Hedge Fund Performance Persistence over Different Market Conditions

Zheng Sun
University of California at Irvine

Ashley W. Wang
Federal Reserve Board

Lu Zheng
University of California at Irvine

This draft: April 2014

We provide novel evidence that hedge fund performance is persistent following periods of relative hedge fund market weakness, but not following periods of relative market strength. Specifically, we construct two performance measures, *DownsideReturns* and *UpsideReturns*, conditioning on whether the overall hedge fund market return is below or above its sample median. After adjusting for risk and fund characteristics, funds in the highest *DownsideReturns* quintile outperform funds in the lowest quintile by 5% in the subsequent year, whereas funds with better *UpsideReturns* do not outperform subsequently. These findings suggest an error-in-measurement problem embedded in the unconditional average historical hedge fund returns, which, in turn, weakens their performance predictability.

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

---

The views presented here are solely those of the authors and do not represent those of the Federal Reserve Board or its staff. We thank George Aragon, Turan Bali, Stephen Brown, Yong Chen, Cristian Tiu, and seminar participants at Aoyama Gakuin University, BIFEC Borsa Istanbul Finance and Economics Conference, Federal Reserve Board, Frankfurt School of Finance and Management, George Mason University, and UC Irvine. Zheng Sun is at the Paul Merage School of Business, University of California at Irvine, CA 92697-3125; tel: (949) 824-6907, email: zsun@merage.uci.edu. Ashley Wang is at the Board of Governors of the Federal Reserve System in Washington, DC; tel: (202) 452-3122, email: ashley.wang@frb.gov. Lu Zheng is at the Paul Merage School of Business, University of California at Irvine, email: luzheng@uci.edu.

1. Introduction

Hedge funds attract institutional investors and high net worth individuals, by offering a prospect of achieving profits in both rising and falling markets. Compared with mutual fund investors, hedge fund investors usually pay high fees and face various investment restrictions, yet, due to insufficient hedge fund disclosure requirements, those investors are often presented with limited information when making investment decisions. Arguably, hedge funds' past performance has become one of the most important metrics for investors to select investments. However, do funds' past returns reliably forecast their future performance? This question has been addressed by many academic studies, but only with mixed findings.[1] Note that most of the existing literature focuses on *unconditional* predictability.[2] In this paper, we approach this question by focusing on *conditional* predictability and investigate whether performance persistence varies with the overall hedge fund market conditions.

Why may market conditions matter for performance persistence? Let's first consider a scenario under which fund performance is determined jointly by investment skills and noises. It is possible that fund performance reveals investment skills to varying extents over different market conditions. For example, Kacperczyk, van Nieuwerburgh, and Veldkamp (2013a) document that mutual funds exhibit a higher dispersion across portfolio positions and returns over recession, despite of stronger co-movement in underlying stock payoffs. This implies that fund managers are likely to become more active over market downturns, collecting and processing their own information and thus making investment decisions that are more different from each other and from the uninformed investors. In addition, Brunnermeier and Nagel (2004) show that skilled

[1] Findings on hedge fund performance persistence will be discussed in details in the later part of Introduction.
[2] One exception is Boyson (2008), which investigates how hedge fund performance persistence varies with fund characteristics.

hedge fund managers 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 tech stocks when the markets were about to decline. Moreover, it may become more difficult and costly for mediocre managers to mimic skilled ones during down markets. For instance, Jiang and Kelly (2013) shows that in bull markets mediocre fund managers are able to generate great returns and appear skillful by simply taking a leveraged put-writing strategy, however they would suffer significant losses following this strategy during market downturns. As such we expect performance over the down market to be more informative about skills and hence better predict future performance.

Even under this scenario, there may exist alternative mechanisms that lead to higher information contents in performance about skills over periods of market strength. For instance, strong market may provide more opportunities for hedge funds to exploit mistakes made by less sophisticated investors, who tend to enter financial markets when the market is high.[3] Indeed, using a panel of U.S. equity mutual funds, Glode, Hollifield, Kacperczyk and Kogan (2012) document evidence of performance persistence following periods of high market returns but not following periods of low market returns.

Let's consider another scenario under which performance is also affected by investor cash flows. Berk and Green (2004) build a theoretical framework, under which investors learn about fund managers' heterogeneous skills through past returns, and efficiently allocate capital accordingly. Such unlimited capital supply combined with scarce managerial skills allows fund managers to

[3] See Grinblatt and Keloharju(2001), Lamont and Thaler(2003), Brunnermeier and Nagel (2004), and Cooper, Gutierrez, and Hameed (2004).

grasp the full gains of active investments, thus driving away performance persistence even in the presence of superior investment skills. Under their model, performance persistence could arise if investors make inefficient capital allocations based on past performance, and the persistence pattern could differ across market states, if the extent of capital allocation inefficiency varies with market conditions.

There are several reasons why the degree of inefficiency may vary with market states. First, investor may pay different amount of attention across market states. For example, several papers document evidences for an "ostrich" effect among investors, under which individuals monitor their investments and attend to information more closely upon receiving good news but choose to tune out after getting bad news.[4] This effect may result in less attention paid to hedge funds' past performance amid relative market weakness, which, in turn, could lead to stronger performance persistence in the down market. Granted that hedge fund investors are a different group from individual stock market participants, whether they exhibit different behaviors across market states is, by itself, an unexplored empirical question.

Second, even if investors pay equal amount of attention in different market states, should past performance in certain market conditions contain more signals about managerial skills than in others, investors would still under-react to such performance measures that better reveal skills, leading to performance persistence.

In light of the arguments above, whether and how performance persistence varies with market conditions, ultimately, is an empirical question. In this study, we examine performance

[4] See Karlsson, Loewenstein, and Seppi (2009), Sicherman et al. (2012), and Hou, Peng, and Xiong (2009).

persistence conditioning on the overall conditions of hedge fund sector. We start by constructing two conditional performance measures, *DownsideReturns* and *UpsideReturns,* which are based on conditional time-series average returns of individual funds when the overall hedge fund sector performance is below (or above) the sample median, respectively.

Our main test concerns the relation between the *DownsideReturns* and *UpsideReturns* measures and future fund performance. Our fund performance evaluation metrics include: Fung-Hsieh seven-factor alpha, appraisal ratio and the Sharpe Ratio. We find that funds with better *DownsideReturns* significantly outperform their peers in all performance metrics over the next 3 months to 2 years. In contrast, funds with better *UpsideReturns* do not outperform subsequently. This finding is robust under both portfolio sorting and regression settings, withstands controlling for fund characteristic and styles, and holds for funds subject to different degrees of share restrictions.

To shed light on why *DownsideReturns* better predict future hedge fund performance, we find that *DownsideReturns* are positively associated with various hedge fund skill proxies proposed by the prior literature, including hedging ability (Titman and Tiu, 2011), strategy innovation skills (Sun, Wang and Zheng, 2012), and market liquidity timing skills (Cao, Chen, Liang and Lo, 2013), whereas *UpsideReturns* are either negatively or uncorrelated with such measures. The findings are consistent with the hypothesis that performance amid market weakness is more informative about skills and hence better predicts future performance.

We also examine whether the performance persistence amid market weakness can be attributed to investors' inefficient capital allocation. We conduct two tests in this regard. First, we test the "ostrich" effect, under which investors generally pay less attention to fund performance during the down market. We study the flow-performance sensitivity over the down and up markets. Consistent with the prior literature, we find that flows actively chase past performance over both market conditions. Interestingly though, flows react more strongly to past performance during the down market than up market. This finding is inconsistent with the prediction of the "ostrich" effect. Thus, the stronger performance persistence amid market weakness is unlikely to be driven by hedge fund investors' lack of attention in the down market.

Of course, even if investors react strongly to downside performance, it does not imply that capital has been allocated up to the optimal level. We then design a second test to directly study capital allocation efficiency by examining whether fund flows predict future fund performance. If investors have allocated capital efficiently, there should be no money left on the table, thus flows should not predict future fund performance. Specifically, we follow a two-way portfolio sorting approach. At each quarter, we first sort funds into quintile portfolios based on their past 2 years' *DownsideReturns* (or *UpsideReturns*), and further sort them into quintile portfolios based on fund flows over the past year. We then calculate performance for each portfolio over the next quarter. The two way sorting controls for performance predictability due to chasing past performance, allowing us to focus on the marginal forecasting power of fund flows. We find that after controlling for funds' past performance over either up or down market states, fund flows are not significantly associated with future fund performance. Therefore, it appears that hedge fund investors' have allocated their capital efficiently.

Overall, we find evidences consistent with *DownsideReturns* better capturing fund managers' skills, and hence better predicting future fund performance. However, we didn't find evidences in supportive of inefficient capital allocation amongst hedge fund investors.

Our paper makes three contributions. First, it contributes to the literature on performance persistence among hedge funds. Several studies have examined this question, yet with no consensus in empirical findings. Brown, Goetzmann, and Ibbotson (1999) estimate the performance of offshore hedge funds and find little persistence in hedge fund alphas. Agarwal and Naik(2000) shows that while there exists persistence in hedge fund performance, most of which is driven by losers. In contrast, Kosowski, Naik and Teo (2007) and Jagannathan, Malakhov and Novikov (2010) find significant performance persistence over 1 to 3 years, especially among superior funds. Joenvaara, Kosowski and Tolonen (2014) find that performance persistence is reduced significantly when fund size and share restrictions are incorporated into rebalancing rules. The lack of consensus on performance persistence casts doubt on the existence of skill and value of active management.

Our paper is the first to link hedge fund performance persistence to variation of hedge fund market conditions, and finds that the persistence depends critically on the state of the market. The unconditional average past performance is contaminated by noises, which are uncorrelated with future performance and dilute its performance forecasting power. We show that by using a conditional past performance measure to filter out some noises, we can restore a much stronger performance forecasting power.

Second, our paper also contributes to the literature that examines time-varying performance and return predictability conditioning on market situations, including Ferson and Schadt (1996), Moskowitz (2000), Cooper, Gutierrez and Hameed (2004), Glode (2011), Kosowski (2011), Kacperczyk, Van Nieuwerburgh, and Weldkamp (2012, 2013b), 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 the return persistence for stocks and mutual funds, respectively, and find stronger persistence following periods of strong markets. Our paper is the first to examine this question for hedge funds, and we find that performance persistence is stronger following periods of relative hedge fund market weakness. Our results suggest that the mechanism underlying performance persistence for hedge funds might be distinct from those for stock and mutual funds.

Finally, our paper contributes to an emerging literature on identifying cross-sectional measures that predict hedge fund performance. For example, funds with greater hedging skills hence exhibiting lower R-squared with respect to systematic risk factors are shown to subsequently outperform those with higher R-squared (Titman and Tiu, 2011). Funds with better strategy innovation skills are shown to outperform in the future (Sun, Wang and Zheng, 2012). Furthermore, funds with superior market liquidity timing skill are shown to outperform (Cao, Chen, Liang and Lo, 2013). Our paper proposes a simple new measure, *DownsideReturns*, to predict hedge fund performance. We show that the conditional performance measure has strong performance forecasting power that is distinguishable from the existing skill measures.

Therefore, our findings highlight the importance of incorporating aggregate market conditions in detecting managerial skills.

Our study also has direct practical implications. Investors pay high fees for hedge fund performance. However, due to the opacity of hedge fund practice, investors often need to resort to funds' past performance to screen for skilled managers. Our study suggests that adopting this simple conditional performance measure that factors into market conditions would enhance hedge fund investors' ability to make investment decisions.

The remainder of the paper is organized as follows. Section 2 introduces the data and metrics for hedge fund performance evaluation. Section 3 defines two conditional performance measures, *DownsideReturns* and *UpsideReturns*, and examines their properties. Section 4 investigates the performance predicting power of *DownsideReturns* and *UpsideReturns* and conducts robustness check. Section 5 compares *DownsideReturns* and *UpsideReturns* with a set of hedge fund skill proxies, shedding light on whether *DownsideReturns* predict performance due to their proxying role for managerial skills. Section 6 focuses on whether the performance predicting power of *DownsideReturns* may be related to inefficient capital allocation by hedge fund investors. Section 7 concludes.

