DOI: 10.1111/fima.12304

ORIGINAL ARTICLE

Financial Management WILEY

Predicting hedge fund performance when fund returns are skewed

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Funding information
Science Foundation Ireland, Grant/Award Number: 18/SPP/3459

Abstract

We show that fund-specific return skewness is associated with managerial skill and future hedge fund performance. Specifically, skewness in fund returns reflects managerial skill in avoiding large drawdowns. Using a new measure of investment skill that accounts for this managerial ability, we demonstrate that traditional performance measures underestimate (overestimate) managerial performance when returns exhibit positive (negative) fund-specific skewness. Our new measure is particularly valuable during periods of economic crisis, when the annual risk-adjusted outperformance is 5.5%.

KEYWORDS

fund-specific skewness, hedge funds, investment skill, performance measurement, performance persistence

JEL CLASSIFICATION

G10, G19, G20

1 | INTRODUCTION

The returns of more than 90% of the hedge funds in the Lipper/TASS database exhibit considerable skewness. Skewness in fund returns could reflect managerial attempts to cater to the skewness preferences of fund investors. Alternatively, it could arise from manager-specific skills such as dynamic trading or superior risk management to minimize large losses. Fund return skewness is more likely to appear during periods of financial crisis because skilled fund managers tend to employ specialized investment and risk management strategies when there is greater potential for large losses.

If fund return skewness is more likely to reflect managerial skill, higher fund skewness should be associated with higher future performance. In contrast, if high fund skewness reflects managerial desire to cater to known skewness preferences of hedge fund investors, higher fund skewness is likely to be associated with lower future performance because idiosyncratic skewness is known to be associated with lower average returns (e.g., Boyer, Mitton, &Vorkink, 2009; Conrad, Dittmar, & Ghysels, 2013). Although investor preference for skewness is well documented, hedge fund studies have not identified a clear relation between historical skewness and future fund returns (Agarwal, Bakshi, & Huij, 2009; Bali, Brown, & Caglayan, 2012). Given this inconclusive evidence, fund-level skewness is likely to reflect both managerial skill and skewness preferences of investors.

In this article, we propose an improved performance measurement framework to more accurately characterize the relation between fund-specific skewness and future hedge fund returns. Specifically, we develop a fund skewness-adjusted alpha (ADJ alpha or α_{ADJ}) measure to predict managerial performance. Our new performance measure is an improvement over traditional factor model alphas, which do not explicitly account for skewness in observed returns. Consequently, these factor models cannot accurately evaluate positive fund return skewness strategies that limit downside risk.

Our ADJ alpha measure is motivated by Leland (1999) and Glode (2011).[1] Specifically, Leland (1999) posits that investors should evaluate a fund's alpha relative to its factor model risk exposure and information on fund-specific skewness because fund investment strategies that generate positive skewness limit downside risk. Comparing a fund manager who can generate a certain alpha to another who can generate the same alpha with more positive fund-specific skewness reveals that the latter is likely to be preferred by a fund investor because the manager may protect the portfolio from extreme negative returns. In fact, Glode (2011) shows that mutual fund managers generate incremental utility for investors through their skill in reducing losses in bad market states, despite appearing to underperform when assessed by unconditional alpha.[2]

Our new performance measure captures this economic intuition and reflects both a fund's traditional alpha relative to its factor model exposure and fund-specific skewness. Specifically, it assigns a higher performance ranking to fund managers with both high alpha and positive fund-specific skewness. We validate this new performance measure (ADJ alpha) using both simulated and actual hedge fund returns data, and then show that ADJ alphas are better than traditional alphas at predicting future hedge fund returns.

In particular, using a large sample of hedge fund returns from the Lipper/TASS database, we decompose total return skewness into systematic skewness and fund-specific skewness. We find that fund-specific skewness is persistent and positively associated with future hedge fund returns. This evidence is consistent with Leland's (1999) conjecture that positive fund-specific skewness likely reflects managerial skill in avoiding large losses. In addition, we demonstrate that funds that have both high alpha and greater fund-specific skewness exhibit superior future performance. This result supports the view that traditional performance measures systematically underrate (overrate) performance when returns have positive (negative) skewness. Consequently, accounting for fund-specific skewness in returns improves performance accuracy and allows us to better identify skilled hedge fund managers on an ex ante basis.

To further demonstrate the superiority of our new performance measure, we use the Fung and Hsieh (2004) factor model specification as the benchmark and compare our ADJ and standard alpha estimates. We find economically significant differences. Repeating this analysis on subsamples of returns drawn from crisis and noncrisis periods, we show that the ability of our measure to identify superior managerial performance ex ante is particularly valuable during periods of economic crisis when hedge fund returns are more likely to exhibit skewness. During these periods, portfolios formed using traditional performance measures underestimate fund alpha by up to 5.50%. This evidence suggests that adjusting for fund-specific skewness is valuable for assessing hedge fund performance during crisis periods.

These findings contribute to the growing hedge fund literature that attempts to identify skilled hedge fund managers' ex ante and cross-sectional determinants of hedge fund performance. Specifically, Aragon (2007) and Agarwal, Daniel, and Naik (2009) show that greater incentives, more discretion, and more stringent lockups are associated with higher future returns. Empirical evidence also suggests that greater exposure to macroeconomic factors and increased

[1] The findings by Goetzmann, Ingersoll, Spiegel, and Welch (2007) provide another motivation for our article. They show that performance measures estimated using standard statistical techniques inappropriately are at risk of manipulation by managers, and they cite hedge funds as a specific example of investments whose returns "can deviate substantially from normality" (p. 1505).

