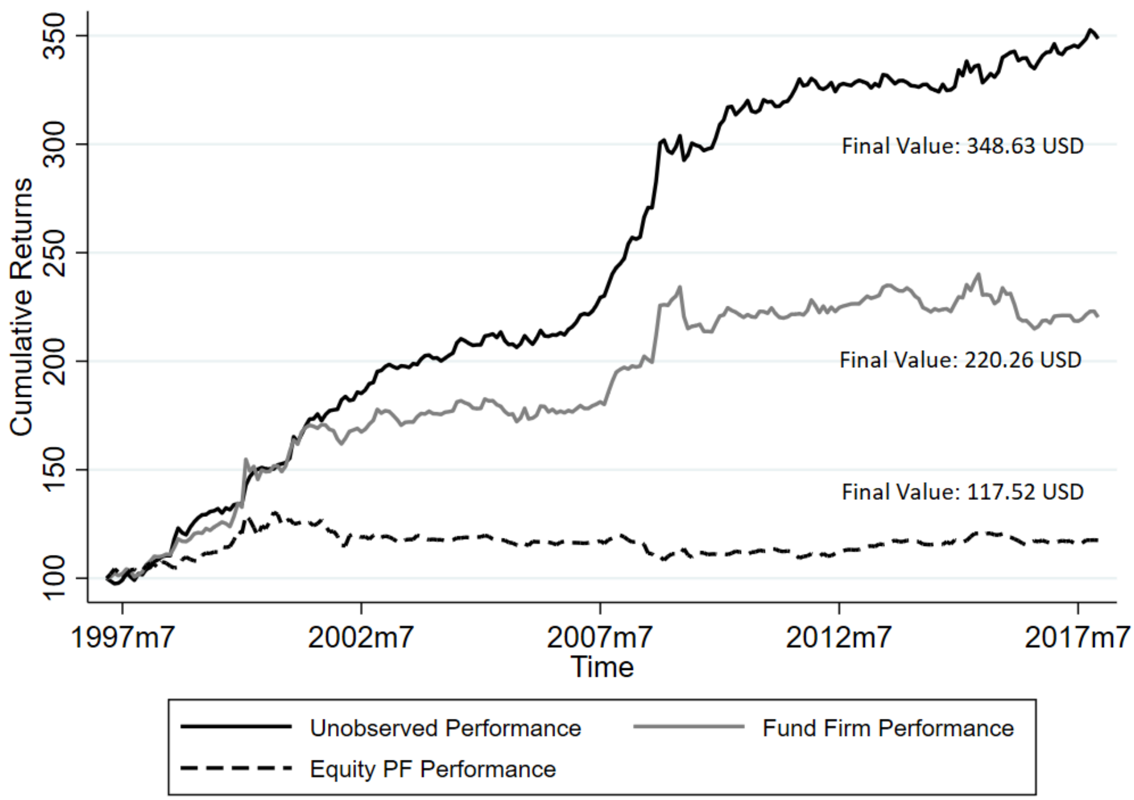


Table 1: Descriptive Statistics

Panel A of this table provides descriptive statistics for the main variables in our empirical study that include the monthly excess fund firm returns (over the risk-free rate), the fund firm's portfolio excess 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 *Fund Firm Performance*, *Equity PF Performance*, and unobserved performance (*UP*) of hedge fund firms. Panel D reports correlations between *UP*, fund 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 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: Returns and Fund Characteristics

Variable	**Mean**	**25%**	**Median**	**75%**	**StdDev**
Fund Firm Return	0.44%	–1.08%	0.50%	2.50%	4.29
Equity Portfolio Return (including transaction costs)	0.64%	–2.34%	0.99%	3.94%	6.29
Unobserved Return Component (URC)	–0.20%	–2.60%	–0.36%	1.96%	5.36
Size	5.32	4.28	5.39	6.52	1.73
Age (in months)	96.47	53.00	84.00	128.00	57.88
Standard Deviation	3.43	1.84	2.79	4.33	2.49
Delta (in $100 thousands)	4.07	0.36	1.36	4.04	7.14
Management Fee (in %)	1.37	1.00	1.44	1.56	0.41
Incentive Fee (in %)	17.80	17.50	20.00	20.00	5.08
Min Investment (in $100 thousands)	16.28	5.00	10.00	14.44	26.70
Lockup Period (in years)	0.45	0.00	0.25	1.00	0.52
Restriction Period (in years)	0.36	0.21	0.33	0.42	0.26
Offshore	0.40	0.00	0.33	0.75	0.39
Leverage	0.78	1.00	1.00	1.00	0.41
HWM	0.82	0.75	1.00	1.00	0.32
Hurdle Rate	0.20	0.00	0.00	0.33	0.34
R^2	0.60	0.45	0.62	0.76	0.19
SDI	0.43	0.22	0.34	0.56	0.43

Panel B: Aggregate *URC* and Risk Factors

	(1) Aggregate Reported Return	(2) Aggregate Equity PF Return	(3) Aggregate URC
S&P	0.374***	0.998***	–0.623***
	(13.34)	(48.58)	(–31.09)
SCMLC	0.238***	0.485***	–0.247***
	(6.69)	(18.30)	(–14.08)
BD10RET	–0.0004	–0.029	0.029*
	(–0.01)	(–0.86)	(1.73)
BAAMTSY	0.182***	0.160***	0.022
	(4.34)	(5.55)	(1.01)
PTFSBD	–0.013***	–0.005	–0.008*
	(–2.96)	(–1.43)	(–1.93)
PTFSFX	0.007***	0.005***	0.002
	(3.69)	(2.77)	(0.92)
PTFSCOM	–0.006	–0.004	–0.002
	(–1.46)	(–0.89)	(–0.63)
HML	–0.092***	–0.105***	0.013
	(–2.72)	(–3.49)	(1.32)
UMD	0.035**	–0.013	0.048***
	(2.14)	(–0.67)	(4.61)
Constant	0.256***	0.046	0.211***
	(2.74)	(0.69)	(3.48)
Observations	277	277	277
Adjusted R^2	0.819	0.969	0.944

