Which Hedge Fund Managers Deliver Alpha?

Assessing Performance When Returns are Skewed

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Abstract: 92 percent of hedge funds in the TASS database have returns which exhibit systematic skewness so the alpha of the managers of these hedge funds is difficult to estimate with OLS. To control for skewness the Residual Augmented Least Squares (RALS) estimator is specified to measure the performance of these hedge funds. We demonstrate that the OLS performance assessment error depends systematically on skewness, is economically significant, and that RALS is not sensitive to this bias. Furthermore, portfolios formed on RALS alphas are more persistent than those formed on OLS alphas, particularly during crisis periods.

Keywords: Hedge funds, Skewness, RALS, Factor models

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Given that it is well documented that hedge fund returns exhibit skewness and that investors have skewness preferences, is OLS the most efficient estimation technique for assessing manager performance? If not, how large are the OLS performance assessment errors, are they systematic, and can they be corrected? These questions are important for institutional and retail investors in hedge funds seeking to identify the best performing managers, and they are particularly relevant during volatile markets. Our paper addresses each of these issues by applying an econometric technique that is robust to skewness to a large sample of hedge fund returns.

Hedge fund manager performance is typically estimated relative to Fung and Hsieh's (2004) risk factors using OLS, despite existing evidence that hedge fund returns exhibit significant systematic skewness.[1] As estimating financial models with methodologies that explicitly control for the effects of small distributional deviations from normality can lead to very different findings (see for example Chan and Lakonishok (1992), Barber and Lyon (1997), Knez and Ready (1997) and Dell'Aquila, Ronchetti and Trojani (2003)) it is important to determine whether the assessment of hedge fund performance can be improved by using an estimator that is robust to skewness in fund returns.[2]

We choose the Im and Schmidt (2008) Residual Augmented Least Squares (RALS) as an alternative to OLS estimation. The innovation of the RALS estimator is that it increases estimation efficiency by augmenting the regression with functions of the OLS residuals that covary with the OLS residuals but not with the Fung and Hsieh (2004) risk factors.[3] [4] The RALS estimator is particularly useful

[1] There is a well-established "robust statistics" literature, (summarized most recently in Huber and Ronchetti (2009), that demonstrates how least squares is inefficient in the presence of outliers or underlying error distributions with skewness, but the issue has received less attention in academic finance.
[2] While we focus on more accurately estimating the level of hedge fund alpha, while controlling for skewness, prior related research has applied the bootstrap methodology to control for skewness when measuring the statistical significance of OLS hedge fund alpha estimates (see Kosowski, Naik and Teo (2007) and Fung, Hsieh, Naik and Ramadori (2008)).
[3] Wooldridge (1993) discusses the statistical improvement that can be obtained by adding orthogonal regressors to an estimation equation.

here because: 1) it provides robust coefficient estimates without imposing any restriction on the distribution of returns, and 2) it is easily estimated using two stage least squares. Comparing robust RALS performance estimates to OLS performance estimates allows us to quantify the OLS performance assessment error, evaluate the source of this error, and measure the impact of correcting for the OLS error on hedge fund performance predictability.

Our empirical results are clear. Although aggregate RALS and OLS estimates are similar, we find non-trivial errors in performance measures estimated by OLS when we classify funds as negatively or positively skewed. Everything else equal, following Kraus and Litzenberger (1976) we expect that funds which have negative skewness will have higher returns than funds with positive skewness.[5] Consequently, when compared with RALS estimates, OLS should overstate the performance of negatively skewed funds and understate the performance of positively skewed funds. This result appears throughout our return data and is robust across all fund categories, to time variation in fund risk exposures and to backfill, incubation and smoothing--known biases in hedge fund databases.

Specifically, we find that *OLS overestimates performance* by 2.4 percent per annum for the *bottom 10 percent of funds* sorted on historical skewness, (the most negatively skewed). Conversely, *for the top 10 percent of funds* sorted on historical skewness, (the most positively skewed), *OLS underestimates performance* by over 5.5 percent per annum. Within strategy groupings the error is most acute for Managed Futures funds, where OLS overstates the performance of the bottom 10 percent of funds sorted on historical skewness by 6 percent per annum while understating performance by 10 percent per annum for the top 10 percent of funds.

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[4] It is interesting to note that RALS also increases efficiency in the presence of kurtosis but we are not aware of any *a priori* reason for kurtosis to affect hedge fund performance so this paper focuses on skewness.

[5] The theoretical rationale for our research rests on the work of Markowitz (1952), Arrow (1971) and Kraus and Litzenberger (1976), who demonstrate that investors prefer positively skewed return distributions if their utility functions exhibit decreasing absolute risk aversion. In equilibrium, this preference should generate a significant risk premium on investments whose returns are negatively skewed.

More importantly, using an estimator that is robust to skewness has implications for hedge fund performance persistence. The performance of portfolios formed using RALS alphas (estimated over the past two years) persists more than the performance of portfolios formed on similarly sorted OLS alphas. Specifically, sorting on RALS alphas yields a top decile *portfolio alpha* of 8.49 percent, which is 1.23 percent per annum higher than that from a sort on OLS alphas. Billio, Getmansky and Pelizzon (2011) demonstrate the importance of considering periods of financial crisis when estimating hedge fund risk. In our sample, we find the difference between performance persistence estimated via RALS and OLS is even more striking during these crisis periods. Then, the alpha of the top decile RALS portfolio is 4.4 percent per annum higher than the corresponding OLS portfolio and the top decile RALS portfolio produces annualized returns of +1.81 percent while the top decile OLS portfolio produces annualized returns of -1.96 percent. Thus, our results show that an investor in hedge funds who considered skewness in returns in addition to the Fung and Hsieh (2004) risk factors when forming portfolios of hedge funds would have avoided funds that performed particularly badly during the recent crisis.

To summarize, our paper makes four distinct contributions: 1) we show that assessments of hedge fund performance estimated using OLS are biased when fund returns exhibit skewness, as most hedge fund returns do, 2) we show that the bias is economically important, that it depends systematically upon the sign of the skewness in a fund's return distribution, and that it can be overcome by using the RALS estimator, 3) we provide evidence on the importance of using an estimator that is robust to skewness in returns when assessing the persistence of hedge fund performance, and 4) we show that the differential persistence in performance of portfolios formed using OLS and RALS alphas is particularly acute during periods of market crisis.

The remainder of the paper is organized as follows. Section I outlines the related literature on skewness preferences and assessing hedge fund performance. Section II provides a review of the data.

Section III describes the risk factor model and the methodology. Section IV presents results. Finally, Section V provides a conclusion.

I. Related Literature

A. Preference for Skewness

Recently there has been much public concern about the performance of institutional investments such as university endowments in negatively skewed asset classes such as hedge funds. For example, the "Yale model", popularized by David Swensen, advocates increased exposure to less liquid asset classes such as hedge funds and private equity funds.[6] An endowment's return distribution is likely to exhibit negative skewness if it follows an investment strategy of this nature and the institution expects to receive a premium over time for bearing this downside risk. Anecdotal evidence from the recent crisis suggests that many of the universities' stakeholders grew used to receiving the risk premium but were not prepared for the eventual losses. A commentary by Andrew M. Rosenfeld in Forbes, March 3rd 2009, captures these issues, *"... the anxiety associated with these losses is consistent with the view that some of the clientèle exhibits rather routine loss aversion and also with the fact that the level of risk routinely taken on in these portfolios was very high and not fully understood by many. The investment strategy employed and the rhetoric used in "investing for the long run" is reminiscent of the gain-seeking nature of the plan and not its propensity to produce substantial loss sometimes… Some of the clientèle of these elite university endowments seem to believe that they could simultaneously enjoy the historical expected average returns of*

[6] For more details on the strategy followed by the Yale endowment see Swensen (2000). A typical example of a university endowment which increased exposure to negative skewness assets is Carnegie Mellon University (CMU). CMU's annual reports contain detailed information on their allocation to alternative investments, which increased substantially from 2001 to 2009. In 2001 less than 13 percent of the endowment was invested in "Other Investments" with an explicit 5 percent target allocation to hedge funds. By 2009 the "Other Investments" allocation had grown to 43 percent, with a target allocation of 15 percent to hedge funds and 22 percent to private equity. In year ended June 30th 2009, in line with other endowments following a similar approach, the endowment returned -26.7 percent net. University officers imposed a one year pay freeze while also offering employees one month unpaid leave.

endowments like Harvard's and Yale's--with the loss exposure of a traditional and more conservatively managed portfolio."

This attitude of university stakeholders towards large losses is consistent with the recognized preference by investors for positively skewed returns if they have utility functions that exhibit decreasing absolute risk aversion (Markowitz (1952), Arrow (1971) and Kraus and Litzenberger (1976)). [7] There is also empirical evidence that investors have a preference for positive skewness, both in studies of mutual funds (Levy and Sarnat (1972)) and portfolio choice (Polkovnichenko (2005)). In a related vein, the behavioral finance literature suggests that investors may also have a preference for positive idiosyncratic, as opposed to systematic, skewness (Barberis and Huang (2008)).

Considerable recent research on the sources of systematic risk has focused on negative skewness in individual stocks and the stock market as a whole. Studies have demonstrated how a preference for positive skewness can generate a risk premium on *negatively skewed* assets (for example Kraus and Litzenberger (1976) and Harvey and Siddique (2000)). We build on this pioneering work by providing evidence that: 1) the preference for positive skewness generates a positive risk premium for hedge funds pursuing strategies exhibiting negative skewness and a negative risk premium for funds exhibiting positive skewness, and 2) performance estimation by RALS is more efficient at capturing this effect than OLS.

B. Assessing Hedge Fund Performance

Our study also relates to existing research which assesses the performance of hedge funds. Given the non-Gaussian features of hedge fund returns, one strand of this research focuses on more accurately

[7] Decreasing absolute risk aversion implies that, in a portfolio context, increases in portfolio skewness are preferred (Harvey and Siddique (2000)). Since adding assets with negative co-skewness to a portfolio will make the portfolio more negatively skewed, assets with more negative co-skewness should also have higher expected returns. Given that investments in hedge funds are generally held by investors as part of a broader portfolio of assets, the pricing of conditional skewness is a non-trivial issue. To investigate this we distinguish between conditional and unconditional skewness later in the paper.

estimating hedge fund performance by specifying contingent claims as risk factors in a linear specification. The idea here is that the payoff of a non-linear strategy will be better captured by a contingent claim risk factor coefficient, which will lead to improvements in performance estimation. Agarwal and Naik (2004) and Mitchell and Pulvino (2001) incorporate short positions in put options as risk factors, while Fung and Hsieh (2001, 2004) choose positions in look-back straddles to capture non-linearities in hedge fund returns. Related research also documents the empirical relationship between hedge fund returns and higher moment risk factors (see Chan, Getmansky, Haas and Lo (2007) and Agarwal, Bakshi and Huij (2009)).

Alternatively, several studies apply different methodologies to more accurately estimate hedge fund performance. Kosowski, Naik and Teo (2007) and Avramov, Kosowski, Naik and Teo (2011), take a Bayesian approach to improving the estimation of hedge fund alphas.. Both studies demonstrate that forward looking portfolios formed using these more precise estimates of historical alpha outperform the OLS alpha portfolios by a considerable margin. Jagannathan, Malakhov and Novikov (2011) use weighted least squares to reduce the measurement errors in estimated alphas and develop a GMM model to measure performance persistence. They find significant performance persistence for the top hedge funds but no evidence that returns persist for inferior funds.

Amin and Kat (2003) control for non-normality in hedge fund returns by adopting a non-parametric payoff distribution pricing model. The bootstrap methodology, which is more closely related to the present paper, has been applied to mutual fund returns (Kosowski, Timmermann, Wermers and White (2005)), to hedge fund returns (Kosowski, Naik and Teo (2007)) and to fund of funds returns (Fung, Hsieh, Naik and Ramadori (2008)). The bootstrap methodology focuses on measuring the statistical significance of OLS alpha estimates more accurately. In this study we use the RALS estimator to more accurately measure the level of alpha while controlling for skewness.

II. Data

We evaluate the performance of hedge funds using monthly net-of-fee returns of live and dead hedge funds in the Lipper/TASS database up to October 2009 - a period that covers several market crises, including the LTCM collapse in 1998, the dot-com crash in 2002 and the sub-prime and credit crises in 2007 and 2008. At the final quarter of 2009, the TASS database contains 5,897 live and 8,058 dead funds, including Fund of Funds.