[2] Similarly, more recently, Barroso and Santa-Clara (2015) show that higher skewness at the portfolio level, through hedging or dynamic risk management, is associated with reduced drawdowns and enhanced future performance.

systematic risk and macroeconomic uncertainty are all associated with higher future returns (Bali, Brown, & Caglayan, 2011, 2012, 2014). Our results extend this literature and establish that managerial ability to limit drawdowns, as reflected in fund-specific return skewness, has incremental predictive power for future hedge fund returns.

We also contribute to the literature on nontraditional performance measurement methods. In particular, Barber and Lyon (1997), Chan and Lakonishok (1992), Knez and Ready (1997), and Dell'Aquila, Ronchetti, and Trojani (2003) show that methods that account for deviations from normality improve the accuracy of empirical results.[3] Amin and Kat (2003) control for nonnormality in returns through a nonparametric payoff distribution pricing model, whereas other studies use bootstrapping.[4] Similarly, Gupta and Liang (2005) propose value-at-risk measures to account for nonnormality in hedge fund returns, whereas Liang and Park (2010) show that risk measures that account for potential nonnormality are better able to predict hedge fund failure.[5]

In related studies, Kosowski, Naik, and Teo (2007) and Avramov, Kosowski, Naik, and Teo (2011) use a Bayesian method to demonstrate that forward-looking portfolios formed using their more precise estimates of historical alphas outperform standard alpha portfolios. Jagannathan, Malakhov, and Novikov (2010) use weighted least squares to reduce measurement errors in estimated alphas and develop a generalized method of moments model to assess the persistence of managerial over- or underperformance. More recently, Buraschi, Kosowski, and Sritrakul (2014) find large differences in skill estimates and improved out-of-sample performance when performance measures are corrected for endogenous risk taking by hedge fund managers.

We extend this line of research and show that hedge fund performance evaluation can be improved if fund-specific return skewness is explicitly taken into account. Our ADJ alpha measure is also related to Back, Crane, and Crotty (2018), who examine the relation between skewness and mutual fund performance. They show theoretically as well as empirically that alpha and residual (co)skewness are negatively correlated in the cross-section of returns. In contrast, we demonstrate that hedge funds with greater fund-specific skewness have superior future performance.

The remainder of our article is organized as follows. Section 2 describes the data and factor model specifications used in the empirical sections. Sections 3 to 5 present the main empirical results. Section 6 concludes.

2 | DATA AND BENCHMARK FACTORS

2.1 | Hedge fund data

We rank the performance of hedge funds using monthly net-of-fee returns of live and dead funds in the Lipper/TASS database. Our sample period is from January 1994 to April 2015. This period includes several extreme market conditions including the Long-Term Capital Management (LTCM) collapse in 1998, the dot-com crash in 2000 and 2001, and the subprime and credit crises in 2007 and 2008. As of the second quarter of 2015, the Lipper/TASS database contains 5,512 live and 14,496 dead hedge funds, including fund of funds.

Hedge fund returns are self-reported to Lipper/TASS, which may lead to inaccuracies.[6] Lipper/TASS does not keep information on funds that died before December 1993, which may lead to survivorship bias. Our sample of fund returns

[3] Our method is also related to the well-established "robust statistics" literature (for a summary, see Huber & Ronchetti, 2009), which demonstrates that the classical regression model's assumption of normally distributed error terms is inefficient when the underlying error distributions exhibit skewness.

[4] Bootstrapping, which has been applied to mutual fund returns (Kosowski, Timmermann, Wermers, & White, 2005), hedge fund returns (Kosowski, Naik, & Teo, 2007), and fund of funds returns (Fung, Hsieh, Naik, & Ramadorai, 2008), differs from our approach as it focuses on the statistical significance of ordinary least squares (OLS) alpha estimates. An ordinary OLS alpha and a bootstrapped OLS alpha are identical when applied to the same underlying data, but the standard error of the bootstrapped OLS alpha is measured more precisely. In contrast, our ADJ alpha measure explicitly accounts for fund-specific skewness and is larger (smaller) than an OLS alpha when returns exhibit positive (negative) skewness.

[5] Although not focusing on hedge funds, Kadan and Liu (2014) demonstrate the importance of including higher moment information when evaluating the performance of private equity funds, mutual funds, and momentum strategies.

[6] Evidence suggests that in some cases funds may misreport returns to the database vendors (see, e.g., Bollen & Pool, 2009; Agarwal, Daniel, & Naik, 2011).

runs from January 1994 to April 2015 to ensure that our results are not affected by survivorship bias.[7] We also remove funds with less than 2 years of returns data, funds that report only gross returns, funds that do not report monthly returns or investment style information, and fund of funds.

We group funds according to the Lipper/TASS classifications: Convertible Arbitrage, Event Driven, Equity Market Neutral, Emerging Markets, Fixed Income Arbitrage, Global Macro, Long–Short Equity Hedge, Managed Futures, and Multi Strategy.[8] Our final sample consists of 3,044 live hedge funds and 4,774 dead hedge funds.

2.2 | Summary statistics

Table 1 presents summary statistics for the funds in our sample. The table lists the number of funds and the equal-weighted cross-sectional mean of each fund's mean monthly return, standard deviation, Sharpe ratio, and skewness. Altogether, 92% of the funds can be classified as having negatively or positively skewed returns that are significant. Funds are then separated into the following six categories based on the significance level of their sample skewness *t*-statistics: (a) live negative skewness (1,695 funds), (b) live no skewness (255 funds), (3) live positive skewness (1,094 funds), (d) dead negative skewness (2,417 funds), (e) dead no skewness (571 funds), and (f) dead positive skewness (1,786 funds).

Among the fund groups, Convertible Arbitrage, Event Driven, Equity Market Neutral, Emerging Markets, Fixed Income Arbitrage, and Multi-Strategy funds have more negative skewness than positive skewness, whereas Long–Short Equity Hedge and Global Macro funds are more balanced. More Managed Futures funds exhibit positive rather than significant negative skewness.

