A new measure for assessing hedge fund performance when fund returns are skewed

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Abstract: This paper proposes a new performance measure for identifying skilled hedge fund managers. Our measure adjusts the OLS alpha estimates for known skewness in samples of hedge fund returns. Using the new performance measure, we find that OLS performance assessment error depends systematically upon the sign of skewness in a fund's returns. Specifically, we find that OLS overstates the performance of funds with most negatively skewed returns by 2.4 percent per annum and understates the performance of funds with most positively skewed returns by over 5.5 percent per annum. Further, our new performance measure is able to identify performance persistence better than previous measures, especially during crisis periods. During crisis periods, mean returns earned on top decile portfolios sorted based on RALS alphas exceed those on portfolios sorted on OLS alphas by 3.77 percent. Overall, our results show that previous performance measures may have mis-estimated the abilities of hedge fund managers.

Keywords: Performance measurement, residual augmented least squares (RALS), hedge funds, return skewness, performance persistence.

JEL Codes: G10, G19, G20

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1. Introduction

The realized returns of hedge fund managers exhibit considerable skewness. For example, about 92 percent of hedge funds in the TASS database have significantly skewed returns. In the presence of skewness in finite samples of realized returns, standard performance measures based on Ordinary Least Squares (OLS) are statistically inefficient and thus poor estimates of true managerial abilities. Furthermore, OLS measurement shortcomings may be amplified during periods of extreme market behavior. In this study, we propose and test a new performance measure for identifying skilled hedge fund managers when returns exhibit significant skewness.

Previous studies have recognized that OLS performance measures cannot accurately measure skill in the presence of skewness in returns. The typical approach is to retain the OLS point estimate of alpha and use the bootstrap method to adjust its confidence interval (see, e.g., Kosowski, Naik, and Teo, 2007; Fung, Hsieh, Naik, and Ramadori, 2008). Unlike these studies, we focus on a new estimator of hedge fund alphas that is more efficient than OLS in finite samples exhibiting skewness.

Our approach is inspired by the well-established "robust statistics" literature (summarized most recently in Huber and Ronchetti, 2009), which demonstrates that least squares is inefficient in the presence of outliers or underlying error distributions with skewness. This issue has received less attention in academic finance, where hedge fund manager performance is still typically assessed relative to Fung and Hsieh's (2004) risk factors using OLS. This tendency is puzzling give that Goetzmann, Ingersoll, Spiegel, and Welch (2007) demonstrate that performance measures estimated using standard statistical techniques inappropriately are at risk of manipulation by managers and cite hedge fund returns as a specific example of investments whose returns "can deviate substantially from normality" (p. 1505).

Estimating financial models with methodologies that explicitly control for the effects of small distributional deviations from normality can lead to very different findings (see, e.g., Chan and Lakonishok, 1992; Barber and Lyon, 1997; Knez and Ready, 1997; Dell'Aquila, Ronchetti, and Trojani, 2003). Therefore, it is important to determine to what degree the assessment of hedge fund performance can be improved upon by using a more efficient estimator in the presence of skewness in fund returns.

We select the Im and Schmidt (2008) Residual Augmented Least Squares (RALS) estimator as an alternative to OLS. The innovation of RALS is that it increases estimation efficiency by augmenting the alpha-regression with functions of the OLS residuals, under the assumption that higher (3rd and 4th) moment of the residuals do not depend on the Fung and Hsieh (2004) risk factors that are used to account for risk.[1] The RALS estimator is particularly useful for analyzing hedge fund returns because (i) it provides more efficient finite-sample estimates under more general distributions of returns, and (ii) it is easily estimated using two stage least squares. Comparing 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 persistence.

Our empirical results indicate that aggregate RALS and OLS estimates are similar *but we find significant systematic errors in performance assessment estimated by OLS when we classify funds as negatively or positively skewed.* Furthermore, the direction of the OLS performance assessment error is consistent in that OLS overstates the performance of managers of negatively skewed funds and understates the performance of managers of positively skewed funds. This result appears throughout our return data and is robust to fund category, to time variation in fund risk exposures and to known biases in hedge fund databases such as backfill, incubation and smoothing.

Specifically, we find that OLS overstates managerial 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 understates managerial performance by over 5.5 percent per annum. More importantly, the performance of portfolios formed using RALS alphas estimated over the past two years persists more than the

[1] Wooldridge (1993) discusses the statistical improvement that can be obtained by adding orthogonal regressors to an estimation equation.

performance of portfolios formed on similarly sorted OLS alphas. Here, sorting on RALS alphas yields a top decile portfolio alpha of 8.49 percent per annum, which is 1.23 percent per annum higher than that from a sort on OLS alphas.

Most importantly, Titman and Tiu (2011) and Billio, Getmansky, and Pelizzon (2011) document the importance of considering periods of financial crisis when analyzing hedge fund returns. During crisis periods, 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, a difference of 3.77 percent. Furthermore, the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measures corroborate the superior performance of the top decile RALS portfolio during crisis periods. Thus, our results show that an investor 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 financial crisis.

To summarize, our paper makes four distinct contributions. First, we show that assessments of hedge fund alphas estimated using OLS are inaccurate when fund returns exhibit skewness (as most hedge fund returns do). Second, we show that the OLS performance assessment error is economically significant, 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. Third, 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. Last, we show that the differences in the persistence of the performance of portfolios formed using OLS and RALS alphas are particularly acute during periods of financial crisis.

Several studies apply methodologies other than OLS to the issue of 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. Alternatively, Jagannathan, Malakhov, and Novikov (2010) use weighted least squares to reduce the measurement errors in estimated alphas and develop a GMM model to assess the persistence of relative hedge fund manager over- or under-performance. They find significant relative performance persistence for the top hedge funds but their model loses predictive power when economic conditions are adverse for the hedge fund industry. Our approach to identifying skilled managers proves to be particularly adept at incorporating the impact of different market conditions, as evidenced by the ability to identify significant differences in performance persistence in both crisis and non-crisis periods.

Amin and Kat (2003) control for non-normality in hedge fund returns by adopting a non-parametric payoff distribution pricing model. Other authors adopt the bootstrap methodology, which 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). Bootstrapping is related to the approach adopted here in that the bootstrap methodology focuses on measuring the statistical significance of OLS alpha estimates more accurately. Specifically, when applied to the same underlying data an ordinary OLS alpha and a bootstrapped OLS alpha will be of identical size but the standard error of the bootstrapped OLS alpha will be measured more precisely.

In this study we use the RALS estimator to more accurately measure the level of alpha while controlling for skewness. In contrast to bootstrapping, an ordinary OLS alpha and a RALS alpha will be of different sizes if the underlying return data exhibits positive or negative skewness. We show that correcting for skewness has a significant impact on the assessment of the size and persistence of the alphas earned by hedge fund managers, especially during periods of financial crisis.

Hedge fund managers often follow non-traditional investment strategies designed to generate asymmetric payoff distributions so it is not surprising that samples of fund returns exhibit both positive and negative skewness. For example, a negatively skewed distribution arises when a fund writes options, collecting a series of small premia unless or until a catastrophic loss occurs. Trend following strategies that place tight stop-loss orders on many unrelated long and short futures positions generate positively skewed returns when significant market movements eventually emerge.[2] Alternatively, spread trades can be designed to limit losses but generate gains when global crises occur. Bali, Brown, and Caglayan (2011) document a positive relationship between exposure to a default risk factor and future hedge fund returns. They also highlight the option-like nature of hedge fund trades by linking their default risk measure to combinations of at-the-money and out-of-the money option implied volatilities.

