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Only Winners in Tough Times Repeat:
Hedge Fund Performance Persistence over Different Market Conditions

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Abstract

We provide novel evidence that hedge fund performance is persistent following weak hedge fund markets, but is not persistent following strong markets. Specifically, we construct two performance measures, *DownsideReturns* and *UpsideReturns*, conditioned on the level of overall hedge fund sector returns. After adjusting for risks, funds in the highest *DownsideReturns* quintile outperform funds in the lowest quintile by about 7% in the subsequent year, whereas funds with better *UpsideReturns* do not outperform subsequently. The *DownsideReturns* can predict future fund performance over a horizon as long as 3 years, for both winners and losers, and for funds with few share restrictions.

JEL classification: G10, G23
Key words: Hedge funds, Conditional performance, Performance persistence

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Hedge Fund Performance Persistence over Different Market Conditions

Abstract

We provide novel evidence that hedge fund performance is persistent following weak hedge fund markets, but is not persistent following strong markets. Specifically, we construct two performance measures, *DownsideReturns* and *UpsideReturns*, conditioned on the level of overall hedge fund sector returns. After adjusting for risks, funds in the highest *DownsideReturns* quintile outperform funds in the lowest quintile by about 7% in the subsequent year, whereas funds with better *UpsideReturns* do not outperform subsequently. The *DownsideReturns* can predict future fund performance over a horizon as long as 3 years, for both winners and losers, and for funds with few share restrictions.

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Hedge fund investors pay high fees for superior investment performance. As investment skills are unobservable, most investors evaluate fund managers based on their past performance. Does the track record of a hedge fund manager reliably forecast future fund performance? This pressing question has been examined by many academic studies, but with mixed findings.[1] The previous studies almost exclusively focus on *unconditional* predictability. In this paper, we center our attention on *conditional* predictability and investigate whether performance persistence varies with the overall hedge fund market conditions. We document strong evidence that hedge fund performance persists following weak markets but *does not* persist following strong markets.

Previous literature suggests that market conditions may affect properties of underlying assets, investment strategies of fund managers, as well as allocation decisions of investors, all of which could affect fund performance and its persistence. For instance, Kacperczyk et al. (2013b) find that mutual fund managers exhibit more stock picking ability in booms and more market timing ability in recessions, based on which they propose a new performance measure to capture time variations in investment skills. Glode et al. (2012) find that mutual fund returns are predictable after periods of high market returns but not after periods of low market returns. Motivated by Berk and Green's (2004) theoretical framework, where investors' learning about fund managers' heterogeneous skills leads to efficient capital allocation and eventually drives away performance persistence, Glode et al. attribute the finding to more unsophisticated investors entering into mutual funds during the up market, hence resulting in less competitive capital allocation.

Our paper is the first to examine time-varying performance predictability among hedge funds. Hedge funds are known to differ from mutual funds in many aspects such as manager incentives, strategies and the scope of investments, as well as investor sophistication. For example, hedge funds are much less restricted in terms of short selling, leverage, liquidity, and accessible asset classes, which could lead to much more versatile strategies than mutual funds. Also, hedge fund investors are mainly institutional investors and high net worth investors who are likely to be sophisticated. Therefore, the findings in the mutual fund setting do not necessarily carry through to the hedge fund setting.

[1] See, for example, Brown, Goetzmann, and Ibbotson (1999) and Liang (2000). Previous findings on hedge fund performance persistence will be discussed in details in the later part of Introduction.

To understand why market conditions may matter for hedge fund performance persistence, let's first consider a scenario under which fund performance is determined jointly by investment skills and luck. It is likely that fund performance may reveal investment skills to varying extents over different market conditions, possibly in part due to increasing difficulty for mediocre managers to mimic the skilled ones during down markets.[2] In addition, skilled managers may have incentives to herd with the mediocre to ride the bubble in up market.[3] As such, performance over the *down* markets may be more informative about the underlying skills and hence better predict future performance. On the other hand, alternative mechanisms may lead to higher information content in performance about skills over *up* markets. For instance, if unsophisticated investors tend to enter financial markets in bull markets,[4] then strong market may provide more opportunities for skilled hedge fund managers to exploit mistakes made by unsophisticated investors in the underlying security market. Finally, performance persistence may also be affected by investor cash flow as discussed in Berk and Green (2004). To the extent that cash flow patterns differ in *up* and *down* markets, we may observe different patterns of performance persistence.

In light of the arguments above, whether and how hedge fund performance persistence varies with market conditions, ultimately, is an empirical question. In this study, we examine performance persistence conditioning on the overall state of the hedge fund sector.[5] Specifically, we construct two conditional performance measures, *DownsideReturns* and *UpsideReturns,* which are based on time-series average returns of individual funds conditioning on whether the overall hedge fund sector return is below or above its historical median.

[2] For instance, Jiang and Kelly (2013) show that in bull markets mediocre fund managers are able to generate great returns and appear skillful by simply following a put-writing strategy. However they would suffer significant losses following this strategy during market downturns. Another example is related to strategies involving leverage, a tool often employed by hedge funds to amplify performance. Leverage tends to be more difficult and costly to obtain during market turbulence, therefore making it harder for unskillful managers to generate good returns.
[3] For instance, Brunnermeier and Nagel (2004) show that skilled managers for equity hedge funds chose to herd with the unsophisticated investors during the bubble building period, but differentiated themselves from the rest of the market participants by reducing their positions in the technology stocks when the markets were about to decline.
[4] See Grinblatt and Keloharju(2001), Lamont and Thaler(2003), Brunnermeier and Nagel (2004), and Cooper, Gutierrez, and Hameed (2004).
[5] Alternative ways of defining market states are discussed in Section 2.1

Our main test concerns the relation between the *DownsideReturns* (*UpsideReturns)* and future fund performance. Our fund performance evaluation metrics include: Fung-Hsieh seven-factor alpha (Fung and Hsieh, 2001), appraisal ratio, and Sharpe ratio. We find that funds with better *DownsideReturns* significantly outperform their peers in all performance metrics over the next three months to three years. The performance predictability comes from both losing and winning sides, and even for funds with few share restrictions. In contrast, funds with better *UpsideReturns* do not outperform subsequently. This finding is robust under both portfolio sorting and regression settings, withstands controls for fund characteristic and styles. Our results suggest that only winners in *down* markets repeat, thus focusing on past *DownsideReturns* could allow investors to better select hedge funds than using unconditional historical returns.

To shed light on why *DownsideReturns* better predicts future hedge fund performance, we investigate whether this measure better reflect underlying managerial skills. First, we find that funds with high *DownsideReturns* outperform their low *DownsideReturns* peers in both subsequent *down* and *up* markets, suggesting that *DownsideReturns* may capture general abilities of fund managers rather than particular strategies that work well only in certain market conditions. Second, we examine funds' tendency to load up on unconventional and less known risk factors, such as tail risk, and document a strong positive (negative) correlation between *UpsideReturns* (*DownsideReturns*) and exposures to such risks. This suggests that *DownsideReturn* may be less contaminated by risk exposures unaccounted for by existing risk models. Third, we relate conditional performance measures to various hedge fund skill proxies proposed by the literature, including hedging ability (Titman and Tiu, 2011), strategy innovation skills (Sun, Wang and Zheng, 2012), market liquidity timing skills (Cao, Chen, Liang and Lo, 2013), and market return timing skills (Chen and Liang, 2007). We find that *DownsideReturns* are generally positively associated with the aforementioned skill measures, whereas *UpsideReturns* are negatively associated with them. Overall, the findings are consistent with performance amid market weakness being more informative about skills, and hence better predicting future performance.

We also examine whether the performance persistence amid market weakness can be attributed to investors' lack of attention to past performance in the *down* market. We compare the flow-performance sensitivity over the *down* and *up* markets. Consistent with the prior literature, we find that flows actively chase past performance under both market conditions. Interestingly though, flows react more strongly to past performance during *down* market than *up* market. This finding is inconsistent with investors' lack of attention as a driving force for the strong performance persistence amid market weakness.

Our paper makes three contributions. First, it contributes to the literature on performance persistence among hedge funds. While several studies have examined this question, the mixed findings lead to an intensifying debate (Brown, Goetzmann, and Ibbotson, 1999; Liang, 2000; Agarwal and Naik 2000; Kosowski, Naik and Teo, 2007; Jagannathan, Malakhov and Novikov, 2010; Fung, Hsieh, Naik and Ramadorai, 2008, Joenvaara, Kosowski and Tolonen, 2014). The lack of consensus on performance persistence casts doubt on the existence of skill and the value of active management. Our paper is the first to link hedge fund performance persistence to the variations of hedge fund market conditions. We show that by using a conditional past performance measure to focus on time periods when information-to-noise ratio is high, we can obtain a much stronger performance forecasting power.

Second, our paper contributes to the literature that examines time-varying asset return and fund performance predictability conditioning on market situations, including Ferson and Schadt (1996), Moskowitz (2000), Cooper, Gutierrez and Hameed (2004), Fung, Hsieh, Naik, and Ramadorai (2008), Glode (2011), Kosowski (2011), Kacperczyk, Van Nieuwerburgh, and Veldkamp (2013a, b), De Souza and Lynch (2012), Glode, Hollifield, Kacperczyk, and Kogan (2012). In particular, Cooper, Gutierrez and Hameed (2004) and Glode, Hollifield, Kacperczyk, and Kogan (2012) study return persistence for stocks and mutual funds, respectively, and find stronger persistence following periods of strong markets. Our finding that hedge fund performance persistence is stronger in *down* markets suggests that the mechanism underlying performance persistence for hedge funds might be distinct from those for stocks and mutual funds.

Finally, our paper contributes to an emerging literature on identifying measures that predict cross-sectional hedge fund performance (Chen and Liang, 2007; Titman and Tiu, 2011; Sun, Wang and Zheng, 2012; Cao, Chen, Liang and Lo, 2013). Rather than focusing on a specific type of skill, our paper highlights the importance of incorporating aggregate market conditions in detecting managerial skills. We show that the conditional performance measure has strong performance forecasting power that is distinct from the existing skill measures.

1. **Data and Fund Performance Evaluation Metrics**

The hedge fund data are from the Lipper TASS database, one of the leading sources of hedge fund information. The main data include monthly hedge fund returns, as well as fund characteristics. We start with a total of 19,963 live and graveyard funds that exist between 1994 and 2014. Following Aragon (2007), we filter out non-monthly filing funds, funds denoted in a currency other than U.S. dollars, and funds with unknown strategies, which results in 10,695 unique funds. To control for backfill bias, we further exclude the first 18 months of returns for each fund, yielding 9,413 unique funds.[6] Another potential problem of hedge fund dataset is survivorship bias. In the internet appendix, we provide a detailed analysis on the drop-out rates of hedge funds, and show that our results are not driven by the survivorship bias.

TASS classifies hedge funds into 11 self-reported style categories including convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity hedge, managed futures, multi-strategies, and fund-of-funds. Long/short equity hedge and fund-of-funds categories each account for one third of the sample. There are about 50 funds in the dedicated short bias category[7]. The rest of the sample is relatively evenly distributed across the remaining hedge fund categories

The abnormal performance of a hedge fund is evaluated relative to certain benchmarks. Given the wide use of derivatives and dynamic trading strategies among hedge funds, we consider a few performance benchmarks to capture the risk-return tradeoff. For our main results, we use the Fung and Hsieh (FH) seven-factor model (Fung and Hsieh, 2001),[8] which includes an equity market factor, a size spread factor, a bond market factor, a credit spread factor, and trend-following factors for bonds, currency, and commodities. In an unreported analysis, we also augment the FH seven-factor model with a Pastor-Stambaugh market liquidity risk factor, and the results remain similar.

[6] We also consider an alternative approach to controlling for backfill bias by removing returns before a fund joins the TASS database, following Aggarwal and Jorion (2009). The results are reported in the internet appendix.
[7] Due to the small sample size, we exclude the dedicated short bias category in Section (6.2): within-style analysis.
[8] http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

In addition, we use a modified version of Treynor and Black's appraisal ratio (1973), which is calculated as the ratio between the mean of the monthly abnormal returns and their standard deviation. The use of the alpha scaled by idiosyncratic risk can mitigate potential survivorship bias, arising from discrepancy between the ex-post observed mean and the ex-ante expected return (Brown, Goetzmann, and Ross, 1995). This measure is also shown by Agarwal and Naik (2000) to be particularly relevant for hedge funds, as it also accounts for differences in leverage across funds.