2. Data and Fund Performance Evaluation Metrics

The hedge fund data used for this study are from the Lipper TASS database, which is recognized as 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 18,378 live and graveyard funds. Then, 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 leaves 10,030 unique funds. We also filter out observations before 1994 and after 2011, which yields 10,020 unique funds. To control for backfill bias, we further exclude the first 18 months of returns for each fund, yielding 8,837 unique funds.[5] To reduce noises in the conditional performance measures, we exclude funds with fewer than 50% observations over the period when total hedge fund performance is below the median of the past 2 years, leading to a sample of 7,653 unique funds. Finally, we filter out funds with assets under management (AUM) of less than 5 million dollars, resulting in a final sample with 5,465 unique funds.

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 30 funds in the dedicated short bias category. 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 adequately capture the risk-return tradeoff. For our main results, we use the Fung and Hsieh (FH) seven-factor model (Fung and Hsieh, 2001),[6] which

[5] 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 Appendix.
[6] http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm.

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 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.[7] 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.

Moreover, we 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 Appendix.

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

The goal of this study is to investigate whether hedge fund performance persistence varies with the states of the markets. To differentiate across market states, we compare the overall hedge fund market performance with its sample median to define the *up* and *down* states of hedge fund markets.

[7] Brown, Goetzmann, and Ross (1995) .

3.1 Quantifying Hedge Fund DownsideReturns and UpsideReturns

While fund performance can only be a noisy signal of managerial talents, the signal-to-noise ratio may differ across the states of the markets. We explore this idea by constructing conditional performance measures based on time-series average return of individual funds (r_{it}) when the overall hedge fund market performance ($r_{HF,t}$) is below (or above) the sample median level, and term it as *DownsideReturns (*or *UpsideReturns*):

$$\begin{aligned} Downside\,\mathrm{Re}turns_i &= \frac{1}{T_i}\sum_{t=1}^{T_i} r_{i,t} \,\middle|\, r_{HF,t} \text{ below 50 percentile} \\ Upside\,\mathrm{Re}turns_i &= \frac{1}{T_i}\sum_{t=1}^{T_i} r_{i,t} \,\middle|\, r_{HF,t} \text{ above 50 percentile} \end{aligned} \tag{1}$$

At the beginning of each quarter, we identify the 12 months over which the overall hedge fund market returns are below (or above) the median level of the past 24-month window. Then for each hedge fund with at least 6 observations over the 12 months, we take the time series sample average of fund returns to get the *DownsideReturns (UpsideReturns)* measure.

3.2 Properties of DownsideReturns and *UpsideReturns*

As reported in Table 1, there is clear evidence of large variations in *DownsideReturns* and *UpsideReturns* across funds. Panel A reports the time-series averages of the cross-sectional summary statistics of the main variables. The *DownsideReturns* measure has a mean (median) of -0.40% (-0.19%) per month, with a standard deviation of 1.77%; whereas the *UpsideReturns* measure has a mean (median) of 2.15% (1.70%) per month, with a standard deviation of 1.99%.

The histograms presented in Figure 1 further confirm the heterogeneous patterns in the conditional performance measures. Panel A reveals that about 60 percent of the sample funds exhibit negative *DownsideReturns*. The distribution is about 30 percent in each of the -0.5% and 0.5% per month *DownsideReturns* bins. Funds scoring higher than 1% per month in *DownsideReturns* account for about 10 percent of the total sample. Panel B shows that 70% of sample funds' *UpsideReturns* fall between 0 to 3% per month, and only 5 percent of sample fund exhibit negative *UpsideReturns.* Overall, the *DownsideReturns(UpsideReturns)* measure is titled to the left (right), consistent with most funds likely to underperform (outperform) when the overall hedge fund markets are weak (strong).

A comparison of the conditional performance measures between the live and graveyard funds shows weaker performance by the graveyard funds (-0.42% and 2.01% per month, Panel A of Table 1) than the live funds (-0.33% and 2.32% per month), on both downside and upside. Moreover, the proportion of the live and graveyard funds remains at about a 40/60 split across bins, as shown in Figure 1. These statistics suggest that findings on the relation between the *DownsideReturns (UpsideReturns)* and fund performance are unlikely driven by the difference between live and graveyard funds. In unreported analysis, 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, *DownsideReturns* appear to be positively associated with fund performance metrics measured by alpha, appraisal ratio, and the Sharpe ratio, whereas the correlations between *UpsideReturns* and performance metrics are mixed and subdued. Third, fund return volatility (*Vol*) is negatively correlated with *DownsideReturns*, but positively correlated with *UpsideReturns*.

4. 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.

4.1 Portfolio Sorting

To gauge the relative 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 previous 24 months. For each quintile portfolio, we compute the equally and value-weighted average buy-and-hold performance levels for the subsequent quarter. We also consider the performance of these quintile portfolios held over the subsequent six months to three years.[8]

We consider various performance measures for each quintile portfolio, including the average FH seven-factor adjusted alpha, a modified version of Treynor and Black's appraisal ratio (1973),

[8] 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 for up to 2-year buy-and-hold horizons.

and the smoothing-adjusted Sharpe ratio.[9] For each fund, we compute the monthly FH seven-factor alpha using a rolling estimation of the prior 24 months. We then compound the monthly alpha to derive the holding-period alpha for each fund, and 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 of its monthly FH seven-factor adjusted returns over the holding period and the standard deviation of the monthly alphas. 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.[10] 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.[11]

4.1.1 Portfolios Sorted on DownsideReturns

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. The corresponding *t*-statistics are adjusted for heteroscedasticity and autocorrelation. As shown, the FH seven-factor alphas increase monotonically with the past *DownsideReturns* measures for all five holding horizons. For a trading strategy with a one-year holding horizon, funds in the highest *DownsideReturns* quintile earn an abnormal return of 7.53% per annum, with a *t*-statistic of 5.85. Those in the lowest *DownsideReturns* quintile yield a return of 2.92% each year after controlling for the FH seven factors. The performance difference between the top and bottom quintiles is 4.61 percentage points per annum, and it is

[9] We exclude extreme values in our analysis. In particular, we filter out observations with absolute monthly alphas of more than 100%, and absolute Sharpe ratios or appraisal ratios of more than 10. The exclusions usually result in less than 1% loss of the sample.
[10] Results based on the raw Sharpe ratios yield similar findings and are available upon request.
[11] Value-weighted portfolios exhibit similar patterns, shown in Appendix A1.

statistically significant. For other holding horizons, funds in the highest *DownsideReturns* quintile consistently outperform those in the lowest quintile by about 2-6% per annum after adjusting for the FH seven factors. To earn these return spreads, one has to adopt a trading strategy that goes long on funds with the best downside performance and shorts those with worst downside performance. The long side of this trading strategy alone can already secure an abnormal return of about 7% per annum for all holding horizons.

When a fund outperforms in down markets, it also deviates from the overall sector and may be exposed to idiosyncratic risk. To take into account different levels of unique risk across funds, we use a modified version of Treynor and Black's appraisal ratio (1973). For the equally weighted portfolios, the appraisal ratio increase almost monotonically with *DownsideReturns*. The difference between the top- and bottom-*DownsideReturns* portfolios is 0.53 with a *t*-statistic of 7.53 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 converges but still remains highly significant at a level of 0.29 with a *t*-statistic of 7.81.

To ensure that our portfolio-sorting results are not specific to the FH seven-factor performance benchmark, we also consider the smoothing-adjusted Sharpe ratio, which is based on the monthly net fee returns in excess of the risk-free rate. The equally weighted portfolio Sharpe ratio increases almost monotonically from the lowest *DownsideReturns* quintile to the highest for all five holding horizons. For the one-year holding horizon, the high-*DownsideReturns* portfolio outperforms the low-*DownsideReturns* portfolio by 0.15, which is significant at the 1% level. In general, the spread in the smoothing-adjusted Sharpe ratio ranges from 0.13 to 0.28 across various holding horizons and is significant at the 1% level.

4.1.2 Portfolios Sorted on UpsideReturns

We conduct similar portfolio sorting analysis based on the lagged *UpsideReturns,* and show results in Panel B of Table 2. There is no significant difference in future alphas and Sharpe ratios between the high and low-*UpsideReturns* quintile portfolios, and the future appraisal ratio of the high-*UpsideReturns* portfolio is even lower than that of the low-*UpsideReturns* portfolio.

Figure 2 provides a graphic presentation of the contrast in the post-formation alphas between extreme quintile portfolios sorted on *DownsideReturns* and *UpsideReturns*, respectively. The plotted alphas are demeaned by the alphas of the corresponding middle quintile portfolios. Clearly, funds in high *Downside* quintile continue to outperform those in the low quintile, but there is no discernible difference in future alphas between high- and low-*UpsideReturns* portfolios.

4.2 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:

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

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;[12] average returns over the previous 24-month period[13]; 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.

[12] To control for data errors, we exclude observations of flow higher than 1,000% or lower than -1,000%.
[13] We also use the average alpha over the previous 24-month period as an alternative specification, and the results are similar.

We use time-series and cross-sectional unbalanced panel data. Given the stale price issue for hedge fund data, which has been documented by Getmansky, Lo, and Makarov (2004), the resulting alphas may be correlated over time for a specific fund. Therefore, we must correct for the fund-clustering effect. Moreover, hedge fund performance may be correlated across funds at a given point in time. Therefore, we need to correct for the time effect. Thus we adopt two approaches. The first approach is a panel regression that adjusts for both fund-clustering and time and style fixed effects. The second approach is the Fama-MacBeth cross-sectional analysis with style fixed effects, and the Newey-West heteroscedasticity and autocorrelation adjustment (HAC). To increase the power of the test, our regressions use data of quarterly frequency.

4.2.1 Panel Regression

For the panel regression, we pooled the time series of all funds together to estimate Equation (3). The results are reported in Tables 3. Panel A of Table 3 shows that for future alpha regression, the estimated coefficient for the *DownsideReturns* is 1.82 with a *t*-statistic of 6.43 when controlling for fund-clustering and for time and style fixed effects. This implies that a one-standard-deviation increase in the *DownsideReturns* predicts an increase in the annualized FH seven-factor returns of 3.24% 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 lengths of the redemption notice period and the lockup period are significantly and positively associated with future fund alpha. 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 incentive fees are significantly and positively related to future alpha. These results are similar to the findings presented by Agarwal, Daniel, and Naik (2009), in which hedge funds are found to outperform when managers are better incentivized. AUM is negatively associated with future alpha, which is consistent with the notion of performance erosion due to increased scale in the mutual fund sector, as discussed by Berk and Green (2004) and by Chen, Hong, Huang, and Kubik (2004). We also utilize the appraisal ratio and smoothing-adjusted Sharpe ratio as alternative performance measures. The results indicate a strong positive association between the *DownsideReturns* and the future appraisal ratio and Sharpe ratio.[14]

Note that the association between *DownsideReturns* and future performance metrics holds regardless of the inclusion of the unconditional average past performance (*AvgPast2YRet*) in the regressor set, both directionally and magnitude wise. This suggests that the performance predicting power of *DownsideReturns* is beyond the performance chasing explanation.

Panel B, however, reveals a negative association between *UpsideReturns* and future fund performance metrics, after controlling for other fund characteristics. The magnitude of the *UpsideReturns* coefficients changes notably after controlling for the unconditional average performance measure.

[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.

4.2.2 The Fama-MacBeth Regression

Table 4 summarizes results from the Fama-MacBeth cross-sectional regression of Equation (3), which are largely consistent with those from the panel regression and the portfolio analyses. Panel A illustrates a significant and positive association between *DownsideReturns* and future performance metrics, whereas in Panel B, the association between *UpsideReturns* and future performance metrics is less robust, ranging from significantly negative to insignificant.

4.3 Robustness Tests

4.3.1 Is It Due to Market Frictions?

Although most hedge funds are often open-ended, there typically exist various restrictions, which 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 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 where the redemption notice and payout periods combined are no more than 45 days, and no lockup period is required, which account for about 40 percent of the whole sample.

Panel A of Table 5 show that funds with higher *DownsideReturns* continue to significantly outperform those with lower *DownsideReturns*, over the next quarter to up to the next two years, even in the absence of market frictions. Panel B of the regression analyses corroborate the findings. Overall, the results based on this subsample are comparable to the main ones using the whole sample, both directionally and magnitude wise. Hence, market frictions are unlikely the primary driver for the performance predicting power of *DownsideReturns*.