Hedge fund returns are self reported to TASS and it is well known that this leads to backfill and incubation biases in the database (Ackermann, McEnally and Ravenscraft (1999) and Fung and Hsieh (2000)).[8] Backfill bias occurs when funds report prior performance to the data vendor because funds will only be motivated to provide these historical returns in the case of good performance. Incubation bias occurs when a fund is set up initially using manager money to establish a track record. The returns of incubated funds are then submitted to the data vendor only if performance is good. To control for backfill and incubation bias, we repeat all analysis omitting the first twelve months of data for each fund.

Furthermore, TASS does not keep information on funds that died before December 1993,which leads to survivorship bias. To control for this, we specify a sample of fund returns from January 1994 to October 2009. We also remove funds with less than two years of returns data, funds which report only gross returns and/or do not report monthly returns and funds which do not provide investment style information. We group funds according to the TASS classifications, Convertible Arbitrage (CA), Event Driven (ED), Equity Market Neutral (EMN), Emerging Markets (EM), Fixed Income Arbitrage (FIA), Fund of Funds (FoF), Global Macro (GM), Long Short Equity Hedge (LSEH), Managed Futures (MF) and

[8] Recent evidence also suggests that in some cases funds may misreport returns to the database vendors (Agarwal, Daniel and Naik (2009) and Bollen and Pool (2009)).

Multi Strategy (MS).[9] [10] Our final sample consists of 2,237 live hedge funds and 3,876 dead hedge funds. We also report results for 1,747 live and 2,020 dead Fund of Funds. Finally, several studies identify serial correlation in the returns of hedge funds.[11] To mitigate this bias, in robustness checks we repeat all analysis using unsmoothed hedge fund returns (Getmansky, Lo and Makarov (2004)).

[Please Insert Table I Here]

Table I contains summary statistics of the TASS funds in the sample. Based on sample skewness t-ratio statistics, $\frac{\hat{S}(r)}{\sqrt{\sigma/T}}$, funds are categorized as being either live negative-skewness (1,222 funds), live no-skewness (251 funds), live positive-skewness (764 funds), dead negative-skewness (2,093 funds), dead no-skewness (224 funds) or dead positive-skewness (1,559 funds). For each fund type, the table lists the number of funds and the equally weighted cross sectional mean of each fund's mean monthly return, standard deviation, Sharpe ratio, skewness and kurtosis.

It is clear that the majority (92 percent) of funds can be classified as negative- or positive-skewness funds. Only 8 percent of hedge funds in our sample (475 funds) have skewness t-ratio statistics which are not significant from zero. Convertible Arbitrage, Event Driven, Equity Market Neutral, Emerging Markets, Fixed Income Arbitrage and Multi-Strategy tend to have more funds classified as negative-skewness, whereas Long Short Equity Hedge and Global Macro funds tend to have an even balance between negative- and positive-skewness funds. Finally, the Managed Futures Funds' largest grouping is positive skewness.

Comparing funds classified as negative-, no- and positive-skewness, the Sharpe ratios progressively improve, both for live funds (0.11, 0.18 and 0.24 respectively) and for dead funds (0.08, 0.16 and 0.22 respectively). This gives us the first hint that a fund's skewness may be related to its performance. Funds

[9] Lipper/TASS do not include the Madoff funds in our version of the database so our results are not driven by the discovery of the Madoff fraud in November 2008.

[10] As there are only 39 funds we do not report results for the Dedicated Short Bias style. They are included in the full sample results.

[11] Illiquidity in the assets held by funds, rather than misreporting, is the primary source of this serial correlation (Cassar and Gerakos (2011)).

classified as positive- and negative-skewness also tend to exhibit higher kurtosis. Standard deviations and skewness and kurtosis measures are all relatively similar for live and dead funds whereas the Sharpe ratios are marginally higher for live than dead funds, primarily due to the higher mean returns on live funds, (e.g. the mean returns of the three categories of live Emerging Market funds are approximately 50 basis points higher than the corresponding dead fund counterparts).

III. The Impact of Skewness When Assessing Hedge Fund Performance

We next benchmark the performance of our hedge fund sample to the Fung and Hsieh (2004) seven-factor model using both OLS and RALS estimators.[12] The details of the Fung and Hsieh (2004) model are reviewed in Subsection A and an overview of the RALS estimator is provided in Subsection B. Subsection C illustrates the source of the OLS performance assessment error via simulation and Subsection D demonstrates introduces cross-sectional regressions which will show that the RALS estimator correctly identifies the skewness risk premium.

A. Fung and Hsieh's Factor Benchmarks

The Fung and Hsieh (2004) model specifies three Trend-Following Risk Factors, specifically Bond (*PTFSBD*), Currency (*PTFSFX*) and Commodity (*PTFSCOM*), augmented with two equity-oriented Risk Factors: *SNPRF*, the excess total return on the Standard & Poor's 500 index, and *SCMLC*, the Size Spread Factor (Wilshire Small Cap 1750 - Wilshire Large Cap 750 monthly return) and two Bond-oriented risk factors: *BD10RET*, the monthly change in the 10-year treasury constant maturity yield (month end-to-month end), and *BAAMTSY*, a credit spread factor (the monthly change in the Moody's Baa yield less 10-

[12] We choose this model because it has been shown to explain much of the variation in hedge fund returns (Fung and Hsieh, 2004).

year treasury constant maturity yield (month end-to-month end)).[13] The general risk-adjusted performance estimation equation is:

$$r_{it} = \hat{\alpha}_i + \sum_{k=1}^{K} \hat{\beta}_k^i F_{k,t} + \hat{\varepsilon}_t^i \tag{1}$$

where r_{it} is the net-of-fees excess return on hedge fund *i* at time *t*, $\hat{\alpha}_i$ is the estimated abnormal performance of the hedge fund, $\hat{\beta}_k^i$ is the estimated risk factor loading of hedge fund *i* for risk factor *k*, $F_{k,t}$ is the return of factor *k* for month *t* and $\hat{\varepsilon}_t^i$ is the estimated residual.

[Please Insert Table II Here]

Table II Panel A contains summary statistics for the Fung and Hsieh (2004) factors we use. The *PTFSBD*, *PTFSFX* and *PTFSCOM* return series are obtained from David Hsieh's website. Data to construct *BD10RET* and *BAAMTSY* come from the US Federal Reserve website and *SNPRF* and *SCMLC* are obtained from DataStream. The excess returns of three of the factors, *BD10RET*, *PTFSBD* and *PTFSCOM,* are negative. Comparing the highest factor Sharpe ratio (*SNPRF*) with those reported for the different equally weighted All Funds categories in Table I, we see that only dead negative-skewness funds have weaker performance than the risk factors chosen to measure that performance.

Table II Panel B contains a correlation matrix to provide an indication of the substitutability of the various risk factors. Generally, the factors have low correlation with each other, with the exception of the two bond related factors, *BD10RET* and *BAAMTSY*, at -0.40. While relatively high correlation amongst explanatory variables can give rise to spurious univariate significance levels, our focus in this paper is on the estimated intercepts, rather than the factor coefficients, and intercept estimates are not affected by multicollinearity.

B. Residual Augmented Least Squares

[13] For details on the construction of the trend following factors see Fung and Hsieh (2001).

Our first challenge in this paper is to determine whether OLS accurately estimates hedge fund performance when the funds' return distributions are skewed. This section reviews the Residual Augmented Least Squares (RALS) estimator proposed by Im and Schmidt (2008), which is robust with respect to skewness.

The RALS estimator, which is closely related to the GMM estimator (Hansen (1982)), is just one of a wide variety of alternative robust estimation techniques which can be specified to more efficiently model non-normal data. The basic types are M-estimators, L-estimators and R-estimators. M-estimators are a generalized form of maximum likelihood estimation (Huber (1973)), whereas the L-estimator class of models (for example the LAD estimator proposed by Bassett and Koenker (1978)) are based on linear combinations of order statistics, while R-estimators are estimates derived from rank tests. In addition there are a number of variations within each of these classes. For example, Phillips, McFarland and McMahon (1996) and Phillips and McFarland (1997) specify FM-LAD, a non-stationary form of the LAD regression procedure, due to Phillips (1995), to model the relationship between daily forward exchange rates and future daily spot prices. We choose the RALS estimator as it is a relatively straightforward extension of a linear regression (augmented with functions of the least squares residuals), is asymptotically equivalent to GMM (Im and Schmidt (2008)) and is easy to estimate via two-stage least squares. A test statistic based on RALS has been used to robustly test for speculative bubbles in stock prices (Taylor and Peel (1998)), and in house prices (Garino and Sarno (2004)), while Gallagher and Taylor (2000) use RALS to robustly estimate the temporary and permanent component of stock prices.[14]

We start with a multivariate linear regression model

$$y_t = \varphi' z_t + u_t \tag{2}$$

[14] These tests are based on an earlier version of the paper, Im (1996).

where $z_t = (1, x_t')'$, x'_t is a $(k-1) \times 1$ vector of time series observed at time t, while $\varphi' = (\alpha\beta')'$ where α is the intercept and β' is the $(k-1) \times 1$ vector of coefficients on x_t. Assume the following moment conditions hold:

$$E[x'(y - x'\beta)] = 0 \tag{3}$$

$$E\{(x \otimes [h(y - x'\beta) - H]\} = 0 \tag{4}$$

where (3) is the least squares moment condition, which asserts that x_t and u_t are uncorrelated, and (4) specifies the additional moment condition that some function of u_t is uncorrelated with x_t. *h(.)* is a *J x 1* vector of differentiable functions and *H* is a *J x 1* vector of constants. Therefore, there are *kJ* additional moment conditions.

Excess kurtosis in the residual implies that the standardized fourth central moment of the series exceeds three, so that:

$$E(u_t^4 - 3\sigma^4) = E[u_t(u_t^3 - 3\sigma^2 u_t)] \neq 0 \tag{5}$$

implying that $u_t^3 - 3\sigma^2 u_t$ is correlated with u_t but not with the regressors, since x_t and u_t are by assumption independent. Similarly, when errors are skewed the standardized third central moment is non-zero so that:

$$E(u_t^3 - \sigma^3) = E[u_t(u_t^2 - \sigma^2)] \neq 0 \tag{6}$$

which implies that $u_t^2 - \sigma^2$ is correlated with u_t but not with the regressors (again, since x_t and u_t are assumed to be independent.)

Im and Schmidt (2008) suggest a simple two stage estimator that can be estimated by OLS of equation (2) augmented with (7).

$$\widehat{w}_t = [(\hat{u}_t^3 - 3\hat{\sigma}^2\hat{u}_t)(\hat{u}_t^2 - \hat{\sigma}^2)]' \tag{7}$$

where $\hat{u}_t$ denotes the residual and $\hat{\sigma}_t$ denotes the standard residual variance estimate obtained from OLS applied to equation (2). The resulting estimator is the RALS estimator of β, β^*. When both the dependent and independent variables are stationary, β^* has an asymptotic distribution given by

$$\sqrt{T}(\beta * -\beta) \rightarrow N[0, \sigma_A^2 Var(x_t)^{-1}] \tag{8}$$

Im and Schmidt (2008) derive a measure of the asymptotic efficiency gain from employing RALS as opposed to OLS through the statistic $\rho*$ constructed as σ_A^2/σ^2 where σ^2 is the asymptotic variance of the OLS estimation of β and σ_A^2 is the asymptotic variance of the RALS estimator:

$$\sigma_A^2 = \sigma^2 - \frac{\mu_3^2(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2) - 2\mu_3(\mu_4 - 3\sigma^4)(\mu_5 - 4\mu_3\sigma^2) + (\mu_4 - 3\sigma^4)^2(\mu_4 - \sigma^4)}{(\mu_4 - \sigma^4)(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2) - (\mu_5 - 4\mu_3\sigma^2)^2} \tag{9}$$

where μ_i denotes the i-th central moment of u_t. *Note that $\rho*$ is small for large efficiency gains*. The inclusion of the RALS estimators is useful in obtaining a more efficient model estimate if the distribution of the error term is non-normal. In contrast, for the normal distribution, OLS is efficient and the ratio equals one.

σ_A^2 can be consistently estimated by replacing the μ_i with the corresponding sample moments, using OLS residuals, yielding $\hat{\sigma}_A^2$. The covariance matrix for β* can then be estimated consistently as

$$V(\beta^*) = \hat{\sigma}_A^2(\tilde{X}' M_{\widetilde{W}} \tilde{X})^{-1} \tag{10}$$

where the idempotent matrix $M_{\widetilde{W}}$ is given by

$$M_{\widetilde{W}} = I_t - \widetilde{W}'\left(\widetilde{W}'\widetilde{W}\right)^{-1}\widetilde{W} \tag{11}$$

where I_t is the $T \times T$ identity matrix and $\tilde{V} = (\tilde{v}_1 \tilde{v}_2 \ldots \tilde{v}_T)', \tilde{v}_t = v_t - T^{-1}\sum v_t$ for $(V, v) = (X, x), (W, w)$.