We also use monthly Sharpe ratio to capture the risk-return tradeoff of hedge fund performance. It is defined as the ratio between the average monthly net fee returns in excess of the risk-free rate and the volatility in the monthly excess returns. To control for illiquidity and smoothing in hedge fund returns, for our main tests, we follow Getmansky, Lo, and Makarov (2004) and construct the smoothing-adjusted Sharpe ratio. Details of the adjustment are provided in the internet appendix.

2. Conditional Performance Measures: ***DownsideReturns*** and ***UpsideReturns***

2.1 Defining Up- and Down-market

The goal of this study is to investigate whether hedge fund performance persistence varies with the states of the market. To determine the states of the market, we compare the overall hedge fund market return with its historical median. We measure the overall hedge fund market return using TASS Dow Jones Credit Suisse Hedge Fund index, a value-weighted average return of its constituents. Specifically, a month is considered as *down* (*up*) if the overall hedge fund sector's return during that month is below (above) its historical median level based on data from 1994 until that time point.

Arguably, one could define market states using alternative ways. One plausible benchmark is the specific hedge fund style performance. This approach would make sense if returns and flows of different strategies were relatively independent of each other, and if funds' styles are representative of their strategies. Boyson, Stahel and Stulz (2010) document an excessive return comovement among funds of different styles. In unreported tests, we also find that fund returns and cash flows respond not only to their own style returns but also to other style returns substantially. These, taken together, highlight the importance of using the broad sector performance to capture market conditions for hedge funds. Indeed, when we repeat our analyses using style returns to define market states in Section 6.3, our findings remain significant but a little weaker, likely due to the aforementioned reasons.

Another plausible benchmark to define market states is the equity market return, which is relevant for equity oriented funds but not for others such as fixed-income and managed future funds. This benchmark also faces the same limitation as the individual style if funds use mixed strategies. In Section 6.3, we repeat the main analysis for a subsample of equity focused funds using equity market returns as our benchmark. Our findings remain similar.

2.2 Quantifying Hedge Fund DownsideReturns and UpsideReturns

At the beginning of each period, for each fund i, we construct two conditional performance measures — *DownsideReturns* and *UpsideReturns*, based on time-series average of fund returns over the most recent 12 *down* (or *up*) months:

$$DownsideReturns_i = \frac{1}{12}\sum_{downmon=1}^{12} r_{i,downmon} \tag{1}$$

$$UpsideReturns_i = \frac{1}{12}\sum_{upmon=1}^{12} r_{i,upmon} \tag{2}$$

where $r_{i,downmon}$ ($r_{i,upmon}$) is the return of fund i over down (up) months. [9]

The number of *down (up)* months and the length of construction window are chosen to strike a balance between minimizing estimation errors and mitigating the survivorship bias. We also calculate *DownsideReturns (UpsideReturns)* under various alternative specifications, as discussed in Section 6.3. Also note that average returns instead of average alphas are used to construct *DownsideReturns (UpsideReturns)* to avoid the potential correlated-measurement-error problem between the performance construction and evaluation periods (Carhart, 1997): If the particular factor model used in calculating alphas is mis-specified, the measurement errors in alphas are likely to be positively serially correlated, leading to spurious performance persistence.

[9] We require the 12 *up* or *down* months occur within the past 3 years. In cases that we have less than 12 *up* or *down* months within the past 3 years, we require at least 6 such months to include the fund in the calculation.

2.3 Properties of DownsideReturns and *UpsideReturns*

Panel A of Table 1 reports the time-series averages of the cross-sectional summary statistics of the main variables. There is a large variation in *DownsideReturns* and *UpsideReturns* across funds. The *DownsideReturns* measure has a mean (median) of -0.47% (-0.31%) per month, with a standard deviation of 2.62%; whereas the *UpsideReturns* measure has a mean (median) of 2.16% (1.73%) per month, with a standard deviation of 1.96%. In an unreported histogram analysis, we find that the *DownsideReturns*(*UpsideReturns*) measure is titled to the left (right), consistent with most funds performing poorly (well) when the overall hedge fund markets are weak (strong); In addition, the proportion of the live and graveyard funds remains stable across bins for both *DownsideReturns* and *UpsideReturns*, which suggests that findings on the relation between the *DownsideReturns (UpsideReturns)* and fund performance are unlikely driven by the difference between live and graveyard funds. Moreover, we find that the distribution of the conditional performance measures is similar across different hedge fund styles, suggesting that the difference in these conditional performance measures is not driven by style difference.

To better understand how *DownsideReturns* and *UpsideReturns* vary across funds with different characteristics, we report the time-series average of the pair-wise correlations between the conditional performance measures and contemporaneous fund characteristics. Panel B of Table 1 yields several noteworthy points. First, *DownsideReturns* are negatively correlated with *UpsideReturns.* Second, the *DownsideReturns* measure appears to be positively associated with fund performance metrics measured by alpha, appraisal ratio, and Sharpe ratio, whereas the correlations between *UpsideReturns* and performance metrics are mixed and more subdued. Third, fund return volatility (*Vol*) is negatively correlated with *DownsideReturns*, but positively correlated with *UpsideReturns*. [10]

[10] The aforementioned correlations are statistically significant. *t-statistics* of the correlations are available upon request.

3. **Predicting Performance by *DownsideReturns* and *UpsideReturns***

In this section, we investigate whether *DownsideReturns* and *UpsideReturns* help predict future fund performance, using both portfolio sorting and multivariate regression approaches.

3.1 Portfolio Sorting

To gauge the future performance of funds with different *DownsideReturns (UpsideReturns)* levels, we sort all hedge funds at the beginning of each quarter into quintile portfolios based on the conditional performance measures over the most recent 12 *down* (*up*) months. For each quintile portfolio, we compute the equal- and value-weighted average buy-and-hold performance levels for the subsequent three months to three years.[11] The corresponding *t*-statistics are adjusted for heteroscedasticity and autocorrelation. Note that the equally-weighted portfolios also include funds where AUMs are missing, while value-weighted ones consist of all funds as long as we can fill in for missing AUMs using the latest available AUMs and interim returns under a zero net-flow assumption.

We consider various performance measures for each quintile portfolio. To calculate monthly alpha for each fund, we estimate Fung Hsieh seven factor loadings using a rolling window of the prior 24 months. We then calculate the average monthly alpha over the subsequent holding-period for the fund, and finally average across funds within each quintile to derive the corresponding portfolio alphas. The appraisal ratio for each fund is calculated as the ratio between the mean and the corresponding standard deviation of its monthly FH seven-factor alphas over the holding period. The smoothing-adjusted Sharpe ratio is calculated in a similar way using the monthly net fee returns in excess of the risk-free rate, as detailed in the Appendix 3.[12] We then take the average across funds within each portfolio to derive the appraisal ratio and the Sharpe ratio of the quintile portfolios.

Results for the equally weighted portfolios are presented in Table 2. Panel A summarizes the time-series averages of the performance metrics for each quintile portfolio sorted on *DownsideReturns*, as well as the differences between the high and low-*DownsideReturns* portfolios.

[11] To increase the statistical power of the test, we consider quarterly overlapping trading strategies for holding horizons beyond three months. In unreported analysis where non-overlapped portfolio rebalancing and trading strategies are employed, we obtain qualitatively similar results.
[12] Results based on the raw Sharpe ratios yield similar findings and are available upon request.

The FH seven-factor alphas increase monotonically with the past *DownsideReturns* measure, for both short- and long-term holding periods. Funds in the highest *DownsideReturns* quintile portfolio continue to earn an average monthly alpha of 0.67% over the next quarter, with a *t*-statistic of 7.88. Those in the lowest *DownsideReturns* quintile yield a much smaller and insignificant return of -0.04% per month.[13] The performance difference between the top and bottom quintiles is 0.71% per month (*t-statistics*=3.89), significant both statistically and economically.

It has been documented that while the average historical hedge fund performance can predict alphas over a quarter, the predictability disappears over longer horizons (See Brown, Goetzmann, and Ibootson, 1999; Liang, 1999; Agarwal and Naik, 2000). The lack of longer-term performance predictability significantly reduces the practical value of historical return information, since hedge fund investors often face trading restrictions such as lock-up periods and redemption notice periods, hence unable to get in and out of a hedge fund timely and frequently. The *DownsideReturns* measure, on the other hand, predicts alphas up to the next 3 years. Moreover, the performance persistence comes from both winner and loser ends. Funds in high *DownsideReturn* quintile outperform those in the middle quintile, and funds in the low quintile underperform the middle quintile.

For the equally- weighted portfolios, the appraisal ratio increases almost monotonically with *DownsideReturns*. The difference between the top- and bottom-*DownsideReturns* portfolios is 0.71 with a *t*-statistic of 11.24 for a holding horizon of three months. When the holding horizon is extended to one year, the difference in the appraisal ratio between the high- and low-*DownsideReturns* portfolios decreases but still remains highly significant at a level of 0.22 with a *t*-statistic of 10.36. The Sharpe ratio of the equally-weighted portfolio also exhibits a similar pattern, increasing almost monotonically from the lowest *DownsideReturns* quintile to the highest one.

Value-weighted portfolio analyses yield similar results, shown in the internet appendix, suggesting that the return predictability of *DownsideReturns* is not confined to small funds in our sample.

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[13] The generally positive Fung-Hsieh seven-factor alphas across quintile portfolios are consistent with the existing literature that documents positive risk-adjusted performance by hedge funds on average. For instance, our sample funds on average offer an annualized Fung-Hsieh alpha of 4.44%, comparable to findings in other studies (e.g., 5.2% as in Joenvaara, Kosowski, Tolonen, (2014), and 5.04% in Kosowski, Naik, and Teo (2007)).

Similar portfolio analyses were repeated based on the lagged *UpsideReturns,* and the results are shown in Panel B of Table 2. In contrast to Panel A of Table 2, we find no significant difference in future alphas and Sharpe ratios between the high and low *UpsideReturns* quintile portfolios, not even at a quarterly horizon. The future appraisal ratio of the high *UpsideReturns* portfolio is even lower than that of the low *UpsideReturns* portfolio. This may potentially be due to some fund managers taking on high idiosyncratic risk or engaging in leveraged trading on strategies that only work temporarily during *up* markets.

3.2 Multivariate Predictive Regression Analyses

The quintile portfolio analysis does not control for hedge fund characteristics that are known to affect future performance. For example, managers with better downside performance may be offered different incentive contracts. Therefore, our finding of a positive association between the *DownsideReturns* measure and future fund performance may be driven by other underlying fund characteristics. To address this issue, we extend our performance predicting analysis using a multivariate regression approach, which can help differentiate alternative explanations by simultaneously controlling for these factors.

To investigate whether the *DownsideReturns (UpsideReturns)* measure has predictive power for future fund performance after controlling for other fund-specific characteristics, we estimate the following regression:

$$AbnormalPerformance_{i,t} = c_{0i} + c_{1i} DownsideReturns(UpsideReturns)_{i,t-1} + C_{2i} Controls_{i,t-1} + e_{i,t}, \quad (3)$$

where $AbnormalPerformance_{i,t}$ is the risk-adjusted fund performance over the subsequent quarter following the construction of the *DownsideReturns(UpsideReturns)* measure. Specifically, we consider the (annualized) alpha, the corresponding appraisal ratio, and the smoothing-adjusted Sharpe ratio.

We use lagged control variables to mitigate potential endogeneity problems. The $Controls_{i,t-1}$ consist of performance volatility, measured as the volatility of prior 24-month fund returns in percent (*Vol*); the length of redemption notice period, measured in units of 30 days; lockup months; indicator variables for whether personal capital is committed and whether there is a high-water mark requirement; management fees; incentive fees; ages of the funds in years; the natural logarithm of AUM; flows into funds within the last year as a percentage of AUM; average returns over the previous 24-month period; minimum investments requirement; and an indicator variable for use of leverage. These variables are suggested by the existing literature on hedge fund characteristics and performance.

Also note that 30% of observations in TASS have missing AUMs, which is consistent with the findings in Joenväärä, Kosowski, and Tolonen (2014). This data limitation could potentially introduce a selection bias. To address this concern, in an unreported result, we find that funds with missing AUMs have similar performance, *DownsideReturns* and *UpsideReturns* as the ones with non-missing AUMs, suggesting that our finding of performance predicting power by *DownsideReturns* is unlikely induced by missing AUMs. To further ensure that our results are not driven by the subset of funds with non-missing AUMs, for funds with missing AUM, we set its AUM to one (i.e. ln(AUM)=0), and we also include an indicator variable in the regressor set that takes a value of 1 if the AUM is missing and 0 otherwise. This allows us to include observations with missing AUMs without distorting the coefficient estimate of ln(AUM).