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

Variable	**Number of Fund Firms**	**Mean**	**25%**	**Median**	**75%**	**StdDev**
Fund Firm Performance	915	0.20%	–0.86%	0.19%	1.22%	2.22
Equity PF Performance	915	0.01%	–1.05%	–0.02%	1.07%	2.44
Unobserved Performance (UP)	915	0.19%	–1.02%	0.16%	1.37%	2.47

***UP* for HF Strategy**	**Number of Fund Firms**	**Mean**	**25%**	**Median**	**75%**	**StdDev**
Emerging Markets	5	0.24%	–1.21%	0.24%	1.59%	2.29
Event Driven	99	0.24%	–1.10%	0.19%	1.55%	2.68
Global Macro	64	0.21%	–1.27%	0.20%	1.66%	2.81
Equity Long	31	0.06%	–1.10%	0.04%	1.17%	2.59
Equity Long–Short	525	0.16%	–1.01%	0.13%	1.31%	2.33
Equity Market Neutral	20	0.28%	–0.70%	0.25%	1.21%	2.13
Multi-Strategy	46	0.28%	–0.93%	0.21%	1.44%	2.55
Relative Value	111	0.29%	–0.96%	0.28%	1.53%	2.72
Others	14	0.15%	–1.14%	0.20%	1.28%	2.65

Panel D: Correlations

	UP	Fund Firm Performance	Equity PF Performance	Size	Age	Standard Deviation	Delta	Management Fee	Incentive Fee	Min Investment	Lockup Period	Restriction Period	Offshore	Leverage	HWM	Hurdle Rate	R^2	SDI
UP	+1.00																	
Fund Firm Performance	+0.52	+1.00																
Equity PF Performance	–0.60	+0.34	+1.00															
Size	+0.01	+0.02	+0.01	+1.00														
Age	–0.04	–0.04	+0.00	+0.12	+1.00													
Std. Dev.	–0.00	+0.01	+0.01	–0.20	–0.05	+1.00												
Delta	+0.02	+0.03	+0.00	+0.52	+0.19	–0.09	+1.00											
Mgmt. Fee	+0.01	+0.00	–0.00	+0.10	–0.04	–0.05	+0.18	+1.00										
Inc. Fee	+0.02	+0.03	+0.01	–0.00	–0.02	+0.04	+0.14	+0.24	+1.00									
Min Inv	+0.02	+0.01	–0.00	+0.25	+0.01	–0.11	+0.26	+0.04	–0.03	+1.00								
Lockup	+0.01	+0.02	+0.00	+0.04	–0.04	+0.07	+0.07	+0.00	+0.22	+0.03	+1.00							
Restriction	+0.00	+0.03	+0.02	+0.10	+0.05	+0.07	+0.14	+0.03	+0.19	+0.06	+0.31	+1.00						
Offshore	–0.00	–0.01	–0.01	+0.17	–0.07	–0.08	+0.16	+0.22	+0.08	+0.01	–0.14	–0.14	+1.00					
Leverage	+0.02	+0.00	+0.00	+0.16	–0.00	–0.05	+0.06	+0.14	+0.08	–0.00	–0.02	–0.03	0.09	+1.00				
HWM	+0.01	+0.01	–0.00	+0.03	–0.02	+0.01	+0.12	+0.17	+0.52	+0.00	+0.17	+0.14	+0.01	+0.13	+1.00			
Hurdle Rate	–0.01	–0.01	+0.01	–0.07	+0.06	+0.02	–0.10	–0.10	+0.03	–0.04	+0.04	–0.02	–0.23	–0.02	–0.01	+1.00		
R^2	–0.05	–0.04	+0.01	+0.06	+0.13	+0.23	+0.00	–0.18	–0.12	–0.04	+0.04	+0.04	–0.16	–0.02	–0.07	+0.05	+1.00	
SDI	+0.04	+0.04	–0.00	–0.12	–0.15	–0.16	–0.07	+0.07	+0.07	+0.11	–0.04	–0.03	+0.03	–0.03	+0.03	–0.01	-0.64	+1.00

Table 2: Determinants of *UP*

This table reports the results of Fama and MacBeth (1973) regressions of *UP* in month *t+1* on fund firm characteristics in month *t*. As fund firm characteristics, we include a fund firm's monthly 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). 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 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.

	(1) UP *t+1*	(2) UP *t+1*	(3) UP *t+1*	(4) UP *t+1*
Fund Firm Return	0.038***		0.039***	0.046***
	(4.75)		(4.54)	(4.52)
Size	–0.039***		–0.046***	–0.032***
	(–4.70)		(–5.56)	(–3.60)
Age	–0.002**		–0.002***	–0.002**
	(–2.50)		(–2.74)	(–2.47)
Standard Deviation	–0.021		–0.020	–0.010
	(–1.03)		(–1.14)	(–0.60)
Delta	0.014***		0.017***	0.015**
	(2.66)		(2.77)	(2.50)
Management Fee		0.074**	0.042*	0.038*
		(2.38)	(1.83)	(1.66)
Incentive Fee		0.001	–0.001	–0.004
		(0.16)	(–0.26)	(–0.72)
Minimum		0.002***	0.001*	0.001*
Investment		(2.66)	(1.77)	(1.80)
Lockup Period		0.113**	0.094**	0.106**
		(1.99)	(2.10)	(2.37)
Restriction Period		–0.109	–0.169	–0.161
		(–0.75)	(–1.50)	(–1.53)
Offshore		–0.028	–0.062	–0.064
		(–0.40)	(–0.77)	(–0.85)
Leverage		0.018	0.009	0.012
		(0.37)	(0.17)	(0.24)
HWM		0.060	0.083*	0.055
		(1.59)	(1.69)	(1.20)
Hurdle Rate		–0.054	–0.023	–0.023
		(–0.59)	(–0.32)	(–0.36)
R^2				–0.164*
				(–1.75)
SDI				0.340***
				(2.92)
Constant	0.601***	0.0708	0.609***	0.494**
	(8.23)	(0.78)	(5.36)	(2.53)
Observations	47,786	54,751	45,449	45,449
Adjusted R^2	0.063	0.059	0.132	0.152

Table 3: *UP* and Interim Trading

This table reports the results of Fama and MacBeth (1973) regressions of *UP* in month *t+1* on portfolio turnover and different portfolio characteristics in month *t*. In columns (1) and (2), portfolio turnover in month *t* is calculated as the total of a firm 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*. 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*. 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 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 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.