Our results are clearly linked to the theoretical preference by investors for positively skewed returns if they have utility functions that exhibit decreasing absolute risk aversion.[3] There is also empirical evidence that investors have a preference for positive skewness, both in studies of mutual funds (Levy and Sarnat, 1972) and in portfolio choice (Polkovnichenko, 2005; Harvey and Siddique, 2000). This preference means that if investors can choose between two assets that have identical means and standard deviations but different skewness levels, they will bid up the price of the asset that has positive skewness relative to the asset that has negative skewness. As a result, managers of hedge funds composed of positively skewed assets will find it more difficult to generate a given risk/return distribution than managers of funds composed of negatively skewed assets.[4]

Harvey and Siddique (2000) and Goetzmann, Ingersoll, Spiegel, and Welch (2007) propose solutions to deal with the economic issue of incorporating investors' probable preference for positively skewed returns. We focus instead on the statistical issues that arise when an investor tries to assess managerial ability in the presence of skewness in samples of hedge fund returns. Since the OLS estimator is not robust in the presence of skewness, the OLS alphas of the positively and negatively skewed funds will be identical but the RALS alphas of the funds with skewed returns will be a function of their inherent skewness. Specifically, we show that the difference between the RALS alpha and the OLS alpha for a

[2] For example, as a result of the large market movements in 2008 the NewEdge CTA-Trend Sub-index, which measures the performance of trend following hedge funds with assets under management greater than $1 billion, returned +20%.

[3] See, for example, Markowitz, 1952, Arrow, 1971 and Kraus and Litzenberger, 1976.

[4] 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).

fund with skewed returns is systematically related to the sign and size of the skewness, is economically significant, and is particularly dramatic in times of economic crisis.

The remainder of the paper is organized as follows. Section 1 provides a review of the data. Section 2 describes the risk factor model and the methodology. Section 3 discusses and demonstrates the impact of skewness when assessing hedge fund performance. Section 4 presents general results while Section 5 focuses on comparative estimator performance during crisis and non-crises periods and Section 6 concludes.

2. Data

We evaluate the performance of hedge funds using monthly net-of-fee returns of live and dead 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. The TASS database contains 5,897 live and 8,058 dead funds, including Fund of Funds, as of the final quarter of 2009.

Hedge fund returns are self-reported to TASS and it is well known that this leads to backfill and incubation biases in the database (see, e.g., Ackermann, McEnally, and Ravenscraft, 1999; Fung and Hsieh, 2000).[5] 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.[6]

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

[6] Aggarwal and Jorion (2010) use an event time methodology to assess the performance of new fund managers and new funds run by experienced managers. They find evidence of superior performance for both categories that diminishes with age after two or three years.

Furthermore, TASS does not keep information on funds that died before December 1993, which leads to survivorship bias. To control for this, our sample of fund returns runs from January 1994 to October 2009. We also remove funds with less than two years of returns data, funds which report only gross returns 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 Multi Strategy (MS).[7] [8] 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.[9] To mitigate this bias we repeat all analysis using unsmoothed hedge fund returns (Getmansky, Lo, and Makarov, 2004) in robustness checks.

Table 1 contains summary statistics of the TASS funds in the sample. 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) based on the significance of their sample skewness t-ratio statistics, $\frac{\hat{S}(r)}{\sqrt{6/T}}$,. 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 significantly different from zero. Convertible Arbitrage, Event Driven, Equity Market Neutral, Emerging Markets, Fixed Income Arbitrage and Multi-Strategy categories tend to have more funds classified as negative-skewness whereas Long Short Equity Hedge and Global Macro funds tend to

[7] 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.
[8] We do not report separate results for the Dedicated Short Bias style because there are only 39 of those funds. They are included in the full sample results however.
[9] Illiquidity in the assets held by funds, rather than misreporting, is the primary source of this serial correlation (Cassar and Gerakos, 2011).

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 and its performance may be related.[10] We investigate this issue further in Section 3, below.

3. The impact of skewness when assessing hedge fund performance

We next assess the performance of the managers in our hedge fund sample relative to the Fung and Hsieh (2004) seven-factor model using both OLS and RALS estimators.[11] The details of the Fung and Hsieh (2004) model are reviewed in subsection 3.1 and an overview of the RALS estimator is provided in Subsection 3.2. Subsection 3.3 illustrates the source of the OLS performance assessment error via simulation and subsection 3.4 introduces cross-sectional regressions which will show that the difference in RALS and OLS performance assessment is due to the fact that the RALS estimator correctly identifies the skewness risk premium.

3.1. 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

[10] Funds classified as positive- and negative-skewness also tend to exhibit higher kurtosis. The RALS estimator 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.

[11] Given that the OLS alpha and the bootstrapped alpha of any given fund are identical, we are benchmarking our RALS procedure estimates of alpha against both the OLS alpha and the "bootstrapped" alpha.

(month end-to-month end), and *BAAMTSY*, a credit spread factor (the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield (month end-to-month end)).[12] The general risk-adjusted performance estimation equation is:

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

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.

Table 2 Panel A contains summary statistics for the Fung and Hsieh (2004) factors we use to benchmark hedge fund returns. The *PTFSBD*, *PTFSFX* and *PTFSCOM* return series are obtained from David Hsieh's data library. 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. *SNPRF*, the excess total return on the Standard & Poor's 500 index, is the risk factor that carries the highest Sharpe ratio in Table 2, at 0.09. This value is less than the Sharpe ratios of all of the equally weighted All Funds categories in Table 1 except for dead negative-skewness funds, (*SR* = 0.08). Therefore, only one of the six combinations of live and dead funds and three skewness categories (negative, non-skewed, and positive) has weaker performance than the risk factors chosen to measure that performance.

Table 2 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. High correlation amongst explanatory variables can give rise to spurious significance levels for independent variables but our focus in this paper is on the estimated intercepts, rather than the factor coefficients. Intercept estimates are not affected by multicollinearity.

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

3.2 Residual augmented least squares

One of the key contributions of this paper is to determine whether OLS assesses hedge fund manager performance accurately when the funds' return distributions are skewed. This sub-section summarized the Residual Augmented Least Squares (RALS) estimator proposed by Im and Schmidt (2008), which is robust with respect to skewness. Additional details about the estimator are presented in Appendix A.

The RALS estimator, which is closely related to the GMM estimator (Hansen, 1982), is one of a wide variety of alternative robust estimation techniques which model non-normal data efficiently. 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 derived from rank tests.[13]

We choose the RALS estimator as it is a relatively straightforward extension of 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 employ the following three-step procedure to generate estimates of hedge fund alphas that are robust to the presence of skewness in hedge fund returns: First, we estimate the Fung and Hsieh 7 factor model with OLS. Second we create a function of $\hat{u}$, the OLS residual time series, which controls for residual non-normality. This function consists of two terms. Term one, $\hat{u}_t^3 - 3\hat{\sigma}^2\hat{u}_t$, relates to kurtosis

[13] 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.

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

and term two, $\hat{u}_t^2 - \hat{\sigma}^2$, relates to skewness, ($\hat{u}_t$ is the OLS residual at time t, and $\hat{\sigma}^2$ is the OLS residual variance). Finally, we re-estimate the Fung and Hsieh 7 factor model using OLS but augment the regression with the two terms as additional explanatory variables. The alpha estimate of this second regression is the Residual Augmented Least Squares alpha, which gives a better assessment of a fund manager's performance than the OLS alpha when returns are skewed. This point is fundamental to the contributions of our paper so we begin the comparative analysis of the properties of RALS and OLS alphas using simulated hedge fund returns.

3.3. A comparison of OLS and RALS alpha estimates via simulation

We use a four-step process to create a series of simulated hedge fund portfolios which are identical with the exception of S_i, the skewness in the error distribution. We allow S_i to vary from -2.0 to +2.0, rising in increments of 0.5.[15] First, we estimate (1) with OLS for the monthly excess returns of the CSFB Tremont Aggregate Hedge Fund Index over the period from January 1994 to September 2009. (Results are reported in Panel A of Table 3.) This yields an OLS alpha estimate ($\hat{\alpha}$ = 0.0035, or 4.24% per annum) and coefficients on each of the Fung and Hsieh (2004) risk factors, $\hat{\beta}_k^i$. For this estimation we find residual standard deviation ($\hat{\sigma}$ = 0.000151), residual kurtosis ($\hat{K}$ = 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 for the Aggregate Hedge Fund Index, (described above) and various skewness levels, S_i, subject to the interval and increment limits noted. We then generate $\tilde{r}_{it}$, a simulated hedge fund return series, as follows.

$$\tilde{r}_{it} = \hat{\alpha}_i + \sum_{k=1}^{K} \hat{\beta}_k^i F_{k,t} + \tilde{e}_t^i \qquad (2)$$

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

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

The results of the simulations are reported in Panels B and C of Table 3. We report simulations with $\hat{\alpha}_i$ = 4.24%, as estimated for the CSFB Tremont Aggregate Hedge Fund Index, and with $\hat{\alpha}_i$ = 0. Note first that the RALS alphas are sensitive to cross sectional differences in S_i whereas the OLS alpha estimates remain invariant. As we would expect, the OLS alphas overstate managerial performance (the RALS alphas are smaller than the OLS alphas) for negative values of S_i and understate managerial performance (the RALS alphas are larger than the OLS alphas) for positive values of S_i. In effect, RALS assesses the performance of a manager of a hedge fund with positively skewed returns as superior to the performance of a manager of an otherwise identical fund with negatively skewed returns while OLS cannot distinguish between the performances of these two managers. 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 the S_i (skewness) term increases in absolute value.