To estimate Equation (3), we use time-series and cross-sectional unbalanced panel data. We adopt a panel regression approach that adjusts for both fund-clustering and time and style fixed effects. As a robustness check, we also use Fama-MacBeth cross-sectional analysis with style fixed effects, and the Newey-West heteroscedasticity and autocorrelation adjustment (HAC).

The panel regression results are reported in Tables 3. Panel A shows that for the future alpha regression, the estimated coefficient for the *DownsideReturns* is 1.86 with a *t*-statistic of 17.50. This implies that a one-standard-deviation increase in the *DownsideReturns* predicts an increase in the annualized FH seven-factor returns of 4.87% (=2.62×1.86%) in the subsequent quarter in the presence of a host of control variables. The signs of the coefficients for other fund characteristics are largely consistent with the existing literature. For example, the length of the redemption notice period is significantly and positively associated with future fund performance. This corroborates the findings in Aragon (2007) and Liang and Park (2008) that funds with more stringent share-restriction clauses offer higher returns to compensate for illiquidity. The high-water mark dummy variable and minimum investment requirement are significantly and positively related to future alpha, consistent with findings presented by Agarwal, Daniel, and Naik (2009), in which hedge funds are found to outperform when managers are better incentivized and monitored. We also utilize the appraisal ratio and smoothing-adjusted Sharpe ratio as alternative performance measures. The results, again, indicate a strong positive association between the *DownsideReturns* and the future performance metrics.[14]

Note that the association between *DownsideReturns* and future performance metrics holds regardless of the inclusion of the unconditional average past returns (*AvgPast2YRet*) in the regressor set, both directionally and magnitude wise. In contrast, results on the performance predicting power by unconditional past returns appear mixed.

Panel B reveals an insignificant association between *UpsideReturns* and future fund alphas. This is consistent with that *UpsideReturns* may reflect luck rather than skills. The coefficient of the *UpsideReturns* turns significantly negative after controlling for the unconditional average performance measure in the alpha regression. Since the unconditional past return can be considered approximately as the average of upside and downside returns, the finding is consistent with portfolio sorting results that only winners in *down* markets repeat. We also find that *UpsideReturns* are negatively associated with future appraisal ratios and Sharpe ratios, consistent with the portfolio sorting results.

Moreover, we conduct Fama-MacBeth cross-sectional regression of Equation (3). Results, shown in the internet appendix, are largely consistent with those from the panel regression and the portfolio analyses.

[14] We exclude lagged volatility from the regressor set for the appraisal ratio and the smoothing-adjusted Sharpe ratio. As both ratios are already scaled by volatility of alphas or excess returns, further regressing these variables on another return volatility measure may cause a mechanical, negative link between them. Nevertheless, our main results on the positive association between the *DownsideReturns* and performance measures remain the same, regardless of the regression specification.

3.3 Predictability in Future Up and Down Markets

Is the strong performance predictability by *DownsideReturns* mainly driven by certain strategies that are likely to outperform only amid market weakness?[15] Or does *DownsideReturns* reflect general ability of hedge fund managers that may lead to outperformance regardless of future market conditions? To answer these questions, we examine performance predictability by the conditional performance measures in future *down* and *up* markets separately. [16] The results are summarized in Table 4. Panels A and B show that funds with high past *DownsideReturns* continue to outperform their low *DownsideReturns* peers not only in future *down* markets, but also in future *up* markets based on alphas and Appraisal ratios. In contrast, as shown in Panels C and D, funds with high past *UpsideReturns* underperform their peers in future *down* markets and show mixed results in future *up* markets based on different performance measures. The generally positive association of *DownsideReturns* with future performance over both *up* and *down* markets suggests that the downside performance measure is likely capturing some general managerial skills that can be utilized under various market conditions.

4. Source of Performance Persistence: Managerial Skills?

Given the evidence of performance predicting power of the *DownsideReturns* measure, a natural question arises as to what drives performance persistence following periods of relative market weakness. One possibility is that the *DownsideReturns* measure better reveals the underlying hedge fund managerial skills.

A hedge fund's abnormal performance, measured based on a certain benchmark, can be driven by true skills of managers or exposures to systematic risk missed by the benchmark. It is possible that unskilled managers may try to mimic skilled ones by simply loading up on less-known risks that are not adequately accounted for by the existing risk benchmark. If the realized premium to the

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[15] For example, if funds adopt a portfolio insurance strategy by buying index put options, they are likely to perform better when the market goes down. However the insurance premium will dilute their performance, leading to lower performance in an up market.

[16] Separately examining the performance predictability for future *down* and *up* market also serves to test a potential alternative hypothesis rooted in time-varying market exposures. Suppose that hedge funds choose to reduce market exposures after experiencing low *DownsideReturns*, this may lead to low future returns, should the market rebound. If our rolling window estimation cannot fully account for such time-varying market exposure, such funds will also show low estimated alphas. Under this hypothesis, funds with low *DownsideReturns* will underperform their peers in future *up* market. This hypothesis, however, cannot explain why such funds continue to underperform in future *down* market.

unidentified risk factor is positive, the mimicking strategy may lead to higher abnormal returns, hence making the unskilled managers appear skillful. Furthermore, if the premium of the unidentified factor is higher when the overall hedge fund market is doing well, the *UpsideReturns* measure may be more distorted by unidentified risk exposure, making it a less reliable indicator of managerial skills.

To examine the potential effect of missing risk factors on predictive power of *DownsideReturns* and *UpsideReturns*, one needs to identify types of risks that may be omitted by standard risk models, yet commonly taken by hedge funds. One prominent example is tail risk, which is shown by Jiang and Kelly (2013) to help explain hedge fund performance. An unskilled hedge fund manager can load up on tail risk by simply writing out-of-money put options, which may lead to superior performance in up market states. This implies a higher correlation between fund returns in the up market and tail risk exposure.

In Table 5, we compare correlations of *UpsideReturns* and *DownsideReturns* with the tail risk beta. We use two proxies for tail risk, both of which are directly related to the premium from writing put options. The first is the Chicago Board Options Exchange (CBOE) VVIX index. VVIX index represents a model-free, risk-neutral measure of the volatility of volatility that is implied by the VIX options. Park (2014) shows that the VVIX index has forecasting power for future tail-risk hedging returns. VVIX, however, is only available from year 2007. Therefore, we adopt a second proxy, the fear index proposed by Bollerslev and Todorov (2011), from 1996 to 2006. We estimate the loadings on the tail risk factors for each hedge fund using a 24-month rolling regression, controlling for funds' exposure to the Fung-Hsieh seven factors. We then examine the correlation of the *UpsideReturns* and *DownsideReturns* with the tail risk betas. Shown in Table 5, for both tail risk measures, *UpsideReturns* is positively and significantly correlated with tail risk beta, confirming our conjecture of unskilled managers boosting their performance by simply loading on tail risk. In contrast, the *DownsideReturns* is negatively correlated with the tail risk beta, suggesting that the performance during *down* market may be less contaminated by tail risk exposures.[17]

[17] Jiang and Kelly (2013) show that hedge funds with high exposure to tail risks tend to lose value during crisis period. This is consistent with our finding that funds with high *UpsideReturns* tend to have high tail-risk exposure and perform worse in future down market (Panel C of Table 4). Also, given their finding that hedge funds earn a positive premium on average for bearing tail-risk, our results suggest that funds with high *UpsideReturns* tend to earn even lower alphas after accounting for the tail-risk.

Of course, tail risk is only one example of risks taken by unskilled managers that have not been fully accounted for by the existing risk models. As econometricians, it may be hard to pin down all possible risks taken by hedge funds. Therefore, to examine whether missing factors may affect the predictive power of *DownsideReturns* and *UpsideReturns* to different extents, we use hedge fund style return as a "catch-all" proxy for unspecified systematic risk. The premise is that any type of risk commonly taken by hedge funds should be reflected in the average returns of a large group of hedge funds. We use hedge fund styles to define hedge fund groups since funds in the same style are likely to follow similar strategies. We estimate a fund's style beta while controlling for Fung and Hsieh (2001) seven factors. Table 5 reports correlations of *UpsideReturns* and *DownsideReturns* with style betas. Similar to the results on tail risk beta, we again find a stronger correlation of *UpsideReturns* with style betas than *DownsideReturns*.

To further examine information contained in *DownsideReturns* and *UpsideReturns* about manager skills, we relate these two measures to several known aspects of managerial skills, including the hedging skills discussed in Titman and Tiu (2011), the strategy innovation skills studied by Sun, Wang, and Zheng (2012), the market liquidity timing skills shown by Cao, Chen, Liang and Lo (2013), and the market return timing ability documented by Chen and Liang (2007).

Titman and Tiu (2011) show that skilled hedge fund managers will choose to have less exposure to systematic risk; hence, their fund returns will exhibit a lower R-squared with respect to the FH seven factors. It is possible that funds with better *DownsideReturns* tend to have low R-squared, and thus their superior performance could be due to managers' ability to hedge away systematic risk.

Sun, Wang and Zheng (2012) document that strategy distinctiveness, or the *SDI*, a measure of correlation with peer funds, predicts future hedge fund performance. Funds with better downside performance may be more likely to adopt distinctive trading strategies, and hence exhibit lower correlations with peer funds as well as with the overall hedge fund sector.

Cao, Chen, Liang, and Lo (2012) show that among equity-oriented hedge funds, skilled managers can deliver superior performances by successfully timing market liquidity. It is possible that outperformance by funds with better *DownsideReturns* is achieved as fund managers strategically adjust risk exposures based on their forecasts of future market liquidity conditions. Following their specification, we exclude funds in fixed income arbitrage, managed futures, and dedicated short bias styles, and measure the timing skills using the coefficient of the interaction term of market liquidity innovations with the equity market returns, λ, as follows,

$$\mathrm{Ret}_{\mathrm{i,t}} = c + \lambda MKT_t \Delta LIQ_t + \sum_{j=1}^{7} \beta_j FH7_t + e_{i,t} \tag{4}$$

We use the Pastor-Stambaugh market liquidity innovation series to measure ΔLIQ_t.[18]

Many academic efforts have been focused on the market timing ability of portfolio managers. For example, Chen and Liang (2007) shows that a sample of self-described market timing hedge funds have the ability to time the U.S. equity market. They also find that timing ability appears relatively strong in bear market conditions. It is possible that hedge funds with higher *DownsideReturns* have better market timing ability, allowing them to make profit even when the market is down. Following the literature, we estimate the market timing ability of equity-oriented hedge funds by regressing individual hedge fund excess returns on squared stock market excess return. In the following regression, γ_i denotes the market return timing ability, with a higher value representing better ability.

$$\mathrm{Ret}_{\mathrm{i,t}} = \alpha_i + (\beta_i + \gamma_i MKT_t) \times MKT_t + e_{i,t} \tag{5}$$

Table 6 presents the time-series average of cross-sectional pair-wise correlation of the conditional performance measures with the aforementioned hedge fund skill proxies. Consistent with the *DownsideReturns* measure better reflecting managerial skills, it generally exhibits a positive correlation with proxies for hedging, strategy innovation, and market return timing skills, whereas *UpsideReturns* are negatively associated with such skill proxies.

Past alpha has also been commonly used by investors as a proxy for hedge fund skills. As seen in Panel B of Table 1, *DownsideReturns* exhibit a higher correlation with alpha than *UpsideReturns*, corroborating the findings that *DownsideReturns* better reflect skills.

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[18] As a robustness test, we also use the tracking portfolio returns on market liquidity innovation to measure ΔLIQ_t in the regression above, which yield similar results.