The quantification of the efficiency gain and the ability to achieve it using the RALS estimation technique depends on the homoskedastic assumption that the third and fourth conditional moments do not depend on the regressors.

C. A Demonstration of RALS Results via Simulation

In order to isolate the effects of skewness on alpha estimation for hedge fund returns, and the efficiency gain from using RALS as opposed to OLS, we create a series of simulated portfolios which are identical with the exception of S_i, the skewness in the error distribution, which we allow to vary from -2.0 to +2.0, rising in increments of 0.5.[15]

As a first step, we estimate (1) with OLS for the monthly returns of the CSFB Tremont Aggregate Hedge Fund Index over the period from January 1994 to September 2009. This yields an alpha estimate ($\widehat{\alpha}$ = 0.0035, or 4.24% per annum) and coefficients on each of the Fung and Hsieh risk factors. The first and second rows report the estimated coefficients and p-values.

α	β_{SNPRF}	β_{SCMLC}	$\beta_{BD10RET}$	$\beta_{BAAMTSY}$	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$	Adj. R^2
0.00	0.25	0.15	-0.04	-0.04	-0.03	0.01	0.02	0.40
0.01	0.00	0.00	0.05	0.01	0.00	0.19	0.07	

For this estimation we find residual standard deviation ($\hat{\sigma}$ = 0.000151), residual kurtosis ($\widehat{K}$ = 5.16) and residual skewness ($\hat{S}$ = 0.14).

We next simulate $\tilde{e}_t^i$, a random series of errors from the distribution in a Pearson system with standard deviation and kurtosis set equal to those estimated above and various skewness levels S_i, subject to the interval and increment limits notes above. We then generate $\tilde{r}_{it}$, a simulated hedge fund return series, as follows.

$$\tilde{r}_{it} = \hat{\alpha}_i + \sum_{k=1}^{K} \hat{\beta}_k^i F_{k,t} + \tilde{e}_t^i \qquad (12)$$

[15] We are constrained to use skewness values ranging from -2.0 to 2.0 as the skewness must be less than the square root of (the kurtosis minus 1) which for the Aggregate Index is ±2.04.

At each S_i we repeat the simulation 1,000 times. We then estimate (1), the general risk-adjusted performance equation, for each of the simulated portfolios with both OLS and RALS.

[Please Insert Table III here]

The results of the simulations are reported in Table III. For completeness we report simulations with $\hat{\alpha}_i$ = 0.0035, as estimated above, and also with $\hat{\alpha}_i$ = 0. As anticipated, the RALS alphas are sensitive to cross sectional differences in S_i whereas the OLS alpha estimates remain invariant. As we would expect given investors preferences for positive skewness and the corresponding equilibrium risk premium on negatively skewed assets, the OLS alphas overstate performance (the RALS alphas are smaller) for negative values of S_i and the OLS alphas understate performance (the RALS alphas are larger) for positive values of S_i. Furthermore, the efficiency gain from using the RALS estimator instead of the OLS estimator, which is reflected in lower values of ρ*, becomes more pronounced as S_i increases, in absolute terms.

D. Source of the OLS Performance Assessment Error

Given that we have documented the existence of systematic performance assessment error when applying OLS estimation to simulated hedge fund return series that are positively or negatively skewed, our second key challenge is to identify whether this error is systematically related to the type of skewness in hedge fund returns. Two cross sectional regression models ((13) and (15)) allow us to investigate whether or not the RALS estimator has captured this skewness risk premium. The first is:

$$z_i = \gamma_0 + \gamma_1 skew_i + \gamma_2 kurt_i + \epsilon \tag{13}$$

where $z_i = \hat{a}_i^{RALS} - \hat{a}_i^{OLS}$, $\hat{a}_i^{RALS}$ is the intercept of the RALS estimated time-series regression of fund *i*'s returns against the Fung and Hsieh benchmark factors, and $\hat{a}_i^{OLS}$ is the intercept of the OLS estimated time-series regression of fund i's returns against the Fung and Hsieh benchmark factors. *Skew* and *kurt* are the estimates of skewness and kurtosis, scaled by their standard errors, for fund i.

The OLS performance assessment error may be also related to conditional skewness because investments in hedge funds are generally held by investors as part of a broader portfolio of assets. To control for this effect we include a measure of coskewness for each fund, β_{SKD}, following Harvey and Siddique (2000). Coskewness, β_{SKD}, is defined as

$$\hat{\beta}_{SKD_{,i}} = \frac{E[u_{i,t+1}u^2_{M,t+1}]}{\sqrt{E[u^2_{i,t=1}]}\,E[u^2_{M,t+1}]'} \tag{14}$$

where $u_{i,t+1} = r_{i,t+1} - \alpha_i - \beta_i(r_{M,t+1})$, the residual from the regression of the excess return of fund i, on the excess return market return. β_{SKD} measures the contribution of the coskewness of each fund to a broad equity portfolio. A negative measure indicates that the fund would add negative skewness.

Aragon (2007) demonstrates that six additional operational variables explain hedge fund performance: *dlock*, *notice*, *min*, $notice^2$, min^2 and *dlock.notice*. The variables *dlock*, *notice*, and *min* correspond to the lockup indicator, redemption notice period (in 30-day units), and minimum investment size (in millions of dollars). The variables $notice^2$ and min^2 allow for non-linearity in the return and share restriction relationships while *dlock.notice* allows for interaction between the lockup and notice period restrictions.

To ensure our results are robust to these alternative reasons for the OLS estimator's performance assessment error, we incorporate the additional control variables discussed above into our hedge fund return regressions in (15):

$$z_i = \gamma_0 + \gamma_1 skew_i + \gamma_2 kurt_i + \sum_{j=1}^{J} \beta_j C_{ji} + \epsilon \tag{15}$$

.

The vector C_{ji} includes Harvey and Siddique's (2000) measure of coskewness for each fund and the set of operational variables that Aragon (2007) uses to explain hedge fund performance.

IV. Results

We present robust estimates of hedge fund performance in Subsection A, examine the relationship between skewness and OLS performance assessment error in Subsection B, and provide robustness checks in Subsection C. Finally we examine persistence in hedge fund performance in Subsection D.

A. Robust Estimates of Performance

We plot the kernel density estimate of both the OLS and RALS estimated alpha distributions in Figure 1 to get a picture of the relative distribution of OLS and RALS performance estimates for the full sample. It is clear that the RALS and OLS alpha distributions have similar means but that the RALS alpha distribution is less peaked and has fatter tails than OLS.

[Please Insert Figure 1 Here]

We report the cross-sectional mean fund results within strategy categories from performance estimated by OLS and RALS, and the ρ* the efficiency gain from estimating by RALS, for the differing fund classifications, (live, dead, and positively-, negatively- or non-skewed) in Table IV.

[Please Insert Table IV Here]

Comparing the alphas of the different categories, it is apparent that OLS performance and RALS performance is positively related to skewness. Specifically, the best performing fund categories are those classified as positive-skewness, whereas the worst performers are classified as negative-skewness. Second, live funds generally perform better than dead funds, whether performance is assessed by OLS or RALS. Comparing performance differences at the disaggregated level makes the OLS performance assessment errors quite apparent. Negative- and positive-skewness funds exhibit significant performance assessment errors ranging from +0.14 percent per month for dead negative-skewness funds to -0.31 percent per month for dead positive-skewness funds, while OLS and RALS produce similar performance estimates for both live and dead funds when fund returns are not skewed. It is difficult to draw firm conclusions due to the small sample sizes in some categories of hedge fund strategies, (for example, the no-skewness live Convertible Arbitrage, Equity Market Neutral, Fixed Income Arbitrage and Global Macro segments each contain less than 10 funds), but the results clearly indicate that the direction of the OLS performance assessment error is related to the sign of skewness when sample sizes are reasonable, (for example, live Long Short Equity Hedge performance assessment errors are +0.14 and -0.14 percent per month for negative- and positive-skewness funds, respectively, while the error is -0.04 percent for no-skewness funds).

To further examine the difference between OLS and RALS performance estimates at the aggregate level for negative-skewness, no-skewness and positive-skewness funds, we compare the alpha estimates in Figure 2.

[Please Insert Figure 2 Here]

Figure 2A plots OLS against RALS performance estimates for all funds. To quantify this relationship we regress the OLS alpha against the RALS alpha. The slope is highly significant with an estimate of 0.5, and the adjusted R^2 of the regression is 68 percent. Figure 2B repeats the analysis but restricts the sample to negatively-skewed funds. Here the slope from regressing the OLS alpha against the RALS alpha is close to that of the full sample (0.6 vs. 0.5) but the adjusted R^2 of the regression is smaller, dropping from 68 percent to 66 percent. Figure 2C shows the relationship between RALS and OLS alpha for no-skewness funds. Both the slope (0.7) and the adjusted R^2 (80 percent) are considerably higher than for the negative-skewness funds. Finally, Figure 2D considers only positively skewed funds and we can see that the slope is again lower, 0.6, and the Adjusted R^2 drops to 66 percent relative to the no-skewness funds. Clearly, the OLS performance assessment errors when compared to performance assessment under RALS are smallest for the no-skewness funds.

B. Source of OLS Performance Assessment Errors

The results in the previous section suggest that standard OLS alpha estimates for hedge fund returns may not be robust if skewness is present in the distribution of a fund's return series. Furthermore, differences can be quite large when comparing the performance of funds estimated by OLS and by RALS. In this section we return to the results of our theoretical work in Section I and examine whether or not the skewness in a fund's distribution is the source of the performance assessment error.

[Please Insert Table V Here]

Table V reports the estimates of the skewness and kurtosis coefficients (from equations 20 and 21) for live (Panel A) and dead (Panel B) negative- and positive-skewness funds.[16] Turning first to Panel A the error is statistically significant, 1.77 percent per annum for negative-skewness live funds. Adding the *skewness* and *kurtosis* variables, (γ_1 and γ_2 in Table V) explains all of this error (in that the constant term is no longer significant), and both coefficients are statistically significantly different from zero. For the positive-skewness funds the error is -3.68 percent per annum, but is again fully explained by the two explanatory (γ) variables. In Panel B, both the dead negative- and positive-skewness funds have significant alpha errors of 1.31 and -2.17 percent per annum but the *skewness* and *kurtosis* factors are statistically significant for both categories of funds and explain all of the OLS performance assessment error. The bottom rows of each panel add the co-skewness (β_1) and administrative control (β_2 - β_7) variables identified in the discussion of Equation (15). The added control variables are seldom significant but both the

[16] For no-skewness funds the alpha error is not significantly different from zero. To save space we do not report the results for these funds here but they are available from the authors on request.

skewness and kurtosis factors remain statistically significant from zero and all of the systematic performance assessment error that arises from estimating returns on skewed distributions via OLS instead of RALS is explained for all categories of funds.

[Please Insert Table VI Here]

We further investigate the importance of skewness in controlling for OLS performance assessment error by both fund category and the direction of the underlying skewness in returns because an investor in hedge funds should be interested in whether our results are consistent across different hedge fund strategies and also whether the OLS performance assessment error is greater at extreme skewness levels. In Panel A of Table VI we report the performance of all funds estimated by OLS and RALS and sorted on skewness. The results are striking. OLS misprices fund performance for all fund deciles with the exception of decile 6, where the mean skewness is close to zero. For funds which have negative skewness, OLS performance overstatement increases from 7 to 20 basis points per month. For funds exhibiting positive skewness OLS performance understatement increases from 7 to 48 basis points per month. Panels B to K of Table VI report disaggregate the results according to fund style. There are no exceptions to the conclusions documented so dramatically in Panel A in that we find no situations where OLS significantly understates performance for negatively skewed funds and no significant overestimation for hedge funds with positive skewness.

The fund style where the OLS performance assessment error is the largest is Managed Futures, where OLS overstates the performance of the most negatively skewed funds by 6 percent and understates the performance of the most positively skewed funds by 7 percent per annum. This is not surprising given that the Managed Futures strategy encompasses several styles which exhibit different characteristics (Bhardwaj, Gorton and Rouwenhorst (2008)). Other strategies where the positively skewed funds' performance is heavily understated by OLS are Emerging Markets (9 percent) and Global Macro (9 percent). At negatively skewed end of the distribution, OLS over-estimates performance by 9.8 percent for Fixed Income Arbitrage funds.