3.4. Source of the OLS performance assessment error

Given the systematic managerial performance assessment error when applying OLS estimation to simulated hedge fund return series that are positively or negatively skewed, our second contribution is to determine whether this error is systematically related to the type of skewness in our samples of actual hedge fund returns. Two cross sectional regression models (see equations (3) and (5), below) allow us to investigate the source of the difference between RALS and OLS alphas for a given fund. The first is

$$z_i = \gamma_0 + \gamma_1 skew_i + \gamma_2 kurt_i + \epsilon, \tag{3}$$

where $z_i = \hat{a}_i^{OLS} - \hat{a}_i^{RALS}$,

$\hat{a}_i^{RALS}$ = the intercept of the RALS estimated time-series regression of fund i's returns against the Fung and Hsieh benchmark factors, and

$\hat{a}_i^{OLS}$ = 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, for fund *i* scaled by their standard errors.

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. Following Harvey and Siddique (2000), coskewness, β_{SKD}, is defined as

$$\hat{\beta}_{SKD,i} = \frac{E[u_{i,t+1}u_{M,t+1}^2]}{\sqrt{E[u_{i,t=1}^2]}\,E[u_{M,t+1}^2]'} \tag{4}$$

where $u_{i,t+1} = r_{i,t+1} - \alpha_i - \beta_i(r_{M,t+1})$, is 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, (i.e. a negative value indicates that the fund adds negative skewness, and vice-versa).

Aragon (2007) demonstrate 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 redemption and minimum investment relationships while *dlock.notice* allows for interaction between the lockup and notice period restrictions.

We incorporate the additional control variables discussed above into regressions that investigate the difference between the RALS alpha and the OLS alphas for a given fund's returns in (5):

$$z_i = \gamma_0 + \gamma_1 skew_i + \gamma_2 kurt_i + \sum_{j=1}^{J} \beta_j C_{ji} + \epsilon \tag{5}$$

The vector C_{ji} includes the Harvey and Siddique (2000) measure of coskewness for each fund and the set of operational variables that Aragon (2007) uses to explain hedge fund performance. Given that RALS can incorporate the impact of skewness and OLS cannot, we expect the skewness variable to dominate as an explanation of the difference in alphas. Furthermore, the sign of the skewness variable will be negative if OLS overstates the performance of managers of funds with negatively skewed returns and understates the performance of managers of funds with positively skewed returns.

4. Empirical analysis and comparison of RALS and OLS alphas

We analyze the statistical relationship between OLS and RALS estimates of alpha for each hedge fund in the sample in subsection 4.1. Then, we identify the determinants of the difference between the OLS alpha and the RALS alpha for each fund in subsection 4.2. Here, we focus on impact of the statistical properties of fund returns, such as skewness and co-skewness, and fund administrative characteristics, such as lockup and redemption notice periods, as explanators of the spread between the OLS and RALS alpha for a given fund. We then provide robustness checks in subsection 4.3 and examine persistence in hedge fund performance in subsection 4.4.

4.1. Robust estimates of performance

We plot the kernel density estimates for the OLS and RALS estimated alphas 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 densities have similar means but that the RALS alpha distribution is less peaked and has fatter tails than the OLS distribution.

We compare the RALS and OLS alpha estimates at the aggregate level for negative-skewness, no-skewness and positive-skewness funds in Figure 2. Specifically, Figure 3A plots OLS alphas against RALS alphas for all funds. We can further quantify the relationship between OLS alpha and RALS alpha for each fund by regressing its OLS alpha against its RALS alpha. For the full sample, the slope coefficient is highly significant with an estimate of 0.5, and the adjusted R^2 of the regression is 68 percent. Figure 3B repeats the analysis but restricts the sample to funds with negatively-skewed returns. Here the slope coefficient 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 3C shows the relationship for the small sample of funds whose returns are not skewed. Both the slope (0.7) and the adjusted R^2 (80 percent) are considerably higher than for the negative-skewness funds. Finally, Figure 3D considers only funds whose returns are positively skewed. We can see that the slope coefficient is smaller than for the non-skewed funds, (0.6 vs. .07), and the Adjusted R^2 drops to 66 percent. Clearly, OLS and RALS performance assessments are most similar for no-skewness funds and diverge as skewness increases in either direction.

We report the cross-sectional mean fund-return results within strategy categories for managerial performance assessments 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 4.[16] Comparing the alphas of the different categories, it is apparent that both OLS alphas and RALS alphas are 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, regardless of whether performance is assessed by OLS or RALS.

The OLS performance assessment errors are quite apparent when RALS and OLS alphas are compared in the center columns of Table 4. For the *All Funds* lines at the bottom of each section, OLS mis-states managerial performance by [0.10 – (-0.04)] = +0.14 percent per month for dead negative-skewness funds and [0.61 – 0.92] = -0.31 percent per month for dead positive-skewness funds. OLS and RALS produce similar performance estimates for both live and dead funds when returns are not skewed. Finally, OLS performance assessment errors are [0.46 – 0.35] = +0.11 percent and [0.89 – 1.07] = -0.18 percent per month for live negative- and positive-skewness funds, respectively. These dramatic differences in performance assessment are not surprising given that the two additional RALS regressors

[16] A fund is classified as being positively and negatively skewed if the estimated return skewness t-ratio statistic is significant at the 5% level. Our results are not materially affected if we classify funds based on first-stage OLS residual skewness t-ratio statistics instead.

are typically significant when hedge fund returns are positively skewed, (see $\%w_1$ and $\%w_2$ in each section of Table 4).

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 segmented by investment strategy clearly indicate that the size and sign of the OLS performance assessment error are related to the sign of the skewness in an individual fund's returns when sample sizes are reasonable, (for example, OLS performance assessment errors for live Long Short Equity Hedge funds are +0.14 and -0.14 percent per month for negatively skewed and positively skewed funds, respectively.

4.2. Source of OLS performance assessment errors

The results in the previous section suggest that standard OLS alpha estimates for samples of hedge fund returns are not robust if either positive or negative skewness is present in the distribution of a fund's return series. Furthermore, differences can be quite large when assessing managerial performance by OLS and by RALS. In this section we turn our attention to identifying the sources of the OLS performance assessment error, which is the difference between the RALS alpha and the OLS alpha estimated for a given fund.

Table 5 first reports the OLS performance assessment error, (Model 1), for live (Panel A) and dead (Panel B) negative- and positive-skewness funds.[17] Model 2 addresses the role of a fund return's skewness and kurtosis values in explaining the OLS assessment error, (Eq. 3), while Model 3 adds a fund return's coskewness measure (Harvey and Siddique, 2000) and the administrative features identified by Aragon (2007), (Eq. 5) as possible explanators..

We turn first to the results for Model 1. In both panels the γ_0 term, which measures the OLS error in assessing managerial performance when hedge fund returns are skewed, is statistically significant in all

[17] This error is not significantly different from zero for non-skewed fund returns. To save space we do not report the results for these funds here but they are available from the authors on request.

four segments (live and dead, positive and negative skewness). Adding the *skewness* and *kurtosis* variables, (γ_1 and γ_2 in Model 2 in Table 5) always explains all of this error (in that the γ_0 term is no longer significant), and both coefficients are always statistically significantly different from zero. Model 3, in the bottom rows of each panel, adds the co-skewness (β_1) and administrative control (β_2 - β_7) variables identified in the discussion of Equation (5). The added control variables are seldom significant but both the 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 four aggregates of funds.