Next, we examine whether the performance predicting power of *DownsideReturns* withstands controlling for the previously documented skill proxies. We run panel and Fama-MacBeth regressions by including both the *DownsideReturns* and the aforementioned skill proxies, as follows:

$$AbnormalPerformance_{i,t} = c_{0i} + c_{1i} Downside\mathrm{Re}turns_{i,t-1} + c_{2i} AlternativeSkills_{i,t-1} + c_{3i} Control_{i,t-1} + e_{i,t} \quad (6)$$

Results are presented in Table 7. For brevity, we only report the estimation results for the coefficient of *DownsideReturns*. Panel A shows that in the presence of hedging skill proxy, both the magnitude and the significance level of the coefficient of the *DownsideReturns* measure are little changed. Panels B, C, D, and E show a similar robust performance predicting power of *DownsideReturns* after controlling for strategy innovation, market liquidity timing skills, market return timing skills, and past 24-month average alphas, respectively. We only consider equity-oriented hedge funds when comparing *DownsideReturns* with market liquidity and return timing skills. Finally, Panel F further confirms the performance predicting power of *DownsideReturns* in the presence of all the aforementioned alternative skill proxies.

All told, while *DownsideReturns* may partly reflect managers' skills of hedging systematic risk, engaging in strategy innovations, and timing market return and liquidity, the performance predicting power by *DownsideReturns* goes beyond such effects, suggesting that *DownsideReturns* capture additional dimensions of skills that have not been documented by the existing literature.

5. Source of Performance Persistence: Investors' Inattention?

In this section, we examine another potential channel which may lead to stronger performance persistence amid market weakness: investors' lack of response to past performance. The potential impact of investors' flows on performance persistence can be inferred by extending the model in Berk and Green (2004) to the hedge fund sector. In their original model, mutual fund investors learn about fund managers' heterogeneous skills through past returns, and efficiently allocate capital accordingly. The efficient capital allocation and diminishing return to scale would lead to no performance persistence. Consistent with their model's implications, performance persistence could arise and vary with the market conditions if investors' flows react differently to past performance across market states.

We examine hedge fund flows' sensitivity to past returns over *up* and *down* markets. Specifically, we construct quarterly flow variables as $flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}}$, and then regress flows to contemporaneous and lagged net fee returns, their interactions with an indicator variable for down markets, as well as control variables, as follows:

$$flow_{i,t} = c_0 + c_1 R_{i,t} + c_2 R_{i,t} \times Down_t + c_3 R_{i,t-1} + c_4 R_{i,t-1} \times Down_{t-1} + c_5 R_{i,t-2} + c_6 R_{i,t-2} \times Down_{t-2} + c_7 Controls_{i,t} + e_{i,t} \qquad (7)$$

where $flow_{i,t}$ is the percentage net flow into fund *i* during quarter *t*, $R_{i,t}$ is the percentage rank of fund i's net fee return within its style during quarter *t*, and $Down_t$ is an indicator variable that equals one if the return of the overall hedge fund industry of quarter *t* is below the historical median from 1994 up to quarter *t*. Following the prior literature, we include the following control variables: natural log of funds' assets under management, natural log of assets managed by funds' families, volatility of prior 24-month fund return in percent (*Vol*), the flow into the fund's style during the contemporaneous quarter, management fee, incentive fee, indicator variables for whether personal capital and leverage are employed and whether there is a high watermark requirement, lengths of redemption notice period and lockup period, age, and minimum investments. Except for the contemporaneous style flow measure, the rest of the control variables are measured at the end of the previous period. We also include the time and style fixed-effects, and cluster the standard errors for each fund.

Table 8 reports how fund flows react to contemporaneous and recent past performance. Consistent with prior literature, we find that hedge fund investors actively chase past performance, evidenced by the positive coefficients for contemporaneous and past quarter returns. However, the coefficients on the interaction terms between fund returns and the *down* market indicator are positive. For example, a 1% increase in performance ranking in quarter *t-1* is associated with an inflow of 6.29 bp in quarter *t* during up markets, as compared to an inflow of 8.32bp (=6.29+2.03) during down markets. The difference of 2.03 bp is highly statistically significant (t-statistics=6.20). Overall, hedge fund investors appear to react more strongly to past performance during *down* markets as rational investors would do given the finding of this paper. This relationship is also consistent with Schmalz and Zhuk (2013), which theoretically argue that risk-averse Bayesian investors assign more weight to cash flow news in downturns than in upturns because downturns reveal information about the cross-section of the value of projects better than upturns. However, the finding is inconsistent with investors' lack of response to past performance as a driving force for the strong performance persistence amid market weakness.

One natural follow-up question arises that, if hedge fund investors actively respond to past performance during the *down* market, why flows have not driven away the performance persistence. There might be more frictions in the hedge fund setting that prevent cash flows from competing away alphas. For example, one possible explanation can be found in Glode and Green (2011) which relates performance persistence to hedge fund investors' bargaining power. Glode and Green (2011) argue that compared with mutual fund managers, hedge fund managers may be more willing to share future profits to retain incumbent investors who may otherwise leave the fund and disclose their secretive strategies to competitors. The bargaining power of hedge fund investors is a unique feature to hedge fund industry that can lead to performance persistence.[19] Our results are consistent with that *DownsideReturns* may better reflect managers' skills, and at the same time, funds with higher *DownsideReturns* may have higher incentive to share profit with investors in order to avoid the costs of information spillover on the existing successful strategy.

6. Robustness Tests

In this section, we summarize the results on a host of robustness tests regarding the performance predictability by *DownsideReturns* and *UpsideReturns.*

6.1 Market Frictions

Although most hedge funds are often open-ended, various restrictions may prevent hedge fund investors from adding or withdrawing capital timely and freely. The delay in flow responses to past performance may give rise to short-term performance persistence. If funds with extreme *DownsideReturns* impose stronger share restrictions than those with extreme *UpsideReturns*, we may observe stronger performance persistence in the *down* market. To investigate this possibility, we

[19] As argued by Berk and Green (2004), mutual fund investors usually have no bargaining power, resulting in mutual fund managers fully extracting the rents. Thus, there is no performance persistence for mutual funds.

repeat both the portfolio sorting and regression analyses using a subsample of funds that are subject to relatively minimal market trading frictions. Specifically, we only consider funds of which the redemption notice and payout periods combined are no more than 45 days and no lockup period is required. This subsample accounts for about 40 percent of the whole sample.

Panel A of Table 9 shows that funds with higher *DownsideReturns* continue to significantly outperform those with lower *DownsideReturns*, over the next quarter to up to the next three years, even in the absence of significant share restrictions. Panel B of the regression analyses corroborate the findings. Overall, the results based on this subsample are comparable to those using the whole sample, both directionally and magnitude wise. Hence, share restrictions are unlikely the primary driver for the performance predicting power of *DownsideReturns*.

6.2 Within-Style Analysis

To investigate whether the performance predicting power of *DownsideReturns* is limited to certain hedge fund styles, we repeat the analysis within each hedge fund style. As seen in Table 10, portfolio sorting results suggest that *DownsideReturns* is positively associated with future performance for all major hedge fund styles, and the positive association is significant for most styles over various holding horizons. On the other hand, *UpsideReturns* is generally insignificantly associated with future alphas and Sharpe ratios, and negatively associated with future appraisal ratios.

6.3 Other Robustness Tests

We conduct an extensive set of additional robustness checks on our main findings and results are reported at the internet appendix. First, we consider alternative ways to define *down* markets. For equity oriented hedge funds, we define *down* markets according to the excess return of the CRSP value-weighted stock index. The stronger performance predicting power of *DownsideReturns* than *UpsideReturns* remains under this specifications. We also define *down* market based on individual hedge fund styles, despite the caveats discussed at Section 2.1. Again, the main results remain. For instance, portfolio sorting results indicate that the higher the *DownsideReturns*, the better future risk adjusted performance is. Fund-level regression analysis results corroborate the finding of a positive association between *DownsideReturns* and future fund performance. However, there is no evidence for a positive association between *UpsideReturns* and future fund performance.

Second, we consider various specifications for the *DownsideReturns* measure. We use different lengths of window to define benchmark sample median: for example, we consider the most recent 6 or 9 down months over the past 2-year or past 3-year window. Third, we use alternative approaches to estimating fund abnormal performance. In particular, the overall positive Fung Hsieh 7-factor alphas for the aggregate hedge fund portfolios suggest that this factor model may not be sufficient in capturing hedge fund risk. Since hedge fund style returns are likely to reflect common risk exposures for funds within the style, we use hedge fund style returns as alternative risk benchmarks to estimate the abnormal fund performance for within-style funds. Overall, the results are consistent with the main analysis and are available upon request.

7. Conclusion

Hedge fund investors aim to identify talented fund managers who can deliver superior performance and help preserve wealth especially amid market declines. Due to limited information on hedge fund trading and holding, assessing managerial ability is a challenging task that relies mainly on learning from funds' historical return information and managers' track records. Academic research has investigated how the overall past fund performance relates to future fund performance. In this paper, we emphasize the unique insights that can be gained by focusing on conditional fund performance during periods of relative hedge fund market weakness.

The conditional fund performance measure is constructed using the conditional time-series fund returns when the broad hedge fund sector performance is above or under its historical median level. We term them as *UpsideReturns* and *DownsideReturns*. On the basis of fund return data from January 1994 to December 2014, we find that *DownsideReturns* can predict future fund performance but *UpsideReturns* cannot. Further tests show that *DownsideReturns* are positively correlated with other skill measures while *UpsideReturns* are positively correlated with noise measures or exposure to tail risk and other missing factors. These findings suggest that the information-to-noise ratio is higher during weak markets, and hence the *DownsideReturns* measure allows us to draw stronger inference about investment skills.

Overall, our evidence supports the existence of managerial skills and suggests that the *DownsideReturns* measure is a useful indicator of managerial talents, and hence beneficial to investors when selecting funds.

References

Agarwal, V., and Naik, N. 2000. Multi-Period Performance Persistence Analysis of Hedge Funds. *Journal of Financial and Quantitative Analysis* 35: 327–342.

Agarwal, V., Daniel, N., and Naik, N. 2009. Role of Managerial Incentives and Discretion in Hedge Fund Performance. *Journal of Finance* 64: 2221–2256.

Aggarwal, R., and Jorion, P. 2009. The Risk of Emerging Hedge Fund Managers. *Journal of Investing* 18: 100-107.

Aragon, G. 2007. Share Restriction and Asset Pricing: Evidence from the Hedge Fund Industry. *Journal of Financial Economics* 83: 33–58.

Berk, J., and Green, R. 2004. Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy* 112: 1269–1295.

Bollerslev, T., and Todorov, V. 2011. Tails, Fears, and Risk Premia. *Journal of Finance* 66: 2165–2211.

Boyson, N., Stahel, C., and Stulz, R., 2010, Hedge Fund Contagion and Liquidity Shocks, The Journal of Finance 55, 1789-1816.

Brown, S., Goetzmann, W., and Ibbotson, R. 1999. Off-Shore Hedge Funds: Survival and Performance. *Journal of Business* 72: 91–117.

Brown, S., Goetzmann, W., and Ross, S. 1995. Survival. *Journal of Finance* 50: 853–873.

Brunnermeier, M., and S. Nagel, 2004. Hedge Funds and the Technology Bubble. *Journal of Finance* 59: 2013–2040.

Cao, C., Chen, Y., Liang, B., and Lo, A. 2013, Can Hedge Funds Time Market Liquidity? *Journal of Financial Economics* 109: 493-516.

Carhart, M. 1997. On Persistence in Mutual Fund Performance. *Journal of Finance* 52: 57–82.

Chen, Y., and B. Liang. 2007. Do Market Timing Hedge Funds Time the Market? *The Journal of Financial and Quantitative Analysis* 42: 827-856.

Cooper, M., R. Gutierrez, and A. Hameed. 2004. Market States and Momentum. *Journal of Finance* 59: 1345-1366.

De Souza, A., and Lunch, A., 2012. Does mutual fund performance vary over the business cycle?, Working paper, New York University.

Ferson, W., and Schadt, R. 1996, Measuring fund strategy and performance in changing economic conditions, *Journal of Finance* 51, 425-461.

Fung, W., and Hsieh, D. 2000. Performance Characteristics of Hedge Funds and CTA Funds: Natural Versus Spurious Biases. *Journal of Financial and Quantitative Analysis* 35: 291–307.

Fung, W., and Hsieh, D. 2001. The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers. *Review of Financial Studies* 14: 313–341.

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

Getmansky, M., Lo, A., and Makarov, I. 2004. An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns. *Journal of Financial Economics* 74: 529–609.

Glode, V. 2011, Why mutual funds underperform?, *Journal of Financial Economics* 42, 297-421.

Glode, V. and Green, R. 2011. Information Spillovers and Performance Persistence for Hedge Funds. *Journal of Financial Economics* 101: 1–17.