Comparing funds classified as negative skewness, no skewness, and positive skewness, the Sharpe ratios improve with skewness for both live funds (0.38, 0.90, and 0.73, respectively) and dead funds (0.42, 0.45, and 0.94, respectively). This evidence provides the first hint that fund skewness and performance may be positively correlated.

2.3 | Choice of benchmark factors

To assess a manager's risk-adjusted performance, we estimate the following factor model:

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

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

The different strategies used by hedge fund managers make it difficult to choose factors that can accurately characterize the return-generating process across the universe of hedge funds. In our main empirical analysis, we focus on the Fung and Hsieh (2004) factor model, which does a particularly good job of characterizing hedge fund returns.

The Fung and Hsieh (2004) model specifies three trend-following risk factors, including bond (*PTFSBD*), currency (*PTFSFX*), and commodity (*PTFSCOM*). This set is augmented by the following two equity-oriented risk factors: *SNPRF*, which is the excess total return on the Standard & Poor's 500 index, and *SCMLC*, which is the size spread factor (Wilshire Small Cap 1750 – Wilshire Large Cap 750 monthly total return). The model also contains the following two bond-oriented risk factors: *BD10RET*, which is the monthly change in the 10-year Treasury constant maturity yield (month-end to month-end), and *BAAMTSY*, which is a credit spread factor (monthly change in the Moody's Baa yield less the 10-year Treasury constant maturity yield [month end to month end]).[9]

[7] See Brown, Goetzmann, and Ibbotson (1999) for a discussion of survivorship bias in hedge fund performance estimates.

[8] We do not report separate results for the Dedicated Short Bias style because the sample has only 114 funds. However, they are included in the full-sample results.

[9] See Fung and Hsieh (2001) for details on the construction of the trend-following factors.

TABLE 1 Summary statistics: Hedge fund returns

	Negative-skewness funds					No-skewness funds					Positive-skewness funds				
	N	μ	σ	SR	Skew	N	μ	σ	SR	Skew	N	μ	σ	SR	Skew
Panel A. Live funds															
Convertible arbitrage	49	6.24	10.12	0.55	−2.08	18	−6.12	10.01	−0.62	0.03	16	−3.24	19.50	−0.03	0.50
Event driven	267	3.00	12.12	0.31	−1.09	39	3.36	14.24	0.42	0.00	102	10.56	16.73	0.69	1.26
Equity market neutral	79	4.08	9.46	0.28	−1.24	11	4.56	8.63	0.38	−0.05	48	8.16	8.14	1.07	0.77
Emerging markets	131	9.96	17.04	0.59	−1.09	11	12.96	14.86	0.87	0.00	81	14.40	18.08	0.97	0.96
Fixed income arbitrage	58	4.44	7.03	0.48	−1.64	2	4.08	7.72	0.55	0.08	35	9.60	11.15	1.11	1.16
Global macro	76	4.44	13.86	0.28	−0.73	21	2.40	14.55	0.07	0.01	76	9.72	14.62	0.62	0.84
Long–short equity hedge	670	6.36	13.82	0.38	−0.80	74	10.32	12.92	0.83	−0.01	439	9.96	15.17	0.62	0.88
Managed futures	86	5.28	17.15	0.35	−0.76	37	4.20	18.26	0.21	0.00	180	9.36	18.53	0.42	0.65
Multi-strategy	220	3.96	9.80	0.31	−1.15	32	1.80	9.87	0.10	−0.03	82	9.72	13.23	0.62	0.94
All funds	1,695	5.40	12.75	0.38	−1.01	255	8.40	13.58	0.90	−0.01	1,094	9.84	15.31	0.73	0.89
Panel B. Dead funds															
Convertible arbitrage	119	5.52	7.52	0.48	−1.32	23	4.44	4.64	0.62	−0.04	38	8.88	7.14	2.11	1.07
Event driven	214	6.36	9.42	0.80	−1.04	42	9.96	12.89	0.87	0.00	111	10.92	13.58	1.07	1.20
Equity market neutral	178	3.84	8.63	0.17	−1.57	47	6.24	6.72	0.62	−0.01	106	8.16	8.97	0.76	0.87
Emerging Markets	283	6.84	17.98	0.38	−1.26	38	7.32	20.33	0.59	0.00	142	14.16	20.58	0.69	0.85
Fixed income arbitrage	158	1.80	10.25	0.80	−2.51	11	3.60	6.20	0.14	0.01	63	9.60	6.03	3.26	1.02
Global macro	112	2.28	12.54	0.03	−0.83	32	3.24	11.33	0.17	−0.01	138	7.68	15.03	0.31	0.95
Long–short equity hedge	817	6.24	15.00	0.35	−0.85	233	7.44	13.51	0.38	0.00	711	13.92	18.53	0.80	0.94
Managed futures	161	4.56	16.04	0.21	−0.87	76	5.04	16.59	0.14	0.00	254	8.40	19.85	0.24	0.74
Multi-strategy	291	1.44	10.29	0.35	−1.43	50	6.84	10.67	0.48	−0.01	141	10.32	10.67	1.49	1.06
All funds	2,417	4.92	12.85	0.42	−1.19	571	6.60	12.82	0.45	0.00	1,786	11.40	16.00	0.94	0.94

Note. This table reports the following summary statistics: number of funds (N); equally weighted averages of the mean monthly return (μ); standard deviation of monthly returns (σ); Sharpe ratio (SR); and skewness (Skew), calculated using all returns for each fund. A fund is classified as negative or positive skewness if the estimated sample skewness t-statistic is significant at the 5% level. The sample period is from January 1994 to April 2015.