Furthermore, the statistically significant skewness coefficient (on γ_1) is always negative in the Table 5 regressions. Given that the dependent variable is ($\alpha^{OLS} - \alpha^{RALS}$), the negative sign means that OLS overstates the performance of managers of funds that have negatively skewed returns and understates the performance of managers of funds that have positively skewed returns. This result demonstrates the importance of controlling for skewness when assessing the performance of hedge fund managers.

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 6 we report the performance of all funds estimated by OLS and RALS but sorted on skewness. The results are striking. OLS misprices fund performance for all fund deciles except of decile 6, where skewness in returns is close to zero. OLS performance overstatement increases from 7 to 20 basis points per month as skewness in returns becomes more negative while OLS performance understatement increases from 7 to 48 basis points per month as skewness in returns becomes more positive. Panels B to K of Table 6 disaggregate the results according to fund style. There are no exceptions to the conclusions documented so dramatically in Panel A. Relative to RALS, OLS significantly and consistently overstates managerial performance for negatively skewed funds and significantly and consistently underestimates managerial performance for hedge funds with positive skewness.

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

4.3. 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. Finally, 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.

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 7. 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 managers of funds with negatively skewed returns and understate the performance of managers of funds with positively skewed returns.

Recent studies have highlighted the importance of time variation in return characteristics when measuring fund performance.[18] Specifically, there is evidence that hedge funds change their risk exposures over time due to sudden financial disruptions such as the Russian crisis and the dotcom collapse (Kosowski, Naik, and Teo, 2007). Using a variation of the CUSUM test, Fung, Hsieh, Naik, and Ramadori (2008) identify 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 7 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.

4.4. Comparative analysis of performance persistence

Our results so far provide dramatic evidence that the performance of manager of hedge funds with positively skewed returns is understated by OLS, on average, while at the same time OLS systematically overstates the performance of managers of funds with negatively skewed returns. While this is an interesting statistical issue, our findings are only relevant to investors in hedge funds if they have economic importance.

In this section we investigate whether hedge fund performance persistence, which is the ability of a hedge fund manager to earn consistently sized returns over time, 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. We then re-sort the portfolios at the beginning of each calendar year and compare the results. By analyzing

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

the continuously re-sorted top decile portfolios we are able to measure the difference in performance that can be achieved by making forward-looking investment decisions based on historical RALS alphas instead of historical OLS alphas.

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 hedge fund 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. These differences correspond to well-known periods of financial crisis and return volatility.

Table 8 reports the statistical characteristics for both the RALS sort and the OLS sort top decile portfolios and for the S&P500. These series allow us to perform a simple mean variance analysis. There is a quite large difference in performance, with mean annual returns for the RALS sort (OLS sort) 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 sort portfolio is larger, at 0.82, versus 0.62 for the OLS sort portfolio and 0.25 for the S&P500. We also report the Goetzmann, Ingersoll, Spiegel, and Welch (2007) Manipulation-Proof Performance Measures $MPPM_3$ and $MPPM_4$ for each portfolio and find they are both larger for the top-decile RALS portfolio than the top-decile OLS portfolio.

Institutional investors who rely on investments in hedge funds to fund current expenditures are quite sensitive to decreases in portfolio value (drawdowns) because these drops often require corresponding cuts in expenditure, as seen in 2008. The RALS sort portfolio has the lowest drawdown during the sample period, 10 percent smaller than that of the OLS sort portfolio and 27 percent smaller than that of the S&P 500.[19]

We next employ the bootstrapped time series method of Ledoit and Wolf (2008) to formally test for differences in Sharpe ratios. Unlike earlier work by Jobson and Korkie (1981) and Memmel (2003),

[19] Drawdown is the maximum annual peak to trough decline in the portfolio's value over the sample period.

the Ledoit and Wolf (2008) test is robust to non-normality and serial correlation, which are particularly relevant for portfolios of hedge funds. The differences in Sharpe ratios and their corresponding significance levels are reported in matrix form in Panel B of Table 8 for the RALS sort and OLS sort portfolios and the S&P 500. The RALS top-decile portfolio Sharpe ratio is statistically significantly greater than both the OLS top-decile portfolio and the S&P500 whereas the OLS top-decile portfolio Sharpe ratio is not statistically different from that of the S&P500.

The results in Table 8 demonstrate that using the RALS estimator instead of the OLS estimator to assess the performance of a given hedge fund manager results in a statistically significant improvement in investment returns on a risk-adjusted basis. Given that periods of economic crisis are accompanied by increases in positively and negatively skewed returns, we expect that the superior performance of the RALS estimator will be particularly apparent in times of financial upheaval. We address that issue in the next section of the paper.

5. Assessment of hedge fund manager performance during crisis and non-crisis periods

The issue of hedge fund performance persistence during crisis periods is particularly important given recent economic events. To address it, we estimate the rolling top-decile RALS sort and OLS sort portfolios' risk adjusted performance for the full sample and also in crisis and non-crisis periods. We follow Billio, Getmansky, and Pelizzon (2011) 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 9 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 under both the RALS sort and the OLS sort and the difference in returns between the two spread portfolios.

According to Panel A of Table 9, the rolling top-decile OLS sort portfolio earns a statistically significant alpha of 7.26 percent per annum across the entire 1994 – 2009 sample period. The alpha of the top-decile RALS sort portfolio is also statistically significant, and is 1.23 percent per annum higher, (this difference is statistically significant). The alpha for the spread between the top and bottom deciles is not significant for either OLS or RALS but 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 9, we report the results of the same persistence tests during the non-crisis periods of our sample. Here the rolling OLS and RALS sort top-decile portfolio alphas are quite similar with the RALS portfolio being marginally higher by 0.52 percent. Again the RALS sort spread portfolio alpha is higher than the OLS sort spread portfolio, this time by a statistically significant 2.74 percent per annum.

We show the results for the crisis periods in the sample in Panel C. Here is where the difference in performance persistence between portfolios formed on RALS estimation and OLS estimation is most striking. The alpha of the OLS sort portfolio is significantly negative and the RALS portfolio alpha is significantly (4.40 percent) higher. For the spread portfolios the RALS sort alpha is also significantly higher, by 6.79 percent. Overall, we find greater persistence for the sort on RALS alpha than for the sort on OLS alpha. It is also evident that this difference in persistence is primarily due to the outperformance during crisis periods, when the mean return and the alpha of the top-decile OLS sort portfolio are significantly negative.

To be sure that the evidence of superior performance assessment demonstrated by the RALS estimator is not due to illiquidity induced smoothing in hedge fund returns or incubation and backfill bias, we repeat the analysis of Table 9 using the Getmansky, Lo, and Makarov (2004) specification to unsmooth hedge fund returns. Also, separately, we control for the effects of backfill bias by removing the first 24 months of returns for each fund.

Results for hedge fund returns corrected for serial correlation appear in Panel A of Table 10 while those in Panel B are adjusted to remove potential backfill bias. A comparison of the almost identical results in Tables 9 and 10 makes it clear that our results are not driven by these two well-known statistical issues with hedge fund returns. It is also a simple matter to use OLS estimation to assess performance persistence for portfolios sorted on rolling RALS alphas. We follow this strategy in unreported results available from the authors and generate additional outcomes that are remarkably similar to those in Tables 9 and 10. These findings demonstrate the importance of using an estimator that is efficient in the presence of skewness to assess the performance of hedge fund managers before making investment decisions, regardless of how that performance is going to be assessed *ex-post*.

The results of our study rely on the underlying assumption that directional skewness in hedge fund returns persists. To investigate this, we divide hedge fund returns into portfolios based on historical skewness estimates over the past twenty-four months each January and then compute realized skewness measures twelve months later. Results, available from the authors, show that negative skewness and no-skewness are significantly persistent across the full sample and separate samples of crisis and non-crisis periods. Positive skewness persists significantly during non-crisis periods and these fund returns are the least negatively skewed during crisis periods.