Glode, V., Hollifield, B., Kacperczyk, M., and Kogan, S. 2012. Time-Varying Predictability in Mutual Fund Returns, Working Paper, University of Pennsylvania.

Grinblatt, M. and M. Keloharju. 2001. What Makes Investors Trade?. Journal of Finance 56: 589-616.

Jagannathan, R., Malakhov, A., and Novikov, D. 2010. Do Hot Hands Exist Among Hedge Fund Managers? An Empirical Evaluation. *Journal of Finance* 65, 217–255.

Jiang, H., and Kelly, B. 2013. Tail Risk and Hedge Fund Returns. Working Paper.

Joenvaara, J., Kosowski, R., Tolonen, P., 2014. Hedge fund performance: What do we know? Working paper.

Kacperczyk, M., Van Nieuwerburgh, S., and Veldkamp, L. 2013a, Rational Attention Allocation over the Business Cycle, Working paper.

Kacperczyk, M., Van Nieuwerburgh, S., and Veldkamp, L. 2013b, Time-Varying Fund Manager Skill, *The Journal of Finance*, forthcoming.

Kosowski, R., 2011, Do mutual funds perform when it matters most to investors? US mutual fund performance and risk in recessions and expansions, *Quarterly Journal of Finance* 1, 607-664.

Kosowski, R., Naik, N., and Teo. M, 2007. Do Hedge Funds Deliver Alpha? A Bayesian and Bootstrap Analysis. *Journal of Financial Economics* 84: 229–264.

Lamont, O. and R. Thaler. 2003. Can the Market Add and Subtract? Mispricing in Tech Stock Carve-Outs, *Journal of Political Economy* 111: 227-268.

Liang, B. 2000. Hedge Funds: The Living and the Dead. *Journal of Financial and Quantitative Analysis* 35: 309–326.

Liang, B., and Park, H. 2008. Share Restriction, Liquidity Premium, and Offshore Hedge Funds. Working Paper, University of Massachusetts.

Lo, A. 2002. The Statistics of Sharpe Ratios. *Financial Analysts Journal* 58: 36–52.

Malkiel, B., and Saha, A. 2005. Hedge Fund: Risk and Return. *Financial Analysts Journal* 61: 80–88.

Moskowitz, T. 2000. Discussion of mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, *Journal of Finance* 55, 1695-1704.

Park, Y., 2014. Volatility of volatility and tail risk premiums, Federal Reserve Board Working Paper.

Schmalz, Martin, and Sergey Zhuk, 2013, Sergey, Revealing Downturns, working paper, University of Michigan.

Sun, Z., Wang, A., and Zheng, L. 2012. The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance. Review of Financial Studies 25: 96-143.

Titman, S., and Tiu, C. 2011. Do the Best Hedge Funds Hedge? *Review of Financial Studies* 24: 123–168.

Treynor, J., and Black, F. 1973. How to Use Security Analysis to Improve Portfolio Selection. *Journal of Business* 46: 66–86.

Table 1: Summary Statistics (1998–2014)

Panel A: Fund Performance and Characteristics

	Full Sample					Live Funds					Graveyard Funds				
	Mean	Median	25th	75th	std	Mean	Median	25th	75th	std	Mean	Median	25th	75th	std
#Fund Per Period	2373	2467	969	3450	730	838	708	153	1888	552	1535	1547	105	2510	636
DownsideReturns (% p.m.)	-0.47	-0.31	-1.09	0.34	2.62	-0.42	-0.28	-1.01	0.35	1.51	-0.48	-0.33	-1.12	0.31	3.01
UpsideReturns (% p.m.)	2.16	1.73	0.99	2.94	1.96	2.35	1.92	1.17	3.08	1.87	2.05	1.63	0.89	2.82	1.96
NetFeeRet(% p.m.)	0.52	0.47	-0.97	1.91	6.00	0.68	0.56	-0.79	1.99	4.24	0.41	0.43	-1.01	1.80	6.06
Alpha(t)	0.33	0.32	-1.29	1.87	7.71	0.50	0.41	-1.07	1.92	4.77	0.21	0.26	-1.41	1.81	8.16
AR	0.23	0.19	0.00	0.40	0.43	0.26	0.22	0.04	0.42	0.42	0.21	0.17	-0.02	0.38	0.41
SR	0.17	0.14	0.02	0.28	0.25	0.19	0.17	0.05	0.30	0.23	0.15	0.13	0.00	0.27	0.25
Vol (% p.m.)	3.67	2.72	1.59	4.63	6.77	3.55	2.69	1.63	4.60	3.20	3.70	2.73	1.59	4.60	7.52
RedemptionNotice Period(Days)	38.26	30.00	22.91	42.34	30.10	39.81	30.00	17.49	45.62	31.49	37.69	30.02	24.22	40.92	29.49
Lockup(months)	3.06	0.00	0.00	0.00	6.41	3.19	0.00	0.00	0.00	6.80	2.95	0.00	0.00	0.00	6.28
PersonalCapDummy	0.32	0.09	0.09	0.09	0.45	0.32	0.00	0.00	0.00	0.46	0.31	0.12	0.12	0.12	0.44
HighWaterMark Dummy	0.60	0.78	0.78	0.78	0.47	0.65	1.00	1.00	1.00	0.47	0.58	0.76	0.76	0.76	0.48
ManagementFee(%)	1.44	1.42	1.11	1.65	0.66	1.42	1.50	1.11	1.60	0.56	1.45	1.40	1.12	1.64	0.68
IncentiveFee(%)	15.08	20.00	20.00	20.00	7.88	14.48	20.00	20.00	20.00	8.28	15.07	20.00	20.00	20.00	7.82
Age(Yr)	7.18	6.06	4.11	9.07	4.16	7.84	6.66	4.42	10.00	4.64	6.79	5.76	3.97	8.46	3.87
AUM(M$)	185.45	45.90	13.75	147.45	571.47	209.96	62.89	20.94	189.58	570.68	154.46	37.40	11.50	117.82	453.55
FlowPast1Y(% p.a.)	7.54	-0.16	-3.68	1.60	63.30	355.17	268.55	162.56	459.54	319.62	369.92	273.01	159.11	460.08	752.37
MinInvestment(M$)	1.11	0.38	0.14	1.00	6.01	0.96	0.35	0.10	1.00	3.13	1.23	0.37	0.15	0.93	7.32
LeverageDummy	0.56	1.00	1.00	1.00	0.49	0.57	1.00	1.00	1.00	0.49	0.54	0.76	0.75	0.78	0.49
DerivativeDummy	0.48	0.44	0.44	0.44	0.50	0.48	0.38	0.37	0.38	0.50	0.49	0.47	0.47	0.47	0.50

Panel A summarizes the time-series average of cross-sectional summary statistics for the main variables for the full sample, and for the live and graveyard fund subsamples. Variables considered are the number of funds per period; *DownsideReturns* (*UpsideReturns*), measured as conditional average returns over the most recent 12 months within the past 3 years when the overall hedge fund sector performance is under (above) the historical median level; and contemporaneous fund characteristics including monthly net of fee returns, monthly FH seven-factor adjusted alphas and the corresponding appraisal ratio (*AR*), the Sharpe ratio (*SR*), the volatility of monthly net fee returns (*Vol*), the lengths of redemption notice and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, AUM, new money flow into funds within the past 12 months as a fraction of AUM, minimum investments requirement, and indicator variables for using leverage and derivatives. We winsorize the alpha, AR and SR at top and bottom 0.5% level.

Table 2: Equally-weighted Portfolio Performance Sorted on *DownsideReturns* and *UpsideReturns*

Panel A: Quintile Portfolios Sorted on *DownsideReturns*

		Alpha (FH 7-factor) (% p.m.)					Appraisal Ratio					Sharpe Ratio (smoothing adjusted)				
	Past Alpha	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
Low *Downside Returns* Port	-1.36	-0.04	-0.02	0.02	0.08	0.10	0.00	0.00	0.01	0.02	0.03	0.23	0.14	0.12	0.10	0.09
(t-statistic)	(-7.40)	(-0.21)	(-0.12)	(0.16)	(0.50)	(0.51)	(-0.07)	(0.10)	(0.31)	(0.46)	(0.65)	(3.21)	(2.95)	(3.14)	(3.94)	(4.37)
Port 2	-0.25	0.24	0.25	0.24	0.23	0.22	0.18	0.12	0.11	0.11	0.10	0.36	0.20	0.16	0.13	0.11
	(-2.12)	(2.17)	(2.39)	(2.32)	(2.26)	(2.10)	(2.86)	(2.62)	(2.49)	(2.17)	(1.92)	(4.45)	(3.71)	(3.71)	(4.00)	(3.51)
Port 3	0.13	0.32	0.31	0.30	0.30	0.28	0.38	0.24	0.21	0.19	0.17	0.43	0.25	0.20	0.17	0.14
	(1.04)	(3.39)	(3.46)	(3.16)	(2.87)	(2.67)	(5.29)	(4.18)	(3.68)	(2.99)	(2.39)	(5.42)	(4.78)	(4.59)	(4.49)	(3.65)
Port 4	0.43	0.44	0.41	0.39	0.36	0.33	0.63	0.40	0.33	0.29	0.25	0.55	0.32	0.25	0.21	0.18
	(3.77)	(5.78)	(5.34)	(4.46)	(3.79)	(3.54)	(9.17)	(6.60)	(5.28)	(3.97)	(3.26)	(8.33)	(6.83)	(6.10)	(5.11)	(4.00)
Hi *Downside Returns* Port	1.14	0.67	0.64	0.59	0.53	0.47	0.71	0.44	0.35	0.28	0.25	0.55	0.30	0.24	0.20	0.17
	(8.69)	(7.88)	(7.71)	(6.62)	(5.26)	(4.59)	(13.95)	(9.54)	(7.66)	(6.36)	(5.93)	(13.09)	(10.91)	(10.14)	(7.91)	(6.67)
High – Low	2.50**	0.71**	0.66**	0.56**	0.45**	0.38**	0.71**	0.44**	0.34**	0.27**	0.22**	0.32**	0.16**	0.12**	0.10**	0.08**
	(12.14)	(3.89)	(5.13)	(4.57)	(3.46)	(2.64)	(11.24)	(11.32)	(10.27)	(8.70)	(10.36)	(5.87)	(4.25)	(3.86)	(4.44)	(4.65)

(continued)

Table 2: Continued

Panel B: Quintile Portfolios Sorted on *UpsideReturns*

	Past Alpha	Alpha (FH 7-factor) (% p.m.) 3m	6m	1y	2y	3y	Appraisal Ratio 3m	6m	1y	2y	3y	Sharpe Ratio (smoothing adjusted) 3m	6m	1y	2y	3y
Low *Upside Returns* Port	0.26	0.25	0.29	0.31	0.31	0.30	0.43	0.29	0.23	0.20	0.17	0.25	0.14	0.12	0.10	0.09
(t-statistic)	(4.20)	(3.16)	(3.01)	(3.10)	(2.94)	(2.87)	(8.25)	(5.48)	(4.29)	(3.52)	(3.14)	(7.07)	(5.19)	(4.64)	(3.52)	(2.89)
Port 2	0.68	0.35	0.34	0.34	0.34	0.31	0.64	0.41	0.33	0.29	0.25	0.50	0.28	0.22	0.18	0.15
	(15.02)	(5.40)	(4.42)	(3.97)	(3.35)	(3.10)	(9.06)	(6.16)	(5.00)	(3.83)	(3.08)	(7.76)	(6.02)	(5.11)	(4.04)	(3.07)
Port 3	0.92	0.37	0.37	0.35	0.34	0.31	0.44	0.28	0.23	0.20	0.18	0.43	0.26	0.20	0.16	0.13
	(14.72)	(4.38)	(4.18)	(3.70)	(3.27)	(3.07)	(6.28)	(4.96)	(4.24)	(3.48)	(2.85)	(5.90)	(5.06)	(4.75)	(4.30)	(3.45)
Port 4	1.26	0.33	0.32	0.31	0.30	0.28	0.27	0.17	0.15	0.14	0.13	0.35	0.20	0.16	0.12	0.10
	(20.29)	(2.94)	(3.67)	(3.45)	(3.31)	(2.97)	(4.40)	(4.23)	(3.89)	(3.23)	(2.77)	(4.81)	(3.82)	(3.60)	(3.42)	(3.15)
Hi *Upside Returns* Port	2.14	0.28	0.24	0.23	0.22	0.20	0.12	0.07	0.07	0.06	0.07	0.27	0.15	0.12	0.09	0.08
	(11.00)	(1.34)	(1.45)	(1.42)	(1.27)	(1.04)	(2.14)	(2.03)	(2.03)	(1.76)	(1.81)	(3.61)	(3.02)	(2.85)	(2.58)	(2.46)
High – Low	1.88**	0.03	-0.05	-0.08	-0.09	-0.10	-0.31**	-0.22**	-0.17**	-0.13**	-0.11**	0.02	0.00	0.00	-0.01	-0.01
	(11.13)	(0.14)	(-0.33)	(-0.53)	(-0.65)	(-0.70)	(-4.69)	(-4.98)	(-4.16)	(-4.03)	(-4.00)	(0.30)	(0.06)	(-0.08)	(-0.17)	(-0.24)

Panel A reports the time-series averages and *t*-statistics of the post-formation average monthly FH 7-factor alphas, FH 7-factor-based Appraisal Ratios, and the smoothing-adjusted Sharpe Ratios for the equally-weighted quintile portfolios sorted on *DownsideReturns*, and Panel B for portfolios sorted on *UpsideReturns*. *DownsideReturns* (*UpsideReturns*) are measured as conditional average returns over the most recent 12 months with the past 3 years when the overall hedge fund market performance is under (above) the historical median level. The performance measures are based on the equally weighted buy-and-hold portfolios sorted every three months and held for three months to three years. We winsorize the alphas, ARs and SRs at the top and bottom 0.5% level. The *t*-statistics reported in italicized font are adjusted for heteroscedasticity and autocorrelation. ** 1% significance; * 5% significance.