The hedge fund literature also contains evidence on the importance of macroeconomic variables for predicting hedge fund returns (see, e.g., Avramov et al., 2011; Avramov, Barras, & Kosowski, 2013; Bali et al., 2011, 2014; Caglayan & Ulutas, 2014). Motivated by these findings, we use a macroeconomic factor model as an alternative. Specifically, hedge fund portfolio returns are benchmarked against long–short portfolios of hedge funds that are formed based on their rolling exposure to a range of macroeconomic variables. The following equation is estimated:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,1}LSDIV_t + \beta_{i,2}LSIP_t + \beta_{i,3}LSINF_t + \beta_{i,4}LSDEF_t + \beta_{i,5}LSNFP_t + \varepsilon_{i,t}. \tag{2}$$

Here, $LSDIV_t$, $LSIP_t$, $LSINF_t$, $LSDEF_t$, and $LSNFP_t$ reflect the monthly dividend yield on the Russell 3000 stock index, and the monthly change in industrial production, inflation, default risk, and nonfarm payrolls, respectively. To create the factors for each macroeconomic variable, each month, we estimate the rolling exposure for each fund to the macroeconomic variable (estimated using a 24-month rolling window). Beginning in January 1996, we sort funds into deciles each month based on their prior-month beta to the factor. Finally, we form the factors as long–short portfolios of hedge funds where we long the top decile and short the bottom decile of funds.

3 | HISTORICAL FUND-SPECIFIC SKEWNESS AND FUTURE HEDGE FUND RETURNS

If fund-specific skewness reflects managerial skill, it should persist over time. In this section, we test for persistence in the skewness of hedge fund returns.

3.1 | Estimating fund-specific skewness

To measure fund-specific skewness, we first estimate Fung and Hsieh's (2004) factor model for each hedge fund. Then, we take the residuals, ε_i, and estimate fund-specific skewness for fund *i* at time *t*, $FSK_{i,t}$, as:

$$FSK_{i,t} = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{\varepsilon_{i,t}-\overline{\varepsilon_i}}{\sigma_{\varepsilon,t}}\right)^3. \tag{3}$$

Here, $\sigma_{\varepsilon,t}$ is the standard deviation of residual returns, and *n* is the number of observations. We also estimate the total skewness, $TSK_{i,t}$, of the fund using its net-of-fee returns, which allows us to estimate the systematic skewness, $SSK_{i,t}$, as:

$$SSK_{i,t} = TSK_{i,t} - FSK_{i,t}. \tag{4}$$

3.2 | *FSK* persistence: Historical versus future *FSK*

To measure skewness persistence, we estimate *FSK* for each fund in our sample with the first 2 years of monthly returns (January 1994 to December 1995) and then use a 24-month rolling window to generate monthly time-series estimates of observed *FSK*. We also estimate 12-, 24-, 36-, and 48-month-ahead values for *FSK* and run the following Fama and MacBeth (1973) cross-sectional regression each month:

$$FSK_{i,t+n} = \gamma_t + \delta_t FSK_{i,t} + \varepsilon_{i,t}. \tag{5}$$

Here, $FSK_{i,t+n}$ is the *n*-month-ahead future fund-specific skewness, $FSK_{i,t}$ is historical fund-specific skewness at time *t*, and γ_t and δ_t are the intercept and slope coefficient estimates, respectively.

The skewness persistence results are reported in Table 2. Our evidence confirms that there is persistence in fund-specific skewness. The average δ coefficients are positive and statistically significant at horizons ranging from 24 to

TABLE 2 Persistence in fund-specific skewness

	N-month-ahead fund-specific skewness					
Intercept	12 Month	24 Month	36 Month	48 Month	Avg. *N*	Avg. R^2
0.00	0.01				1,501	0.09%
(0.33)	(1.22)					
0.03***		0.06***			1,286	0.48%
(3.50)		(10.34)				
0.04***			0.09***		1,099	0.76%
(3.74)			(12.36)			
0.06***				0.11***	937	0.99%
(4.24)				(9.29)		

Note. This table reports average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of future fund-specific skewness on historical fund-specific skewness. In the first stage, fund-specific skewness is estimated for each fund from the time-series regressions of hedge fund excess returns on the Fung and Hsieh (2004) factors over a 24-month rolling window. In the second stage, each month the cross-section of future funds' fund-specific skewness is regressed on the current month funds' fund-specific skewness. Results are reported for 12-, 24-, 36-, and 48-month-ahead fund-specific skewness. Newey–West (1987) adjusted *t*-statistics are reported in parentheses below mean coefficient estimates. The sample period is January 1996 to April 2015.
***Significant at the 0.01 level.

48 months, with *t*-statistics ranging from 9.29 to 12.36. The statistical significance disappears only when we consider the relatively short 12-month-ahead skewness estimation window. The *t*-statistic of 1.22 in this instance suggests that 12 fund-month observations yield noisy estimates of fund-specific skewness.

3.3 | Fund-specific skewness and future hedge fund returns

We next use both cross-sectional regressions and sorting methods to assess the relation between fund-specific skewness and future hedge fund returns more accurately.

3.3.1 | Regression estimates

We begin by estimating the fund-specific skewness for each fund in our sample. We start with first 2 years of monthly returns (January 1994 to December 1995) and then use a 24-month rolling window estimation period to generate monthly time-series estimates of fund-specific skewness. In the second stage, which begins in January 1996, we run a series of Fama and MacBeth (1973) cross-sectional regressions of 1- and 12-month-ahead individual fund benchmark-adjusted fund returns on fund-specific skewness:

$$BAR_{i,t+1:t+n} = \gamma_t + \delta_t FSK_{i,t} + \varepsilon_{i,t}. \tag{6}$$

Here, $BAR_{i,t+1:t+n}$ is the benchmark-adjusted return on fund *i* for period $t+1$ to $t+n$, $FSK_{i,t}$ is the fund-specific skewness estimate at time *t* generated in the first stage, and γ_t and δ_t are the intercept and slope coefficients, respectively.