4.3.2 Other Robustness Tests

In unreported analyses, we also consider alternative specifications for the *DownsideReturns* measure: we use the past 2- and 3-year as the look-back windows to construct the conditional performance measures; we use the overall hedge fund sector performance as well as the specific hedge fund style performance to gauge the states of market conditions; and we use the median as well as the top/bottom 1/3 cutoff points to define the *up* and *down* states of hedge fund markets. In addition to the FH seven-factor benchmark, we use returns on various hedge fund styles as alternative risk benchmarks to estimate the abnormal fund performance. To verify whether the performance predicting power of *DownsideReturns* is limited to certain hedge fund styles, we repeat the regression analysis within major individual styles. Overall, the results are consistent with the main analysis and are available upon request.

5. Source of Performance Persistence: Skill Related?

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 *DownsideReturns* better reveal the underlying hedge fund managerial skills. In this subsection, we relate *DownsideReturns* to several 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), and the market liquidity timing skills shown by Cao, Chen, Liang and Lo (2013).

Titman and Tiu (2011) show that skilled hedge fund managers will choose 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 of hedging away of 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,

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

We use the Pastor-Stambaugh market liquidity innovation series to measure ΔLIQ_t.[15]

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 *DownsideReturns* better reflecting managerial skills, it generally exhibit a positive correlation with proxies for hedging, strategy innovation, and market liquidity timing skills, whereas *UpsideReturns* are negatively associated with such skill proxies.

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

$$AbnormalPerformance_{i,t} = c_{0i} + c_{1i}DownsideReturns_{i,t-1} + c_{2i}AlternativeSkills_{i,t-1} + c_{3i}Control_{i,t-1} + e_{i,t} \quad (5)$$

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 and C show a similar robust performance predicting power of *DownsideReturns* after controlling for strategy innovation and market liquidity timing skills, respectively. Finally, Panel D further confirm the performance predicting power of *DownsideReturns* in the presence of the aforementioned skill proxies simultaneously.

---

[15] 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.

All told, while *DownsideReturns* may partly reflect managers' skills of hedging systematic risk, engaging in strategy innovations, and timing market liquidity, the reasons for the performance predicting power go beyond such effects. In light of the heightened scrutiny and enhanced disclosure requirements on hedge funds since the financial crisis, it may be fruitful to conduct future research to further pin down specific skills that are manifest in the *DownsideReturns* measure.

6. Source of Performance Persistence: Inefficient Capital Allocation?

In this section, we examine whether the strong performance persistence in down markets is due to investors' inefficient capital allocation. There exist at least two mechanisms that could lead to such inefficiency: first, if investors exhibit an "ostrich" effect by paying less attention to their investments upon receiving negative outcomes, fund flows may be less sensitive to past *DownsideReturns*, which in turn, could lead to under-reaction and hence persistence in performance. Second, even if investors react equally to both downside and upside performance, our earlier findings of *DownsideReturns* being more revealing about managers' skills imply that investors would still under-react to *DownsideReturns*, which again could induce stronger performance persistence in down markets.

To test for the "ostrich" effect, we examine the sensitivity of fund flows to past *DownsideReturns* and *UpsideReturns,* respectively. We follow the methodology in Sirri and Tufano (1998) by imposing a piecewise linear relation between fund flows and past performance. Specifically, for each period t we calculate fund i*'s* fraction rank ($Rank_{i,t-1}$) , which is the percentage ranking of its past 24 months' *DownsideReturns* (or *UpsideReturns*) relative to other funds in the same style. We then create three performance variables for fund *i* based on $Rank_{i,t-1}$:

$$Bottom\ Performance_{i,t-1} = min(1/3, Rank_{i,t-1});$$

$$Middle\ Performance_{i,t-1} = min(1/3, Rank_{i,t-1} - Bottom\ Performance_{i,t-1}); \qquad (6)$$

$$Top\ Performance_{i,t-1} = min(1/3, Rank_{i,t-1} - Bottom\ Performance_{i,t-1} - Middle\ Performance_{i,t-1}).$$

We construct 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 over the next quarter up to the next year on the three lagged performance variables, along with other controls, at the quarterly frequency, as follows,

$$Flow_{i,t} = c_{0i} + c_{1i}Bottom_{i,t-1} + c_{2i}Middle_{i,t-1} + c_{3i}Top_{i,t-1} + c_{3i}Control_{i,t-1} + e_{i,t} \quad (7)$$

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.

Panels A and B in Table 8 report how fund flows react to past *DownsideReturns* and *UpsideReturns* over the next 3 months to 1 year, respectively. Consistent with prior findings in the literature, we find that hedge fund investors actively chase past performance by withdrawing from past losing funds and investing in past winning funds, as most of the coefficients of *Bottom-, Middle- and Top- Performance* variables are significantly positive. However, results in Panel C do not suggest weaker flow-performance sensitivity amid market weakness implied by the “ostrich” effect. Panel C summarizes results for the tests on equality of flow-performance sensitivity to past *DownsideReturns* and *UpsideReturns*. Take the post 1-year flow response to past performance as an example, a 1% increase in *Bottom-performance* based on *DownsideReturns* is associated with an inflow of 0.30%, yet only 0.12% inflow for *UpsideReturns*-based *Bottom-performanc*e variable. The difference of 0.18% is statistically significant. Overall, hedge fund investors appear to react more strongly to *DownsideReturns* than to *UpsideReturns*, consistent with our earlier finding that downside performance is a better reflection of manager skill.

We further examine the performance predictability of fund flows, with the idea that efficient capital allocation should leave no money on the table and hence no performance predictability by flows. Specifically, to distinguish the impact on fund performance due to past performance and past flow, we conduct a two-way sorting by first sorting funds into quintile portfolios based on past 2-year conditional returns, then within each quintile, further sorting funds into 5 portfolios based on past 1-year flows. As shown in Table 9, after controlling for past returns, fund flows are not significantly associated with future fund performance, consistent with efficient capital allocation by hedge fund investors.[16] In summary, our finding is not in supportive of capital inefficiency as a primary driver for hedge fund performance persistence amid market weakness.

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 into 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 under its sample median. We term it as *DownsideReturns*. On the basis of fund return data from January 1994 to December 2011, we document substantial cross-sectional variations in the *DownsideReturns*, indicating much heterogeneity in fund's ability of handling weak market conditions. Further analysis indicates that the *DownsideReturns* measure is related to a number of fund characteristics, such as past fund performance, return volatility, size, the lengths of the redemption notice periods,

[16] Note that efficient capital allocation by investors does not necessarily imply absence of performance persistence. For example, Glode and Green (2011) and Hochberg, Ljungqvist, and Vissing-Jorgensen (2013) have proposed models in which investors rationally react to past performance, but performance persistence still arises.

management and incentive fees, minimum investments requirements, use of high water mark provisions, and risk management practice.

Our main results show that the *DownsideReturns* measure is associated with future fund performance. Funds with higher *DownsideReturns* tend to perform consistently better, after adjusting for differences in their risks and styles. We establish these evidences using both portfolio sorting and multivariate regression approaches. Overall, our evidences are consistent with *DownsideReturns* being a potentially useful indicator of managerial talents, and hence beneficial to investors when selecting funds.

Appendix: Smoothing-adjusted Sharpe Ratio

We use the smoothing-adjusted Sharpe ratio rather than the regular Sharpe ratio. Lo (2002) points out that hedge fund returns are subject to high serial correlations that can bias the *annualized* Sharpe ratio when measured using monthly returns if autocorrelation in returns is not taken into account. Moreover, Getmansky, Lo, and Makarov (2004) show that due to illiquidity and smoothing, the unobserved true economic returns differ from the observed smoothed returns. Therefore, even the *monthly* Sharpe ratio, which itself is based on the observed returns, will be biased. Getmansky et al. (2004) further propose an econometric model of return smoothing, as well as an estimator for the smoothing-adjusted Sharpe ratio. In particular, the true return of a hedge fund R_t is determined by a linear factor model, as described below:

$$R_t = \mu + \beta\Lambda_t + \varepsilon_t, \quad \varepsilon_t, \Lambda_t \sim IID \text{ (A1)}$$

The true return, R_t, is not observable. Instead, we observed the smoothed returns, R_t^o, as follows:

$$\begin{aligned} &R_t^o = \theta_0 R_t + \theta_1 R_{t-1} + \ldots + \theta_k R_{t-k} \\ &\theta_j \in [0,1], j = 0,\ldots,k \text{ and } \theta_0 + \theta_1 + \ldots\theta_k = 1 \end{aligned} \quad \text{(A2)}$$

Getmansky et al.'s paper shows that the Sharpe ratio of the true unobserved return can be obtained by multiplying the regular Shape ratio based on the smoothed return by $\sqrt{\theta_0^2 + \theta_1^2 + \ldots + \theta_k^2}$. The coefficients ($\theta_0, \theta_{1,} \ldots\theta_k$) in Equation (A2) can be estimated using the maximum likelihood method. We assume that the observed returns depend on lagged true returns up to time (t - 2). Thus, the smoothing-adjusted Sharpe ratio is:

$$SR = \sqrt{\theta_0^2 + \theta_1^2 + \theta_2^2}\, SR^o$$

where SR^o is the regular Sharpe ratio calculated using observed monthly hedge fund returns.

References

Abraham, J., Goetzmann, W., and Wachter, J. 1994. Homogeneous Groupings of Metropolitan Housing Markets. *Journal of Housing Economics* 3: 186–206.

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

Ackermann, C., McEnally, R., and Ravenscraft, D. 1999. The Performance of Hedge Funds: Risk, Return, and Incentives. *Journal of Finance* 54: 833–874.

Adrian, T., and Brunnermeier, M. 2011. CoVaR. Working paper, 2011.

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., and Naik, N. 2004. Risks and Portfolio Decisions Involving Hedge Funds. *Review of Financial Studies* 17: 63–98.

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.

Arrow, K., 1962. The Economic Implications of Learning by Doing. *Review of Economic Studies* 29: 155-173.

Bali, T., Brown, S., and Caglayan, M. 2012. Systematic Risk and the Cross-Section of Hedge Fund Returns. *Journal of Financial Economics* 106: 114-131.

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

Brown, S., and Goetzmann, W. 1997. Mutual Fund Styles. *Journal of Financial Economics* 43: 373–399.

Brown, S., and Goetzmann, W. 2003, Hedge Funds with Style. *Journal of Portfolio Management* 29: 101–112.

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 Park, J. 2001. Careers and Survival: Competition and Risk in the Hedge Fund and CTA Industry. *Journal of Finance* 56: 1869–1886.

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

Brown, S., Huang, I., In, F., and Kim, T. 2011. Systemic Risk and Cross-sectional Hedge Fund Returns. Working Paper.

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, J., Hong, H., Huang, M., and Kubik, J. 2004. Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. *The American Economic Review* 90: 1276–1302.

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. 1997. Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. *Review of Financial Studies* 10: 275–302.

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., and Hsieh, D. 2002. Benchmarks of Hedge Fund Performance: Information Content and Measurement Biases. *Financial Analysts Journal* 58: 22–34.

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

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

Gray, W., and Kern, A. 2010. Do Hedge Fund Managers Identify and Share Profitable Ideas? University of Chicago Booth School of Business Working Paper.

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.

Goetzmann, W., and Wachter, S. 1995. Clustering Methods for Real Estate Portfolios. *Real Estate Economics* 23: 271–310.

Goetzmann, W., Ingersoll, J., and Ross, S. 2003. High-Water Marks and Hedge Fund Management Contracts. *Journal of Finance* 58: 1685–1717.

Hou, K., L. Peng, and W. Xiong. 2009. A tale of two anomalies: The implication of investor attention for price and earnings momentum. Working paper. Ohio State University.

Hochberg Y., A. Ljungqvist, and A. Vissing-Jorgensen. 2013. Informational Holdup and Performance Persistence in Venture Capital. *Review of Financial Studies*, Forthcoming.

Ibbotson, R., and Chen, P. 2006. The A, B, Cs of Hedge Funds: Alphas, Betas, and Costs, Yale ICF Working Paper No. 06–10.

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.

Jenter, D., and Kanaan, F. 2010. CEO Turnover and Relative Performance Evaluation. *Journal of Finance, forthcoming.*

Jiang, H., and Kelly, B. 2012. Tail Risk and Hedge Fund Returns. Working Paper.

Joenvaara, J., 2011. Hedge Fund Performance and Systemic Risk. 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.