	(1) UP *t+1*	(2) UP *t+1*	(3) UP *t+1*	(4) UP *t+1*
Portfolio Turnover	0.632***	0.651***		
(*13F based*)	(5.77)	(6.59)		
Portfolio Turnover			0.198***	0.330***
(*Transaction-Based*)			(2.78)	(2.66)
Number of Stocks		–0.003*		0.007
		(–1.93)		(1.33)
Herfindahl Index		0.708**		–0.881
		(2.13)		(–0.46)
Size		0.0002		–0.001
		(1.12)		(–1.41)
Beta		0.019		–0.195***
		(1.09)		(–3.39)
Illiquidity		0.007		0.012
		(0.45)		(0.22)
Book-To-Market		0.0003		–0.016***
		(0.29)		(–4.23)
Constant	0.0343	–0.175*	0.638*	0.949**
	(1.57)	(–1.71)	(1.69)	(2.34)
Observations	59,114	58,025	2,306	2,304
Adjusted R^2	0.012	0.069	0.095	0.571

Table 4: *UP* and Derivatives Usage

Panel A of this table reports the results of Fama and MacBeth (1973) regressions of *UP* of hedge fund firm *i* in month *t+1* on a hedge fund firm's sensitivity to the Agarwal and Naik (2004) out-of-the money (OTM) and at-the-money (ATM) call- and put option factors. We estimate a fund firm's sensitivity to the respective factor based on a rolling window of 36 monthly returns. 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 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 the Shanken (1992) correction to control for the errors-in-variables problem. Panel B of this table reports the results of Fama and MacBeth (1973) regressions of *UP* of hedge fund firm *i* in month *t+1* 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. 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.

Panel A: Sensitivities to Option Factors

	(1) UP *t+1*	(2) UP *t+1*	(3) UP *t+1*	(4) UP *t+1*	(5) UP *t+1*	(6) UP *t+1*
$\beta_{OTMCall}$	–6.040 (–1.27)					
β_{OTMPut}		9.898*** (2.65)			10.040*** (2.63)	
$\beta_{ATMCall}$			–5.962 (–1.45)			
β_{ATMPut}				9.611*** (2.61)		9.740** (2.58)
Control Variables	No	No	No	No	Yes	Yes
Constant	0.335*** (6.86)	0.373*** (7.43)	0.336*** (6.94)	0.373*** (7.38)	0.0750 (1.04)	0.0748 (1.04)
Observations	59,166	59,166	59,166	59,166	58,099	58,099
Adjusted R^2	0.020	0.021	0.020	0.021	0.083	0.083

Panel B: Actual Filed Option Positions

	(1) UP *t+1*	(2) UP *t+1*	(3) UP *t+1*	(4) UP *t+1*	(5) UP *t+1*	(6) UP *t+1*
Number of Different Call Positions	–0.002 (–0.50)	–0.001				
Number of Different Put Positions	0.006*** (2.86)	0.009*** (2.78)				
log (1+Number of Equity Shares Underlying the Call Positions)			–0.002 (–0.40)	0.0001 (0.01)		
log (1+Number of Equity Shares Underlying the Put Positions)			0.008** (2.35)	0.008** (1.98)		
log (1+Value of Equity Shares Underlying the Call Positions)					–0.002 (–0.46)	–0.0001 (–0.03)
log (1+Value of Equity Shares Underlying the Put Positions)					0.007*** (2.75)	0.006** (2.32)
Control Variables	No	Yes	No	Yes	No	Yes
Constant	0.237*** (6.21)	–0.053 (–0.57)	0.224*** (5.51)	–0.050 (–0.51)	0.223*** (5.43)	–0.053 (–0.54)
Observations	59,365	58,233	59,365	58,233	59,365	58,233
Adjusted R^2	0.005	0.065	0.009	0.070	0.009	0.070

Table 5: *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+1* on a hedge fund firm's short-selling activities. In columns (1) and (2), short-selling activity is measured as a fund firm's sensitivity to the Rapach, Ringgenberg, and Zhou (2016) aggregate short index in month *t*. The sensitivity is computed based on a rolling window of 36 monthly returns. In columns (3) to (8), short-selling activity in month *t* is calculated 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 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 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.

	(1) UP *t+1*	(2) UP *t+1*	(3) UP *t+1*	(4) UP *t+1*	(5) UP *t+1*	(6) UP *t+1*	(7) UP *t+1*	(8) UP *t+1*
$\beta_{ShortInterest}$	0.912*** (3.16)	0.974*** (3.02)						
Number of Different Short Positions			0.001*** (7.30)	0.001*** (3.70)				
log (1+Number of Equity Shares Underlying the Short Positions)					0.250*** (6.07)	0.232*** (4.83)		
log (1+Value of Equity Shares Underlying the Short Positions)							0.271*** (6.26)	0.295*** (5.63)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Constant	0.275*** (5.97)	–0.019 (–0.21)	–0.195** (–2.24)	0.215 (0.54)	–4.062*** (–8.59)	–3.254*** (–3.63)	–5.206*** (–6.91)	–5.110*** (–4.83)
Observations	58,924	57,858	2,389	2,381	2,389	2,381	2,389	2,381
Adjusted R^2	0.025	0.085	0.085	0.540	0.104	0.585	0.109	0.587