Table 3: Panel Regression of Fund Performance on *DownsideReturns* and *UpsideReturns*

Panel A: Regression on *DownsideReturns*

	Alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR	Alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR
DownsideReturns	1.86**	0.12**	0.04**	1.76**	0.13**	0.03**
(t-statistic)	(17.50)	(26.36)	(8.88)	(15.49)	(24.83)	(5.28)
VolPast2Y(%p.m)	0.02			0.02		
	(0.53)			(0.45)		
RedemptionNotice(30Days)	0.01*	0.00**	0.00**	0.01	0.00**	0.00**
	(1.99)	(5.97)	(4.85)	(1.95)	(6.03)	(4.79)
Lockup(months)	0.01	0.00	0.00	0.01	0.00	0.00
	(0.47)	(0.85)	(1.46)	(0.38)	(0.98)	(1.37)
PersonalCapitalDummy	-0.03	0.00	0.03	-0.05	0.00	0.03
	(-0.15)	(0.07)	(1.27)	(-0.22)	(0.16)	(1.20)
HighWaterMarkDummy	0.98**	0.00	0.02	0.97**	0.00	0.02
	(4.32)	(-0.02)	(1.20)	(4.33)	(0.04)	(1.18)
MgmtFee(%)	0.13	-0.04**	-0.04**	0.12	-0.04**	-0.05**
	(0.67)	(-3.14)	(-2.95)	(0.65)	(-3.10)	(-3.02)
IncentiveFee(%)	0.02	0.00	0.00**	0.02	0.00	0.00
	(0.92)	(-1.23)	(-3.02)	(0.91)	(-1.18)	(-3.04)
Age(years)	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.04)	(-0.77)	(1.10)	(-0.06)	(-0.74)	(1.05)
Missing AUM	1.45	0.50**	0.46**	1.25	0.53**	0.44**
	(1.10)	(5.93)	(5.46)	(0.95)	(6.17)	(5.24)
ln(AUM)	0.05	0.03**	0.02**	0.03	0.03**	0.02**
	(0.64)	(5.37)	(4.96)	(0.48)	(5.63)	(4.75)
FlowPast1Y(% p.a.)	-0.50**	-0.02*	0.01	-0.54**	-0.01	0.00
	(-3.65)	(-1.96)	(1.04)	(-3.92)	(-1.06)	(0.39)
AvgPast2YRet(% p.m.)				0.34	-0.05**	0.04**
				(1.80)	(-7.57)	(5.50)
ln(MinInvestment+1)	0.15**	0.01**	0.01*	0.15**	0.01*	0.01**
	(3.52)	(2.58)	(2.54)	(3.56)	(2.53)	(2.60)
Leverage	0.22	-0.03	-0.02	0.21	-0.03	-0.02
	(1.15)	(-1.45)	(-1.01)	(1.10)	(-1.38)	(-1.07)
AdjR2(%)	9.90	11.24	16.06	9.91	11.31	16.11
#FundQtrObs.	147,825	146,150	115,838	147,825	146,150	115,838

Table 3: (Continued)

Panel B: Regression on *UpsideReturns*

	Alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR	Alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR
UpsideReturns	0.06	-0.05**	-0.01	-0.49**	-0.08**	-0.03**
(t-statistic)	(0.61)	(-12.87)	(-1.70)	(-5.31)	(-17.90)	(-6.07)
VolPast2Y(%p.m)	0.00			0.00		
	(0.13)			(-0.02)		
RedemptionNotice(30Days)	0.01*	0.00**	0.00**	0.01*	0.00**	0.00**
	(2.57)	(6.19)	(4.89)	(2.34)	(6.08)	(4.84)
Lockup(months)	-0.01	0.00	0.00	-0.01	0.00	0.00
	(-0.26)	(0.66)	(1.43)	(-0.30)	(0.66)	(1.41)
PersonalCapitalDummy	-0.04	0.00	0.03	-0.08	0.00	0.03
	(-0.18)	(0.15)	(1.27)	(-0.36)	(0.06)	(1.24)
HighWaterMarkDummy	1.11**	0.00	0.03	1.02**	0.00	0.02
	(4.62)	(0.13)	(1.39)	(4.54)	(-0.13)	(1.22)
MgmtFee(%)	0.11	-0.05**	-0.04**	0.07	-0.05**	-0.05**
	(0.57)	(-3.42)	(-3.00)	(0.36)	(-3.63)	(-3.10)
IncentiveFee(%)	0.02	0.00	0.00**	0.02	0.00	0.00**
	(1.06)	(-0.69)	(-2.84)	(0.83)	(-0.96)	(-3.08)
Age(years)	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.90)	(-1.24)	(0.69)	(-0.16)	(-0.71)	(1.04)
Missing AUM	5.51**	0.72**	0.53**	3.24*	0.60**	0.45**
	(3.89)	(7.93)	(6.14)	(2.43)	(6.78)	(5.28)
ln(AUM)	0.27**	0.04**	0.03**	0.14*	0.03**	0.02**
	(3.43)	(7.41)	(5.66)	(1.97)	(6.29)	(4.82)
FlowPast1Y(% p.a.)	-0.04	0.02*	0.02*	-0.46**	0.00	0.00
	(-0.28)	(2.50)	(2.53)	(-3.22)	(-0.16)	(0.47)
AvgPast2YRet(% p.m.)				2.22**	0.12**	0.09**
				(11.70)	(16.80)	(13.17)
ln(MinInvestment+1)	0.18**	0.01**	0.01**	0.16**	0.01**	0.01**
	(3.75)	(3.39)	(2.86)	(3.62)	(3.15)	(2.70)
Leverage	0.25	-0.02	-0.02	0.23	-0.03	-0.02
	(1.21)	(-1.30)	(-1.02)	(1.19)	(-1.38)	(-1.09)
AdjR2(%)	9.20	10.51	15.92	9.52	10.88	16.17
#FundQtrObs.	144,583	142,950	115,578	144,583	142,950	115,578

Table 3 reports the panel regression results for hedge fund performance on *DownsideReturns(UpsideReturns)* at the quarterly frequency as follows: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i} Downside\mathrm{Re}turns(Upside\mathrm{Re}turns)_{i,t-1} + c_{2i} Control_{i,t-1} + e_{i,t}$. Alpha is the annualized FH seven-factor adjusted performance over the subsequent one quarter in percentage. *AR*, and *SR* are the corresponding appraisal ratio and smoothing-adjusted Sharpe ratio. We winsorize the alphas, ARs and SRs at the top and bottom 0.5% level. Control variables are the lagged fund characteristics, including volatility of monthly net fee returns (*Vol*), lengths of the redemption notice and lockup periods, indicator variables for personal capital commitment and high-water mark, management fees, incentive fees, fund age, missing AUM indicator, ln (AUM), past year percentage flow, average return over the past 2 years, minimum investments requirement, and an indicator variable for the use of leverage. The *t*-statistics reported in italicized font are adjusted for fund-clustering effect and for time and style fixed effects. ** 1% significance; * 5% significance.

Table 4: Performance Predictability of *DownsideReturns* and *UpsideReturns* in Future *Up* and *Down* Markets

Panel A: Performance Predictability of *DownsideReturns* in Future *Down* Markets

	Alpha(FH 7-factor) (% p.m.)					Appraisal Ratio				Sharpe Ratio (smoothing adjusted)			
	3m	6m	1y	2y	3y	6m	1y	2y	3y	6m	1y	2y	3y
Low *Downside Returns* Port	-0.45	-0.29	-0.26	-0.29	-0.30	-0.12	-0.07	-0.06	-0.06	-0.36	-0.26	-0.26	-0.26
Port 2	-0.11	-0.03	-0.06	-0.12	-0.16	-0.08	-0.07	-0.06	-0.06	-0.33	-0.25	-0.26	-0.27
Port 3	-0.03	0.03	0.01	-0.03	-0.07	0.00	0.00	-0.01	-0.02	-0.25	-0.21	-0.21	-0.23
Port 4	0.12	0.12	0.09	0.04	-0.01	0.27	0.18	0.13	0.10	-0.07	-0.07	-0.10	-0.12
High *Downside Returns* Port	0.24	0.23	0.17	0.09	0.03	0.35	0.25	0.17	0.13	0.06	0.05	0.00	-0.02
High – Low	0.69*	0.53**	0.43**	0.38*	0.33*	0.47**	0.32**	0.23**	0.19**	0.42**	0.30**	0.26**	0.23**
(t-statistic)	(2.57)	(3.01)	(2.63)	(2.27)	(2.39)	(7.06)	(6.52)	(5.37)	(6.77)	(8.58)	(7.53)	(11.02)	(13.33)

Panel B: Performance Predictability of *DownsideReturns* in Future *Up* Markets

	Alpha(FH 7-factor) (% p.m.)					Appraisal Ratio				Sharpe Ratio (smoothing adjusted)			
	3m	6m	1y	2y	3y	6m	1y	2y	3y	6m	1y	2y	3y
Low *DownsideReturns*	0.30	0.19	0.30	0.44	0.53	0.18	0.14	0.14	0.17	0.87	0.70	0.57	0.56
Port 2	0.56	0.52	0.55	0.57	0.59	0.45	0.36	0.32	0.33	1.10	0.90	0.74	0.71
Port 3	0.61	0.56	0.58	0.60	0.59	0.72	0.53	0.45	0.42	1.17	0.94	0.77	0.73
Port 4	0.70	0.67	0.69	0.67	0.66	0.88	0.64	0.54	0.49	1.06	0.83	0.69	0.66
High *DownsideReturns*	1.08	1.06	1.07	1.00	0.94	0.86	0.63	0.48	0.43	0.77	0.60	0.48	0.45
High – Low	0.78**	0.87**	0.76**	0.56**	0.41*	0.68**	0.49**	0.34**	0.26**	-0.10	-0.10	-0.09	-0.11
(t-statistic)	(3.39)	(3.97)	(3.89)	(3.02)	(2.32)	(9.48)	(9.57)	(10.75)	(10.76)	(-0.85)	(-1.40)	(-1.21)	(-1.51)