C. Robustness Checks

We focus on a sample period subsequent to 1993 so our sample is relatively free of survivorship bias. However, incubation and backfill bias and illiquidity-induced serial correlation have been shown to affect hedge fund performance estimates. Likewise, there is a growing literature highlighting the time varying nature of hedge fund risk exposures. Furthermore, our results may be biased by the inclusion of funds with relatively short return series. We address these issues by repeating the analysis (1) for funds that have at least thirty-six months of return data available, (2) after removing the first twelve months of returns for each hedge fund to eliminate backfill bias, (3) unsmoothing returns following Getmansky, Lo and Makarov (2004), and (4) controlling for structural breaks identified in the literature.

[Please Insert Table VII Here]

OLS and RALS alphas for the full sample of funds with returns of at least thirty-six months duration are reported in Panel A of Table VII. Panel B reports the full-sample alpha results after adopting the Getmansky, Lo and Makarov (2004) coefficients to unsmooth our hedge fund returns. We next eliminate the first twelve months of each fund's return to remove potential backfill bias (Panel C). There are no exceptions to our finding that OLS misprices fund performance in a significant, systematic manner. Specifically, OLS continues to overstate the performance of funds with negatively skewed returns and understate the performance of funds with positively skewed returns in our robustness tests for the impact of the length of the return series, backfill bias and serial correlation induced by illiquidity.

Recent studies have highlighted the importance of time variation in return characteristics when measuring fund performance.[17] Specifically, there is evidence that hedge funds change their risk exposures over time due to sudden financial disruptions such as the Russian crisis and dotcom collapse (Kosowski, Naik and Teo (2007)). Using a variation of the CUSUM test, Fung, Hsieh, Naik and Ramadori (2008) identify two common structural break points, in October 1998 and in March 2000. We repeat our tests using a dummy regression to allow for these break points, and for a break in October 2007 (the onset of the subprime and credit crises). These results are reported in Panel D of Table VIII and are completely consistent with earlier findings. In summary these robustness checks indicate that our results are not driven by backfill bias, choice of minimum number of observations, illiquidity induced serial correlation or time varying risk exposures.

D. RALS analysis of Performance Persistence

Our results so far provide evidence that the performance of positively skewed hedge funds is understated by OLS, on average, while at the same time, OLS appears to systematically overstate the performance of negatively skewed hedge funds. While this is an interesting statistical issue, our findings are only relevant to investors in hedge funds if they have economic importance - either through an increase in expected risk adjusted returns or through a reduction in expected downside risk.

In this section, we investigate whether hedge fund performance persistence is greater when funds are sorted on RALS alphas instead of OLS alphas. We first sort funds into decile portfolios using their OLS alphas estimated over the preceding 24 months and then repeat the process using the funds' RALS alphas. By analyzing the relative performance of the top decile portfolios we are able to measure the difference in performance that can be achieved by utilizing RALS rather than OLS alphas.

[17] See Bollen and Whaley (2009) for more in-depth insight into the importance of time variation in fund exposures when assessing fund performance.

As OLS favors negatively skewed assets, we anticipate that the returns of the OLS portfolios will be worse during crisis periods. The intuition can be explained as follows. As investors should prefer right-skewed to left-skewed investments, otherwise identical assets with negative skewness should command higher expected returns with accompanying infrequent large losses. Conversely, assets with positive skewness should command lower expected returns with infrequent large profits.

[Please Insert Figure 3 Here]

The cumulative returns from January 1996 to October 2009 for the RALS and OLS top decile portfolios are displayed in Figure 3. The cumulative total returns of the S&P500 are also included for comparison. It is apparent that the returns of both portfolios are very high over the period and track each other quite closely. Interestingly, divergence between the portfolios sorted on RALS alphas and those sorted on OLS alphas occurs in late 1998, again beginning in early 2000, and, most strikingly, during 2007 and 2008.

[Please Insert Table VIII Here]

Table VIII reports the statistical characteristics for both the RALS and OLS top decile portfolios, and for the S&P500, which allows us to perform a simple mean variance analysis. There is a quite large difference in performance, with mean annual returns for the RALS (OLS) portfolio of 12.9 (11.6) percent and standard deviations of 11.6 and 13.2 percent respectively. Consequently the Sharpe ratio of the RALS portfolio is larger, at 0.82, versus 0.62 for the OLS portfolio and 0.25 for the S&P500. Institutional investors who rely on their investments in hedge funds to fund current expenditures are quite sensitive to decreases in portfolio value (drawdowns) because these drops in portfolio value often require corresponding cuts in expenditure, as seen in 2008. The RALS portfolio has the lowest drawdown during the sample period, 10 percent higher than the OLS portfolio and 27 percent higher than the S&P 500.

We next employ the boot strapped time series test of Ledoit and Wolf (2008) to formally test for differences in Sharpe ratios.[18] Unlike earlier work by Jobson and Korkie (1981) and Memmel (2003), the Ledoit and Wolf (2008) test is robust to non-normality and serial correlation, which is particularly relevant for portfolios of hedge funds. The differences in Sharpe ratio and their corresponding significance levels are reported in matrix form in Panel B of Table VIII for the RALS and OLS portfolios and the S&P 500. The RALS portfolio Sharpe ratio is statistically significantly greater than both the OLS portfolio and the S&P500 whereas the OLS portfolio Sharpe ratio is not statistically different from that of the S&P500.

Next, we estimate the portfolios' risk adjusted performance for the full sample and also in crisis and non crisis periods. We follow Billio, Getmansky and Pelizzon (2010) and define crises periods as Asian (June 1997 - January 1998), Russian and LTCM (August 1998 - October 1998), Brazilian (January 1999 - February 1999), Internet Crash (March 2000 - May 2000), Argentinean (October 2000 - December 2000), September 11, 2001, drying up of merger activities, increase in defaults, and WorldCom accounting problems (June 2002 - October 2002), the 2007 subprime mortgage crisis (August 2007 – January 2008), and the 2008 Global financial crisis (September 2008 - November 2008). In Table IX we report persistence results for the sorts on rolling two year OLS and RALS alphas for the top decile portfolios. We also consider spread portfolios formed by taking long positions in the top alpha hedge funds and short positions in the bottom alpha hedge funds.

[Please Insert Table IX Here]

According to Panel A of Table IX, when sorting on OLS alphas across the entire 1993 – 2009 sample period the top decile portfolio generates a statistically significant alpha of 7.26 percent per annum. The alpha of the RALS portfolio is also statistically significant and is 1.23 percent higher. The alpha for

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[18] We are grateful to Dan Wunderli for his assistance in implementing this test.

the spread between the top and bottom deciles is not significant for either OLS or RALS but the difference in alpha is 1.32%, the mean return for the RALS-based spread portfolio is 1.8 percent higher than for the OLS-based spread portfolio and the RALS-based spread portfolio's standard deviation is 2.37 percent lower.

In Panel B of Table IX, we report persistence results during the no crisis periods of our sample. Here the OLS and RALS portfolio alphas are quite similar with the RALS portfolio being marginally higher by 0.52 percent. Again the RALS spread portfolio alpha is higher than OLS, this time by 2.74 percent per annum.

Finally, in Panel C we show the results for the crisis periods in the sample. It is here that the performance difference between RALS and OLS estimation is the greatest. The alpha of the OLS portfolio is significantly negative and the RALS portfolio alpha is 3.77 percent higher. The difference is even greater for the spread portfolios where the RALS portfolio is 6.79 percent higher.

Overall, we find greater persistence for the sort on RALS alpha than for the sort on OLS alpha. It is also evident that the difference in persistence is primarily due to the outperformance during the crisis periods when the mean returns and alpha of the OLS portfolio are negative.

As before, it is possible that the evidence of outperformance of the RALS portfolios may be due to illiquidity induced smoothing in hedge fund returns or incubation and backfill bias. To eliminate these possibilities we repeat the analysis of Table IX: 1) using the Getmansky, Lo and Makarov (2004) specification to unsmooth hedge fund returns, and 2) creating a sample of true returns. Also, separately, we control for the effects of backfill bias by removing the first 12 months of returns for each fund.

[Please Insert Table X Here]

From Panel A of Table X (the unsmoothed hedge fund returns) it is clear that the results are not driven by serial correlation. After correcting for this effect, the RALS portfolio top decile alpha is a statistically significant 8.15 percent per annum, which is 1.38 percent greater than the OLS alpha. During the crisis periods the OLS alpha is significantly negative and the RALS portfolio alpha is 4.94 percent higher. Excluding the first 12 months of returns in Panel B of Table X leads to lower overall performance but the RALS alpha is statistically significant 6.54 percent per annum, 1.67 percent greater than the OLS portfolio and during the crisis period the alpha difference is now 8.13 percent.

The results presented in this section of the paper have demonstrated that OLS systematically misestimates performance of hedge funds, and that this assessment error is induced by the skewness in the distributions of individual hedge fund returns. What is surprising is the scale of the error. We estimate that for funds with highly positively (negatively) skewed returns the OLS estimation error is in the region of 6 percent (2 percent) per annum. For institutional investors and Fund of Funds these are very important issues. What is considered positive alpha when measured by OLS is often due to a fund benefiting from a risk premium for pursuing a negatively skewed strategy. Likewise a fund that OLS estimation would label a poor performer that has positively skewed returns is often simply being penalized due to the statistical characteristics of its strategy.

We can also demonstrate the economic importance of the persistence issue. An investor who formed a portfolio based upon RALS alphas estimated over rolling 24 months windows outperformed an investor who followed a similar strategy using OLS alphas 1.23 percent across the entire sample 1993 – 2009 period. While this difference may seem marginal, it is driven primarily by the difference in performance during crises periods. Here portfolios formed on alphas estimated by RALS outperform those estimated by OLS alphas by an impressive 4.4 percent per annum.

V. Conclusions

There is a growing body of literature examining skewness preference. Consistent with expectations from a utility framework, we show that hedge fund managers' returns are in part attributable to their exposure to a skewness risk premium. As OLS estimation is inefficient in the presence of fat tailed error distributions, performance measures estimated by OLS overstate the performance of some funds and understate the performance of others. These finding have broader implications both within and beyond the hedge fund industry. Our results support the hypothesis that investors prefer to avoid negatively skewed assets so there is a risk premium for holding them. We show that the RALS methodology is more efficient than OLS in capturing this risk premium when assessing hedge fund performance.

When our sample of hedge funds is divided into skewness and no-skewness sub-samples there is a considerable variation in the accuracy of OLS performance estimates. While OLS is quite efficient at estimation performance for the no-skewness funds, the performance assessment error ranges from 1.77 percent per annum for negative skewness funds to -3.68 percent per annum for positive skewness funds. When we examine the source of the error using a cross sectional model, there is strong evidence that skewness explains the difference between the RALS and OLS performance estimates, even after specifying a range of control variables. To get a perspective on the economic significance of the OLS performance assessment errors, we sort funds into deciles based upon historical skewness. Here, the scale of the OLS performance assessment error is non-trivial. For funds within the top 10 percent sorted on historical returns skewness this represents approximately 6 percent per annum of performance assessment error. For the bottom 10 percent of funds, ranked by skewness, this represents an error of 2.4 percent per annum.

Our final contribution comes from our ability to document differences in persistence in hedge fund returns measured using RALS and OLS during periods of calm and periods of crisis. Differences in investment results based on using historical data to forecast persistence are not large during periods when markets are not in flux, but portfolios formed on alphas estimated by RALS outperform those estimated by OLS alphas by an impressive amount during periods of market crisis.