Table 3 reports the skewness-return regression estimates for the full sample. Crisis and noncrisis subsample results are also included to assess the skewness-return relation under different market conditions.[10] We find that historical fund-specific skewness is positively related to 1- and 12-month-ahead benchmark-adjusted returns for the full sample

[10] We follow Billio et al. (2011) and define crisis 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). We extend this, adding the 2009 European Debt crisis (December 2009–September 2010) and the U.S. debt downgrade (August 2011).

TABLE 3 Historical skewness and future returns: Fama–MacBeth cross-sectional regression estimates

	1-month-ahead returns			12-month-ahead returns				
Intercept	FS	Crisis	No Crisis	FS	Crisis	No Crisis	Avg. *N*	Avg. R^2
0.36***	0.16***						1,725	0.34%
(6.82)	(4.58)							
0.54***		0.00					2,193	0.18%
(4.29)		(–0.02)						
0.34***			0.17***				1,732	0.35%
(5.75)			(4.83)					
0.38***				0.09***			1,501	0.45%
(9.98)				(3.82)				
0.50***					0.15**		1,839	0.20%
(12.63)					(2.52)			
0.36***						0.09***	1,528	0.49%
(7.99)						(3.13)		

Note. This table reports average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of future benchmark-adjusted hedge fund returns on current fund-specific skewness. In the first stage, monthly fund-specific skewness is estimated for each fund from the time-series regressions of hedge fund excess returns on the Fung and Hsieh (2004) factors over a 24-month rolling window. In the second stage, each month the cross-section of funds' future benchmark-adjusted return is regressed on the funds' fund-specific skewness. In rows 1–3, we report coefficients for 1-month-ahead benchmark-adjusted returns for the full sample (FS), crisis (Crisis), and noncrisis (No Crisis) periods. In rows 4–6, we report coefficients for 12-month-ahead benchmark-adjusted returns. Newey–West (1987) adjusted *t*-statistics are reported in parentheses below mean coefficient estimates. Crisis and noncrisis periods are classified following Billio et al. (2011). The sample period is January 1996 to April 2015.
***Significant at the 0.01 level.
**Significant at the 0.05 level.

and in three of the four subsamples, with *t*-statistics ranging from 2.52 to 4.83. The relation is not significant for 1-month-ahead results in crisis periods. This evidence is not surprising, given the elevated volatility and accompanying noise in short-term hedge fund return during periods of economic uncertainty (Billio, Getmansky, & Pelizzon, 2011).

3.3.2 | Sorting results

In the next test, each month from January 1996 to April 2015, we form quintile portfolios by sorting hedge funds based on their fund-specific skewness estimated from the residuals from the Fung and Hsieh (2004) factor model. Quintile 1 contains funds with the lowest fund-specific skewness and Quintile 5 contains funds with the highest fund-specific skewness. For each portfolio, we report the 1-month-ahead mean return, Sharpe ratio, Fung and Hsieh (2004) alpha, and macroeconomic factor alpha. The results reported in Table 4 confirm the positive relation between fund-specific skewness and 1-month-ahead hedge fund return. The top quintile portfolio outperforms the bottom quintile portfolio by 2.44% on a risk-adjusted basis.

We also conduct double sorts using historical fund-specific skewness and Fung and Hsieh (2004) alpha estimates.[11] The results reported in Table 5 provide further evidence on the relation among historical fund-specific skewness, historical alpha, and future hedge fund return. For the subset of the most positively skewed funds, the annual risk-adjusted return for the high historical alpha tercile is 8% higher than the return for the low historical alpha tercile, with *t*-statistics of 4.64 for the Fung and Hsieh (2004) alpha and 3.63 for the macroeconomic alpha. This return differential is

[11] Each month, funds are sorted into tercile portfolios based on historical fund-specific skewness estimated using the preceding 24 months of returns. Within each tercile, funds are then sorted into terciles based on the historical Fung and Hsieh (2004) alpha estimated using the preceding 24 months of returns.

TABLE 4 Performance of funds sorted on fund-specific skewness

	Fund-specific skewness quintile					
	1	2	3	4	5	Diff.
Mean return	7.70***	7.46***	8.31***	8.83***	9.94***	2.24**
	(5.50)	(4.88)	(5.39)	(5.85)	(7.07)	(2.21)
Sharpe ratio	0.84	0.73	0.85	0.95	1.19	0.36
FH alpha	3.48***	3.01***	3.85***	4.46***	5.91***	2.44*
	(3.22)	(3.35)	(3.99)	(4.65)	(6.34)	(1.71)
Macro alpha	4.50***	4.39***	5.17***	5.50***	6.73***	2.23
	(3.76)	(3.73)	(4.19)	(4.45)	(5.75)	(1.33)

Note. In this table, each month funds are sorted into quintile portfolios based upon Fung and Hsieh (2004) fund-specific skewness, estimated using the preceding 24 months of returns. Mean returns, Sharpe ratios, Fung and Hsieh (2004) alphas (FH alpha), and macroeconomic alphas (Macro alpha) are reported. The final column shows the differences in monthly returns, the difference in Sharpe ratios, the difference in alphas with respect to the Fung and Hsieh (2004) model, and the difference in alphas with respect to the macroeconomic model between Quintiles 5 and 1. Newey–West (1987) adjusted *t*-statistics are reported in parentheses below coefficient estimates. Performance measures are estimated using all available returns from January 1996 to April 2015.
***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

about 4% per year, with slightly lower statistical significance for the medium skewness tercile and marginal statistical significance for the lowest skewness tercile. Overall, the sorting results provide further support for our key conjecture that fund-specific return skewness can predict future fund performance.

4 | IDENTIFYING SKILLED HEDGE FUND MANAGERS

In this section, we present our new performance measure (ADJ alpha) that accounts for skewness in fund returns.