Karlsson, N., G. Loewenstein, and D. Seppi. 2009. The “Ostrich Effect”: Selective attention to information. Journal of Risk and Uncertainty 38: 95-115.

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.

Kothari, S., Shu, S., and Wysocki, P. 2009. Do Managers Withhold Bad News? *Journal of Accounting Research* 47: 241-276.

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. 1999. On the Performance of Hedge Funds. *Financial Analysts Journal* 55: 72–85.

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.

Manconi, A., and Spalt, O. 2012. Learning by Doing and the Value of Experience for Mutual Fund Managers. Working Paper, Tilburg University.

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.

Petersen, M. 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies* 22: 435-480.

Pollet, J., and Wilson, M. 2008. How Does Size Affect Mutual Fund Behavior? *Journal of Finance* 63: 2941–2969.

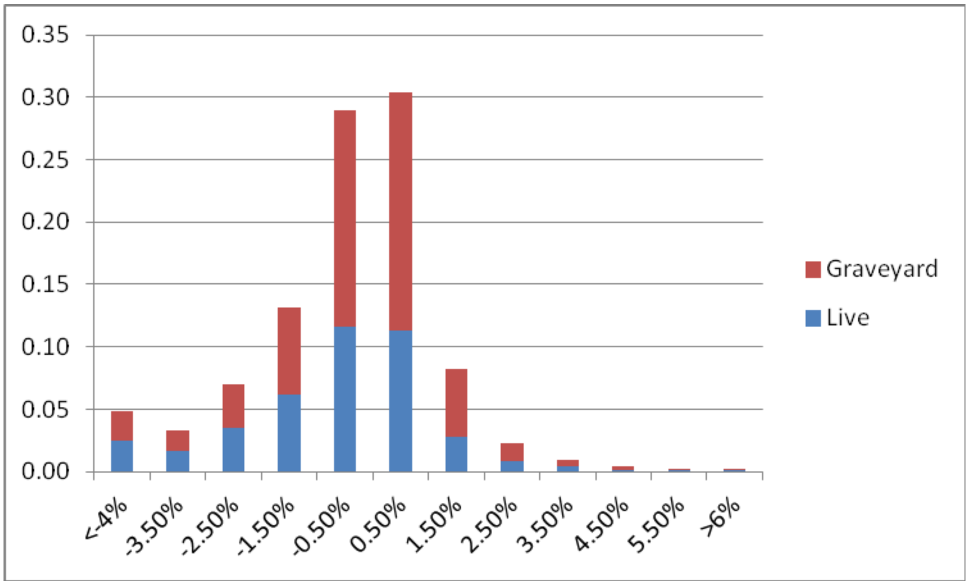
Sicherman, N., G. Loewenstein, D. J. Seppi, and S. P. Utkus. 2012. To look or not to look: Financial attention and online account logins. Working Paper. Columbia University.

Sirri, E., and P. Tufano, 1998, Costly Search and Mutual Fund Flows, *Journal of Finance* 53: 1589-1622.

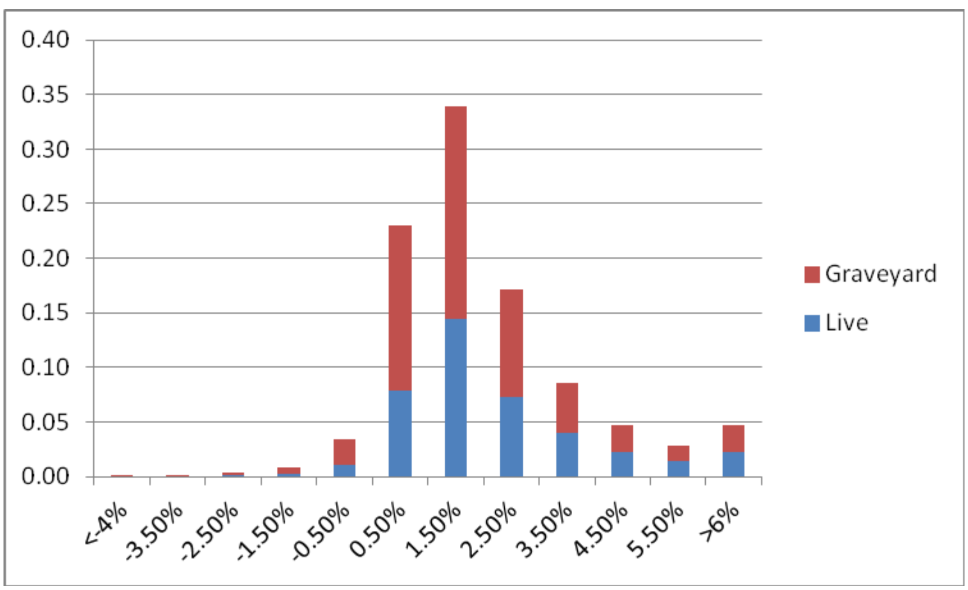
Sun, Z., Wang, A., and Zheng, L. 2012. The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance. Review of Financial Studies 25: 96-143.

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.



Panel A: Histogram of *DownsideReturns*



Panel B: Histogram of *UpsideReturns*

Figure 1: Histograms of Hedge Fund *DownsideReturns* and *UpsideReturns*

Panels A and B of Figure 1 represent histograms of the *DownsideReturns* and *UpsideReturns* measures for all funds for the period 1996-2011. They also depict the breakdown between the live and graveyard funds in the distributions.

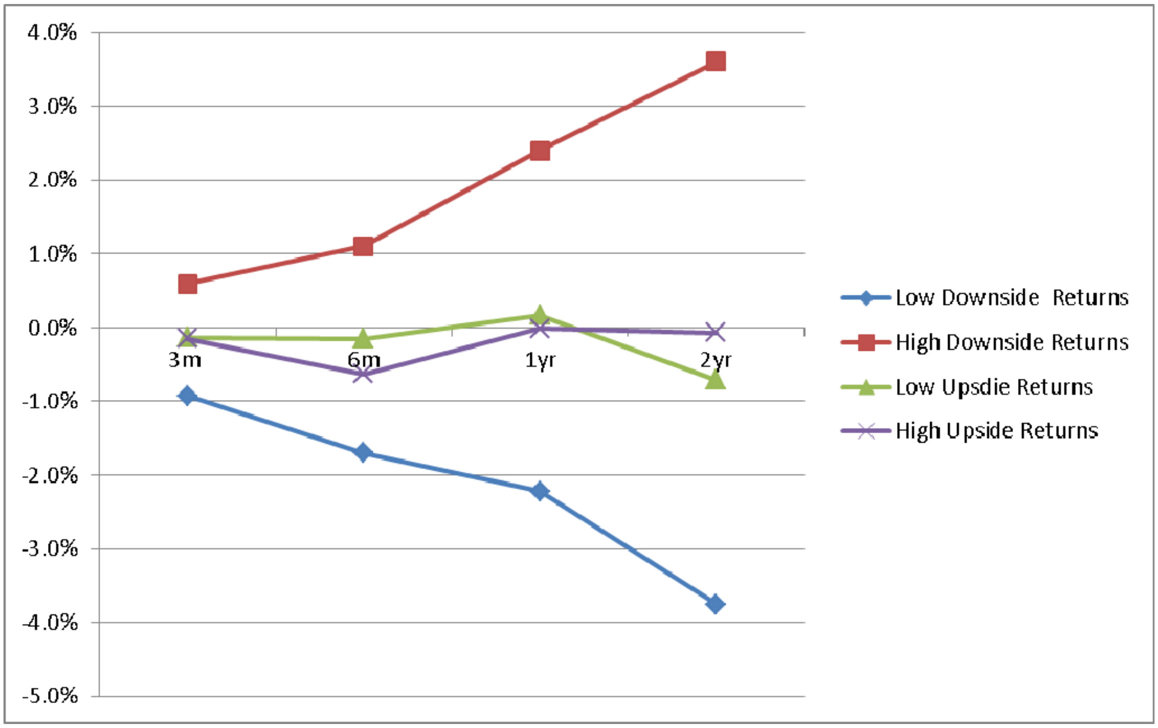


Figure 2: Post-Formation Performance by Quintile Portfolios Sorted by *DownsideReturns* and by *UpsideReturns*

Figure 2 graphs the post-formation performance by the top and bottom quintile portfolios sorted by past *DownsideReturns* and by *UpsideReturns*, respectively. Specifically, at the beginning of each quarter, we short funds into quintile portfolios based on their *DownsideReturns (UpsideReturns*) estimated over the past 24 months. We then compute the future 3-month to 2-year alpha for each portfolio. The numbers reported in this graph are the alphas for the top/bottom quintile portfolios demeaned by the alphas of the corresponding middle quintile portfolios.

Table 1: Summary Statistics (1996–2011)

Panel A: Fund Performance and Characteristics

	Full Sample (5465 unique funds)					Live Funds (1744 unique funds)					Graveyard Funds (3721 unique funds)				
	Mean	Median	Min	Max	Std	Mean	Median	Min	Max	Std	Mean	Median	Min	Max	Std
#Funds per period	1381	1447	329	2228	588	566	382	60	1634	482	815	807	156	1301	337
DownsideReturns (% p.m.)	-0.40	-0.19	-10.74	10.78	1.77	-0.33	-0.15	-7.97	6.37	1.70	-0.42	-0.20	-10.02	9.95	1.76
UpsideReturns (% p.m.)	2.15	1.70	-5.30	16.52	1.99	2.32	1.86	-2.93	12.83	1.95	2.01	1.61	-5.01	14.39	1.92
NetFeeRet(% p.m.)	0.86	0.67	-24.71	32.16	4.11	1.05	0.78	-17.97	24.33	4.17	0.73	0.59	-21.97	28.57	4.01
Alpha(% p.m.)	0.65	0.58	-6.14	9.55	1.22	0.76	0.66	-3.78	7.33	1.19	0.57	0.53	-5.56	9.16	1.20
AR	0.47	0.37	-1.84	7.03	0.70	0.50	0.41	-1.17	4.41	0.63	0.44	0.34	-1.76	6.70	0.72
SR	0.26	0.22	-2.55	5.49	0.41	0.28	0.25	-2.47	3.55	0.40	0.24	0.19	-1.04	4.83	0.41
Vol(%p.m)	3.68	2.88	0.05	24.18	2.86	3.78	2.90	0.11	20.66	2.97	3.58	2.85	0.12	21.92	2.76
RedemptionNoticePeriod(days)	37.61	29.70	0.00	240.70	28.38	40.25	30.00	0.00	189.33	28.05	37.41	30.55	0.00	200.23	28.29
Lockup(months)	3.26	0.00	0.00	62.63	6.36	3.58	0.00	0.00	61.66	6.88	3.20	0.00	0.00	49.88	6.18
PersonalCapDummy	0.43	0.33	0.00	1.00	0.48	0.43	0.30	0.00	1.00	0.49	0.43	0.31	0.00	1.00	0.48
HighWaterMarkDummy	0.56	0.66	0.00	1.00	0.47	0.65	1.00	0.00	1.00	0.47	0.54	0.63	0.00	1.00	0.46
MgmtFee(%)	1.43	1.29	0.00	8.80	0.70	1.41	1.37	0.00	6.73	0.65	1.43	1.27	0.00	7.72	0.73
IncentiveFee(%)	15.87	20.00	0.00	47.81	7.39	16.02	20.00	0.00	35.16	7.24	15.83	20.00	0.00	44.48	7.39
Age(years)	6.96	5.94	2.60	29.88	3.86	7.40	6.28	2.61	29.88	4.33	6.72	5.73	2.60	25.83	3.63
AUM(M$)	200.25	58.14	5.00	9691.62	541.81	221.06	69.59	5.17	8232.44	550.11	181.59	51.53	5.00	6990.25	495.88
Flowpast1Y(%p.a.)	13.64	-0.91	-138.65	838.18	75.87	18.35	2.20	-102.00	690.84	74.60	10.82	-2.52	-130.57	775.30	75.09
MinInvestment(M$)	0.94	0.50	0.00	40.23	2.13	1.05	0.50	0.00	40.23	2.80	0.93	0.48	0.00	27.03	1.88
Leverage	0.60	1.00	0.00	1.00	0.49	0.63	1.00	0.00	1.00	0.48	0.58	0.84	0.00	1.00	0.49
Derivatives	0.52	0.71	0.00	1.00	0.50	0.52	0.65	0.00	1.00	0.50	0.52	0.73	0.00	1.00	0.50