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Figure 1

Kernel density estimate of the OLS and RALS estimated alpha distribution for all funds

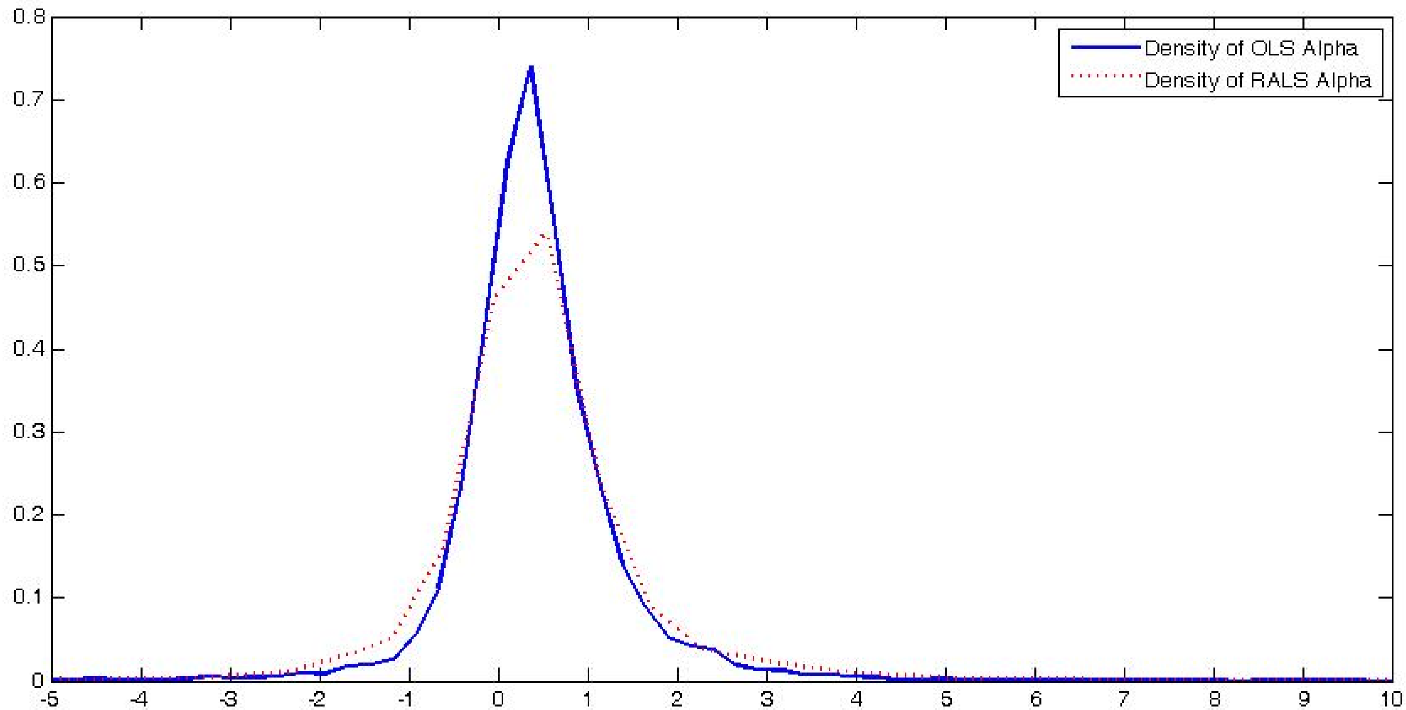
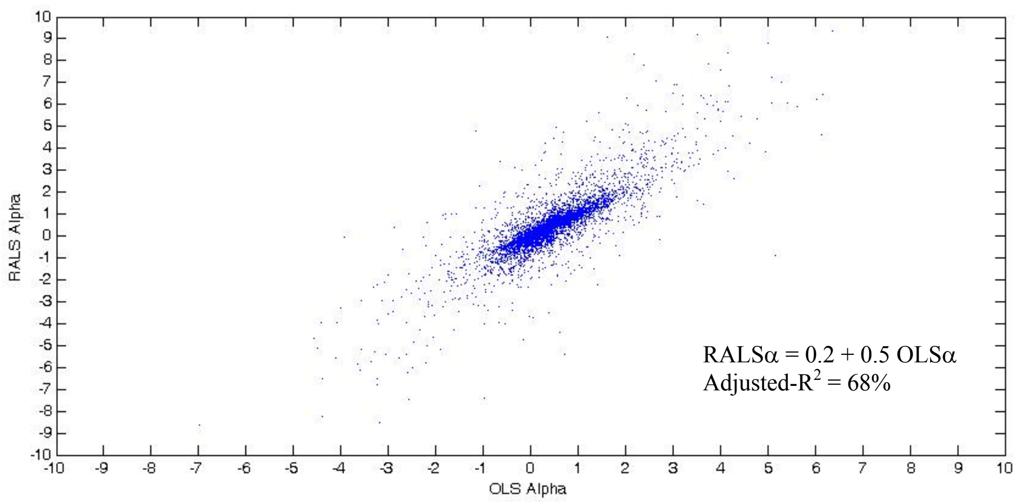


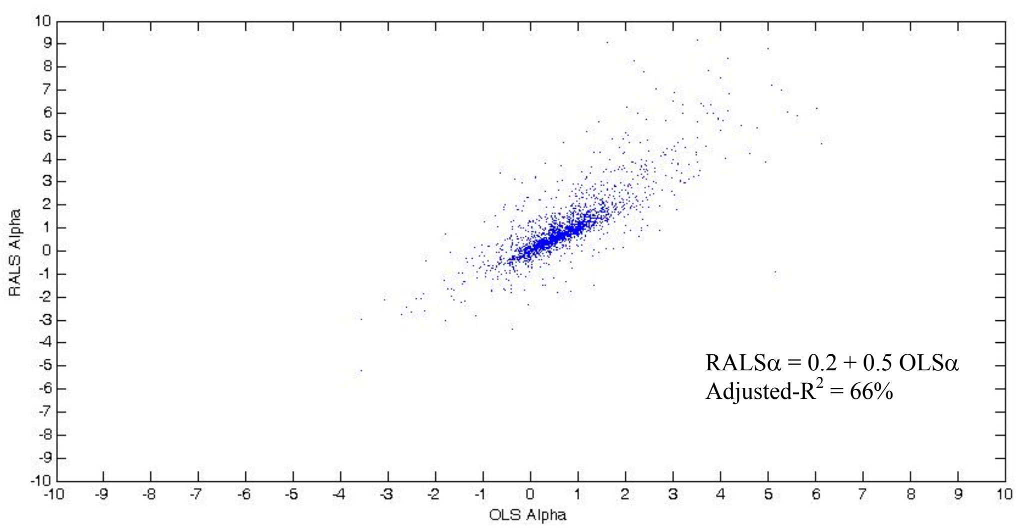
Figure 2 Impact of switching model on performance estimates

The two sets of alphas are (1) the OLS alpha and (2) the RALS alpha. Figure 6A shows alphas when the model is estimated for all funds. Figure 6B shows alphas when the models are estimated only for funds which exhibit -normally distributed OLS fund residuals. Figure 6C shows alphas when the models are estimated for funds exhibiting non-normally distributed OLS fund residuals. Residuals are considered non-normal if Jarque and Bera (1987) tests of normality are rejected at the 5% level. Results from regressing RALS alpha on OLS alpha are also included in each figure.

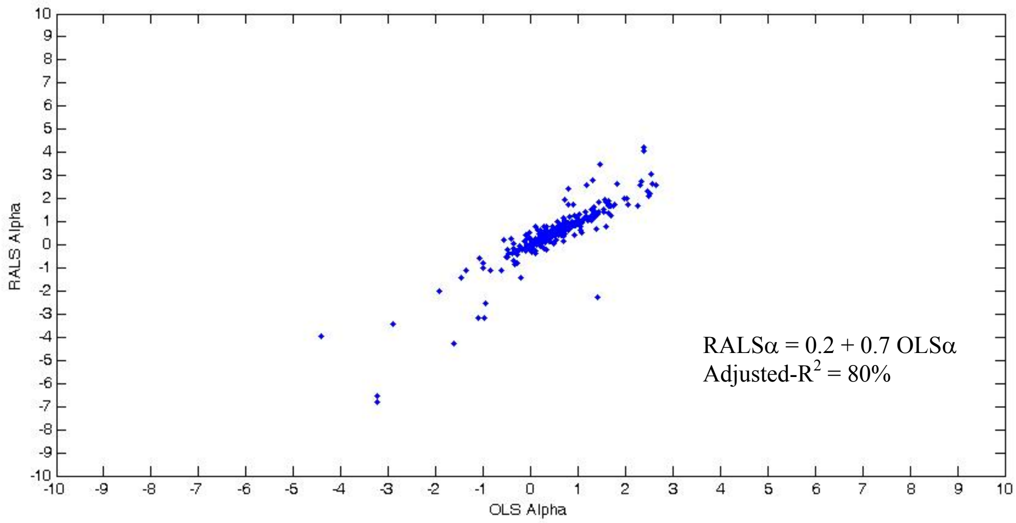
(A) All Funds



(B) Negative-Skewness Funds



(C) No-Skewness Funds



(D) Positive-Skewness Funds

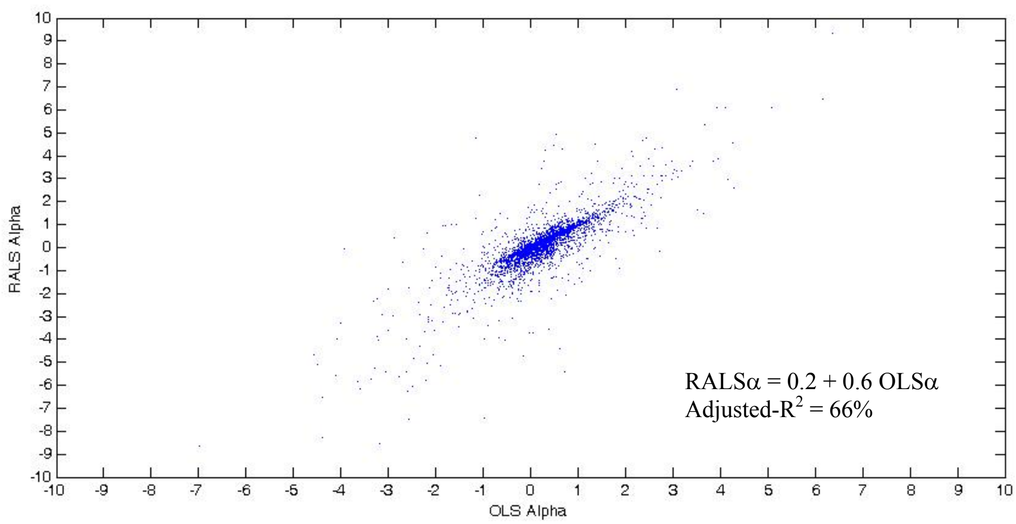


Figure 3 Portfolio Cumulative Returns

This figure reports the cumulative returns of two hedge fund portfolios and the S&P500. RALS and OLS are portfolios of hedge funds formed as follows. Hedge funds, excluding Fund of Funds, by fund category, are sorted on January 1 each year (from 1996 to Oct 2009) into decile portfolios, based on their Fung and Hsieh (2004) RALS alpha and OLS alpha, respectively. Funds with the highest past performance measure are allocated into the reported portfolios. We use the most recent 24 months of return observations proceeding the evaluation period for estimation. The portfolios are equally weighted monthly, so the weights are re-adjusted whenever a fund disappears. The total return on the S&P500 is included for comparison.

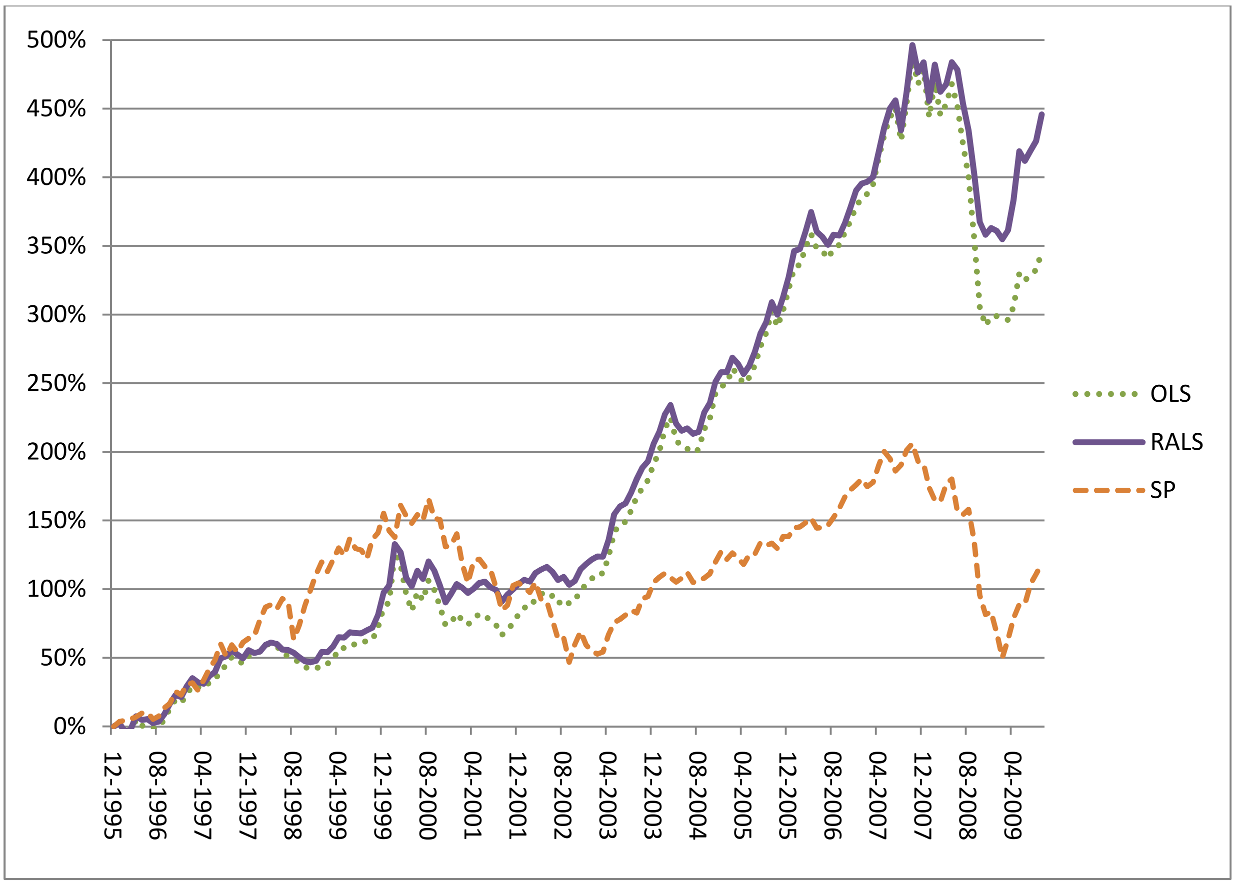


Table I

Summary Statistics of Reported Monthly Returns

The summary statistics are the numbers of funds, *N*, and the equally-weighted averages of the mean monthly return, μ,standard deviation of monthly returns, σ, the Sharpe Ratio, SR, the skewness, Skew and the excess kurtosis, Kurt. A fund is classified as Negative or Positive-skewness if the estimated sample skewness t-ratio statistic, $\frac{\hat{S}(r)}{\sqrt{6/T}}$, is significant at the 5% level.