Results presented in Ang, Gorovyy, and van Inwegen (2011) provide a possible explanation for why even the best hedge fund managers cannot returns that are significantly positively skewed during periods of crisis. Hedge fund managers rely on leverage to magnify the returns to their base strategies. Ang, Gorovyy, and van Inwegen (2011) note that the amount of hedge fund leverage is pro-cyclical, meaning that opportunities to magnify returns by increasing leverage dry up as crisis conditions appear.

The results presented in this section of the paper have demonstrated that OLS estimation errs in a systematic fashion when assessing the performance of hedge fund managers when the returns earned on their portfolios are skewed, and that the difference in performance is driven primarily by crisis periods.

As such, we shed some light on an important issue raised by Jagannathan, Malakhov, and Novikov (2010), namely whether or not the relative performance of hedge fund managers is dependent on market conditions. The answer suggested by our research is an unequivocal “yes”. Furthermore, the scale of the OLS performance assessment errors is not trivial.

6. Summary and conclusions

There is a growing body of literature examining the impact of skewness in returns from both a theoretical and an applied perspective. We first show that most hedge fund returns are significantly skewed. As OLS estimation is inefficient in the presence of skewness and fat tailed error distributions, performance assessment estimated by OLS will overstate the performance of some funds and understate the performance of others.

We next show that the RALS methodology is more efficient than OLS in assessing the performance of hedge fund managers when returns are skewed. When our sample of hedge funds is divided into skewed and non-skewed sub-samples there is a considerable variation in the accuracy of OLS performance assessment estimates. While OLS is quite efficient at estimating performance for the non-skewed 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 OLS performance assessment error using a cross sectional model, there is strong evidence that skewness explains the difference between the RALS and OLS performance estimates in the expected manner, even after specifying a range of control variables.

We next sort funds into deciles based upon historical skewness. Here, the scale of the OLS performance assessment error is non-trivial for most deciles and increases as skewness in returns grows in absolute value. Furthermore, we document that rolling two-year sort top decile portfolios composed using the results of RALS estimation dominate the returns on similar portfolios created based on the results of OLS estimation, and dominate the return on the Standard and Poor's 500 index, during our 1994 – 2009 sample period.

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 selecting managers using OLS or RALS 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. Taken as a whole, our results demonstrate the relevance of RALS estimation for investors seeking to identify the best performing managers of hedge funds, especially during periods of financial upheaval.

APPENDIX

A. RALS methodology

We start with a multivariate linear regression model

$$y_t = \varphi' z_t + u_t \tag{6}$$

Where:

$z_t = (1, x_t')'$,

x'_t = a $(k-1)$ x 1 vector of time series observed at time t, and

$\varphi' = (\alpha\beta')'$ where α is the intercept and β' is the $(k-1)$ x 1 vector of coefficients on x_t.

Assume the following moment conditions hold:

$$E[x'(y - x'\beta)] = 0 \tag{7}$$

$$E\{(x \otimes [h(y\text{-}x'\beta)\text{-}H]\} = 0 \tag{8}$$

where (7) is the least squares moment condition, which asserts that x_t and u_t are uncorrelated, and (8) 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 means that the standardized fourth central moment of the series exceeds three, so that:

$$E(u_t^4 - 3\sigma^4) = E[u_t(u_t^3 - 3\sigma^2 u_t)] \neq 0 \tag{9}$$

which implies 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). Similarly, the standardized third central moment is non-zero when the errors are skewed so that:

$$E(u_t^3\text{-}\sigma^3) = E[u_t(u_t^2\text{-}\sigma^2)] \neq 0 \tag{10}$$

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 (6) augmented with (11).

$$\hat{w}_t = [(\hat{u}_t^3 - 3\hat{\sigma}^2\hat{u}_t)(\hat{u}_t^2 - \hat{\sigma}^2)]' \tag{11}$$

where $\hat{u}_t$ denotes the residual and $\hat{\sigma}_t$ denotes the standard residual variance estimate obtained from OLS applied to equation (6). 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

$$\sqrt{T}(\beta^*\text{-}\beta) \rightarrow N[0, \sigma_A^2 \mathrm{Var}(x_t)^{-1}] \tag{12}$$

Im and Schmidt (2008) derive ρ^*, a measure of the asymptotic efficiency gain from employing RALS as opposed to OLS. ρ^* is 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:

$$\sigma_A^2 = \sigma^2 - \frac{\mu_3^2(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2) - 2\mu_3(\mu_4 - 3\sigma^4)(\mu_5 - 4\mu_3\sigma^2) + (\mu_4 - 3\sigma^4)^2(\mu_4 - \sigma^4)}{(\mu_4 - \sigma^4)(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2) - (\mu_5 - 4\mu_3\sigma^2)^2} \tag{13}$$

where μ_i denotes the *i*-th central moment of u_t. *Note that ρ^* is small for large efficiency gains.* The inclusion of the RALS terms that are functions of the first-stage OLS residuals generates a more efficient model estimate if the distribution of the error term is non-normal. For normally distributed first-stage errors, OLS is efficient and the ratio equals one.

σ_A^2 can be estimated consistently 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

$$V(\beta^*) = \hat{\sigma}_A^2(\tilde{X}'M_{\tilde{W}}\tilde{X})^{-1} \tag{14}$$

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

$$M_{\tilde{W}} = I_t - \tilde{W}'\left(\tilde{W}'\tilde{W}\right)^{-1}\tilde{W} \tag{15}$$

where I_t is the $T \times T$ identity matrix and $\tilde{V} = (\tilde{v}_1\tilde{v}_2 \ldots \tilde{v}_T)'$, $\tilde{v}_t = v_t\text{-}T^{-1}\sum v_t$ for $(V, v) = (X, x), (W, w)$. The quantification of the efficiency gain and the ability to achieve it using the RALS estimation technique depend on the homoscedastic assumption that the third and fourth conditional moments are independent of the regressors.

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Figure 1
Kernel density estimate of the OLS and RALS estimated alpha distributions for all funds