4.1 | ADJ alpha estimation

To compute the new ADJ alpha measure, we use the residual augmented least squares (RALS) method of Im and Schmidt (2008).[12] In particular, we adjust the risk-adjusted performance ranking of managers upward (downward) if they generate the same level of return as the ordinary least square (OLS) alpha, but with positive (negative) return skewness. We choose the RALS estimator for this performance adjustment because it is relatively easy to estimate using two-stage least squares. Specifically, we augment the linear factor model with two new variables that are functions of the OLS residuals derived from that factor model to account for skewness in fund returns.

We use a three-step procedure. First, we estimate the factor model using OLS and all available return data for the fund. Next, we create the skewness function $\hat{w}$ using each fund's OLS residual. This function consists of two terms: (a) $\hat{u}_t^2 - \hat{\sigma}^2$ and (b) $\hat{u}_t^3 - m_3 - 3\hat{\sigma}^2\hat{u}_t$. Here, $\hat{u}_t$ is the OLS residual at time t, m_3 is the OLS residual skewness, and $\hat{\sigma}^2$ is the OLS residual variance. By setting $m_3 = 0$, we can estimate the linear factor model augmented with $\hat{u}_t^2 - \hat{\sigma}^2$ and $\hat{u}_t^3 - 3\hat{\sigma}^2\hat{u}_t$. The residual skewness is reflected in the new ADJ alpha.[13] For estimation purposes, the two new regressors

[12] See the Appendix for details of the RALS estimator.

[13] If $m_3 = \frac{\sum u_t^3}{T}$, the RALS alpha coefficient is invariant to skewness, though the RALS coefficients are estimated more precisely than OLS (Im & Schmidt, 2008). Taylor and Peel (1998), Sarno and Taylor (1999), Gallagher and Taylor (2000), and Garino and Sarno (2004) use an identical specification.

TABLE 5 Performance of funds sorted on historical fund-specific skewness and alpha

Panel A. Portfolios sorted by fund-specific skewness and alpha

	Low fund–specific skewness			Medium fund–specific skewness			High fund–specific skewness		
	Low alpha	Medium alpha	High alpha	Low alpha	Medium alpha	High alpha	Low alpha	Medium alpha	High alpha
Mean return	6.65***	6.08***	9.96***	6.64***	7.06***	11.23***	5.96***	8.43***	14.04***
	(3.32)	(5.26)	(5.57)	(3.97)	(5.73)	(5.45)	(3.76)	(7.28)	(7.29)
Sharpe ratio	0.46	0.69	0.94	0.55	0.83	0.96	0.49	1.15	1.36
FH alpha	1.86	2.23***	5.62***	1.96*	3.13***	6.60***	1.45	4.60***	9.82***
	(1.07)	(3.16)	(4.35)	(1.75)	(4.21)	(4.35)	(1.33)	(6.20)	(6.83)
Macro alpha	2.73	3.71***	6.92***	3.34**	4.15***	7.66***	2.70**	5.48***	10.64***
	(1.54)	(4.15)	(4.35)	(2.48)	(4.39)	(4.24)	(2.00)	(5.95)	(6.16)

Panel B. Performance difference between high and low alpha portfolios

	Low fund–specific skewness High – low alpha	Medium fund–specific skewness High — low alpha	High fund–specific skewness High — low alpha
Mean return	3.31	4.59***	8.08***
	(1.63)	(2.95)	(5.67)
Sharpe ratio	0.48	0.40	0.87
FH alpha	3.76*	4.65**	8.37***
	(1.74)	(2.47)	(4.64)
Macro alpha	4.19*	4.32*	7.95***
	(1.76)	(1.92)	(3.63)

Note. In this table, each month funds are sorted into tercile portfolios based on fund-specific skewness, estimated using the preceding 24 months of returns. Within each tercile, funds are sorted into terciles based on the Fung and Hsieh (2004) alpha, estimated using the preceding 24 months of returns. Mean returns, Sharpe ratios, Fung and Hsieh (2004) alphas (FH alpha), and macroeconomic alphas (Macro alpha) are reported in Panel A. Panel B shows the differences in monthly returns, differences in Sharpe ratios, differences in alphas with respect to the Fung–Hsieh (2004) model, and differences in alphas with respect to the macroeconomic model between alpha Terciles 3 and 1. Newey–West (1987) adjusted *t*-statistics are reported in parentheses below coefficient estimates. Performance measures are estimated using all available returns from January 1996 to April 2015.

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

act as additional risk factors and are functions of the third and fourth moments of the first-stage residuals constructed under the assumption that first-stage residuals are independent of the initial factors used to account for fund risk.[14]

4.2 | Skewness-sensitive performance estimates

We present our main empirical results using both simulations and actual hedge fund data. Our key finding is that OLS performance estimates systematically underrate managers when fund returns exhibit positive skewness and systematically overrate managers when the returns exhibit negative skewness. Our ADJ alpha measure allows us to identify superior hedge fund managers on an ex ante basis because it can detect performance persistence more effectively than traditional performance measures.

[14] To ensure that our results are robust to the assumption that the first-stage residuals are independent of the initial factors used to benchmark risk, we repeat all analysis limiting our sample to the 3,870 funds that fully satisfy this condition. In unreported results, we find that our results are stronger for this group of funds. There is a larger performance differential between portfolios sorted on skewness-adjusted and OLS alphas.