	Negative-Skewness Funds						No-Skewness Funds						Positive-Skewness Funds					
Fund Category	N	μ	σ	SR	Skew	Kurt	N	μ	σ	SR	Skew	Kurt	N	μ	σ	SR	Skew	Kurt
Panel A: Live Funds																		
Convertible Arbitrage	38	0.62	3.38	0.13	-2.44	14.78	2	0.72	2.22	0.19	-1.12	10.95	5	-0.37	13.80	0.11	0.57	4.01
Event Driven	148	0.49	3.09	0.13	-1.46	5.95	42	0.91	2.66	0.30	-0.52	3.51	79	1.38	3.87	0.59	0.94	3.64
Equity Market Neutral	66	0.28	2.97	0.05	-1.36	6.92	8	0.58	2.82	0.13	0.04	2.52	34	0.70	2.37	0.21	0.80	3.65
Emerging Markets	115	1.14	6.44	0.17	-1.07	3.95	5	1.44	6.75	0.18	-0.03	2.85	58	1.59	6.31	0.28	0.75	2.78
Fixed Income Arbitrage	45	0.46	2.08	0.12	-1.42	7.55	3	0.73	3.49	0.14	-2.46	26.68	30	0.87	3.49	0.38	1.24	8.45
Fund of Funds	1472	0.25	2.23	0.04	-1.56	5.58	112	0.59	2.74	0.13	-0.25	3.80	163	0.77	3.58	0.18	1.08	6.28
Global Macro	50	0.61	4.44	0.09	-0.64	1.93	8	0.86	4.09	0.17	0.08	0.49	56	1.05	4.08	0.21	0.77	2.61
Long Short Equity Hedge	552	0.60	4.11	0.11	-0.89	3.21	111	1.02	4.57	0.19	0.10	3.13	314	1.00	4.23	0.18	0.95	4.70
Managed Futures	48	0.82	5.10	0.12	-0.69	2.87	58	0.91	6.09	0.11	0.23	1.25	129	1.04	5.71	0.16	0.70	2.27
Multi-Strategy	158	0.45	3.22	0.06	-1.22	5.13	14	0.64	3.00	0.16	-0.56	7.96	53	0.99	4.24	0.22	0.94	5.04
All Funds	1222	0.60	3.98	0.11	-1.09	4.51	251	0.93	4.46	0.18	-0.05	3.26	764	1.06	4.55	0.24	0.88	3.97
Panel B: Dead Funds																		
Convertible Arbitrage	124	0.44	2.09	0.11	-1.25	6.25	8	0.58	1.32	0.58	0.00	1.45	37	0.75	2.19	0.54	1.05	5.96
Event Driven	153	0.65	2.25	0.19	-1.15	5.15	21	1.04	3.31	0.28	0.00	1.69	86	1.08	3.35	0.38	1.17	4.60
Equity Market Neutral	178	0.32	2.52	0.04	-1.53	8.69	19	0.45	1.90	0.11	0.10	2.16	105	0.68	2.58	0.21	0.81	2.86
Emerging Markets	240	0.55	5.61	0.08	-1.36	6.15	33	0.88	7.14	0.14	-0.08	2.59	127	1.16	6.14	0.18	0.83	3.87
Fixed Income Arbitrage	143	0.15	3.11	0.23	-2.67	15.46	6	0.43	2.89	0.10	0.01	2.03	53	0.81	1.82	0.97	0.96	5.02
Fund of Funds	1564	0.18	2.52	0.01	-1.44	5.17	92	0.40	2.39	0.08	0.02	1.28	364	0.58	2.96	0.16	0.78	3.75
Global Macro	103	0.21	3.63	0.00	-0.75	2.42	6	0.30	3.51	0.02	0.02	0.90	124	0.68	4.33	0.08	0.90	3.18
Long Short Equity Hedge	755	0.49	4.40	0.07	-0.85	2.93	93	0.82	4.70	0.14	0.00	0.99	654	1.12	5.22	0.19	0.88	3.29
Managed Futures	146	0.38	4.92	0.00	-0.88	3.15	23	0.54	5.78	0.03	-0.03	0.29	239	0.73	5.93	0.07	0.69	2.04
Multi-Strategy	242	0.02	3.15	0.01	-1.48	6.06	12	1.12	4.01	0.31	-0.08	1.85	117	0.84	3.13	0.37	0.97	4.74
All Funds	2093	0.39	3.86	0.08	-1.21	5.36	224	0.77	4.59	0.16	-0.01	1.43	1559	0.94	4.72	0.22	0.87	3.39

Table II
Summary Statistics and Correlation Matrix of Factors Used to Analyze Hedge Fund Returns

The summary statistics are the mean monthly return, μ, standard deviation of monthly returns, σ, the Sharpe Ratio, *SR*, the skewness, *Skew* and the excess kurtosis, *Kurt*.

Panel A: Summary Statistics

	μ	σ	*SR*	*Skew*	*Kurt*
SNPRF	0.40	4.48	0.09	-0.74	1.10
SCMLC	0.04	3.55	0.01	0.29	4.73
BD10RET	-0.08	6.59	-0.01	0.33	3.97
BAAMTSY	0.56	8.68	0.06	1.31	5.88
PTFSBD	-1.22	14.78	-0.10	1.44	2.95
PTFSFX	0.33	19.94	0.00	1.34	2.54
PTFSCOM	-0.24	13.93	-0.04	1.28	2.58

Panel B: Correlation Matrix

	SNPRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM
SNPRF	1.00						
SCMLC	0.01	1.00					
BD10RET	0.11	0.09	1.00				
BAAMTSY	-0.30	-0.20	-0.40	1.00			
PTFSBD	-0.16	-0.07	-0.18	0.18	1.00		
PTFSFX	-0.18	0.00	-0.14	0.24	0.22	1.00	
PTFSCOM	-0.16	-0.02	-0.09	0.20	0.20	0.37	1.00

Table III

RALS Simulation Results

Panel A reports the estimated performance measures for simulated CSFB Tremont Aggregate monthly funds returns with different levels of residual skewness and OLS alpha set equal to 0, for the period January 1994 to September 2009. Panel B show the results with OLS alpha set equal to 4.24. The first (last) column in each Panel reports the results for the 1,000 simulated fund returns with the most negative (positive) skewness. In each panel the first and second rows report the mean annualized OLS alpha estimate and p-value for each skewness level. The third and fourth rows report the mean annualized RALS alpha estimate and p-value for each skewness level. The fifth and sixth rows report the difference between the mean annualized RALS alpha and OLS alpha and p-value at each skewness level. The seventh row reports ρ^*, the efficiency gain from using RALS relative to OLS. Coefficients and P-Values are bold if significant at the 5% level.

	Residual skewness								
	-2.0	*-1.5*	*-1.0*	*-0.5*	*0.0*	*0.5*	*1.0*	*1.5*	*2.0*
Panel A: OLS alpha = 0									
OLS alpha	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p-value	0.51	0.51	0.51	0.49	0.52	0.49	0.54	0.50	0.48
RALS alpha	**-0.08**	**-0.05**	-0.02	0.00	0.00	0.00	0.02	**0.05**	**0.08**
p-value	**0.00**	**0.00**	0.25	0.45	0.49	0.47	0.29	**0.00**	**0.00**
OLS alpha error	**0.08**	**0.05**	**0.02**	0.00	0.00	0.00	**-0.02**	**-0.05**	**-0.08**
p-value	**0.00**	**0.00**	**0.00**	0.28	0.23	0.13	**0.00**	**0.00**	**0.00**
ρ^*	0.01	0.24	0.70	0.90	0.93	0.90	0.71	0.25	0.01
Panel B: OLS alpha = 0.0035									
OLS alpha	**4.24**	**4.24**	**4.24**	**4.24**	**4.24**	**4.24**	**4.24**	**4.24**	**4.24**
p-value	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
RALS alpha	**4.16**	**4.19**	**4.22**	**4.24**	**4.24**	**4.24**	**4.25**	**4.29**	**4.32**
p-value	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
OLS alpha error	**0.08**	**0.05**	**0.02**	0.00	0.00	0.00	**-0.02**	**-0.05**	**-0.08**
p-value	**0.00**	**0.00**	**0.00**	0.45	0.54	0.29	**0.00**	**0.00**	**0.00**
ρ^*	0.02	0.25	0.70	0.92	0.92	0.90	0.73	0.24	0.01

Table IV

Summary Statistics and Tests of Normality on Hedge Fund Residuals

This table reports the distributional properties of hedge fund returns by investment objective. Column one reports the number of funds in each investment category. Columns two and three report the mean OLS estimated alpha and t-statistic of alpha, respectively. Columns four and five report the mean RALS estimated alpha and t-statistic of alpha. Column six reports the mean efficiency gain from RALS estimation.

	Negative-Skewness Funds				No-Skewness Funds				Positive-Skewness Funds			
Fund Category	*N*	*OLSa*	*RALSa*	ρ*	*N*	*OLSa*	*RALSa*	ρ*	*N*	*OLSa*	*RALSa*	ρ*
Panel A: Live Funds												
Convertible Arbitrage	38	0.53	0.51	0.73	2	0.39	0.46	0.62	5	2.49	3.45	0.74
Event Driven	148	0.26	0.23	0.69	42	0.59	0.58	0.85	79	1.13	1.52	0.65
Equity Market Neutral	66	0.11	0.04	0.66	8	0.28	0.31	0.79	34	0.45	0.60	0.69
Emerging Markets	115	1.10	1.12	0.74	5	1.19	1.29	0.81	58	1.58	1.97	0.71
Fixed Income Arbitrage	45	0.29	0.24	0.74	3	0.38	0.28	0.69	30	0.60	0.83	0.63
Fund of Funds	1472	0.04	-0.11	0.68	112	0.29	0.23	0.84	163	0.57	0.73	0.68
Global Macro	50	0.53	0.48	0.82	8	0.60	0.51	0.85	56	0.78	0.89	0.82
Long Short Equity Hedge	552	0.46	0.32	0.78	111	0.66	0.70	0.84	314	0.80	0.94	0.73
Managed Futures	48	0.73	0.29	0.74	58	0.65	0.58	0.89	129	0.85	0.86	0.80
Multi-Strategy	158	0.26	0.15	0.70	14	0.37	0.49	0.66	53	0.84	1.16	0.70
All Funds	1222	0.46	0.35	0.75	251	0.62	0.63	0.84	764	0.89	1.07	0.73
Panel B: Dead Funds												
Convertible Arbitrage	124	0.15	0.05	0.66	8	0.29	0.26	0.93	37	0.44	0.57	0.69
Event Driven	153	0.29	0.23	0.76	21	0.61	0.58	0.89	86	0.81	1.23	0.60
Equity Market Neutral	178	0.04	-0.07	0.62	19	0.21	0.21	0.82	105	0.44	0.64	0.68
Emerging Markets	240	0.30	0.20	0.70	33	0.32	0.23	0.82	127	0.80	1.30	0.68
Fixed Income Arbitrage	143	0.02	-0.18	0.55	6	0.42	0.44	0.69	53	0.61	0.62	0.68
Fund of Funds	1564	-0.05	-0.21	0.64	92	0.05	0.04	0.80	364	0.25	0.39	0.72
Global Macro	103	-0.07	-0.32	0.67	6	0.01	0.03	0.81	124	0.43	0.72	0.71
Long Short Equity Hedge	755	0.14	0.02	0.72	93	0.38	0.44	0.79	654	0.71	1.06	0.69
Managed Futures	146	-0.03	-0.37	0.65	23	0.26	0.04	0.78	239	0.44	0.74	0.73
Multi-Strategy	242	-0.10	-0.30	0.60	12	-0.10	-0.70	0.81	117	0.54	0.68	0.65
All Funds	2093	0.10	-0.04	0.68	224	0.33	0.29	0.81	1559	0.61	0.92	0.69

Table V

Source of alpha estimation error

This table reports the estimated parameters from the following cross sectional regressions $z_i = \gamma_0 + \gamma_1 skew_i + \gamma_2 kurt_i + \epsilon$; $z_i = \gamma_0 + \gamma_1 skew_i + +\gamma_2 kurt_i + \sum_{j=1}^{J} \beta_j C_{ji} + \epsilon$ where $z_i = \hat{a}_i^{RALS} - \hat{a}_i^{OLS}$, $skew_i$ and $kurt_i$ are estimates of skewness and kurtosis (scaled by their standard errors) and C_{ji} is a horizontal vector of control variables, $\beta_{SKDi}, dlock_i, notice_i, min_i, notice_i^2, min_i^2$ and $dlock.notice_i$. Results are reported for negative-skewness and positive-skewness live (Panel A) and dead (Panel B) fund samples. Coefficients and P-Values are bold if significant at the 5% level.