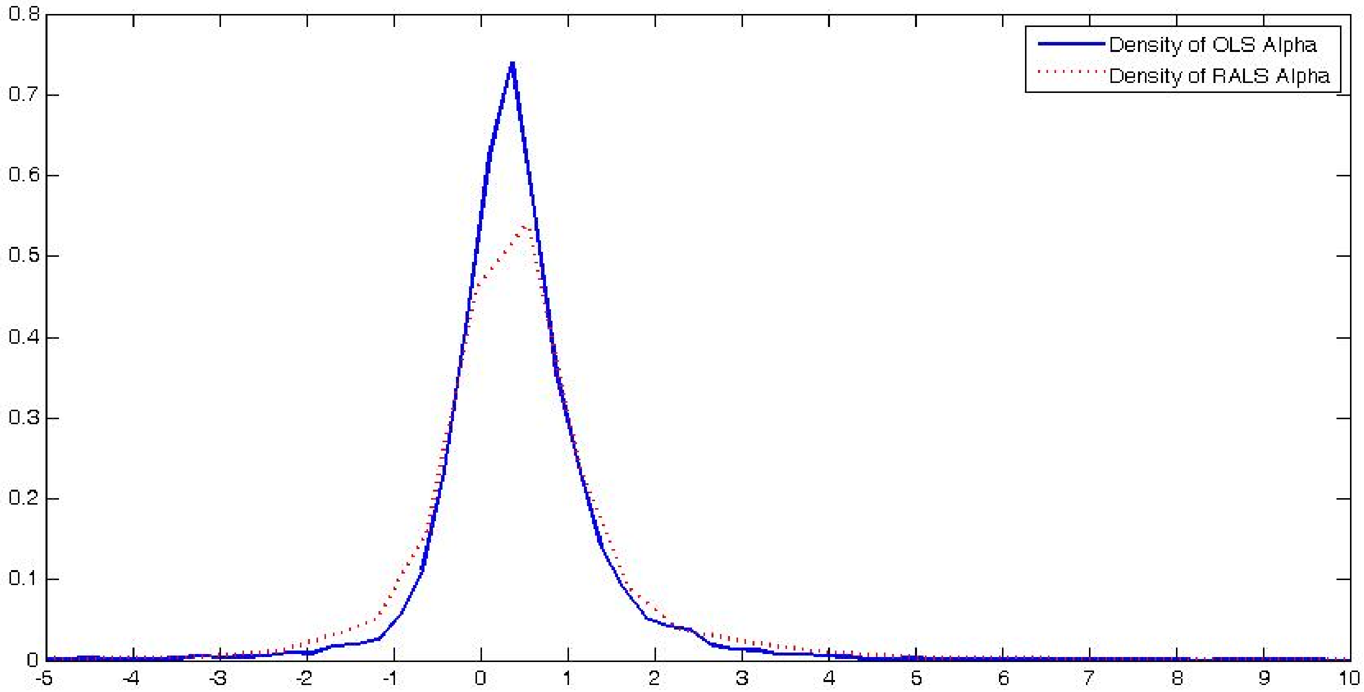
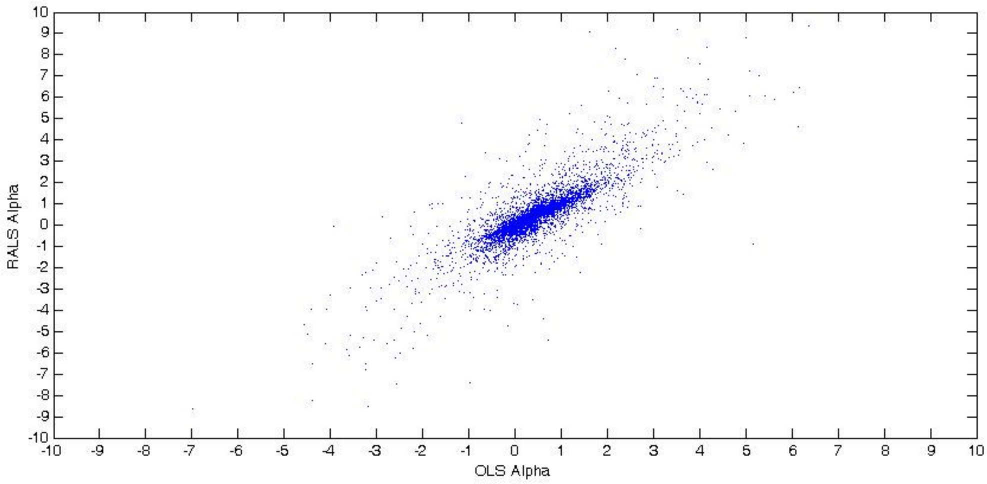


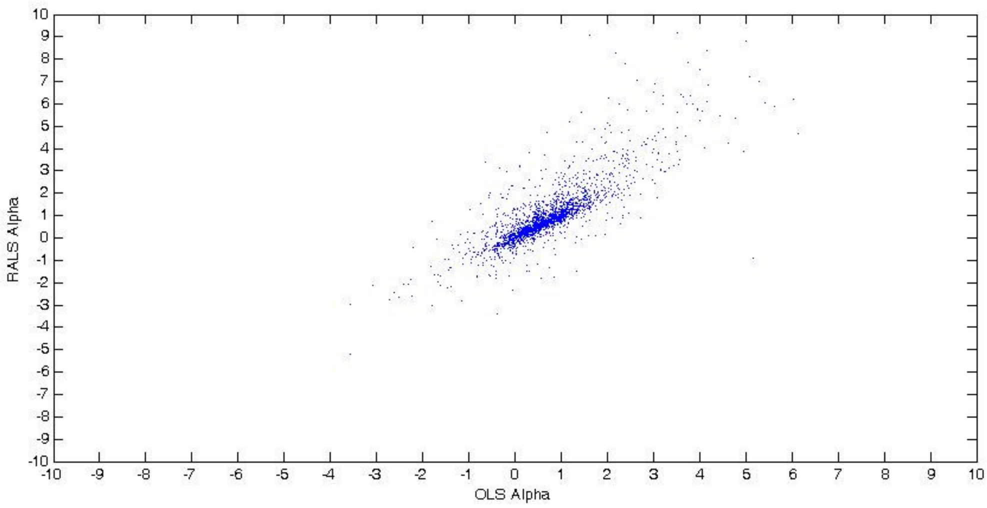
Figure 2
Graphical representation of the distribution of OLS and RALS alphas

The two sets of alphas are (1) the OLS alpha and (2) the RALS alpha. Figure 3A shows alphas when the model is estimated for all funds. Figure 3B shows alphas when the models are estimated only for funds which exhibit negatively skewed returns. Figure 3C shows alphas when the models are estimated only for funds exhibiting non-skewed returns. Figure 3D shows alphas when the models are estimated only for funds which exhibit positively skewed returns. Results from regressing RALS alphas on OLS alphas are also included in each figure.

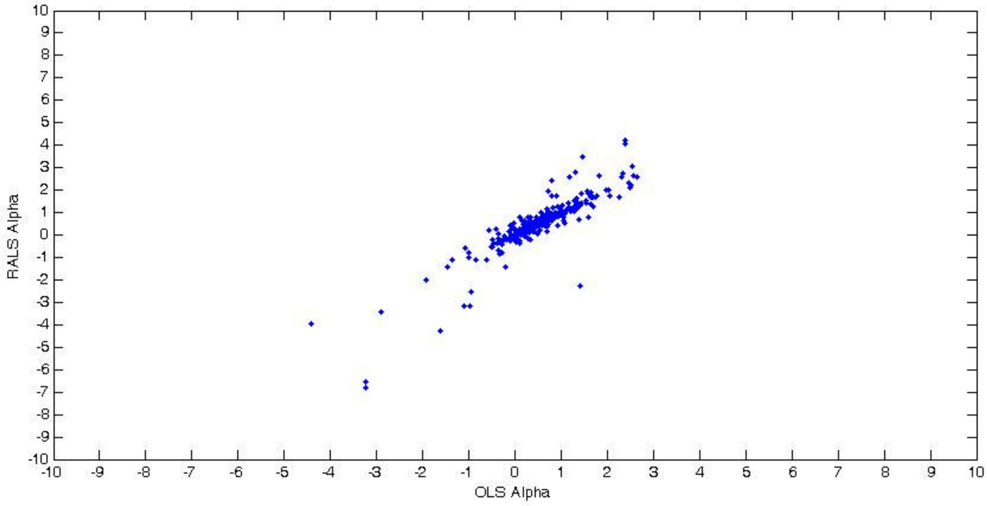
(A) All funds



(B) Negative-skewness funds



(C) No-skewness funds



(D) Positive-skewness funds

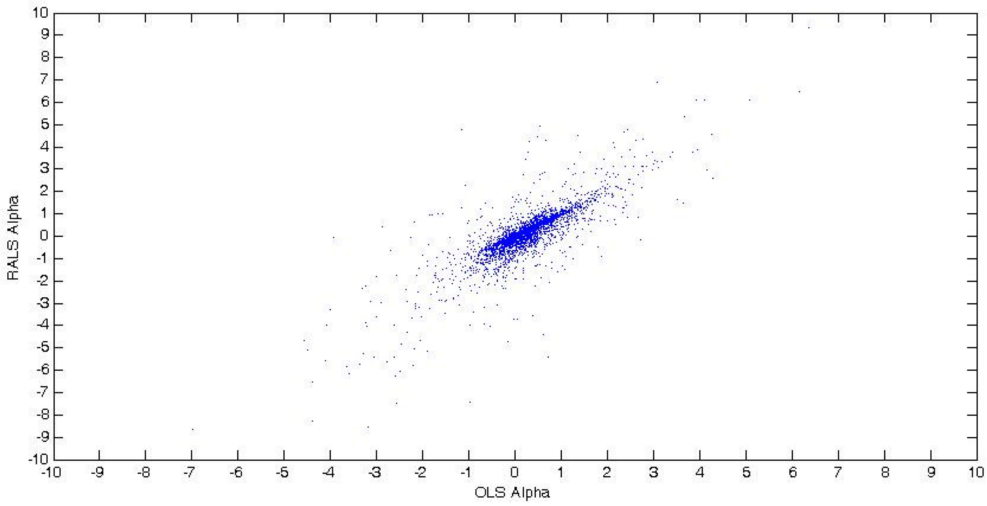


Figure 3
Cumulative portfolio returns

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, 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.