(continued)

Table 1 Continued

Panel B: Correlations

	Downside Returns	Upside Returns	NetFee Ret	Alpha	AR	SR	Vol	Redemp-tion Notice	Lockup	Personal Cap Dummy	HighWat erMark Dummy	Mgmt Fee	Incentiv eFee	Age	AUM	FlowPast 1Y	MinInvest ment	Leverage
UpsideReturns(% p.m.)	-0.31																	
NetFeeRet(% p.m.)	0.10	0.17																
Alpha(% p.m.)	0.49	0.33	0.16															
AR	0.33	-0.02	0.05	0.42														
SR	0.40	0.11	0.09	0.36	0.81													
Vol(%p.m)	-0.35	0.62	0.09	0.13	-0.27	-0.23												
RedemptionNoticePeriod(days)	0.09	-0.04	0.00	0.04	0.18	0.18	-0.20											
Lockup(months)	0.03	0.06	0.02	0.06	0.05	0.06	0.01	0.27										
PersonalCapDummy	-0.02	0.06	0.01	0.02	0.00	0.01	0.06	0.06	0.02									
HighWaterMarkDummy	0.07	0.03	0.03	0.07	0.08	0.10	0.00	0.20	0.24	-0.02								
MgmtFee(%)	0.00	0.01	0.01	0.02	-0.03	-0.03	0.10	-0.16	-0.10	-0.04	-0.09							
IncentiveFee(%)	0.06	0.08	0.03	0.11	0.06	0.07	0.19	-0.02	0.12	0.10	0.30	0.07						
Age(years)	-0.07	0.01	0.00	-0.04	-0.06	-0.06	0.02	-0.09	-0.07	0.13	-0.15	0.04	-0.07					
AUM(M$)	0.03	0.03	0.01	0.04	0.06	0.08	-0.06	0.07	0.02	-0.01	0.00	0.01	-0.02	0.17				
Flowpast1Y(%p.a.)	0.09	0.02	0.01	0.07	0.06	0.08	-0.02	0.01	0.00	-0.03	0.03	0.01	0.01	-0.05	0.02			
MinInvestment(M$)	0.06	-0.03	0.01	0.03	0.11	0.10	-0.09	0.11	0.10	0.04	0.14	-0.03	0.03	0.09	0.18	0.01		
Leverage	0.01	0.04	0.01	0.04	0.00	0.00	0.10	-0.08	-0.05	0.16	0.04	0.10	0.22	0.02	0.01	0.01	-0.02	
Derivatives	-0.02	0.06	0.01	0.02	-0.02	-0.01	0.10	-0.09	-0.07	0.18	0.00	0.07	0.19	0.06	0.01	0.01	-0.02	0.73

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 when the overall hedge fund sector performance is under (above) the median level of the past 24 months; and contemporaneous fund characteristics including monthly net of fee returns, 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. Panel B reports the time-series average of the pair-wise correlation between these variables.

Table 2
Equally Weighted Portfolio Performance Sorted on *DownsideReturns* and *UpsideReturns* (1996–2011)

Panel A: Quintile Portfolios Sorted on *DownsideReturns*

	Alpha(FH 7-factor)					Appraisal Ratio					Sharpe Ratio (smoothing adjusted)				
	3m (% p.q.)	6m (% p.sa.)	1y (% p.a.)	2y (% p.2y)	3y (% p.3y)	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
Low Downside Returns Port	0.31	0.91	2.92	7.02	12.99	0.00	0.02	0.03	0.03	0.04	0.15	0.11	0.09	0.06	0.04
t-stat	*0.56*	*0.93*	*1.87*	*2.78*	*3.37*	*0.06*	*0.58*	*1.24*	*1.38*	*1.81*	*1.99*	*1.94*	*1.93*	*1.94*	*1.69*
Port 2	1.16	2.32	4.43	9.13	14.25	0.22	0.16	0.14	0.13	0.13	0.27	0.17	0.13	0.10	0.07
t-stat	*3.02*	*3.34*	*4.06*	*6.12*	*9.08*	*3.09*	*3.26*	*3.99*	*4.69*	*5.95*	*3.32*	*2.87*	*2.74*	*2.86*	*2.59*
Port 3	1.23	2.60	5.13	10.77	16.42	0.39	0.29	0.25	0.23	0.23	0.33	0.22	0.16	0.13	0.11
t-stat	*3.30*	*3.80*	*4.53*	*6.02*	*7.21*	*4.28*	*4.50*	*5.08*	*5.58*	*6.66*	*4.56*	*3.98*	*3.62*	*3.98*	*3.85*
Port 4	1.62	3.16	6.16	12.28	18.33	0.64	0.48	0.41	0.37	0.34	0.49	0.33	0.26	0.22	0.19
t-stat	*5.46*	*5.47*	*6.07*	*6.77*	*7.45*	*6.81*	*6.71*	*7.19*	*7.45*	*8.81*	*6.82*	*6.19*	*5.61*	*5.57*	*5.49*
Hi Downside Returns Port	1.82	3.71	7.53	14.38	20.25	0.54	0.39	0.33	0.27	0.25	0.42	0.30	0.23	0.19	0.17
t-stat	*5.70*	*5.82*	*5.85*	*7.14*	*7.38*	*8.44*	*7.96*	*8.03*	*8.71*	*10.09*	*7.89*	*7.78*	*7.53*	*8.37*	*10.43*
Hi - Low	1.51***	2.80***	4.61***	7.36**	7.26	0.53***	0.37***	0.29***	0.24***	0.21***	0.28***	0.19***	0.15***	0.13***	0.13***
t-stat	*2.72*	*2.94*	*2.70*	*2.43*	*1.38*	*7.53*	*8.02*	*7.81*	*8.32*	*7.64*	*4.18*	*3.48*	*3.62*	*4.48*	*6.51*
Hi-Low Annualized Alpha (% p.a.)	6.20	5.68	4.61	3.61	2.36										

(continued)

Table 2
Continued

Panel B: Quintile Portfolios Sorted on *UpsideReturns*

	Alpha(FH 7-factor)					Appraisal Ratio					Sharpe Ratio (smoothing adjusted)				
	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
	(% p.q.)	(% p.sa.)	(% p.a.)	(% p.2y)	(% p.3y)										
Low Upside Returns Port	1.16	2.64	5.46	10.44	14.90	0.45	0.35	0.30	0.27	0.25	0.26	0.20	0.16	0.14	0.12
t-stat	*3.22*	*3.83*	*4.67*	*6.00*	*6.92*	*5.03*	*5.16*	*5.46*	*5.98*	*7.43*	*5.66*	*6.07*	*6.67*	*8.88*	*9.30*
Port 2	1.34	2.73	5.32	11.04	16.70	0.57	0.43	0.37	0.32	0.31	0.46	0.30	0.24	0.20	0.17
t-stat	*4.39*	*4.67*	*5.31*	*6.12*	*7.59*	*5.50*	*5.74*	*6.24*	*6.81*	*8.68*	*5.86*	*5.58*	*5.74*	*5.91*	*5.41*
Port 3	1.30	2.78	5.29	11.14	17.16	0.41	0.30	0.25	0.22	0.22	0.38	0.25	0.19	0.15	0.13
t-stat	*3.97*	*4.38*	*4.89*	*6.01*	*7.32*	*5.05*	*5.08*	*5.45*	*5.80*	*6.80*	*4.97*	*4.54*	*4.42*	*4.46*	*4.17*
Port 4	1.16	2.28	4.72	9.86	15.81	0.24	0.18	0.16	0.15	0.14	0.28	0.18	0.15	0.11	0.09
t-stat	*3.49*	*3.90*	*4.89*	*6.60*	*9.64*	*3.86*	*4.13*	*4.86*	*5.34*	*5.89*	*3.81*	*3.31*	*3.32*	*3.38*	*3.27*
Hi Upside Returns Port	1.15	2.16	5.28	11.07	17.73	0.12	0.08	0.08	0.08	0.08	0.24	0.15	0.12	0.09	0.07
t-stat	*1.58*	*1.69*	*2.54*	*4.17*	*5.49*	*2.19*	*2.12*	*2.89*	*3.26*	*3.47*	*3.16*	*2.65*	*2.64*	*2.44*	*2.21*
Hi - Low	-0.01	-0.48	-0.19	0.64	2.83	-0.33***	-0.26***	-0.22***	-0.19***	-0.17***	-0.02	-0.05	-0.04	-0.05	-0.05*
t-stat	*-0.02*	*-0.33*	*-0.08*	*0.19*	*0.67*	*-3.24*	*-3.59*	*-3.58*	*-3.85*	*-4.24*	*-0.26*	*-1.05*	*-1.06*	*-1.42*	*-1.89*
Hi-Low Annualized Alpha (%	-0.06	-0.96	-0.19	0.32	0.93										

Panel A reports the time-series averages and *t*-statistics of the post-formation 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 when the overall hedge fund market performance is under (above) the median level of the past 24 months. 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. The *t*-statistics reported in parentheses are adjusted for heteroscedasticity and autocorrelation. *** 1% significance; ** 5% significance; * 10% significance.

Table 3
Panel Regression of Hedge Fund Performance on *DownsideReturns* and *UpsideReturns* (1996–2011)

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	1.57***	0.07***	0.03***	1.82***	0.09***	0.02***
(t-stat)	8.69	18.46	7.98	6.43	19.47	5.18
VolPast2Y(%p.m)	1.12***			1.25***		
	8.74			7.29		
RedemptionNotice(30Days)	0.26*	0.06***	0.05***	0.27*	0.06***	0.05***
	1.72	4.36	4.42	1.75	4.33	4.43
Lockup(months)	0.04*	0.00	0.00	0.04*	0.00	0.00
	1.81	-0.55	0.84	1.85	-0.28	0.76
PersonalCapitalDummy	0.12	0.00	0.03**	0.14	0.01	0.03**
	0.38	0.29	2.28	0.45	0.55	2.20
HighWaterMarkDummy	0.57*	0.02	0.03**	0.58*	0.02	0.03**
	1.66	1.37	2.14	1.69	1.44	2.13
MgmtFee(%)	0.00	-0.02*	-0.01	-0.02	-0.02*	-0.01
	-0.02	-1.83	-1.53	-0.06	-1.86	-1.59
IncentiveFee(%)	0.06**	0.00	-0.00**	0.06**	0.00	-0.00**
	2.19	-0.27	-2.21	2.10	-0.13	-2.26
Age(years)	0.03	0.00	0.00	0.03	0.00	0.00
	0.96	1.21	-1.16	1.00	1.27	-1.17
ln(AUM)	-0.37***	0.02***	0.01***	-0.34***	0.02***	0.01***
	-3.79	3.69	3.51	-3.34	4.05	3.38
FlowPast1Y(%)	-0.00**	0.00	0.00	-0.00*	0.00	0.00
	-2.24	0.07	1.30	-1.92	0.89	1.02
AvgPast2YRet(% p.m.)				-0.56	-0.05***	0.02***
				-1.47	-8.52	2.63
ln(MinInvestment+1)	0.39***	0.02***	0.02***	0.39***	0.02***	0.02***
	5.25	6.02	4.28	5.24	5.86	4.32
Leverage	0.53*	0.00	0.01	0.52*	0.00	0.01
	1.84	-0.02	0.51	1.80	0.10	0.47
AdjR2(%)	10.56	13.04	18.55	10.57	13.14	18.56
#FundQtrObs.	87314	87314	70397	87314	87314	70397