	Negative-Skewness Funds										Positive-Skewness Funds									
Model	γ_0	γ_1	γ_2	β_1	β_2	β_3	β_4	β_5	β_6	β_7	γ_0	γ_1	γ_2	β_1	β_2	β_3	β_4	β_5	β_6	β_7
	Panel A: Live Funds																			
1	**1.77**										**-3.68**									
	0.00										**0.00**									
2	-0.13	**-0.09**	**-0.06**								1.08	**-0.23**	**0.10**							
	0.63	**0.00**	**0.00**								0.11	**0.00**	**0.00**							
3	0.36	**-0.09**	**-0.05**	0.11	-0.04	**-1.17**	0.01	0.00	**0.41**	0.01	0.92	**-0.23**	**0.10**	**-3.83**	-0.35	0.47	-0.09	0.00	-0.04	-0.55
	0.35	**0.00**	**0.00**	0.80	0.94	**0.01**	0.61	0.88	**0.00**	0.76	0.15	**0.00**	**0.00**	**0.00**	0.70	0.44	0.28	0.11	0.71	0.14
	Panel B: Dead Funds																			
1	**1.31**										**-2.17**									
	0.00										**0.00**									
2	0.30	**-0.07**	**-0.04**								0.65	**-0.17**	**0.08**							
	0.29	**0.00**	**0.00**								0.12	**0.00**	**0.00**							
3	0.43	**-0.08**	**-0.05**	**-3.64**	-0.49	-0.20	0.03	0.00	0.07	0.01	1.78	**-0.17**	**0.08**	-0.85	0.52	**-1.55**	-0.13	0.00	0.15	0.03
	0.24	**0.00**	**0.00**	**0.00**	0.31	0.50	0.50	0.84	0.10	0.86	0.11	**0.00**	**0.00**	0.08	0.40	**0.00**	0.41	0.38	0.02	0.68

Table VI

Alpha of Funds Sorted on Historical Skewness by Investment Objective

Panel A reports the statistical significance of performance measures for all funds. Panels B to K show the results for the subsample of funds in specific investment categories. The first (last) column in each Panel reports the decile of funds with the lowest (highest) skewness, followed by results for the next decile of funds with the second lowest (highest) skewness. In each panel the first row reports the mean estimate of skewness for each decile. The second and third rows report the mean OLS alpha estimate based on heteroscedasticity and autocorrelation consistent standard errors as well as the p-value of alpha for each decile. The fourth and fifth rows report the mean RALS alpha estimate as well at the p-value of alpha. The sixth and seventh rows report the estimated OLS performance assessment error as well as the p-value of the error. Coefficients and P-Values are bold if significant at the 5% level.

Panel A: All Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-3.31	-1.38	-0.84	-0.52	-0.28	-0.06	0.14	0.40	0.79	2.07
OLS alpha	-0.04	0.19	0.28	0.37	0.33	0.39	0.49	0.63	0.68	1.02
p-value	0.36	0.35	0.37	0.35	0.34	0.32	0.32	0.28	0.25	0.23
RALS alpha	-0.25	-0.01	0.11	0.29	0.26	0.37	0.55	0.82	0.95	1.50
p-value	0.22	0.26	0.30	0.30	0.32	0.26	0.25	0.22	0.19	0.16
OLS alpha error	**0.20**	**0.19**	**0.18**	**0.08**	**0.07**	0.02	**-0.07**	**-0.19**	**-0.27**	**-0.48**
p-value	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.36	**0.00**	**0.00**	**0.00**	**0.00**

Panel B: Convertible Arbitrage Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-5.23	-2.59	-1.46	-1.03	-0.73	-0.44	-0.27	-0.10	0.15	1.53
OLS alpha	0.05	0.51	0.29	0.26	0.26	0.27	0.28	0.01	0.32	0.92
p-value	0.49	0.20	0.18	0.26	0.12	0.28	0.32	0.24	0.28	0.14
RALS alpha	-0.09	0.47	0.16	0.10	0.16	0.14	0.35	0.02	0.32	1.30
p-value	0.33	0.09	0.20	0.17	0.12	0.30	0.23	0.23	0.15	0.09
OLS alpha error	0.14	0.04	0.13	**0.16**	0.10	**0.13**	-0.07	0.00	0.00	**-0.38**
p-value	0.36	0.65	0.06	**0.01**	0.14	**0.01**	0.25	0.92	0.96	**0.01**

Panel C: Event Driven Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-3.53	-1.84	-1.34	-0.95	-0.65	-0.30	-0.02	0.24	0.77	2.29
OLS alpha	-0.07	0.13	0.23	0.19	0.52	0.52	0.65	0.69	0.80	1.36
p-value	0.27	0.27	0.28	0.26	0.16	0.21	0.16	0.21	0.18	0.06
RALS alpha	-0.19	0.10	0.19	0.09	0.54	0.50	0.64	0.86	1.41	**1.79**
p-value	0.14	0.13	0.20	0.19	0.09	0.15	0.14	0.15	0.10	**0.04**
OLS alpha error	0.11	0.03	0.04	**0.10**	-0.02	0.02	0.02	**-0.17**	**-0.60**	**-0.43**
p-value	0.22	0.39	0.42	**0.01**	0.78	0.39	0.66	**0.01**	**0.01**	**0.02**

Panel D: Equity Market Neutral Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-4.50	-1.34	-0.85	-0.51	-0.30	-0.11	0.06	0.33	0.70	1.78
OLS alpha	-0.05	0.03	0.20	0.11	0.09	0.24	0.21	0.35	0.40	0.62
p-value	0.49	0.48	0.33	0.43	0.37	0.31	0.41	0.26	0.29	0.20
RALS alpha	-0.08	-0.31	-0.03	0.05	-0.03	0.26	0.21	0.43	0.57	1.03
p-value	0.23	0.29	0.16	0.40	0.30	0.21	0.34	0.20	0.26	0.14
OLS alpha error	0.03	**0.34**	**0.23**	**0.06**	**0.11**	-0.02	0.00	**-0.08**	-0.18	**-0.41**
p-value	0.86	**0.00**	**0.00**	**0.02**	**0.01**	0.56	0.97	**0.01**	0.12	**0.02**

Panel E: Emerging Market Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-3.44	-1.88	-1.19	-0.71	-0.43	-0.19	0.02	0.27	0.62	1.72
OLS alpha	0.18	0.18	0.44	1.19	0.89	0.72	0.42	0.92	0.82	1.66
p-value	0.33	0.41	0.30	0.30	0.27	0.29	0.27	0.23	0.26	0.20
RALS alpha	-0.03	0.23	0.26	1.10	0.97	0.82	0.42	1.24	1.31	2.42
p-value	0.19	0.29	0.22	0.26	0.18	0.24	0.26	0.17	0.18	0.15
OLS alpha error	0.21	-0.06	0.18	0.09	-0.07	-0.09	0.00	**-0.32**	**-0.48**	**-0.75**
p-value	0.09	0.81	0.16	0.48	0.42	0.23	0.99	**0.00**	**0.00**	**0.00**

Table VI Cont'd

Panel F: Fixed Income Arbitrage Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-6.47	-4.01	-2.66	-1.53	-0.83	-0.53	-0.15	0.20	0.58	2.33
OLS alpha	-0.31	-0.24	0.05	0.26	0.31	0.23	0.35	0.45	0.57	0.81
p-value	0.33	0.36	0.47	0.24	0.31	0.29	0.30	0.21	0.08	0.25
RALS alpha	-1.13	-0.31	-0.11	0.28	0.29	0.18	0.33	0.45	0.59	1.05
p-value	0.12	0.25	0.23	0.22	0.40	0.35	0.29	0.17	0.07	0.17
OLS alpha error	**0.82**	0.07	0.16	-0.02	0.01	0.04	0.02	0.01	-0.02	-0.23
p-value	**0.00**	0.71	0.30	0.62	0.70	0.19	0.76	0.83	0.47	0.24

Panel G: Fund of Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-3.96	-2.27	-1.70	-1.36	-1.08	-0.82	-0.59	-0.30	0.08	1.17
OLS alpha	-0.33	-0.06	-0.03	-0.02	0.05	0.06	0.10	0.18	0.19	0.41
p-value	0.37	0.42	0.46	0.47	0.47	0.44	0.42	0.37	0.34	0.30
RALS alpha	-0.46	-0.25	-0.21	-0.20	-0.14	-0.11	-0.05	0.11	0.19	0.59
p-value	0.20	0.24	0.29	0.27	0.31	0.30	0.32	0.32	0.29	0.24
OLS alpha error	**0.13**	**0.19**	**0.18**	**0.18**	**0.19**	**0.17**	**0.16**	**0.06**	0.00	**-0.19**
p-value	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.86	**0.00**

Panel H: Global Macro Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-1.64	-0.77	-0.45	-0.22	0.00	0.20	0.41	0.65	1.01	2.31
OLS alpha	-0.16	0.03	0.23	0.44	0.21	0.32	0.39	0.72	0.54	0.81
p-value	0.39	0.42	0.41	0.38	0.48	0.43	0.32	0.32	0.34	0.28
RALS alpha	-0.40	-0.30	-0.05	0.45	0.18	0.50	0.48	0.75	0.79	1.57
p-value	0.35	0.44	0.38	0.35	0.42	0.33	0.25	0.22	0.25	0.26
OLS alpha error	0.23	**0.33**	**0.28**	-0.01	0.03	-0.17	-0.08	-0.03	**-0.25**	-0.76
p-value	0.09	**0.00**	**0.00**	0.95	0.73	0.17	0.13	0.89	**0.02**	0.09

Panel I: Long Short Equity Hedge Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-2.19	-1.04	-0.68	-0.43	-0.23	-0.03	0.18	0.46	0.89	2.15
OLS alpha	0.06	0.30	0.33	0.36	0.33	0.43	0.55	0.70	0.73	1.01
p-value	0.41	0.42	0.41	0.34	0.34	0.31	0.31	0.27	0.22	0.24
RALS alpha	-0.14	0.07	0.20	0.29	0.26	0.48	0.64	0.94	1.00	1.48
p-value	0.30	0.33	0.37	0.32	0.34	0.24	0.23	0.20	0.16	0.16
OLS alpha error	**0.20**	**0.23**	**0.13**	**0.07**	**0.07**	**-0.06**	**-0.09**	**-0.24**	**-0.27**	**-0.47**
p-value	**0.00**	**0.00**	**0.00**	**0.04**	**0.02**	**0.04**	**0.00**	**0.00**	**0.00**	**0.00**

Panel J: Managed Futures Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-1.80	-0.55	-0.22	-0.01	0.12	0.25	0.40	0.59	0.88	1.91
OLS alpha	-0.04	0.19	0.35	0.43	0.33	0.40	0.52	0.54	0.62	1.11
p-value	0.45	0.41	0.41	0.39	0.37	0.45	0.34	0.30	0.32	0.27
RALS alpha	-0.60	-0.09	0.07	0.24	0.28	0.50	0.69	0.75	0.76	1.72
p-value	0.30	0.35	0.35	0.33	0.35	0.36	0.31	0.26	0.24	0.21
OLS alpha error	**0.56**	**0.27**	**0.28**	**0.19**	0.05	-0.10	**-0.17**	**-0.21**	**-0.15**	-0.62
p-value	**0.00**	**0.02**	**0.01**	**0.04**	0.45	0.11	**0.01**	**0.01**	**0.01**	0.08