TABLE 6 Descriptive statistics of simulated hedge fund monthly returns at different fund-specific skewness levels

	Fund-Specific skewness									
	−2.0	−1.5	−1.0	−0.5	0.0	0.5	1.0	1.5	2.0	Diff.
Mean	8.40	8.40	8.40	8.40	8.40	8.40	8.40	8.40	8.40	0.00
Std. dev.	6.93	6.93	6.93	6.93	6.93	6.93	6.93	6.93	6.93	0.00
Max.	5.20	5.30	5.40	5.60	5.80	6.10	6.50	6.90	7.30	2.10
Min.	−9.30	−8.90	−8.50	−8.10	−7.80	−7.60	−7.40	−7.30	−7.20	2.10
Max. DD	−31.80	−31.10	−30.20	−28.80	−27.20	−28.00	−26.00	−23.90	−22.50	9.30

Note. This table reports the return distributions of simulated hedge funds from January 1994 to April 2015. Descriptive statistics of the simulated returns with fund-specific skewness from −2.0 to + 2.0 are reported. Mean and Std. dev. are the annualized mean and standard deviation and Min. and Max. are the minimum and maximum of monthly returns for the 1,000 simulated hedge fund distributions estimated at each skewness level. Max. DD is the maximum peak to trough drawdown an investor would have experienced by investing in simulated hedge fund returns at each skewness level. The final column shows the difference in mean, standard deviation, minimum and maximum monthly returns, and maximum drawdowns between the +2.0 and −2.0 fund-specific skewness simulations.

The ADJ alphas are performance metrics that have the advantages of OLS alphas but also increase (decrease) the ranking of a manager to reflect the positive (negative) fund-specific skewness in their returns. An investor benefits if a fund manager can generate the same alpha as another manager but can do it with more positive fund-specific skewness because positive fund-specific skewness reflects the skill needed to avoid exposing the portfolio to extreme negative returns and drawdowns.

4.2.1 | Skewness and performance rankings: Simulation-based evidence

We first use simulations to demonstrate differences between OLS and ADJ alphas. We allow for fund-specific skewness in returns by considering hedge fund portfolios that are identical except for skewness in the error distribution. This exercise allows us to compare performance ratings based on OLS and ADJ alphas for different levels of fund-specific skewness.

In our simulations, we first estimate Equation (1) with OLS for the monthly excess returns of the HFRI Aggregate Hedge Fund Index over January 1994 to April 2015. Next, we simulate $\tilde{e}_t^i$, a random series of errors from the Pearson distribution with standard deviation and kurtosis set equal to those estimated for the Aggregate Hedge Fund Index, and various skewness levels S_i. We allow S_i to vary between −2.0 and +2.0 in increments of 0.5.[15] We then generate $\tilde{r}_{it}$, a simulated hedge fund return series, as follows:

$$\tilde{r}_{it} = \hat{\alpha}_i + \sum_{k=1}^{K} \hat{\beta}_k^i F_{k,t} + \tilde{e}_t^i. \tag{7}$$

We repeat the simulation 1,000 times for each S_i.

Table 6 reports descriptive statistics for simulated hedge funds from January 1994 to April 2015. The mean returns and standard deviations are identical across the fund groups, but large differences occur in exposure to large profits and losses. For example, for the most positive (negative) fund-specific skewness funds, the maximum monthly return is +7.3% (+5.2%) and the most negative (positive) fund-specific skewness funds have maximum monthly losses of −9.3% (−7.2%). Figure 1, which compares the maximum drawdowns, is striking. The most negative fund-specific skewness funds have maximum drawdowns of −31.8% compared to −22.5% for the most positive fund-specific skewness funds, a difference of 9.3%.

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

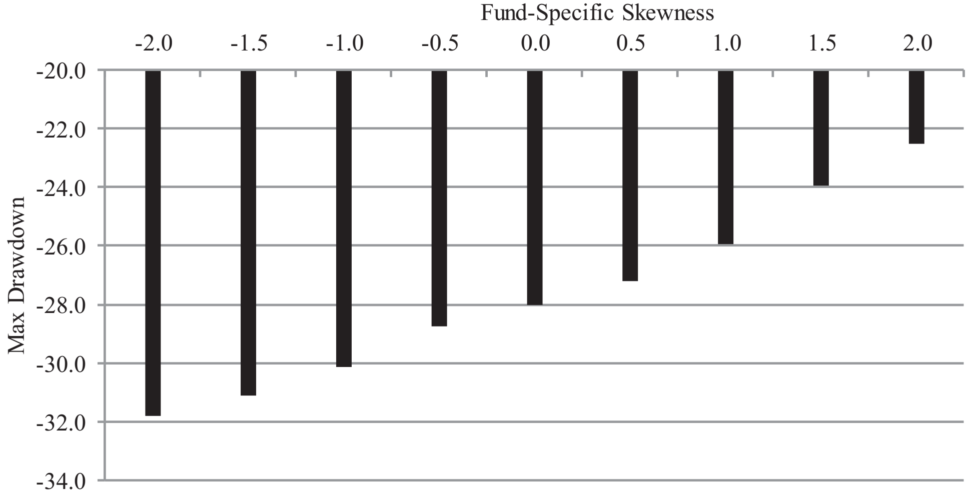

FIGURE 1 **Simulated maximum drawdown at different fund-specific skewness levels**
Note. This figure reports the maximum peak to trough drawdown of simulated hedge fund returns with fund-specific skewness ranging from −2.0 to +2.0. Max drawdown is the maximum peak to trough drawdown, reported from 1,000 simulated hedge fund distributions estimated at each fund-specific skewness level. Simulated hedge fund returns are formed as follows. We first estimate Equation (1) with ordinary least squares for the monthly excess returns of the HFRI Aggregate Hedge Fund Index from January 1994 to April 2015. We next generate a random series of errors from the Pearson distribution with standard deviation and kurtosis set equal to those estimated for the Aggregate Hedge Fund Index and the relevant fund-specific skewness level. Finally, we generate a simulated hedge fund return series using the Fung and Hsieh (2004) factor returns, estimated coefficients, and generated errors

In Panel A of Table 7, we report the OLS alpha estimate ($\hat{\alpha} = 0.29\%$, 3.52% annualized) and coefficient estimates of each of the Fung and Hsieh (2004) risk factors, that is, $\hat{\beta}_k^i$. We also present the residual standard deviation ($\hat{\sigma} = 0.01$), residual kurtosis ($\hat{K} = 5.35$), and residual skewness ($\hat{S} = 0.06$). Last, we estimate both OLS and ADJ alphas for each of the simulated portfolios. In Panel B, we report simulation results with annualized $\hat{\alpha}_i = 3.53\%$, as estimated for the HFRI Aggregate Hedge Fund Index.