Panel C: Performance Predictability of *UpsideReturns* in Future *Down* Markets

	Alpha(FH 7-factor) (% p.m.)					Appraisal Ratio				Sharpe Ratio (smoothing adjusted)			
	3m	6m	1y	2y	3y	6m	1y	2y	3y	6m	1y	2y	3y
Low *Upside Returns* Port	-0.03	0.03	0.01	-0.03	-0.07	0.18	0.16	0.11	0.09	0.00	0.02	-0.02	-0.04
Port 2	0.09	0.10	0.08	0.06	0.02	0.26	0.17	0.13	0.10	-0.05	-0.06	-0.10	-0.12
Port 3	0.05	0.07	0.05	0.03	-0.03	0.08	0.04	0.02	0.01	-0.18	-0.16	-0.18	-0.20
Port 4	-0.04	0.02	0.00	-0.06	-0.09	-0.01	0.00	-0.01	-0.02	-0.29	-0.22	-0.23	-0.24
High *Upside Returns* Port	-0.29	-0.18	-0.21	-0.32	-0.34	-0.05	-0.04	-0.05	-0.06	-0.36	-0.27	-0.26	-0.26
High – Low	-0.26	-0.21	-0.22	-0.29**	-0.27**	-0.23**	-0.19**	-0.16**	-0.14**	-0.35**	-0.28**	-0.24**	-0.22**
(t-statistic)	(-0.89)	(-1.23)	(-1.52)	(-2.63)	(-3.29)	(-2.74)	(-3.10)	(-4.32)	(-5.88)	(-5.87)	(-6.60)	(-8.17)	(-10.34)

Panel D: Performance Predictability of *UpsideReturns* in Future *Up* Markets

	Alpha(FH 7-factor) (% p.m.)					Appraisal Ratio				Sharpe Ratio (smoothing adjusted)			
	3m	6m	1y	2y	3y	6m	1y	2y	3y	6m	1y	2y	3y
Low *UpsideReturns* Port	0.55	0.58	0.61	0.52	0.47	0.64	0.50	0.40	0.36	0.49	0.40	0.35	0.34
Port 2	0.62	0.58	0.59	0.56	0.54	0.90	0.67	0.54	0.50	1.08	0.84	0.70	0.66
Port 3	0.67	0.63	0.64	0.64	0.62	0.77	0.56	0.46	0.43	1.18	0.94	0.79	0.74
Port 4	0.65	0.58	0.62	0.65	0.66	0.54	0.40	0.34	0.34	1.12	0.90	0.73	0.70
High *UpsideReturns* Port	0.79	0.67	0.77	0.91	1.00	0.29	0.23	0.22	0.24	1.00	0.81	0.63	0.60
High – Low	0.25	0.09	0.17	0.39	0.53**	-0.34**	-0.26**	-0.17**	-0.11**	0.50**	0.41**	0.28**	0.26**
(t-statistic)	(0.78)	(0.26)	(0.56)	(1.73)	(3.01)	(-4.76)	(-4.98)	(-3.94)	(-3.18)	(4.75)	(5.43)	(3.59)	(4.07)

Panel A (B) of Table 5 reports the time-series averages and *t*-statistics of the post-formation performance of quintile portfolios sorted on *DownsideReturns* over future months where the overall hedge fund sector performance is below (above) the historical median level. Panel C (D) reports results based on quintile portfolios sorted on *UpsideReturns. DownsideReturns* (*UpsideReturns*) are measured as conditional average returns over the most recent 12 months within the past 3 years when the overall hedge fund market performance is under (above) the historical median level. Performance measures include FH 7-factor alphas, FH 7-factor-based Appraisal Ratios, and the smoothing-adjusted Sharpe Ratios. We winsorize the alphas, ARs and SRs at the top and bottom 0.5% level. The portfolios are equally weighted buy-and-hold portfolios sorted every three months and held for three months to three years. The *t*-statistics reported in italicized font are adjusted for heteroscedasticity and autocorrelation. ** 1% significance; * 5% significance.

Table 5: Correlation of *DownsideReturns* and *UpsideReturns* with Risk Measures

	Tail Risk Beta (2007-2014)	Tail Risk Beta (1996-2006)	Style Beta (1996-2014)
Upside Returns	0.11*	0.13**	0.44**
(t-statistic)	(2.15)	(4.84)	(17.15)
DownsideReturns	-0.24**	-0.17**	-0.25**
	(-2.67)	(-7.38)	(-12.86)
Diff	0.35**	0.31**	0.69**
	(3.39)	(8.44)	(21.44)

Table 5 reports the time series averages of the cross-sectional correlation between *DownsideReturns, UpsideReturns* and various risk measures. Tail Risk Beta (2007-2014) represents loadings of hedge fund returns on a tail risk factor proxied by Chicago Board Options Exchange (CBOE) VVIX index. Tail Risk Beta (1996-2006) represents loadings of hedge fund returns on a tail risk factor proxied by the fear factor proposed by Bollerslev and Todorov (2011). Style beta (1996-2014) represents loadings of hedge fund returns on the fund's own style (style factor). For each fund at each quarter, we estimate betas by regressing its past 24 months of returns on the corresponding risk factors, while controlling for Fung-Hsieh (2004) seven factors. We require a fund to have at least 12 months of observations to be included in the analysis. ** 1% significance; * 5% significance.

Table 6: Comparing *DownsideReturns* and *UpsideReturns* with Other Skill Measures

	DownsideReturns	*UpsideReturns*	*Hedging*	*SDI*	*MktLiqTiming*
UpsideReturns	-0.23**				
(t-statistic)	(-9.67)				
Hedging	0.19**	-0.19**			
	(19.43)	(-12.86)			
SDI	0.27**	-0.31**	0.40**		
	(19.97)	(-22.00)	(29.40)		
MktLiqTiming	0.09*	0.03	0.02*	0.02*	
	(2.04)	(0.72)	(2.44)	(2.27)	
MktRetTiming	0.09**	-0.08**	0.04**	0.09**	0.06
	(5.28)	(-4.21)	(3.52)	(7.16)	(1.87)

Table 6 reports the time-series averages and t-statistics of the pair-wise correlation of *DownsideReturns* and *UpsideReturns* with contemporaneous hedge fund skill measures used in the existing literature, including hedging skills (*Hedging*), strategy distinctiveness (*SDI*), market liquidity timing skills (*MktLiqTiming*), and market return timing ability (*MktTiming*). Note that sample funds are restricted to equity styles for *MktLiqTiming* and *MktRetTiming* related analysis. ** 1% significance; * 5% significance.

Table 7: Does Predicting Power of *DownsideReturns* Withstand the Control of Other Skill Measures

	Panel Regression			Fama-MacBeth		
Panel A: Controlling for Hedging Effect						
	Alpha(% p.a.)	AR	SR	Alpha(% p.a.)	AR	SR
DownsideReturns	1.63**	0.12**	0.05**	2.00**	0.15**	0.06**
(t-statistic)	(13.40)	(25.83)	(8.81)	(2.69)	(8.68)	(5.14)
Panel B: Controlling for Strategy Distinctiveness (*SDI*) effect						
	Alpha(% p.a.)	AR	SR	Alpha(% p.a.)	AR	SR
DownsideReturns	1.74**	0.11**	0.04**	1.95**	0.14**	0.06**
(t-statistic)	(13.57)	(26.74)	(9.47)	(2.80)	(8.03)	(5.44)
Panel C: Controlling for Market Liquidity Timing (*MktLiqTiming*) effect						
	Alpha(% p.a.)	AR	SR	Alpha(% p.a.)	AR	SR
DownsideReturns	1.74**	0.13**	0.05**	2.16**	0.15**	0.06**
(t-statistic)	(14.89)	(24.78)	(7.47)	(3.25)	(9.07)	(4.26)
Panel D: Controlling for Market Return Timing (*MktRetTiming*) effect						
	Alpha(% p.a.)	AR	SR	Alpha(% p.a.)	AR	SR
DownsideReturns	1.64**	0.13**	0.05**	2.40**	0.16**	0.07**
(t-statistic)	(14.24)	(24.39)	(7.49)	(3.49)	(9.17)	(5.38)
Panel E: Controlling for Past 24-Month Alphas						
	Alpha(% p.a.)	AR	SR	Alpha(% p.a.)	AR	SR
DownsideReturns	1.92**	0.12**	0.05**	1.41*	0.14**	0.06**
(t-statistic)	(15.27)	(26.22)	(9.19)	(2.33)	(9.27)	(4.64)
Panel F: Controling for All Skill Measures Above						
	Alpha(% p.a.)	AR	SR	Alpha(% p.a.)	AR	SR
DownsideReturns	1.82**	0.10**	0.04**	1.94**	0.12**	0.06**
(t-statistic)	(13.54)	(25.37)	(8.77)	(3.53)	(8.44)	(6.16)

Table 7 reports panel and Fama-MacBeth regression results for hedge fund performance on *DownsideReturns,* while controlling for other skill measures and fund characteristics at quarterly frequency as follows:
$AbnormalPerformance_{i,t} = c_{0i} + c_{1i}DownsideReturns_{i,t-1} + c_{2i}AlternativeSkills_{i,t-1} + c_{3i}Control_{i,t-1} + e_{i,t}$. Alternative Skill measures considered include hedging skills as 1-R2(FH7) (Titman and Tiu (2011)), strategy innovation skills, *SDI,* as in Sun, Wang, and Zheng (2012), market liquidity timing skills (Cao, Chen, Liang and Lo, 2013), market return timing skills (Chen and Liang, 2007), and average monthly alpha over the past 24 months. We winsorise the alphas, ARs and SRs at the top and bottom 0.5% level. Control variables are the same as column 4-6 in Table 3. Panel regression is adjusted for the fund-clustering effect, and time and style fixed effects. The Fama-MacBeth regression controls for style dummies, and is adjusted for heteroscedasticity and autocorrelation in standard errors. For brevity, only the estimation results for the *DownsideReturns* are reported here. Note that sample funds are restricted to equity oriented styles only for *MktLiqTiming* and *MktRetTiming* related analysis. ** 1% significance; * 5% significance.

Table 8: Flow Performance Sensitivity In *Up* and *Down* Markets

	(% p.q.)	(% p.q.)
Ret (i,t)	3.99**	4.14**
(t-statistic)	(16.21)	(16.58)
Ret (i,t) * Down (t)	0.73*	0.17
	(2.30)	(0.52)
Ret (i,t-1)	6.25**	6.29**
	(25.79)	(25.97)
Ret (i,t-1) * Down (t-1)	2.42**	2.03**
	(7.37)	(6.20)
Ret (i,t-2)	5.23**	5.21**
	(22.08)	(21.71)
Ret (i,t-2) * Down (t-2)	2.36**	2.02**
	(7.24)	(6.18)
Ln(AUM)		-0.22**
		(-3.95)
Ln(Family AUM)		-0.18**
		(-3.33)
VolPast2Y(% p. m.)		-0.02
		(-1.73)
Styleflow (i,t)		98.05**
		(35.69)
ManagementFee (%)		-0.05
		(-0.44)
IncentiveFee (%)		-0.03*
		(-2.42)
HighWaterMarkDummy		0.82**
		(5.00)
Leverage		0.10
		(0.71)
PersonalCapitalDummy		0.13
		(0.88)
RedemptionNotice(days)		0.01**
		(4.73)
Lockup(months)		-0.02
		(-1.79)
Age (months)		-0.02**
		(-11.72)
MinInvestment		0.10*
		(2.52)
AdjR2(%)	8.14	10.75
#FundQtrObs.	122,554	117,663

Table 8 reports the sensitivity of quarterly fund flows to contemporaneous and past quarter returns. Specifically, we conduct the following panel regression: $flow_{i,t} = c_0 + c_1 R_{i,t} + c_2 R_{i,t} \times Down_t + c_3 R_{i,t-1} + c_4 R_{i,t-1} \times Down_{t-1} + c_5 R_{i,t-2} + c_6 R_{i,t-2} \times Down_{t-2} + controls + e_{i,t}$ where $flow_{i,t}$ is the percentage net flow into fund i during quarter t, $R_{i,t}$ is the percentage rank of fund i's net fee return within its style during quarter t, and $Down_t$ is an indicator variable that equals one if the return of the overall hedge fund sector performance in quarter t is below the historical median. The control variables include: fund AUM, assets managed by funds' families, volatility of prior 24-month fund return in percent, flow into the fund's style during the contemporaneous quarter, management fee, incentive fee, indicator variables for whether personal capital and leverage are employed and whether there is a high watermark provision, lengths of redemption notice period and lockup period, age, and minimum investments. We also include the time and style fixed-effects, and cluster the standard errors for each fund. We winsorize the flow variable at the top and bottom 2%. ** 1% significance; * 5% significance.

Table 9: Is it Caused by Trading Restrictions?