Table 6: *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+1* 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. The sample period for confidential holdings is from April 1999 to December 2017. 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. 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+1*	(2) UP *t+1*	(3) UP *t+1*	(4) UP *t+1*	(5) UP *t+1*	(6) UP *t+1*
Number of Different Confidential Holdings	0.008*** (2.64)	0.005** (2.00)				
log (1+Number of Equity Shares Underlying the Confidential Holdings)			0.008** (2.05)	0.006** (2.29)		
log (1+Value of Equity Shares Underlying the Confidential Holdings)					0.007** (2.20)	0.004** (2.32)
Control Variables	No	Yes	No	Yes	No	Yes
Constant	0.235*** (5.99)	–0.047 (–0.50)	0.237*** (6.10)	–0.042 (–0.45)	0.237*** (6.10)	–0.042 (–0.44)
Observations	59,365	58,233	59,365	58,233	59,365	58,233
Adjusted R^2	0.004	0.064	0.005	0.065	0.005	0.065

Table 7: *UP* as well as Interim Trading, Derivatives Usage, Short-Selling Activities, and Confidential Holdings

This table reports the results of Fama and MacBeth (1973) regressions of *UP* of hedge fund firm *i* in month *t+1* on measures of interim trading, derivative usage, short-selling activitiy, and confidential holdings in month *t*. As our measure for interim trading, we compute portfolio turnover in month *t* as the total of a firm 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*. As our measure for derivatives usage, we first use hedge fund firm *i*'s sensitivity to the Agarwal and Naik (2004) out-of-the money (OTM) put option factor based on a rolling window of 36 monthly returns. Second, we use a hedge fund firm *i*'s value of equity shares underlying the put positions (*Value of Equity Shares Underlying the Put Positions*, in millions of dollars). As our measure for short-selling activity, we compute a hedge fund firm's sensitivity to the Rapach, Ringgenberg, and Zhou (2016) aggregate short index based on a rolling window of 36 monthly returns. As our measure for confidential holdings, we use a hedge fund firm *i*'s value of equity shares underlying the confidential holdings positions (*Value of Equity Shares Underlying the Confidential Holdings*, in millions of dollars). As control variables, we 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* in our model. All control variables are based on the fund firm's disclosed holdings. 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 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.

	(1) UP *t+1*	(2) UP *t+1*	(3) UP *t+1*	(4) UP *t+1*	(5) UP *t+1*	(6) UP *t+1*
Portfolio Turnover	0.632*** (5.77)				0.533*** (4.94)	0.554*** (5.02)
β_{OTMPut}		9.610*** (2.68)			9.346** (2.19)	9.177** (2.01)
log (1+Value of Equity Shares Underlying the Put Positions)		0.004** (2.24)			0.004* (1.89)	0.004* (1.82)
$\beta_{ShortInteest}$			0.912*** (3.16)		1.582*** (5.26)	1.631*** (5.13)
log (1+Value of Equity Shares Underlying the Confidential Holdings)				0.007** (2.20)	0.004* (1.88)	0.006** (2.12)
Control Variables	No	No	No	No	No	Yes
Constant	0.034 (1.57)	0.362*** (8.40)	0.275*** (5.97)	0.235*** (5.99)	0.187*** (3.42)	–0.038 (–0.46)
Observations	59,114	59,166	58,924	59,365	58,674	57,650
Adjusted R^2	0.012	0.029	0.025	0.005	0.077	0.127

Table 8: *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 *Fund Firm Performance*, *Equity PF Performance*, *UP* and the difference between *UP* and *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 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 column "5-1" reports the difference in monthly average alphas with corresponding statistical significance. Our sample is the intersection of 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: Excess Returns (in *t+3)*

Portfolio	(1) Fund Firm Performance	(2) Equity PF Performance	(3) UP	(4) UP – Fund Firm Performance	(5) UP – Equity PF Performance
1 (Lowest)	0.34%**	0.46%***	0.25%	–0.11%	–0.21%
	(2.28)	(4.15)	(1.26)	(–0.56)	(–1.59)
2	0.41%***	0.41%***	0.38%**	–0.03%	–0.03%
	(3.26)	(3.89)	(2.32)	(–0.05)	(–0.11)
3	0.44%***	0.46%***	0.45%***	0.01%	–0.01%
	(4.18)	(4.22)	(3.67)	(0.06)	(–0.03)
4	0.53%***	0.49%***	0.57%***	0.04%	0.08%
	(4.11)	(4.57)	(5.56)	(0.13)	(0.81)
5 (Highest)	0.68%***	0.53%***	0.76%***	0.08%	0.23%*
	(4.99)	(4.25)	(5.92)	(1.02)	(1.76)
5-1	0.34%**	0.07%	0.51%***	0.19%**	0.44%***
	(2.26)	(0.92)	(3.46)	(2.30)	(3.07)

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

Portfolio	(1) Fund Firm Performance	(2) Equity PF Performance	(3) UP	(4) UP – Fund Firm Performance	(5) UP – Equity PF Performance
1 (Lowest)	–0.08%	0.16%	–0.17%**	–0.09%*	–0.33%***
	(–0.91)	(1.43)	(–2.25)	(–1.81)	(–3.13)
2	0.10%	0.07%	0.05%	–0.05%	–0.02%
	(1.32)	(0.89)	(0.75)	(–0.86)	(–0.62)
3	0.17%**	0.13%	0.13%	–0.04%	0.00%
	(2.56)	(1.19)	(1.15)	(–0.36)	(0.11)
4	0.26%***	0.17%	0.27%***	0.01%	0.10%
	(3.02)	(1.30)	(3.12)	(0.28)	(1.27)
5 (Highest)	0.36%**	0.20%*	0.45%***	0.09%*	0.25%**
	(2.56)	(1.85)	(3.29)	(1.86)	(2.30)
5-1	0.44%***	0.04	0.62%***	0.18%**	0.58%***
	(3.67)	(0.46)	(4.47)	(2.43)	(3.86)