Panel K: Multi Strategy Funds

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-4.06	-2.05	-1.28	-0.89	-0.56	-0.35	-0.10	0.18	0.60	2.16
OLS alpha	-0.37	0.06	0.00	0.09	0.08	0.18	0.22	0.38	0.67	0.85
p-value	0.22	0.31	0.33	0.40	0.42	0.33	0.39	0.34	0.21	0.27
RALS alpha	-0.54	-0.35	-0.24	-0.04	0.08	0.13	0.03	0.62	0.88	1.02
p-value	0.13	0.18	0.15	0.28	0.34	0.25	0.27	0.24	0.11	0.15
OLS alpha error	0.17	**0.40**	**0.23**	**0.14**	0.01	0.05	**0.19**	**-0.23**	**-0.20**	-0.17
p-value	0.36	**0.00**	**0.00**	**0.01**	0.88	0.34	**0.08**	**0.00**	**0.02**	0.29

Table VII

Robustness Checks Alpha of Funds Sorted on Historical Skewness

Panel A reports the statistical significance of performance measures for all funds estimated with a minimum of 3 years data. Panels B and C show the results for the Full Sample corrected for return serial correlation and backfill bias respectively. Finally, Panel D reports results when we control for structural breaks in October 1998 and April 2000. The first (last) column in each Panel reports the decile of funds with the lowest (highest) skewness, followed by results for the next decile of funds with the second lowest (highest) skewness. In each panel the first row reports the mean estimate of skewness for each decile. The second and third rows report the mean OLS alpha estimate based on heteroscedasticity and autocorrelation consistent standard errors as well as the p-value of alpha for each decile. The fourth and fifth rows report the mean RALS alpha estimate as well at the p-value of alpha. The sixth and seventh rows report the estimated OLS performance assessment error as well as the p-value of the OLS error. Coefficients and P-Values are bold if significant at the 5% level.

Panel A: All Funds (3 Years)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-3.43	-1.40	-0.85	-0.53	-0.27	-0.05	0.15	0.41	0.80	2.12
OLS alpha	-0.00	0.23	0.33	0.40	0.40	0.46	0.54	0.66	0.73	0.98
p-value	0.35	0.33	0.36	0.32	0.32	0.30	0.29	0.27	0.23	0.20
RALS alpha	-0.15	0.11	0.17	0.30	0.35	0.46	0.58	0.79	0.91	1.29
p-value	0.22	0.26	0.30	0.30	0.32	0.26	0.24	0.21	0.17	0.16
OLS alpha error	**0.15**	**0.12**	**0.16**	**0.10**	**0.04**	0.00	**-0.04**	**-0.13**	**-0.18**	**-0.31**
p-value	**0.00**	**0.00**	**0.00**	**0.00**	**0.02**	0.81	**0.01**	**0.00**	**0.00**	**0.00**

Panel B: All Funds (Unsmoothed)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-3.31	-1.38	-0.84	-0.52	-0.28	-0.06	0.15	0.41	0.80	2.07
OLS alpha	-0.06	0.16	0.26	0.36	0.31	0.38	0.46	0.59	0.66	0.97
p-value	0.36	0.36	0.37	0.35	0.34	0.33	0.32	0.29	0.25	0.23
RALS alpha	-0.26	-0.02	0.09	0.29	0.24	0.36	0.53	0.77	0.92	1.45
p-value	0.22	0.26	0.30	0.30	0.31	0.26	0.25	0.22	0.19	0.16
OLS alpha error	**0.20**	**0.19**	**0.17**	**0.07**	**0.07**	0.02	**-0.07**	**-0.18**	**-0.26**	**-0.47**
p-value	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.45	**0.00**	**0.00**	**0.00**	**0.00**

Panel C: All Funds (No Backfill)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-3.24	-1.38	-0.88	-0.58	-0.34	-0.13	0.09	0.33	0.69	1.81
OLS alpha	-0.06	0.15	0.23	0.35	0.35	0.37	0.44	0.54	0.61	0.87
p-value	0.36	0.39	0.37	0.36	0.34	0.33	0.33	0.33	0.28	0.25
RALS alpha	-0.28	-0.05	0.03	0.19	0.28	0.34	0.52	0.70	0.82	1.23
p-value	0.23	0.26	0.29	0.30	0.28	0.27	0.26	0.23	0.20	0.17
OLS alpha error	**0.23**	**0.20**	**0.20**	**0.16**	**0.08**	0.02	**-0.08**	**-0.16**	**-0.21**	**-0.36**
p-value	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	0.37	**0.00**	**0.00**	**0.00**	**0.00**

Panel D: All Funds (Time Varying Risk Exposure)

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Skewness	-3.31	-1.38	-0.84	-0.52	-0.28	-0.06	0.14	0.40	0.79	2.07
OLS alpha	0.12	0.31	0.38	0.46	0.39	0.41	0.51	0.66	0.69	0.98
p-value	0.35	0.31	0.35	0.33	0.35	0.32	0.33	0.30	0.28	0.24
RALS alpha	-0.03	0.11	0.19	0.38	0.29	0.43	0.56	0.91	0.97	1.52
p-value	0.22	0.21	0.26	0.24	0.29	0.22	0.24	0.21	0.19	0.15
OLS alpha error	**0.15**	**0.21**	**0.19**	**0.08**	**0.10**	-0.02	**-0.05**	**-0.25**	**-0.28**	**-0.54**
p-value	**0.00**	**0.00**	**0.00**	**0.03**	**0.00**	0.50	**0.08**	**0.00**	**0.00**	**0.00**

Table VIII Portfolio Statistical Characteristics and Differences in Sharpe Ratios

Panel A reports descriptive statistics for two hedge fund portfolios and the S&P500. RALS and OLS are portfolios of hedge funds formed as follows. Hedge funds, excluding Fund of Funds, by fund category, are sorted on January 1 each year (from 1996 to Oct 2009) into decile portfolios, based on their Fung and Hsieh (2004) RALS alpha and OLS alpha, respectively. S&P500 is the total return on the S&P500. Worst Drawdown is the maximum peak to trough decline in the portfolio over the sample period. Panel B reports results from the Ledoit and Wolf (2008) studentized time series bootstrap test for differences in Sharpe ratio. Coefficients and P-Values are bold if significant at the 5% level.

	RALS	OLS	S&P500
Panel A: Key Statistics			
Sharpe Ratio	0.82	0.62	0.25
Worst Drawdown	-23.7%	-33.2%	-50.9%
Mean	12.9%	11.6%	7.4%
Std Dev	11.6%	13.2%	16.2%
Skew	0.27	0.22	-0.70
Kurt	1.32	3.13	0.96
Panel B: LW Test for Differences in Sharpe Ratios			
RALS	0.00		
	1.00		
OLS	**0.20**	0.00	
	0.01	1.00	
S&P500	**0.57**	0.37	0.00
	0.05	0.21	1.00

Table IX Portfolio formed on OLS and RALS Alphas for Different Periods

This table reports estimated Fung and Hsieh (2004) alphas and risk factor coefficient estimates for the OLS, RALS and 10% Spread portfolios. Hedge funds, excluding Fund of Funds, by fund category, are sorted on January 1 each year (from 1996 to Oct 2009) into decile portfolios, based on their Fung and Hsieh (2004) RALS alpha and OLS alpha. Funds with the highest past performance measure are allocated into the OLS and RALS portfolios. The 10% Spread portfolios are formed as the difference between the highest and lowest past performance decile portfolios. Crisis and Non-Crisis periods are classified following Getmansky et al (2010).

	Mean	Std Dev	Alpha	T-Stat	P-Val	SNPRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	R2	JB
Panel A: Full Sample														
OLS	11.63	13.22	7.26	2.81	0.01	0.34	0.31	-0.05	-0.10	0.01	0.02	0.06	0.50	0.09
RALS	12.93	11.59	8.49	3.74	0.00	0.36	0.29	-0.04	-0.08	0.00	0.02	0.05	0.50	0.11
OLS 10% SPREAD	2.86	12.27	-0.76	-0.25	0.80	-0.09	0.09	-0.05	-0.08	-0.01	0.00	0.05	0.21	0.13
RALS 10% SPREAD	4.66	9.90	0.56	0.24	0.81	-0.04	0.05	-0.05	-0.05	0.01	0.00	0.05	0.30	0.23
Panel B: No Crisis														
OLS	15.89	12.20	9.33	3.01	0.00	0.28	0.29	-0.06	0.00	0.00	0.06	0.03	0.39	0.18
RALS	16.43	10.68	9.85	3.64	0.00	0.30	0.28	-0.05	0.00	0.00	0.05	0.03	0.39	0.14
OLS 10% SPREAD	4.29	12.23	1.24	0.36	0.72	-0.14	-0.04	-0.04	-0.04	0.01	0.05	0.01	0.26	0.50
RALS 10% SPREAD	5.80	9.72	3.98	1.55	0.12	-0.08	-0.04	-0.02	-0.06	0.03	0.05	0.01	0.33	0.28
Panel C: Crisis														
OLS	-1.96	15.79	-6.87	-2.62	0.01	0.39	0.37	-0.17	-0.13	-0.01	0.06	0.01	0.94	0.00
RALS	1.81	13.98	-2.47	-0.59	0.56	0.42	0.27	-0.12	-0.08	0.00	0.07	0.04	0.81	0.00
OLS 10% SPREAD	-1.07	12.61	-5.23	-0.83	0.41	-0.01	0.26	-0.13	-0.09	-0.01	0.06	-0.04	0.44	0.00
RALS 10% SPREAD	1.60	10.61	1.56	0.24	0.82	0.00	0.23	-0.10	-0.09	-0.01	0.07	0.01	0.06	0.12

Table X Robustness Checks

This table reports estimated Fung and Hsish (2004) alphas and risk factor coefficient estimates for the OLS, RALS and 10% Spread portfolios. Coefficients are estimated using RALS. Hedge funds, excluding Fund of Funds, by fund category, are sorted on January 1 each year (from 1996 to Oct 2009) into decile portfolios, based on their Fung and Hsieh (2004) RALS alpha and OLS alpha. Funds with the highest past performance measure are allocated into the OLS and RALS portfolios. The 10% Spread portfolios are formed as the difference between the highest and lowest past performance decile portfolios. Crisis and Non-Crisis periods are classified following Getmansky et al (2010).

	Mean	Std Dev	Alpha	T-Stat	P-Val	SNPRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	R2	JB
Panel A: Unsmoothed Returns														
OLS Full Sample	11.08	13.06	6.77	2.63	0.01	0.35	0.30	-0.05	-0.10	0.00	0.01	0.06	0.49	0.10
RALS Full Sample	12.57	11.46	8.15	3.59	0.00	0.35	0.29	-0.04	-0.08	0.00	0.02	0.05	0.49	0.14
OLS No Crisis	15.36	12.02	9.04	2.93	0.00	0.28	0.28	-0.06	0.00	0.00	0.06	0.02	0.38	0.20
RALS No Crisis	15.95	10.56	9.30	3.43	0.00	0.29	0.28	-0.05	0.00	0.00	0.05	0.03	0.38	0.18
OLS Crisis	-2.77	15.63	-7.27	-2.63	0.01	0.41	0.35	-0.17	-0.15	0.00	0.07	0.00	0.93	0.00
RALS Crisis	1.78	13.82	-2.33	-0.55	0.59	0.42	0.26	-0.13	-0.09	0.00	0.07	0.03	0.80	0.00
Panel B: No Backfill														
OLS Full Sample	9.45	12.43	4.87	1.48	0.14	-0.08	0.03	0.02	0.07	-0.05	0.01	-0.01	0.13	0.14
RALS Full Sample	10.97	10.82	6.54	2.21	0.03	-0.07	0.03	0.02	0.07	-0.05	0.01	-0.01	0.06	0.13
OLS No Crisis	14.57	11.54	7.71	2.41	0.02	0.22	0.40	-0.06	0.01	0.00	0.04	0.02	0.35	0.31
RALS No Crisis	15.02	10.05	7.91	2.89	0.00	0.25	0.34	-0.06	0.02	-0.01	0.03	0.02	0.37	0.50
OLS Crisis	-2.47	15.89	-7.08	-2.23	0.03	0.47	0.38	-0.16	-0.15	0.01	0.07	0.01	0.91	0.00
RALS Crisis	2.64	13.87	1.05	0.23	0.82	0.43	0.28	-0.13	-0.10	0.02	0.08	0.03	0.73	0.00