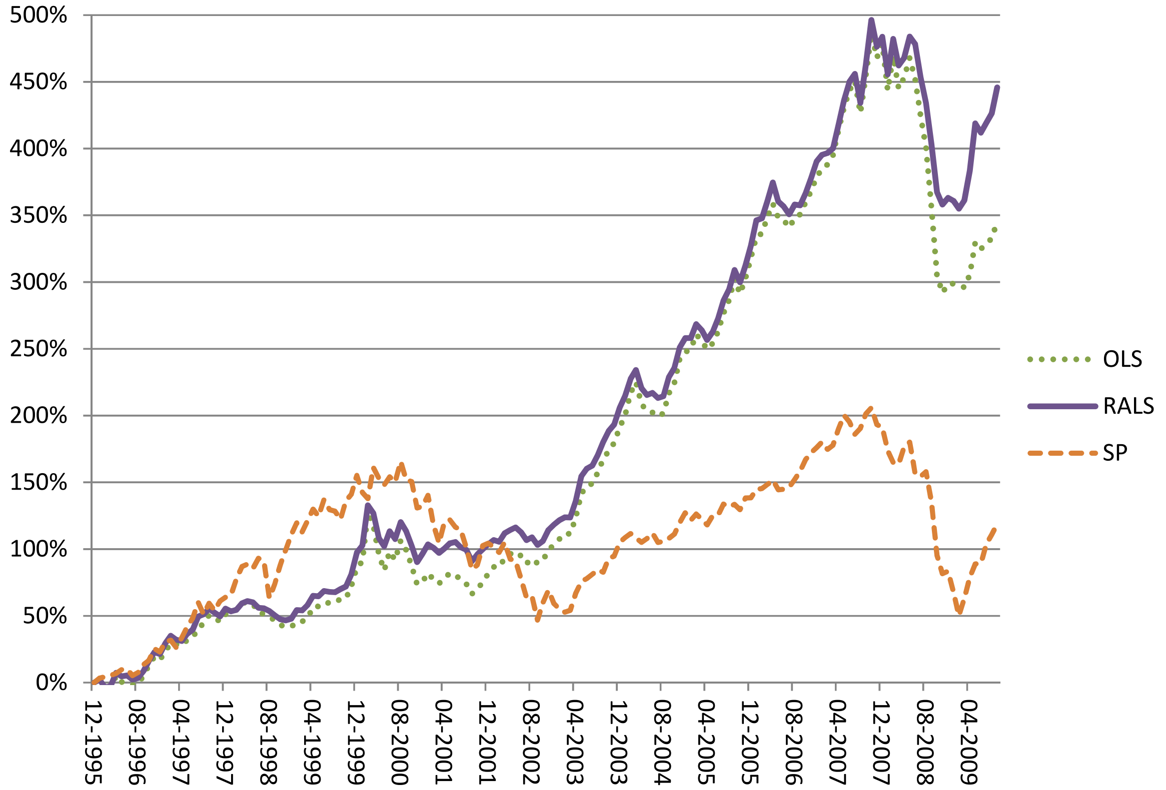


Table 1
Summary statistics of reported monthly returns

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 2
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 3
RALS simulation results

Panel A reports results for estimating the Fung and Hsieh 7 factor model, 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 ($\hat{\alpha}$ = 0.0035, or 4.24% per annum) and coefficients on each of the Fung and Hsieh risk factors. Also reported are residual standard deviation, $\hat{\sigma}$, residual kurtosis, $\hat{K}$, and residual skewness, $\hat{S}$. Panel B 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 C show the results with annual 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 $\rho*$, the efficiency gain from using RALS relative to OLS. Coefficients and P-Values are bold if significant at the 5% level.

α_{ANNUAL}	β_{SNPRF}	β_{SCMLC}	$\beta_{BD10RET}$	$\beta_{BAAMTSY}$	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$	$\bar{R}^2$	$\hat{\sigma}$	$\hat{K}$	$\hat{S}$
Panel A: CSFB Tremont index 7 factor model results											
4.24	**0.25**	**0.15**	**-0.04**	**-0.04**	**-0.03**	**0.01**	**0.02**	**0.40**	0.00015	5.16	0.14
0.01	**0.00**	**0.00**	**0.05**	**0.01**	**0.00**	**0.19**	**0.07**	**0.01**			

	Residual skewness								
	-2.0	*-1.5*	*-1.0*	*-0.5*	*0.0*	*0.5*	*1.0*	*1.5*	*2.0*
Panel B: Performance measures at different skewness levels (annual 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**
$\rho*$	0.01	0.24	0.70	0.90	0.93	0.90	0.71	0.25	0.01
Panel C: Performance measures at different skewness levels (annual OLS alpha = 4.24)									
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**
$\rho*$	0.02	0.25	0.70	0.92	0.92	0.90	0.73	0.24	0.01

Table 4
OLS and RALS alphas

This table reports the mean OLS alpha, RALS alpha and efficiency gain for different categories of hedge funds. Column one reports the number of funds in each investment category. Columns two and three report the mean OLS estimated alpha and the mean RALS estimated alpha. Columns four and five report the percentage of RALS coefficients, which are statistically significant at the 5% level (%w_1 and %w_2). Column six reports the mean efficiency gain from RALS estimation.

	Negative-skewness funds						No-skewness funds						Positive-skewness funds					
Fund category	*N*	*OLSa*	*RALSa*	%w_1	%w_2	ρ^*	*N*	*OLSa*	*RALSa*	%w_1	%w_2	ρ^*	*N*	*OLSa*	*RALSa*	%w_1	%w_2	ρ^*
Panel A: Live funds																		
Convertible arbitrage	38	0.53	0.51	26	61	0.73	2	0.39	0.46	0	100	0.62	5	2.49	3.45	20	40	0.74
Event driven	148	0.26	0.23	36	55	0.69	42	0.59	0.58	24	74	0.85	79	1.13	1.52	47	58	0.65
Equity market neutral	66	0.11	0.04	44	67	0.66	8	0.28	0.31	13	75	0.79	34	0.45	0.60	56	71	0.69
Emerging markets	115	1.10	1.12	47	57	0.74	5	1.19	1.29	0	80	0.81	58	1.58	1.97	50	50	0.71
Fixed income arbitrage	45	0.29	0.24	56	73	0.74	3	0.38	0.28	33	100	0.69	30	0.60	0.83	50	60	0.63
Fund of funds	1472	0.04	-0.11	68	60	0.68	112	0.29	0.23	30	68	0.84	163	0.57	0.73	42	63	0.68
Global macro	50	0.53	0.48	42	48	0.82	8	0.60	0.51	13	63	0.85	56	0.78	0.89	50	38	0.82
Long short equity hedge	552	0.46	0.32	49	59	0.78	111	0.66	0.70	34	66	0.84	314	0.80	0.94	45	56	0.73
Managed futures	48	0.73	0.29	58	50	0.74	58	0.65	0.58	31	66	0.89	129	0.85	0.86	39	61	0.80
Multi-strategy	158	0.26	0.15	55	65	0.70	14	0.37	0.49	50	86	0.66	53	0.84	1.16	55	43	0.70
All funds	1222	0.46	0.35	47	60	0.75	251	0.62	0.63	30	69	0.84	764	0.89	1.07	46	55	0.73
Panel B: Dead funds																		
Convertible arbitrage	124	0.15	0.05	53	60	0.66	8	0.29	0.26	25	38	0.93	37	0.44	0.57	49	65	0.69
Event driven	153	0.29	0.23	38	56	0.76	21	0.61	0.58	24	43	0.89	86	0.81	1.23	60	59	0.60
Equity market neutral	178	0.04	-0.07	51	65	0.62	19	0.21	0.21	47	58	0.82	105	0.44	0.64	44	65	0.68
Emerging markets	240	0.30	0.20	44	64	0.70	33	0.32	0.23	12	79	0.82	127	0.80	1.30	47	56	0.68
Fixed income arbitrage	143	0.02	-0.18	64	62	0.55	6	0.42	0.44	17	83	0.69	53	0.61	0.62	51	60	0.68
Fund of funds	1564	-0.05	-0.21	60	60	0.64	92	0.05	0.04	25	71	0.80	364	0.25	0.39	40	59	0.72
Global macro	103	-0.07	-0.32	49	69	0.67	6	0.01	0.03	50	67	0.81	124	0.43	0.72	48	56	0.71
Long short equity hedge	755	0.14	0.02	43	56	0.72	93	0.38	0.44	31	62	0.79	654	0.71	1.06	52	62	0.69
Managed futures	146	-0.03	-0.37	47	62	0.65	23	0.26	0.04	43	61	0.78	239	0.44	0.74	43	60	0.73
Multi-strategy	242	-0.10	-0.30	55	64	0.60	12	-0.10	-0.70	42	58	0.81	117	0.54	0.68	51	66	0.65
All funds	2093	0.10	-0.04	47	60	0.68	224	0.33	0.29	31	62	0.81	1559	0.61	0.92	49	61	0.69