Table 9: *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 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 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*), the Agarwal, Ruenzi, and Weigert (2017) tail risk factor *(Tailrisk)*, and the Agarwal, Arisoy, and Naik (2017) volatility of aggregate volatility factor (*Vola).* As 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 based on monthly data except from the US Private Equity index which is quarterly. Our sample is the intersection of 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: 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	–0.057***	–0.058***	–0.079***	–0.053***	–0.040**	–0.061**	–0.133***	–0.090**	–0.088*
	(–3.30)	(–3.53)	(–5.73)	(–3.34)	(–2.05)	(–2.34)	(–4.91)	(–2.21)	(–1.93)
SCMLC	0.028	0.028	0.010	0.026	0.038	0.038	–0.055	0.025	0.018
	(0.84)	(0.84)	(0.31)	(0.75)	(1.06)	(1.03)	(–1.44)	(0.59)	(0.37)
BD10RET	–0.053	–0.050	–0.049	–0.057	–0.073	–0.069	–0.082**	–0.069	–0.063
	(–1.14)	(–0.98)	(–0.90)	(–1.17)	(–1.16)	(–1.25)	(–2.19)	(–1.26)	(–0.89)
BAAMTSY	–0.120*	–0.122*	–0.077	–0.130*	–0.170***	–0.170***	–0.078*	–0.175***	–0.154**
	(–1.77)	(–1.76)	(–1.33)	(–1.90)	(–2.84)	(–2.84)	(–1.80)	(–2.73)	(–2.33)
PTFSBD	0.019**	0.018**	0.017*	0.019**	0.023*	0.022**	–0.005	0.020**	0.020*
	(2.00)	(2.02)	(1.86)	(2.08)	(1.97)	(2.25)	(–0.74)	(2.06)	(1.67)
PTFSFX	–0.000002	0.000004	0.0009	–0.0002	–0.008*	–0.006	0.007**	–0.007	–0.006
	(–0.00)	(0.00)	(0.14)	(–0.04)	(–1.74)	(–1.25)	(2.08)	(–1.51)	(–1.32)
PTFSCOM	0.003	0.003	0.001	0.004	0.012	0.010	0.013***	0.011*	0.010
	(0.46)	(0.46)	(0.19)	(0.52)	(1.60)	(1.62)	(3.18)	(1.71)	(1.19)
HML	0.009	0.009	0.056**	0.010	–0.00003	0.012	0.146***	0.030	0.063***
	(0.42)	(0.43)	(2.42)	(0.44)	(–0.00)	(0.57)	(2.90)	(1.17)	(2.83)
UMD	0.027	0.026	0.050***	0.031	0.022	0.021	0.078***	0.031	0.043
	(1.13)	(1.00)	(2.69)	(1.13)	(0.84)	(0.87)	(4.84)	(1.06)	(1.59)
PS Liqui		0.007							0.026
		(0.29)							(0.92)
BAB			–0.076***						–0.075**
			(–3.73)						(–2.10)
Macro				0.041					0.029
				(1.64)					(0.98)
Senti					0.002*				0.002
					(1.82)				(1.65)
Corr						–0.012			–0.014
						(–1.26)			(–1.17)
Tailrisk							0.062		0.0140
							(1.46)		(0.21)
Vola								–0.005*	
								(–1.73)	
Constant	0.622***	0.618***	0.657***	0.617***	0.582***	0.663***	0.720***	0.637***	0.654***
	(4.47)	(4.47)	(5.41)	(4.61)	(4.45)	(4.29)	(5.62)	(3.61)	(4.99)
Observations	249	249	249	249	249	189	189	94	189
Adjusted R^2	0.192	0.192	0.225	0.196	0.214	0.214	0.215	0.525	0.254

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	–0.057***	–0.060*	–0.061***	–0.057***	–0.057***	–0.061***	–0.024	–0.053	–0.033
	(–3.30)	(–1.66)	(–3.75)	(–3.37)	(–3.05)	(–3.75)	(–0.82)	(–0.91)	(–0.79)
SCMLC	0.028	0.027	0.026	0.028	0.028	0.026	0.054	–0.042	0.051
	(0.84)	(0.73)	(0.78)	(0.84)	(0.83)	(0.78)	(1.29)	(–0.52)	(1.13)
BD10RET	–0.053	–0.053	–0.063	–0.053	–0.053	–0.063	–0.019	–0.140	–0.029
	(–1.14)	(–1.12)	(–1.39)	(–1.11)	(–1.10)	(–1.39)	(–0.39)	(–1.34)	(–0.58)
BAAMTSY	–0.120*	–0.122*	–0.119*	–0.120*	–0.120*	–0.119*	–0.092	–0.182	–0.095
	(–1.77)	(–1.80)	(–1.77)	(–1.76)	(–1.78)	(–1.77)	(–1.49)	(–1.03)	(–1.53)
PTFSBD	0.019**	0.019**	0.019**	0.019*	0.019*	0.019**	0.018*	0.030*	0.020**
	(2.00)	(2.19)	(2.06)	(1.95)	(1.97)	(2.06)	(1.94)	(1.73)	(2.17)
PTFSFX	–0.000002	–0.00005	–0.0002	–0.000002	–0.0000003	–0.0002	–0.0002	–0.004	–0.001
	(–0.00)	(–0.01)	(–0.04)	(–0.00)	(–0.00)	(–0.04)	(–0.03)	(–0.40)	(–0.10)
PTFSCOM	0.003	0.003	0.003	0.003	0.003	0.003	0.003	–0.009	0.003
	(0.46)	(0.46)	(0.40)	(0.46)	(0.45)	(0.40)	(0.43)	(–0.74)	(0.34)
HML	0.009	0.010	0.003	0.009	0.009	0.003	0.037	0.007	0.035
	(0.42)	(0.42)	(0.13)	(0.39)	(0.43)	(0.13)	(1.35)	(0.20)	(1.38)
UMD	0.027	0.027	0.025	0.027	0.027	0.025	0.023	–0.023	0.021
	(1.13)	(1.13)	(1.10)	(1.14)	(1.11)	(1.10)	(1.03)	(–0.77)	(0.96)
EM Equity		0.003							0.008
		(0.12)							(0.32)
Europe Equity			0.017						0.020
			(1.64)						(1.53)
Gov Bond				–0.001					–0.0001
				(–0.01)					(–0.00)
Corp Bond					0.001				–0.014
					(0.01)				(–0.32)
Commodity						0.017			0.011
						(1.64)			(1.14)
Real Estate							–0.049		–0.053
							(–1.22)		(–1.36)
Private Equity								–0.013	
								(–0.12)	
Constant	0.622***	0.622***	0.632***	0.622***	0.622***	0.632***	0.614***	2.123***	0.632***
	(4.47)	(4.56)	(4.47)	(4.46)	(4.47)	(4.47)	(4.52)	(4.87)	(4.57)
Observations	249	249	249	249	249	249	249	83	249
Adjusted R^2	0.192	0.192	0.198	0.192	0.192	0.198	0.200	0.199	0.216