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	-0.50***	-0.04***	0.00	-1.69***	-0.08***	-0.02***
(t-stat)	-2.63	-14.69	-0.63	-6.01	-18.88	-5.19
VolPast2Y(%p.m)	0.93***			1.25***		
	6.33			7.21		
RedemptionNotice(30Days)	0.31*	0.06***	0.05***	0.28*	0.06***	0.05***
	1.90	4.53	4.49	1.78	4.35	4.43
Lockup(months)	0.04*	0.00	0.00	0.04*	0.00	0.00
	1.72	-0.30	0.73	1.82	-0.21	0.75
PersonalCapitalDummy	0.14	0.01	0.03**	0.10	0.01	0.03**
	0.44	0.64	2.19	0.32	0.56	2.20
HighWaterMarkDummy	0.60	0.03	0.03**	0.54	0.02	0.03*
	1.62	1.46	2.17	1.57	1.34	2.13
MgmtFee(%)	0.10	-0.02*	-0.01	0.04	-0.02*	-0.01
	0.33	-1.69	-1.49	0.16	-1.76	-1.58
IncentiveFee(%)	0.08***	0.00	-0.00*	0.06**	0.00	-0.00**
	2.68	0.24	-1.91	1.99	-0.22	-2.25
Age(years)	0.01	0.00	0.00	0.03	0.00	0.00
	0.20	0.20	-1.59	1.03	0.96	-1.16
ln(AUM)	-0.25**	0.03***	0.02***	-0.33***	0.02***	0.01***
	-2.40	5.28	4.12	-3.34	4.05	3.37
FlowPast1Y(%)	0.00	0.00***	0.00**	-0.00*	0.00	0.00
	0.27	*3.70*	*2.33*	*-1.82*	*1.25*	*1.02*
AvgPast2YRet(% p.m.)				2.86***	0.11***	0.06***
				7.93	*14.78*	*8.74*
ln(MinInvestment+1)	0.44***	0.03***	0.02***	0.40***	0.02***	0.02***
	5.49	*6.16*	*4.53*	*5.38*	*5.88*	*4.32*
Leverage	0.54*	0.00	0.01	0.43	0.00	0.01
	1.77	*0.21*	*0.54*	*1.48*	*0.02*	*0.47*
AdjR2(%)	10.07	12.69	18.42	10.43	13.13	18.56
#FundQtrObs.	85903	85903	70394	85903	85903	70394

Table 3 reports the panel regression results for hedge fund performance on *DownsideReturns(UpsideReturns)* at the quarterly frequency as follows: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i} Downside\,Returns(Upside\,Returns)_{i,t-1} + c_{2i} Control_{i,t-1} + e_{i,t}$. Survivorship and backfill biases are controlled for to the extent that the data allow. Alpha is the annualized FH seven-factor adjusted performance over the subsequent one quarter in percentage terms. *AR,* and *SR* are the corresponding appraisal ratio and smoothing-adjusted Sharpe ratio. 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, AUM, new money flow into funds within the preceding 12 months as a fraction of AUM (as a percentage), average return over the past 2 years, minimum investments requirement, and an indicator variable for the use of leverage. The *t*-statistics reported in parentheses are adjusted for fund-clustering effect and for time and style fixed effects. *** 1% significance; ** 5% significance; * 10% significance.

Table 4
Fama-MacBeth Analysis of Hedge Fund Performance on *DownsideReturns* and *UpsideReturns*. (1996–2011)

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	1.67***	0.09***	0.04***	1.95**	0.11***	0.03**
(t-stat)	3.00	5.74	4.15	2.29	4.95	2.51
VolPast2Y(%p.m)	1.35***			1.58***		
	3.98			4.89		
RedemptionNotice(30Days)	0.54**	0.07***	0.06***	0.61**	0.08**	0.06**
	2.23	5.02	4.87	2.37	5.06	4.96
Lockup(months)	0.10**	0.00	0.00	0.11***	0.00	0.00
	2.51	0.86	1.40	2.68	1.29	1.29
PersonalCapitalDummy	-0.01	0.00	0.04***	0.00	0.00	0.04***
	-0.02	0.15	2.87	0.00	0.32	2.86
HighWaterMarkDummy	0.49	0.02	0.03***	0.53	0.02	0.03***
	0.77	0.98	2.68	0.87	1.01	2.63
MgmtFee(%)	0.37	-0.01	-0.01	0.44	-0.01	-0.01
	0.95	-0.91	-1.22	1.13	-0.57	-1.23
IncentiveFee(%)	0.05**	0.00	-0.00*	0.06**	0.00	-0.00*
	1.98	-0.64	-1.71	2.32	-0.24	-1.82
Age(years)	-0.02	0.00	-0.00*	-0.03	0.00	-0.00*
	-0.36	1.13	-1.85	-0.78	0.72	-1.90
ln(AUM)	-0.45*	0.02**	0.02**	-0.33	0.02***	0.02***
	-1.88	2.32	2.87	-1.54	2.90	2.95
FlowPast1Y(%)	0.00	0.00	0.00	0.00	0.00	0.00
	-0.53	-0.16	-0.51	-0.44	0.77	-0.65
AvgPast2YRet(% p.m.)				-0.69	-0.06***	0.03**
				-0.67	-2.31	2.09
ln(MinInvestment+1)	0.46***	0.03***	0.01***	0.47***	0.03***	0.01***
	3.43	5.70	4.18	3.73	5.63	4.39
Leverage	0.21	-0.02	0.01	0.25	-0.02	0.01
	0.43	-1.07	0.40	0.53	-0.87	0.39
AdjR2(%)	13.58	10.72	12.14	15.68	11.68	12.88

Table 4
(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
DownsideReturns	-0.48	-0.05***	0.00	-1.75	-0.11	0.00
(t-stat)	-0.87	-3.63	0.47	-2.03	-4.79	0.47
VolPast2Y(%p.m)	1.32***			1.55***		
	4.11			4.80		
RedemptionNotice(30Days)	0.65**	0.08***	0.06***	0.60**	0.08***	0.06***
	2.16	5.09	5.22	2.23	4.99	5.22
Lockup(months)	0.11**	0.00	0.00	0.11***	0.00	0.00
	2.55	1.32	1.39	2.71	1.31	1.39
PersonalCapitalDummy	0.04	0.01	0.03***	-0.06	0.00	0.03***
	0.09	0.63	2.82	-0.13	0.35	2.82
HighWaterMarkDummy	0.44	0.02	0.03***	0.49	0.02	0.03***
	0.70	0.94	2.66	0.80	0.99	2.66
MgmtFee(%)	0.41	-0.01	-0.01	0.49	-0.01	-0.01
	1.07	-0.67	-0.98	1.30	-0.66	-0.98
IncentiveFee(%)	0.08***	0.00	-0.00***	0.06**	0.00	-0.00***
	2.59	0.08	-1.66	2.15	-0.32	-1.66
Age(years)	-0.07*	0.00	-0.00***	-0.03	0.00	-0.00***
	-1.65	-0.58	-2.47	-0.62	0.44	-2.47
ln(AUM)	-0.24	0.03***	0.02***	-0.34	0.02***	0.02***
	-1.07	3.66	3.80	-1.60	2.89	3.80
FlowPast1Y(%)	0.00	0.00	0.00	0.00	0.00	0.00
	0.29	3.10	0.53	-0.30	1.00	0.53
AvgPast2YRet(% p.m.)				2.91***	0.16***	0.02***
				2.63	5.67	4.78
ln(MinInvestment+1)	0.51***	0.03***	0.02***	0.49***	0.03***	0.01
	3.51	5.77	4.78	3.69	5.81	0.40
Leverage	0.23	-0.02	0.01	0.15	-0.02	0.06
	0.51	-0.86	0.40	0.35	-0.94	0.41
AdjR2(%)	13.73	10.79	12.17	15.86	11.76	12.17

Table 4 reports the Fama-MacBeth regression results for hedge fund performance on *DownsideReturns*(*UpsideReturns)* and other fund characteristics at the quarterly frequency as follows: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i} Downside\,\mathrm{Re}\,turns(Upside\,\mathrm{Re}\,turns)_{i,t-1} + c_{2i} Control_{i,t-1} + e_{i,t}$. Survivorship and backfill biases are controlled for to the extent that the data allow. Alpha is the annualized FH seven-factor adjusted performance over the subsequent one quarter in percentage terms. *AR and SR* are the corresponding appraisal ratio and smoothing-adjusted Sharpe ratio, respectively. Control variables are the lagged fund characteristics, including volatility of monthly net fee returns volatility, lengths of the redemption 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 preceding 12 months as a fraction of AUM (as a percentage), average returns over the past two years, minimum investments requirement, and an indicator variable for the use of leverage. Style dummies are included in the regressor set. The *t*-statistics (reported below the estimated coefficients in italics) are adjusted for heteroscedasticity and autocorrelation. *** 1% significance; ** 5% significance; * 10% significance.

Table 5
Is Performance Persistence Caused by Market Frictions? (1996-2011)

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

	Alpha(FH 7-factor)					Appraisal Ratio					Sharpe Ratio (smoothing adjusted)				
	3m (% p.q.)	6m (% p.sa.)	1y (% p.a.)	2y (% p.2y)	3y (% p.3y)	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
Low Downside Returns Port	-0.01	0.14	0.98	3.22	7.47	-0.04	-0.02	-0.02	-0.02	-0.02	0.12	0.09	0.06	0.04	0.03
t-stat	*-0.02*	*0.10*	*0.44*	*0.94*	*1.56*	*-0.75*	*-0.57*	*-0.49*	*-0.67*	*-0.60*	*1.67*	*1.67*	*1.48*	*1.16*	*1.01*
Port 2	1.04	1.83	2.97	5.33	7.88	0.15	0.09	0.06	0.05	0.04	0.20	0.12	0.08	0.05	0.03
t-stat	*2.49*	*2.55*	*2.70*	*3.44*	*4.27*	*2.57*	*2.08*	*1.62*	*1.30*	*1.11*	*2.80*	*2.32*	*1.99*	*1.58*	*1.38*
Port 3	1.01	2.04	3.57	7.21	10.20	0.29	0.19	0.14	0.11	0.09	0.24	0.15	0.09	0.06	0.04
t-stat	*2.92*	*3.21*	*3.57*	*4.86*	*5.50*	*4.04*	*3.54*	*3.03*	*2.60*	*2.26*	*3.58*	*3.15*	*2.45*	*1.92*	*1.56*
Port 4	1.43	2.67	4.85	8.60	11.69	0.46	0.33	0.27	0.22	0.19	0.30	0.19	0.16	0.12	0.11
t-stat	*5.37*	*5.02*	*5.33*	*5.81*	*5.86*	*6.85*	*5.87*	*5.15*	*4.42*	*4.08*	*5.64*	*4.67*	*4.06*	*3.65*	*3.50*
Hi Downside Returns Port	1.42	2.98	6.07	10.93	14.26	0.43	0.32	0.25	0.21	0.18	0.31	0.22	0.17	0.13	0.12
t-stat	*3.92*	*4.12*	*4.68*	*5.64*	*5.67*	*6.99*	*6.93*	*6.54*	*6.12*	*6.38*	*6.35*	*6.26*	*6.31*	*6.51*	*7.07*
Hi - Low	1.43**	2.84**	5.09**	7.70**	6.78	0.48***	0.34***	0.27***	0.23***	0.20***	0.19***	0.13**	0.12**	0.20***	0.09***
t-stat	*1.96*	*2.09*	*2.14*	*2.21*	*1.31*	*5.91*	*6.43*	*6.19*	*6.49*	*6.22*	*2.56*	*2.19*	*2.29*	*3.01*	*3.41*
Annualized Alpha	5.84	5.76	5.09	3.78	2.21										

Panel B: Regressions

	Panel Regression			Fama-MacBeth		
	Alpha(% p.a.) FH 7-factor	AR (FH)	SR	Alpha(% p.a.) FH 7-factor	AR (FH)	SR
DownsideReturns	1.64***	0.05***	0.02***	1.90*	0.10***	0.03**
t-stat	*5.89*	*8.37*	*3.13*	*1.82*	*4.42*	*2.17*

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 means 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 parentheses 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: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i} Downside\,Returns_{i,t-1} + c_{2i} Control_{i,t-1} + e_{i,t}$. Control variables are as the same as in Table 3. Panel regression is adjusted for the fund-clustering effect, and time and style fixed effects, and 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; * 10% significance.

Table 6
Comparing *DownsideReturns* and *UpsideReturns* with Other Skill Measures (1996–2011)

	DownsideReturns	UpsideReturns	Hedging	SDI
UpsideReturns	-0.31			
Hedging	0.25	-0.21		
SDI	0.36	-0.33	0.42	
MktLiqTiming	0.04	-0.09	0.02	0.06

Table 6 reports the time-series average 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*), and market liquidity timing skills (*MktLiqTiming*). Note that sample funds are restricted to equity styles only for *MktLiqTiming* related analysis.