Table 5
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 $z_i = \hat{a}_i^{OLS} - \hat{a}_i^{RALS}$, $skew_i$ 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.

Model	Negative-skewness funds										Positive-skewness funds									
	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 6
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 6 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 7
Alpha of funds sorted on historical skewness robustness checks

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 8
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. $MPPM_3$ and $MPPM_4$ are the of Goetzmann, Ingersoll, Spiegel, and Welch (2007) Manipulation-Proof Performance Measure (ρ = 3, 4). Worst Drawdown is the maximum annual peak to trough decline in the portfolio's value over the sample period. Panel B reports results from the Ledoit and Wolf (2008) studentized time series bootstrap test for differences in Sharpe ratio. 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
$MPPM_3$	0.08	0.06	0.00
$MPPM_4$	0.07	0.05	-0.02
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 9

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, 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. We perform a means test for differences in alpha and also report differences in $MPPM_3$ and $MPPM_4$ for the RALS and OLS portfolios. Crisis and Non-Crisis periods are classified following Billio, Getmansky, and Pelizzon (2011). Alphas and differences in alphas in bold are significant at the 5% level.

	Mean	Std dev	$MPPM_3$	$MPPM_4$	Alpha	SNPRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	$\bar{R}^2$
Panel A: Full sample													
RALS	12.93	11.59	0.08	0.07	**8.49**	0.36	0.29	-0.04	-0.08	0.00	0.02	0.05	0.50
OLS	11.63	13.22	0.06	0.05	**7.26**	0.34	0.31	-0.05	-0.10	0.01	0.02	0.06	0.50
RALS-OLS			0.02	0.02	**1.23**								
$RALS_{10\%\ SPREAD}$	4.66	9.90	0.00	-0.01	0.56	-0.04	0.05	-0.05	-0.05	0.01	0.00	0.05	0.30
$OLS_{10\%\ SPREAD}$	2.86	12.27	-0.07	-0.08	-0.76	-0.09	0.09	-0.05	-0.08	-0.01	0.00	0.05	0.21
$RALS\text{-}OLS_{10\%\ SPREAD}$			0.07	0.07	1.32								
Panel B: No crisis													
RALS	16.43	10.68	0.11	0.11	**9.85**	0.30	0.28	-0.05	0.00	0.00	0.05	0.03	0.39
OLS	15.89	12.20	0.10	0.10	**9.33**	0.28	0.29	-0.06	0.00	0.00	0.06	0.03	0.39
RALS-OLS			0.01	0.01	0.52								
$RALS_{10\%\ SPREAD}$	5.80	9.72	0.01	0.01	3.98	-0.08	-0.04	-0.02	-0.06	0.03	0.05	0.01	0.33
$OLS_{10\%\ SPREAD}$	4.29	12.23	-0.01	-0.02	1.24	-0.14	-0.04	-0.04	-0.04	0.01	0.05	0.01	0.26
$RALS\text{-}OLS_{10\%\ SPREAD}$			0.02	0.03	**2.74**								
Panel C: Crisis													
RALS	1.81	13.98	-0.04	-0.05	-2.47	0.42	0.27	-0.12	-0.08	0.00	0.07	0.04	0.81
OLS	-1.96	15.79	-0.09	-0.10	**-6.87**	0.39	0.37	-0.17	-0.13	-0.01	0.06	0.01	0.94
RALS-OLS			0.05	0.05	**4.40**								
$RALS_{10\%\ SPREAD}$	1.60	10.61	-0.03	-0.04	1.56	0.00	0.23	-0.10	-0.09	-0.01	0.07	0.01	0.06
$OLS_{10\%\ SPREAD}$	-1.07	12.61	-0.24	-0.28	-5.23	-0.01	0.26	-0.13	-0.09	-0.01	0.06	-0.04	0.44
$RALS\text{-}OLS_{10\%\ SPREAD}$			0.21	0.24	**6.79**								

Table 10
Portfolio formed on OLS and RALS alphas robustness checks

This table reports estimated Fung and Hsieh (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, 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. Panels A and B show the results for the Full Sample corrected for return serial correlation and backfill bias respectively. We perform a means test for differences in alpha and also report differences in $MPPM_3$ and $MPPM_4$ for the RALS and OLS portfolios. Crisis and Non-Crisis periods are classified following Billio, Getmansky, and Pelizzon (2011). Alphas and differences in alphas in bold are significant at the 5% level.

	Mean	Std dev	$MPPM_3$	$MPPM_4$	Alpha	SNPRF	SCMLC	BD10RET	BAAMTSY	PTFSBD	PTFSFX	PTFSCOM	$\bar{R}^2$
Panel A: Unsmoothed returns													
RALS full sample	12.57	11.46	0.07	0.07	**8.15**	0.35	0.29	-0.04	-0.08	0.00	0.02	0.05	0.49
OLS full sample	11.08	13.06	0.05	0.04	**6.77**	0.35	0.30	-0.05	-0.10	0.00	0.01	0.06	0.49
RALS-OLS full sample			0.02	0.03	**1.38**								
RALS no crisis	15.95	10.56	0.13	0.13	**9.30**	0.29	0.28	-0.05	0.00	0.00	0.05	0.03	0.38
OLS non-crisis	15.36	12.02	0.13	0.12	**9.04**	0.28	0.28	-0.06	0.00	0.00	0.06	0.02	0.38
RALS-OLS non-crisis			0.00	0.01	0.26								
RALS crisis	1.78	13.82	-0.18	-0.19	-2.33	0.42	0.26	-0.13	-0.09	0.00	0.07	0.03	0.80
OLS crisis	-2.77	15.63	-0.26	-0.27	**-7.27**	0.41	0.35	-0.17	-0.15	0.00	0.07	0.00	0.93
RALS-OLS crisis			0.08	0.08	**4.94**								
Panel B: No backfill													
RALS full sample	10.97	10.82	0.06	0.05	**6.54**	-0.07	0.03	0.02	0.07	-0.05	0.01	-0.01	0.06
OLS full sample	9.45	12.43	0.04	0.03	4.87	-0.08	0.03	0.02	0.07	-0.05	0.01	-0.01	0.13
RALS-OLS full sample			0.02	0.02	**1.67**								
RALS non-crisis	15.02	10.05	0.11	0.11	**7.91**	0.25	0.34	-0.06	0.02	-0.01	0.03	0.02	0.37
OLS non-crisis	14.57	11.54	0.11	0.10	**7.71**	0.22	0.40	-0.06	0.01	0.00	0.04	0.02	0.35
RALS-OLS non-crisis			0.00	0.01	0.20								
RALS crisis	2.64	13.87	-0.17	-0.18	1.05	0.43	0.28	-0.13	-0.10	0.02	0.08	0.03	0.73
OLS crisis	-2.47	15.89	-0.26	-0.27	**-7.08**	0.47	0.38	-0.16	-0.15	0.01	0.07	0.01	0.91
RALS-OLS crisis			0.09	0.09	**8.13**								