Table 10: Bivariate Dependent Portfolio Sorts

This table reports the results of dependent bivariate portfolio sorts based on *UP* and *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 *Fund Performance* and *UP*. First, we form quintile portfolios based on *Fund Firm Performance* in month *t*. Then, within each quintile, 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 *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*. Our sample is the intersection of 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: Fund Firm Performance and UP

	Fund Firm Performance 1	Fund Firm Performance 2	Fund Firm Performance 3	Fund Firm Performance 4	Fund Firm Performance 5	Average
UP 1	0.08%	0.32%	0.30%	0.33%	0.44%	0.29%
UP 2	0.21%	0.38%	0.39%	0.55%	0.50%	0.41%
UP 3	0.37%	0.29%	0.34%	0.53%	0.70%	0.45%
UP 4	0.47%	0.48%	0.59%	0.55%	1.08%	0.63%
UP 5	0.46%	0.55%	0.64%	0.67%	0.85%	0.63%
UP 5 - UP 1	0.38%**	0.23%	0.34%**	0.34%**	0.41%***	0.34%**
	(2.01)	(1.36)	(2.08)	(2.11)	(2.78)	(2.07)
FH-9-Factor	0.59%***	0.20%	0.26%*	0.25%*	0.42***	0.34%**
	(3.63)	(1.56)	(1.86)	(1.81)	(2.98)	(2.37)

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	0.44%	0.08%	0.22%	0.14%	0.41%	0.26%
UP 2	0.32%	0.28%	0.22%	0.42%	0.42%	0.33%
UP 3	0.55%	0.32%	0.38%	0.50%	0.32%	0.41%
UP 4	0.49%	0.59%	0.45%	0.64%	0.80%	0.60%
UP 5	0.53%	0.78%	1.15%	0.91%	0.83%	0.84%
UP 5 - UP 1	0.09%	0.70%***	0.93%***	0.76%***	0.42%**	0.58%***
	(0.47)	(3.96)	(4.61)	(3.43)	(2.64)	(3.02)
FH-9-Factor	0.24%	0.88%***	1.06%***	0.80%***	0.40%*	0.68%***
	(1.64)	(6.32)	(5.33)	(3.64)	(1.71)	(3.76)

Table 11: Bivariate 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 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 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 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 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. 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 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: 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	0.22%	0.25%	0.33%	0.34%	0.43%	0.31%
UP 2	0.15%	0.41%	0.36%	0.45%	0.56%	0.39%
UP 3	0.18%	0.34%	0.56%	0.61%	0.71%	0.48%
UP 4	0.32%	0.38%	0.61%	0.69%	0.89%	0.58%
UP 5	0.34%	0.44%	0.67%	0.71%	0.84%	0.60%
UP 5 - UP 1	0.12%	0.19%	0.34%**	0.37%***	0.41%***	0.29%**
	(1.01)	(1.23)	(2.34)	(3.21)	(3.65)	(2.29)
FH-9-Factor	0.24%	0.23%*	0.33%**	0.35%**	0.40%***	0.31%**
	(1.32)	(1.82)	(2.02)	(2.54)	(3.56)	(2.25)

Panel B: SDI and *UP*

	SDI 1	SDI 2	SDI 3	SDI 4	SDI 5	Average
UP 1	0.19%	0.24%	0.35%	0.41%	0.39%	0.32%
UP 2	0.17%	0.23%	0.45%	0.49%	0.52%	0.37%
UP 3	0.18%	0.37%	0.46%	0.60%	0.64%	0.45%
UP 4	0.39%	0.41%	0.59%	0.63%	0.81%	0.57%
UP 5	0.54%	0.47%	0.60%	0.73%	0.76%	0.62%
UP 5 - UP 1	0.35%***	0.23%	0.25%*	0.32%**	0.37%***	0.30%**
	(2.98)	(1.43)	(1.82)	(2.39)	(3.81)	(2.49)
FH-9-Factor	0.24%**	0.23%	0.33%**	0.35%**	0.40%***	0.31%**
	(2.04)	(1.53)	(2.43)	(2.51)	(3.02)	(2.31)