Table 7
Does Predicting Power of *DownsideReturns* Withstand Controlling for Other Skill Measures (1996-2011)

	Panel Regression			Fama-MacBeth		
Panel A: Controling for Hedging Effect						
	Alpha(% p.a.) FH 7-factor	AR (FH)	SR	Alpha(% p.a.) FH 7-factor	AR (FH)	SR
DownsideReturns	1.72***	0.07***	0.02***	1.85**	0.10***	0.04***
t-stat	*5.87*	*16.36*	*5.87*	*2.17*	*4.56*	*3.16*
Panel B: Controling for Strategy Distinctiveness (SDI) effect						
	Alpha(% p.a.) FH 7-factor	AR (FH)	SR	Alpha(% p.a.) FH 7-factor	AR (FH)	SR
DownsideReturns	1.74***	0.08***	0.03***	1.75**	0.12***	0.04***
t-stat	*5.43*	*16.81*	*6.53*	*2.04*	*4.83*	*4.31*
Panel C: Controling for Market Liquidity Timing (MktLiqTiming) effect						
	Alpha(% p.a.) FH 7-factor	AR (FH)	SR	Alpha(% p.a.) FH 7-factor	AR (FH)	SR
DownsideReturns	1.99***	0.09***	0.03***	2.47***	0.14***	0.04**
t-stat	*6.34*	*18.85*	*5.61*	*2.89*	*5.12*	*2.54*
Panel D: Controling for All Skill Measures Above						
	Alpha(% p.a.) FH 7-factor	AR (FH)	SR	Alpha(% p.a.) FH 7-factor	AR (FH)	SR
DownsideReturns	1.92***	0.08***	0.04***	2.27***	0.15***	0.06***
t-stat	*4.86*	*14.60*	*8.19*	*2.66*	*4.80*	*4.68*

Table 7 reports the 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), and market liquidity timing skills as in Cao, Chen, Liang and Lo (2013). Control variables are the same as in Table 3. Panel regression is adjusted for the fund-clustering effect, and time and style fixed effects, and 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 styles only for MktLiqTiming related analysis. Survivorship and backfill biases are controlled for to the extent that the data allow. *** 1% significance; ** 5% significance; * 10% significance.

Table 8
Flows' Sensitivity to *DownsideReturns* and *UpsideReturns*

Panel A: Rank Funds Based on Past *DownsideReturns*

	Panel Regression			Fama-MacBeth		
	3m (% p.q.)	6m (% p. sa.)	1yr (% p.a.)	3m (% p.q.)	6m(% p.sa.)	1yr (% p.a.)
Breakdown of Rank:						
Bottom Performance	5.71***	12.33***	30.48***	9.53***	18.62***	38.27***
t-stat	*6.29*	*6.25*	*6.64*	*7.69*	*8.73*	*6.01*
Middle Performance	7.92***	15.65***	27.55***	7.47***	14.27***	25.44***
	10.57	*9.65*	*7.19*	*8.85*	*9.05*	*6.64*
Top Performance	11.01***	20.67***	35.41***	9.08***	18.40***	32.68***
	10.15	*8.62*	*6.13*	*8.85*	*9.40*	*4.56*
Ln(AUM)	-0.20***	-1.14***	-4.59***	-0.38***	-1.58***	-5.61***
	-2.80	*-6.78*	*-10.09*	*-4.23*	*-8.94*	*-8.77*
Ln(Family AUM)	-0.21***	-0.25*	0.08	-0.04	0.05	0.54*
	-3.23	*-1.67*	*0.19*	*-0.68*	*0.46*	*1.74*
VolPast2Y(% p. m.)	-0.01	-0.02**	-0.07***	0.16***	0.23***	0.18
	-0.87	*-2.38*	*-6.12*	*4.26*	*3.12*	*0.82*
Styleflow	101.99***	102.30***	101.84***	94.40***	94.85***	94.21***
	32.58	*27.78*	*21.74*	*7.92*	*8.29*	*51.72*
MgmtFee (%)	0.03	0.15	0.65	-0.06	-0.02	0.33
	0.22	*0.48*	*0.82*	*-0.53*	*-0.09*	*0.30*
IncentiveFee (%)	-0.06***	-0.13***	-0.24***	-0.07***	-0.14***	-0.26***
	-4.92	*-4.47*	*-3.39*	*-7.34*	*-7.99*	*-5.21*
HighWaterMarkDummy	1.05***	2.60***	6.07***	1.11***	2.79***	7.12***
	5.60	*6.11*	*5.68*	*6.88*	*8.64*	*4.97*
Leverage	0.00	0.18	0.68	0.19	0.32	0.70
	0.02	*0.46*	*0.70*	*1.23*	*1.20*	*0.75*
PersonalCapitalDummy	0.52***	0.71*	0.21	0.37**	0.47*	-0.03
	2.98	*1.79*	*0.21*	*2.46*	*1.68*	*-0.03*
RedemptionNotice(days)	0.01***	0.02***	0.06***	0.02***	0.03***	0.06***
	3.36	*3.11*	*3.07*	*5.83*	*5.75*	*3.08*
Lockup(months)	0.01	0.00	-0.07	0.01	0.00	-0.07
	0.92	*-0.18*	*-1.15*	*0.86*	*0.13*	*-0.64*
Age (months)	-0.01***	-0.02***	-0.06***	-0.01***	-0.03***	-0.07***
	-4.53	*-5.33*	*-5.95*	*-5.62*	*-7.16*	*-5.16*
MinInvestment	0.16***	0.45***	1.25***	0.13***	0.43***	1.32***
	2.64	*3.15*	*3.21*	*3.60*	*6.41*	*5.17*
Intercept	2.36**	12.91***	51.19***	1.60	13.64***	58.42***
	2.26	*5.48*	*8.42*	*1.11*	*5.14*	*6.94*
AdjR2(%)	8.98	10.42	11.40	6.46	8.19	9.96
Observations	84893	79284	69396	1348	1279	1157

Panel B: Rank Funds Based on Past *UpsideReturns*

	Panel Regression			Fama-MacBeth		
	3m (% p.q.)	6m (% p.sa.)	1yr (% p.a.)	3m (% p.q.)	6m (%p.sa.)	1yr(%p.a.)
Breakdown of Rank:						
Bottom Performance	7.44***	11.86***	12.33**	6.46***	9.48***	5.67
t-stat	*6.75*	*4.95*	*2.18*	*5.11*	*4.65*	*0.94*
Middle Performance	8.30***	16.49***	30.70***	8.23***	16.60***	31.50***
	10.38	*9.26*	*7.44*	*7.97*	*8.71*	*4.29*
Top Performance	-0.44	-1.81	-6.06	4.72***	9.77***	17.14**
	-0.42	*-0.75*	*-1.03*	*3.47*	*4.12*	*2.63*
Ln(AUM)	-0.13*	-1.01***	-4.34***	-0.39***	-1.58***	-5.55***
	-1.87	*-5.80*	*-9.22*	*-4.58*	*-9.13*	*-9.46*
Ln(Family AUM)	-0.25***	-0.33**	-0.05	-0.18***	-0.23**	0.02
	-3.74	*-2.10*	*-0.12*	*-2.79*	*-1.97*	*0.06*
VolPast2Y(% p. m.)	-0.02	-0.05	-0.14	-0.33***	-0.73***	-1.53***
	-1.56	*-1.52*	*-1.55*	*-7.85*	*-9.18*	*-7.38*
Styleflow	99.23***	98.92***	98.37***	90.46***	90.40***	89.49***
	30.94	*26.32*	*20.57*	*5.61*	*6.45*	*38.26*
MgmtFee (%)	0.13	0.36	1.15	0.10	0.30	1.02
	0.93	*1.11*	*1.41*	*0.86*	*1.17*	*0.94*
IncentiveFee (%)	-0.02	-0.05*	-0.15**	-0.01	-0.03*	-0.10*
	-1.44	*-1.78*	*-1.98*	*-1.03*	*-1.86*	*-1.85*
HighWaterMarkDummy	1.01***	2.55***	6.03***	0.93***	2.41***	6.26***
	5.25	*5.78*	*5.44*	*5.40*	*6.80*	*4.30*
Leverage	0.09	0.34	1.02	0.31**	0.63**	1.38
	0.53	*0.84*	*1.02*	*2.05*	*2.33*	*1.50*
PersonalCapitalDummy	0.26	0.25	-0.87	0.19	0.11	-1.03
	1.43	*0.60*	*-0.82*	*1.30*	*0.40*	*-0.99*
RedemptionNotice (days)	0.01***	0.03***	0.08***	0.02***	0.03***	0.07***
	4.18	*4.05*	*3.87*	*5.68*	*5.95*	*3.71*
Lockup (months)	-0.01	-0.05*	-0.16**	0.00	-0.01	-0.08
	-1.07	*-1.75*	*-2.14*	*0.26*	*-0.38*	*-0.63*
Age (months)	-0.01***	-0.03***	-0.08***	-0.02***	-0.04***	-0.09***
	-7.73	*-8.14*	*-7.91*	*-7.89*	*-9.15*	*-5.94*
MinInvestment	0.23***	0.60***	1.58***	0.19***	0.54***	1.56***
	3.67	*4.00*	*3.86*	*5.72*	*8.51*	*6.48*
Intercept	0.81	10.88***	51.07***	5.52***	22.42***	77.07***
	0.76	*4.50*	*8.06*	*3.44*	*7.23*	*7.54*
AdjR2(%)	7.96	9.12	10.01	5.81	7.33	8.86
Observations	85069	79503	69667	1350	1282	1161

Panel C: Test of Equality of Flow Performance Sensitivity Between Down and Up Markets

	Panel Regression			Fama-MacBeth		
	3m	6m	1yr	3m	6m	1yr
Breakdown of Rank:						
Bottom Performance	-1.73	0.47	18.15**	3.07*	9.14**	32.60***
t-stat	*-1.21*	*0.15*	*2.49*	*1.74*	*3.10*	*3.71*
Middle Performance	-0.38	-0.84	-3.15	-0.76	-2.33	-6.06
	-0.35	*-0.35*	*-0.56*	*-0.57*	*-0.94*	*-0.73*
Top Performance	11.45	22.48***	41.46***	4.36**	8.63***	15.54
	7.59	*6.60*	*5.02*	*2.56*	*2.81*	*1.61*

Table 8 reports the sensitivity of fund flows to past 24 months' *DownsideReturns* and *UpsideReturns*. Following Sirri and Tufano (1998), we construct three piece-wise linear performance rank variables, *Bottom-, Middle- and Top-performance*, based on *DowsideReturn (UpsideReturns).* We then regress future flows to such rank variables following both panel and Fama-MacBeth regressions as follows: $Flow_{i,t} = c_{0i} + c_{1i} Bottom_{i,t-1} + c_{2i} Middle_{i,t-1} + c_{3i} Top_{i,t-1} + c_{3i} Control_{i,t-1} + e_{i,t}$, at quarterly frequency. The control variables include: fund AUM, assets managed by funds' families, volatility of prior 24-month fund return in percent, 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. For panel regressions, we include time fixed effect, and cluster the standard errors for each fund. For Fama-Macbeth regressions, the standard errors are adjusted for heteroscedasticity and autocorrelation. We winsorize the flow variable at the top and bottom 2%. Panel A and B report the flow performance sensitivity regression for *DownsideReturns* and *UpsideReturns*., respectively. Panel C tests the equality of the flow performance sensitivity between the down and market markets.

Table 9
Test of Capital Allocation Efficiency in Down and Up Markets (1996-2011)

Panel A: Sort funds into quintile portfolios based on DownsideReturns, then within each quintile, further sort funds into 5 portfolios based on PastFlows.