Panel A: Performance of Equally-weighted Quintile Portfolios Sorted on *DownsideReturns.*

	Alpha (FH 7-factor, % p.m.)					Appraisal Ratio					Sharpe Ratio (smoothing adjusted)				
	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
Low *Downside Returns* Port	-0.06	-0.02	0.03	0.07	0.10	-0.06	-0.02	-0.01	0.00	0.02	0.19	0.12	0.10	0.08	0.08
Port 2	0.23	0.23	0.22	0.21	0.20	0.13	0.08	0.07	0.07	0.07	0.30	0.17	0.13	0.10	0.08
Port 3	0.27	0.26	0.25	0.26	0.25	0.27	0.16	0.14	0.13	0.12	0.31	0.17	0.14	0.11	0.09
Port 4	0.39	0.36	0.34	0.31	0.29	0.46	0.29	0.24	0.20	0.18	0.38	0.21	0.17	0.14	0.12
Hi *Downside Returns* Port	0.58	0.55	0.52	0.48	0.43	0.52	0.33	0.26	0.22	0.20	0.38	0.21	0.17	0.15	0.13
Hi – Low	0.64**	0.57**	0.49**	0.41**	0.33*	0.58**	0.35**	0.27**	0.22**	0.18**	0.20**	0.09*	0.07*	0.06**	0.05*
(t-statistic)	(3.30)	(3.91)	(3.46)	(3.01)	(2.27)	(8.61)	(9.01)	(8.57)	(7.43)	(7.78)	(3.37)	(2.16)	(2.00)	(2.67)	(2.53)

Panel B: Regressions

	Panel Regression			Fama-MacBeth		
	Alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR	Alpha(% p.a.) FH 7-factor	AR FH 7-factor	SR
DownsideReturns	1.83**	0.11**	0.03**	1.94*	0.13**	0.04*
(t-statistic)	(10.50)	(18.89)	(4.95)	(2.56)	(7.63)	(2.45)

The sample consists of funds less subject to market trading frictions, where redemptions notice and payout periods combined are less than 45 days and no lockup restrictions. Panel A reports the time-series averages and *t*-statistics of the post-formation FH 7-factor alphas, FH 7-factor-based appraisal ratios (AR), and the smoothing-adjusted Sharpe Ratios (SR) for the equally-weighted quintile portfolios sorted on *DownsideReturns*. The performance measures are based on portfolios sorted every three months and held for three months to three years. The *t*-statistics reported in italicized font are adjusted for heteroscedasticity and autocorrelation. Panel B reports the panel regression and Fama-MacBeth regression results for hedge fund performance on *DownsideReturns* and other fund characteristics at quarterly frequency as follows: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i} Downside\,Returns_{i,t-1} + c_{2i} Control_{i,t-1} + e_{i,t}$. We winsorise the alphas, ARs and SRs at the top and bottom 0.5% level. Control variables are as the same as column 4-6 in Table 3. Panel regression is adjusted for the fund-clustering effect, and time and style fixed effects. The Fama-MacBeth regression controls for style dummies, and is adjusted for heteroscedasticity and autocorrelation in standard errors. For brevity, only the estimation results for *DownsideReturns* are reported here. Survivorship and backfill biases are controlled for to the extent that the data allow. ** 1% significance; * 5% significance.

Table 10: Equally-weighted Portfolio Performance Sorted on *DownsideReturns* and *UpsideReturns* within Each Hedge Fund Style

Panel A: High-Minus-Low Quintile Portfolios Sorted on *DownsideReturns*

	Alpha(FH 7-factor, % p.m.)					Appraisal Ratio					Sharpe Ratio				
	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
Convertible Arbitrage	1.16	1.19	1.37	1.30	1.44	1.13	0.84	0.71	0.61	0.51	0.56	0.28	0.21	0.19	0.16
(t-statistic)	(2.13)	(2.11)	(2.28)	(2.06)	(1.92)	(6.46)	(6.35)	(5.54)	(4.72)	(4.51)	(3.94)	(4.08)	(3.99)	(3.76)	(3.21)
Emerging Markets	0.72	0.69	0.56	0.54	0.65	0.80	0.43	0.32	0.23	0.17	0.44	0.23	0.16	0.12	0.08
	(2.27)	(2.74)	(2.69)	(2.82)	(3.52)	(8.72)	(6.23)	(4.58)	(3.68)	(3.56)	(5.84)	(7.65)	(5.16)	(3.77)	(3.60)
Equity Market Neutral	0.61	0.54	0.36	0.11	0.10	0.56	0.38	0.31	0.27	0.22	0.40	0.18	0.14	0.11	0.10
	(2.41)	(2.72)	(2.15)	(0.83)	(0.90)	(6.11)	(6.39)	(5.88)	(4.35)	(3.79)	(3.54)	(4.70)	(5.17)	(3.99)	(3.91)
Event Driven	1.23	1.17	1.02	0.85	0.70	0.87	0.56	0.44	0.36	0.31	0.53	0.36	0.28	0.20	0.15
	(5.00)	(4.97)	(4.10)	(2.91)	(2.07)	(9.31)	(9.10)	(7.91)	(6.91)	(8.12)	(6.72)	(6.83)	(7.56)	(6.14)	(5.34)
Fixed Income	0.54	0.51	0.51	0.37	0.40	1.27	0.76	0.57	0.46	0.40	0.65	0.28	0.20	0.18	0.13
	(1.82)	(1.54)	(1.71)	(1.55)	(1.69)	(7.59)	(5.03)	(3.76)	(2.72)	(2.22)	(5.18)	(3.58)	(3.34)	(2.79)	(1.89)
Global Macro	0.67	0.67	0.56	0.49	0.46	0.44	0.29	0.23	0.19	0.17	0.17	0.06	0.04	0.03	0.02
	(2.97)	(3.42)	(2.93)	(2.97)	(2.27)	(4.80)	(5.61)	(5.31)	(5.97)	(5.49)	(1.90)	(1.27)	(1.05)	(1.13)	(1.72)
Long/Short Equity	0.61	0.55	0.47	0.33	0.34	0.44	0.27	0.21	0.16	0.14	0.15	0.08	0.06	0.04	0.03
	(3.09)	(3.65)	(3.69)	(3.07)	(2.86)	(6.30)	(7.07)	(7.03)	(6.67)	(7.34)	(2.56)	(1.93)	(1.84)	(1.47)	(1.27)
Managed Futures	0.53	0.49	0.41	0.31	0.22	0.59	0.33	0.23	0.16	0.10	0.35	0.14	0.10	0.06	0.05
	(1.53)	(1.83)	(1.84)	(1.35)	(1.19)	(5.31)	(4.02)	(3.18)	(2.61)	(2.27)	(4.48)	(3.03)	(2.60)	(2.56)	(2.59)
Multi-Strategy	0.77	0.71	0.72	0.64	0.62	0.95	0.57	0.43	0.36	0.31	0.40	0.24	0.20	0.17	0.15
	(3.03)	(4.51)	(5.08)	(3.98)	(3.04)	(9.37)	(10.37)	(10.09)	(11.07)	(15.21)	(4.94)	(4.12)	(3.56)	(3.57)	(4.04)
Fund-of-Funds	0.90	0.81	0.70	0.54	0.43	0.74	0.47	0.37	0.29	0.24	0.31	0.18	0.14	0.12	0.10
	(5.26)	(5.59)	(5.22)	(3.86)	(2.80)	(10.66)	(10.32)	(9.68)	(7.72)	(6.28)	(5.11)	(3.86)	(3.44)	(3.33)	(2.57)

(continued)

Table 10: (Continued)

Panel B: High-Minus-Low Quintile Portfolios Sorted on UpsideReturns

	Alpha(FH 7-factor, % p.m.)					Appraisal Ratio					Sharpe Ratio				
	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
Convertible Arbitrage	0.17	0.07	-0.09	-0.14	-0.30	-0.17	-0.15	-0.09	-0.03	0.01	-0.14	-0.03	-0.01	0.02	0.01
	(0.25)	(0.10)	(-0.15)	(-0.20)	(-0.38)	(-1.23)	(-1.46)	(-1.00)	(-0.34)	(0.13)	(-1.11)	(-0.36)	(-0.17)	(0.22)	(0.09)
Emerging Markets	0.39	0.42	0.48	0.56	0.43	-0.08	-0.05	0.03	0.00	0.01	0.24	0.19	0.21	0.15	0.13
	(1.10)	(1.21)	(1.68)	(2.29)	(1.96)	(-0.31)	(-0.46)	(0.28)	(0.03)	(0.10)	(1.04)	(1.34)	(1.97)	(1.57)	(1.53)
Equity Market Neutral	-0.04	-0.08	-0.12	-0.04	0.04	-0.27	-0.19	-0.12	-0.07	-0.04	-0.20	-0.12	-0.08	-0.04	-0.02
	(-0.12)	(-0.22)	(-0.34)	(-0.15)	(0.19)	(-3.16)	(-3.18)	(-2.03)	(-1.56)	(-1.75)	(-2.99)	(-3.19)	(-3.15)	(-2.02)	(-0.97)
Event Driven	0.24	0.14	0.16	0.11	0.10	-0.29	-0.23	-0.17	-0.12	-0.09	-0.02	0.01	0.01	0.01	0.01
	(0.75)	(0.94)	(1.39)	(0.84)	(0.53)	(-2.48)	(-2.56)	(-2.21)	(-2.12)	(-1.80)	(-0.20)	(0.13)	(0.17)	(0.19)	(0.42)
Fixed Income	0.25	0.31	0.33	0.32	0.43	-0.28	-0.20	-0.15	-0.12	-0.10	-0.07	-0.08	-0.08	-0.06	-0.05
	(1.11)	(1.50)	(1.52)	(2.44)	(2.57)	(-3.19)	(-3.27)	(-2.58)	(-2.23)	(-1.92)	(-0.83)	(-1.54)	(-1.74)	(-1.23)	(-1.12)
Global Macro	0.01	-0.09	-0.02	0.07	0.01	0.26	0.14	0.15	0.12	0.09	0.57	0.32	0.23	0.17	0.13
	(0.05)	(-0.41)	(-0.07)	(0.35)	(0.07)	(1.85)	(1.23)	(1.54)	(1.31)	(0.98)	(4.19)	(3.31)	(2.82)	(1.91)	(1.46)
Long/Short Equity	-0.21	-0.27	-0.29	-0.31	-0.33	-0.03	-0.05	-0.02	0.02	0.03	0.06	0.04	0.01	0.00	0.00
	(-0.88)	(-1.54)	(-1.89)	(-2.00)	(-2.28)	(-0.42)	(-0.87)	(-0.37)	(0.38)	(0.79)	(0.65)	(0.69)	(0.21)	(0.11)	(0.28)
Managed Futures	-0.19	-0.28	-0.33	-0.20	-0.02	-0.24	-0.18	-0.13	-0.11	-0.09	0.01	-0.01	-0.03	-0.05	-0.05
	(-0.50)	(-0.85)	(-0.99)	(-0.66)	(-0.08)	(-2.94)	(-3.86)	(-3.40)	(-3.17)	(-2.76)	(0.20)	(-0.27)	(-0.64)	(-0.94)	(-1.02)
Multi-Strategy	-0.17	-0.30	-0.34	-0.35	-0.37	-0.30	-0.16	-0.12	-0.09	-0.04	-0.17	-0.09	-0.07	-0.06	-0.03
	(-0.68)	(-1.54)	(-1.63)	(-1.48)	(-1.50)	(-3.67)	(-2.77)	(-2.51)	(-1.95)	(-1.51)	(-1.77)	(-2.10)	(-2.14)	(-2.97)	(-2.64)
Fund-of-Funds	0.00	-0.06	-0.10	-0.10	-0.10	-0.44	-0.27	-0.23	-0.19	-0.17	-0.08	-0.11	-0.13	-0.13	-0.13
	(0.01)	(-0.34)	(-0.62)	(-0.72)	(-0.69)	(-4.42)	(-3.89)	(-3.34)	(-2.95)	(-2.57)	(-0.79)	(-1.57)	(-1.90)	(-1.69)	(-1.75)

Panel A of Table10 reports style-by-style analysis for the time-series averages and *t*-statistics of the difference in post-formation performances between high and low quintile portfolios sorted on *DownsideReturn.* Panel B reports results for portfolios sorted on *UpsideReturns*. Performance measures include FH 7-factor alphas, FH 7-factor-based Appraisal Ratios, and the smoothing-adjusted Sharpe Ratios. The portfolios are equally-weighted buy-and-hold portfolios sorted every three months and held for three months to three years. The *t*-statistics reported in italicized font are adjusted for heteroscedasticity and autocorrelation.