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)	0.25%	0.34%**	0.29%*	–0.09%	–0.04%
	(1.26)	(2.04)	(1.67)	(–0.71)	(–0.16)
2	0.38%**	0.39%**	0.35%**	–0.01%	–0.03%
	(2.32)	(2.21)	(2.04)	(–0.06)	(–0.09)
3	0.45%	0.50%***	0.40%***	–0.05%	0.05%
	(3.67)	(3.65)	(3.57)	(–0.16)	(0.08)
4	0.57%	0.59%***	0.45%***	–0.02%	0.12%
	(5.56)	(5.24)	(5.01)	(–0.16)	(0.56)
5 (Highest)	0.76%	0.59%***	0.58%***	0.17%	0.18%
	(5.92)	(5.63)	(5.71)	(1.43)	(1.26)
5-1	0.51%***	0.25%*	0.29%*	0.26%**	0.22%*
	(3.46)	(1.75)	(1.82)	(2.14)	(1.82)
FH-9-Factor	0.42%***	0.31%**	0.34%**	0.20%*	0.17%
	(3.28)	(2.10)	(2.13)	(1.77)	(1.42)

Table 12: *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 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 (5) of Panel A) in times of positive / negative excess market returns, high (low) market volatility, and in subsamples in the period from 1996–2007 and 2008–2017. 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 (5) of Panel A. As the dependent variable we use the *t+1* and *t+2* excess returns, as well as the 2-month, 3-month, 6-month, and 12-month cumulative future excess returns. Our sample is the intersection of 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: 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	0.069***	0.036***	0.059***	0.035***	0.039***	0.022***
	(3.62)	(3.14)	(3.39)	(2.98)	(3.46)	(3.40)
Fund Firm Return		0.030		0.012	0.003	0.031***
		(1.02)		(0.55)	(0.15)	(3.16)
Size		–0.015		–0.043	–0.028	0.006
		(–0.44)		(–1.15)	(–0.82)	(0.39)
Age		–0.001		–0.001***	–0.002***	–0.001**
		(–0.91)		(–3.69)	(–4.79)	(–2.32)
Standard Deviation		0.073**		0.066**	0.063**	–0.009
		(2.45)		(2.24)	(2.33)	(–0.45)
Delta		0.009*		0.016***	0.013**	0.009*
		(1.75)		(3.04)	(2.43)	(1.79)
Management Fee			0.019	–0.033	–0.040	–0.028
			(0.18)	(–0.29)	(–0.35)	(–0.41)
Incentive Fee			–0.005	–0.014	–0.013	–0.002
			(–0.55)	(–1.44)	(–1.20)	(–0.38)
Minimum Investment			0.003*	0.002	0.002*	0.001
			(1.96)	(1.36)	(1.72)	(1.19)
Lockup Period			0.021	0.022	0.020	0.024
			(0.49)	(0.43)	(0.39)	(0.52)
Restriction Period			0.228*	0.144	0.187*	0.068
			(1.89)	(1.43)	(1.89)	(0.92)
Offshore			–0.088	–0.140**	–0.100	–0.078
			(–1.18)	(–2.01)	(–1.55)	(–1.38)
Leverage			0.035	0.076*	0.061	0.022
			(0.76)	(1.84)	(0.81)	(0.39)
HWM			0.024	0.116	0.125	0.081
			(0.20)	(0.81)	(0.90)	(1.13)
Hurdle Rate			–0.140	–0.164	–0.196	–0.101
			(–1.17)	(–1.54)	(–1.39)	(–1.18)
R^2					–0.267*	–0.145**
					(1.76)	(–2.56)
SDI					0.137	0.239***
					(1.64)	(3.33)
Constant	0.470***	0.312	0.423*	0.678**	0.354	0.282
	(4.31)	(1.32)	(1.79)	(2.18)	(1.42)	(1.60)
Observations	56,721	46,384	52,401	44,147	44,147	43,178
Adjusted R^2	0.016	0.168	0.103	0.247	0.286	0.207

Panel B: Alphas associated with UP in Different States of the World

	(1) *MKTRF*> 0	(2) *MKTRF* < 0	(3) High Market Volatility	(4) Low Market Volatility	(5) Subsample 1996 - 2007	(6) Subsample 2008 - 2017
UP	0.039***	0.038*	0.041*	0.034***	0.042**	0.035**
	(3.19)	(1.77)	(1.85)	(3.11)	(2.42)	(2.59)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,439	16,708	17,930	21,100	18,345	25,802
Adjusted R^2	0.277	0.300	0.318	0.258	0.313	0.254

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-month	(5) Fund Firm Return Cumulative 3-month	(6) Fund Firm Return Cumulative 6-month	(7) Fund Firm Return Cumulative 12-month
UP	0.039***	0.023**	0.021**	0.045**	0.093***	0.146***	0.254**
	(3.46)	(2.35)	(2.01)	(2.55)	(3.06)	(3.01)	(2.44)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,147	45,330	45,142	38,848	38,848	38,848	38,848
Adjusted R^2	0.286	0.295	0.289	0.280	0.285	0.282	0.277

Table 13: *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 monthly 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), apply the Sharpe ratio as performance measure in (4), apply the Treynor ratio as performance measure in (5), apply the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measure (MPPM) with risk aversion parameters of two and three as our performance measure in (6) and (7), estimate *UP* using a rolling horizon of 24 months in (8), use gross returns instead of net returns in the estimation of *UP* in (9), restrict our sample to hedge fund firms with an equity long-short strategy in (10), restrict our sample to hedge fund firms with only one fund in the analysis in (11), restrict our sample to hedge fund firms listed in the TASS database in (12), 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 (13), use the Getmansky, Lo, and Makarov (2004) methodology to unsmooth hedge fund returns in (14), account for another computation of the backfill bias as illustrated in Jorion and Schwarz (2019) in (15), and assign a delisting return of –1.61% to those hedge funds that leave the database as in Hodder, Jackwerth, and Kolokolova (2014) in (16). Panel A displays the results of from the same univariate portfolio sorts as in Panel B of Table 8 (column 3), risk-adjusted for 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 12 (column 6) of future performance in month *t+3* on *UP* and different fund firm characteristics measured in month *t*. Our sample is the intersection of 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. We only display the results of the relation between *UP* and future performance (control variables are included but suppressed in the table for the sake of brevity).