	Alpha (% p.q.) FH 7-Factor						t-statistics					
	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)
Low DownsideReturns Port	0.49	0.72	0.43	0.26	-0.17	-0.66	0.77	1.32	0.66	0.52	-0.24	-1.48
Port 3	1.35	1.10	1.22	1.28	1.30	-0.05	3.24	3.11	2.94	3.52	2.95	-0.25
Hi DownsideReturns Port	1.81	1.58	1.69	2.22	1.95	0.14	5.48	3.75	4.34	6.19	4.89	0.41
	AR FH 7-Factor						t-statistics					
	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)
Low DownsideReturns Port	0.01	0.02	0.00	0.00	-0.01	-0.02	0.22	0.35	-0.05	-0.03	-0.13	-0.59
Port 3	0.39	0.35	0.39	0.36	0.45	0.06	4.01	3.95	3.97	3.61	4.98	1.08
Hi DownsideReturns Port	0.46	0.56	0.53	0.59	0.54	0.08	6.02	8.46	7.57	8.84	7.48	1.23
	SR						t-statistics					
	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)
Low DownsideReturns Port	0.19	0.16	0.11	0.14	0.16	-0.03	2.55	2.07	1.34	1.82	2.08	-0.83
Port 3	0.33	0.29	0.33	0.31	0.36	0.03	4.34	3.68	4.26	3.95	4.56	0.84
Hi DownsideReturns Port	0.39	0.36	0.41	0.46	0.43	0.04	7.04	4.88	7.13	8.37	8.43	0.89

Panel B: Sort funds into quintile portfolios based on UpsideReturns, then within each quintile, further sort funds into 5 portfolios based on PastFlows.

	Alpha (% p.q.) FH 7-Factor						t-statistics					
	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)
Low UpsideReturns Port	1.22	1.10	1.53	0.92	1.32	0.10	3.92	3.18	3.38	2.20	3.24	0.34
Port 3	1.55	1.24	1.14	1.38	1.31	-0.24	3.83	3.42	3.61	3.91	3.80	-0.84
Hi UpsideReturns Port	1.29	0.93	0.98	1.18	1.31	0.02	1.50	1.31	1.38	1.39	1.64	0.04
	AR FH 7-Factor						t-statistics					
	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)
Low UpsideReturns Port	0.34	0.40	0.47	0.45	0.58	0.24***	4.30	4.58	4.93	4.83	5.08	2.89
Port 3	0.32	0.38	0.41	0.45	0.50	0.18***	4.31	4.21	4.81	5.17	5.66	4.36
Hi UpsideReturns Port	0.09	0.06	0.16	0.15	0.15	0.06	1.65	1.01	2.32	2.56	2.31	1.33
	SR						t-statistics					
	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)	Low PastFlow Port.	Port 2	Port 3	Port 4	Hi PastFlow Port	Spread (Hi-Lo)
Low UpsideReturns Port	0.23	0.23	0.25	0.22	0.35	0.12***	3.87	4.18	4.57	4.37	7.98	2.87
Port 3	0.33	0.34	0.36	0.41	0.44	0.12***	4.49	4.34	4.29	4.80	5.54	3.15
Hi UpsideReturns Port	0.26	0.21	0.22	0.26	0.27	0.01	3.13	2.52	2.49	3.63	3.77	0.36

Panel A and B report the time-series averages and *t*-statistics of the post-formation performance for a selected subset of 5 by 5 quintile portfolios. The 25 portfolios are constructed by sorting funds into quintile portfolios based on *DownsideReturns (UpsideReturns)*, and then within each quintile, sorting funds into quintile portfolios based on *PastFlows*. The performance measures are based on the equally-weighted buy-and-hold portfolios sorted every three months and held for three months. The *t*-statistics reported in parentheses are adjusted for heteroscedasticity and autocorrelation. *** 1% significance; ** 5% significance; * 10% significance.

Appendix A1
Robustness: Value Weighted Portfolio Performance Sorted on *DownsideReturns* and *UpsideReturns* (1996–2011)

Panel A: Quintile Portfolios Sorted on *DownsideReturns*

	Alpha(FH 7-factor)					Appraisal Ratio					Sharpe Ratio (smoothing adjusted)				
	3m (% p.q.)	6m (% p.sa.)	1y (% p.a.)	2y (% p.2y)	3y (% p.3y)	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
Low Downside Returns Port	0.10	0.61	1.70	2.77	7.16	0.02	0.05	0.04	0.04	0.05	0.13	0.12	0.09	0.06	0.05
t-stat	*0.15*	*0.51*	*0.80*	*0.82*	*1.49*	*0.34*	*1.11*	*1.19*	*1.29*	*1.94*	*1.52*	*1.92*	*1.86*	*1.88*	*2.14*
Port 2	1.31	2.00	3.75	9.30	14.78	0.28	0.17	0.16	0.16	0.16	0.31	0.18	0.14	0.12	0.09
t-stat	*2.45*	*2.40*	*2.72*	*3.85*	*5.86*	*2.99*	*2.95*	*3.40*	*4.16*	*4.98*	*3.35*	*2.62*	*2.64*	*3.12*	*3.33*
Port 3	1.24	2.94	6.43	14.48	20.62	0.41	0.32	0.29	0.28	0.28	0.36	0.26	0.20	0.18	0.14
t-stat	*3.65*	*3.92*	*4.23*	*4.56*	*5.26*	*3.95*	*4.32*	*4.74*	*5.12*	*6.07*	*3.83*	*3.99*	*3.80*	*4.38*	*4.20*
Port 4	1.60	3.26	5.95	12.43	19.58	0.71	0.55	0.48	0.44	0.40	0.57	0.40	0.32	0.27	0.24
t-stat	*4.49*	*5.08*	*5.08*	*6.22*	*6.55*	*6.57*	*6.38*	*6.60*	*6.95*	*8.38*	*6.37*	*5.77*	*5.51*	*5.70*	*5.77*
Hi Downside Returns Port	1.60	3.23	6.86	12.31	17.59	0.66	0.47	0.39	0.33	0.30	0.51	0.34	0.26	0.22	0.20
t-stat	*3.40*	*3.78*	*4.09*	*4.67*	*5.24*	*7.54*	*6.98*	*7.13*	*7.34*	*8.19*	*7.59*	*7.60*	*6.03*	*5.97*	*6.73*
Hi - Low	1.50***	2.62***	5.16***	9.53**	10.43	0.64***	0.42***	0.35***	0.29***	0.24***	0.38***	0.22***	0.17***	0.16***	0.15***
t-stat	2.60	2.78	2.69	2.42	1.45	6.79	7.21	6.95	7.15	6.45	4.49	3.53	3.59	4.20	5.48
Hi-Low Annualized Alpha (% p.a.)	6.13	5.32	5.16	4.66	3.36										

(continued)

A1
Continued

Panel B: Quintile Portfolios Sorted on *UpsideReturns*

	Alpha(FH 7-factor)					Appraisal Ratio					Sharpe Ratio (smoothing adjusted)				
	3m (% p.q.)	6m (% p.sa.)	1y (% p.a.)	2y (% p.2y)	3y (% p.3y)	3m	6m	1y	2y	3y	3m	6m	1y	2y	3y
Low Upside Returns Port	1.09	2.30	4.18	7.97	12.02	0.63	0.51	0.44	0.40	0.36	0.39	0.30	0.25	0.21	0.20
t-stat	2.27	2.66	2.75	3.35	3.93	5.57	5.60	5.67	5.70	7.43	7.74	7.15	6.87	6.94	6.79
Port 2	1.51	3.25	6.17	12.98	19.51	0.66	0.51	0.43	0.38	0.37	0.52	0.36	0.29	0.25	0.21
t-stat	4.44	4.66	4.90	5.56	6.49	5.40	5.86	6.15	6.56	8.20	5.56	5.37	5.60	6.05	5.64
Port 3	1.32	2.77	5.75	12.69	20.02	0.50	0.37	0.32	0.30	0.29	0.46	0.30	0.25	0.21	0.19
t-stat	3.62	3.84	4.35	5.46	6.72	5.37	5.27	5.51	5.95	6.65	5.26	4.67	4.82	5.41	5.46
Port 4	1.37	2.65	6.12	13.40	19.57	0.34	0.25	0.23	0.23	0.22	0.29	0.22	0.18	0.16	0.13
t-stat	3.35	3.91	4.45	5.00	6.09	4.13	4.62	5.13	5.84	6.01	3.12	3.52	3.52	3.97	4.10
Hi Upside Returns Port	1.05	2.08	4.07	7.23	11.17	0.17	0.11	0.10	0.09	0.08	0.26	0.16	0.11	0.08	0.06
t-stat	1.62	1.80	2.31	2.49	2.90	2.43	2.54	2.93	2.80	2.77	2.96	2.58	2.09	1.85	1.71
Hi - Low	-0.04	-0.22	-0.11	-0.74	-0.85	-0.46***	-0.40***	-0.34***	-0.32***	-0.28***	-0.13	-0.15**	-0.14***	-0.14***	-0.14***
t-stat	-0.05	-0.17	-0.05	-0.21	-0.17	-4.38	-4.55	-4.47	-4.60	-5.72	-1.47	-2.32	-2.72	-3.25	-3.66
Hi-Low Annualized Alpha (%	-0.16	-0.44	-0.11	-0.37	-0.28										

Panel A reports the time-series means and *t*-statistics of the post-formation FH 7-factor alphas, FH 7-factor-based Appraisal Ratios, and the smoothing-adjusted Sharpe Ratios for the value weighted quintile portfolios sorted on *DownsideReturns*, and Panel B for portfolios sorted on *UpsideReturns*. *DownsideReturns* (*UpsideReturns*) are measured as conditional average returns when the overall hedge fund sector performance is under (above) the median level of the past 24 months The performance measures are based on the equally buy-and-hold portfolios sorted every three months and held for three months to three years. The *t*-statistics reported in parentheses are adjusted for heteroscedasticity and autocorrelation. *** 1% significance; ** 5% significance; * 10% significance.

Appendix A2: Robustness: Alternative Backfill Bias Control (1997–2011)

Panle A: Performance of Quintile Portfolios Sorted on DownsideReturns

EW	Alpha (FH 7-factor) (% p.a.)	AR	SR	VW	Alpha (FH 7-factor) (% p.a.)	AR	SR
Low DownsideReturns Port	-1.43	-0.04	0.10	Low DownsideReturns Po	-2.58	0.00	0.13
tstat	*-0.55*	*-0.74*	*1.11*	*tstat*	*-0.55*	*-0.04*	*1.41*
Port2	2.81	0.16	0.24	Port2	1.94	0.15	0.24
	-0.55	*2.29*	*2.69*		*-0.55*	*1.77*	*2.37*
Port3	4.39	0.34	0.29	Port3	4.32	0.41	0.38
	-0.55	*3.62*	*3.64*		*-0.55*	*3.71*	*4.17*
Port4	5.57	0.60	0.44	Port4	5.40	0.69	0.56
	-0.55	*6.24*	*5.88*		*-0.55*	*5.74*	*5.17*
Hi DownsideReturns Port	7.53	0.55	0.45	Hi DownsideReturns Port	5.76	0.68	0.49
	-0.55	*8.37*	*7.86*		*-0.55*	*7.23*	*6.77*
Hi-Lo	8.95	0.59	0.35***	Hi-Lo	8.33***	0.68***	0.35***
	*3.51****	*9.63****	*4.20*		*3.51*	*6.50*	*3.68*

Panle B: Regression Analysis

(Other control variables in Table 5 are included in the regression but are not reported for brevity.)

	Panel Regression			Fama-MacBeth Regression		
	Alpha (FH 7-factor) (% p.a.)	AR	SR	Alpha (FH 7-factor) (% p.a.)	AR	SR
DownsideReturns	2.71	0.09	0.01	2.42	0.12	0.02
t-stat	*9.78****	*19.41****	*2.86****	*2.82****	*5.16****	*0.96*
AdjR2(%)	11.26	13.06	19.11	16.05	11.43	11.65
#FundsQtrObs	66292	66292	48486			

Appendix A2 summarizes the results when the backfill bias is controlled for by filtering out data prior to a fund entering the TASS database. Panel A reports the time-series means of the post-formation FH seven-factor alphas, FH seven-factor-based appraisal ratios (*AR*), and the smoothing-adjusted Sharpe ratios (*SR*) for the *DownsideReturns*-sorted quintile portfolio. The performance measures are based on the equally and value-weighted buy-and-hold portfolios sorted every three months and held for one quarter. In italicized font, we report *t*-statistics that 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: $AbnormalPerformance_{i,t} = c_{0i} + c_{1i} Downside\,\mathrm{Re}turns_{i,t-1} + c_{2i} Control_{i,t-1} + e_{i,t}$. Control variables are the same as in Table 3. Panel regression is adjusted for fund-clustering effect and time- and style-fixed effects. The Fama-MacBeth regression controls for style dummies, and adjusts for heteroscedasticity and autocorrelation in standard errors. For brevity, only the estimation results for the *DownsideReturns* are reported here. *** 1% significance; ** 5% significance; * 10% significance.