Panel A: Portfolio Sorts

	(1) Baseline	(2) 7-Factor Model	(3) 4-Factor Model	(4) Sharpe Ratio	(5) Treynor Ratio	(6) MPPM RA=2	(7) MPPM RA=3	(8) 24-month Estimation
5-1 *UP*	0.62%***	0.56%***	0.61***	0.49%***	0.54%***	0.39%**	0.38%**	0.53***
	(4.47)	(4.12)	(4.26)	(3.51)	(3.75)	(2.49)	(2.37)	(3.98)

	(9) Gross Returns	(10) Long-Short Equity	(11) Single Fund	(12) TASS Funds	(13) Funds with similar Leverage	(14) Return Smoothing	(15) Backfill Bias	(16) Delisting Return
5-1 *UP*	0.60%***	0.56%***	0.45%***	0.52%***	0.61%***	0.43%***	0.47%***	0.63%***
	(4.21)	(4.83)	(3.03)	(3.58)	(4.01)	(2.96)	(3.56)	(4.49)

Panel B: Fama-MacBeth Regressions

	(1) Baseline	(2) 7-Factor Model	(3) 4-Factor Model	(4) Sharpe Ratio	(5) Treynor Ratio	(6) MPPM RA=2	(7) MPPM RA=3	(8) 24-month Estimation
UP	0.039***	0.034***	0.038***	0.013***	0.092***	0.027**	0.024**	0.031***
	(3.46)	(3.01)	(3.22)	(3.17)	(3.25)	(2.45)	(2.32)	(2.83)

	(9) Gross Returns	(10) Long-Short Equity	(11) Single Fund	(12) TASS Funds	(13) Funds with similar Leverage	(14) Return Smoothing	(15) Backfill Bias	(16) Delisting Return
UP	0.040***	0.027**	0.027**	0.034***	0.040***	0.028**	0.028**	0.039***
	(3.89)	(2.45)	(2.39)	(3.06)	(3.88)	(2.31)	(2.28)	(3.49)

Table 14: *UP* and Hedge Fund Firm Performance: Persistence Analysis and Fund Firm Flows

Panel A of this table reports the results of Fama and MacBeth (1973) regressions of (1) *UP* in month *t+1* on *UP* in month *t*, (2) *Fund Firm Performance* in month *t+1* on *Fund Firm Performance* in month *t,* and (3) *Equity PF Performance* in month *t+1* on *UP* in month *t*. We also display differences in coefficient estimates between *UP* and *Fund Firm Performance*, as well as *UP* and *Equity PF Performance* in columns (4) and (5). Panel B of 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), *Fund Firm Performance* in year *t* (column 2), *Equity PF Performance* in year *t* (column 3), and all three variables simultaneously (column 4). As fund firm characteristics, we include a fund firm's monthly return, 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, the R^2 measure of Titman and Tiu (2011), and the *SDI* measure of Sun, Wang, and Zheng (2012), all measured in year *t*. 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 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: Persistence Analysis

	(1) UP *t+1*	(2) Fund Firm Performance *t+1*	(3) Equity PF Performance *t+1*	(4) Difference	(5) Difference
UP(t)	0.161*** (13.21)				
Fund Firm Performance(t)		0.102*** (10.55)			
Equity PF Performance (t)			0.0543*** (5.35)		
UP – Fund Performance				+0.059*** (4.92)	
UP – Equity PF Performance					+0.107*** (8.90)
Observations	57,482	57,482	57,482		
Adjusted R^2	0.046	0.040	0.035		

Panel B: Fund Firm Flows as well as UP, Fund Firm Performance, and Equity PF Performance

	(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	0.206			–1.004
	(1.40)			(–1.30)
Fund Firm Performance		0.960***		1.811***
		(7.45)		(4.23)
Equity PF Performance			0.543*	–0.711
			(1.79)	(–1.28)
Size	–7.383***	–7.642***	–7.467***	–7.209***
	(–4.40)	(–4.98)	(–5.19)	(–4.95)
Age	–0.116***	–0.099***	–0.119***	–0.093***
	(–4.61)	(–3.62)	(–4.21)	(–2.97)
Standard Deviation	–1.590***	–1.985***	–1.884***	–1.405**
	(–3.85)	(–3.32)	(–3.74)	(–2.75)
Delta	0.726**	0.485*	0.715**	0.744*
	(2.15)	(1.70)	(2.15)	(1.79)
Management Fee	2.495	4.872*	5.901	4.870
	(0.75)	(1.84)	(1.37)	(1.15)
Incentive Fee	–0.410	–0.205	–0.450	–0.418
	(–1.02)	(–0.50)	(–1.22)	(–0.99)
Minimum Investment	0.098**	0.132*	0.076	0.039
	(2.35)	(2.68)	(1.16)	(0.65)
Lockup Period	1.659	2.657	3.059	2.758
	(0.48)	(1.16)	(0.95)	(0.83)
Restriction Period	0.148	–5.256*	–3.802	–3.752
	(0.04)	(–1.73)	(–1.10)	(–1.08)
Offshore	6.469	4.769	4.527	7.323
	(0.70)	(0.65)	(0.51)	(0.76)
Leverage	–1.990	–0.450	–0.878	–2.327
	(–0.71)	(–0.17)	(–0.30)	(–0.91)
HWM	–4.318	–6.730	–3.847	–3.476
	(–0.77)	(–1.45)	(–0.81)	(–0.73)
Hurdle Rate	9.929	8.939	11.71	11.90
	(1.05)	(1.09)	(1.23)	(1.17)
R^2	10.12	14.47	3.752	9.146
	(1.34)	(1.36)	(0.50)	(1.31)
SDI	4.087	3.845	1.176	–0.0774
	(0.65)	(0.86)	(0.20)	(–0.01)
Constant	49.16***	42.84***	53.05***	44.15***
	(3.44)	(3.01)	(3.68)	(2.93)
Observations	4,404	4,404	4,404	4,404
Adjusted R^2	0.163	0.175	0.173	0.198

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