We find that the ADJ alphas, which allow for fund-specific skewness in returns, are sensitive to cross-sectional differences in S_i, but the OLS alpha estimates are similar. Furthermore, the OLS alphas overstate managerial performance for negative values of S_i (i.e., ADJ alphas are smaller than OLS alphas), but the OLS alphas understate managerial performance for positive values of S_i (i.e., ADJ alphas are larger than OLS alphas).

Overall, the simulation evidence confirms that the preference for positive fund-specific skewness and the avoidance of negative fund-specific skewness are rational if they do not come at the cost of the traditional alpha. Furthermore, the efficiency gain obtained from using an estimator that allows for fund-specific skewness in fund returns, which is reflected in higher values of ρ^*, becomes more pronounced as the return skewness, S_i, increases in absolute value.

4.2.2 | Actual performance rankings

When we consider the actual returns of individual hedge funds, we find results that are similar to the simulation results. Table 8 reports the performance of all funds in the sample estimated by the two approaches when funds are sorted into skewness deciles. The results are striking. OLS misstates fund performance for all fund deciles except decile 6, where skewness is close to zero. The OLS performance overstatement increases from 0.48% to 2.28% per year as skewness in returns becomes more negative, and the OLS performance understatement increases from 0.72% to 4.68% per year as skewness in returns becomes more positive.

TABLE 7 Skewness adjusted (ADJ) alpha simulation results

Panel A. HFRI index Fung and Hsieh factor model											
α	β_{SNPRF}	β_{SCMLC}	$\beta_{BD10RET}$	β_{BAAMTS}	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$	$\bar{R}^2$	$\hat{\sigma}$	$\hat{K}$	$\hat{S}$
3.52***	0.31***	0.20***	−0.02	−0.04***	−0.01	0.01	0.00	0.71	0.01	5.35	0.06
(4.38)	(18.74)	(9.58)	(−1.60)	(−3.68)	(−1.40)	(1.55)	(0.21)				

Panel B. Fung and Hsieh performance measures at different fund-specific skewness levels									
Fund-specific skewness	−2.0	−1.5	−1.0	−0.5	0.0	0.5	1.0	1.5	2.0
OLS alpha	3.52***	3.53***	3.52***	3.54***	3.54***	3.53***	3.53***	3.53***	3.51***
	(4.46)	(4.52)	(4.47)	(4.44)	(4.39)	(4.37)	(4.37)	(4.38)	(4.35)
ADJ alpha	−1.01***	−0.84**	−0.35	1.02*	3.54***	6.03***	7.45***	8.00***	8.00***
	(−3.57)	(−2.51)	(−0.80)	(1.94)	(5.96)	(11.44)	(17.97)	(24.74)	(30.30)
OLS alpha error	4.53***	4.38***	3.87***	2.51***	0.00	−2.50***	−3.92***	−4.46***	−4.49***
	(233.30)	(283.51)	(279.61)	(165.41)	(0.30)	(−163.71)	(−291.66)	(−274.72)	(−245.98)
ρ^*	0.94	0.89	0.78	0.59	0.43	0.59	0.78	0.89	0.94

Note. Panel A reports results for estimating the Fung and Hsieh (2004) factor model, with ordinary least squares (OLS), for the monthly returns of the HFRI Aggregate Hedge Fund Index from January 1994 to April 2015. This yields an annualized alpha estimate ($\hat{\alpha} = 3.52$) and coefficients on each of the Fung and Hsieh (2004) risk factors: excess return on the market (β_{SNPRF}), size spread (β_{SCMLC}), change in the 10-year yield ($\beta_{BD10RET}$), credit spread (β_{BAAMTS}), and bond (β_{PTFSBD}), FX (β_{PTFSFX}), and commodity ($\beta_{PTFSCOM}$) trend-following factors. Also reported are adjusted R^2 ($\bar{R}^2$) residual standard deviation ($\hat{\sigma}$), residual kurtosis ($\hat{K}$), and residual skewness ($\hat{S}$). Panel B reports the estimated performance measures for simulated HFRI Aggregate monthly returns with fund-specific skewness from −2.0 to + 2.0 and annualized ordinary least square (OLS) alpha set equal to 3.52 from January 1994 to April 2015. The first (last) column in Panel B reports the results for the 1,000 simulated fund returns with the most negative (positive) skewness. In Panel B, the first row reports the mean annualized OLS alpha estimate for each skewness level, the second row reports the mean annualized ADJ alpha (alpha adjusted for skewness) estimate for each skewness level, the third row reports the difference between the mean annualized ADJ alpha and OLS alpha at each skewness level, and the final row reports ρ^*, the efficiency gain from using the ADJ alpha estimator relative to OLS. Newey–West (1987) adjusted *t*-statistics are reported in parentheses below coefficient estimates.

***Significant at the 0.01 level.

*Significant at the 0.10 level.

TABLE 8 Alphas of individual hedge funds sorted on historical skewness

Skewness Decile	1	2	3	4	5	6	7	8	9	10
Skewness	−3.13	−1.24	−0.75	−0.47	−0.25	−0.06	0.14	0.39	0.78	1.02
OLS alpha	−0.96	1.08	2.04	2.52	2.40	2.40	4.08	5.64	7.08*	11.64**
	(0.44)	(0.83)	(0.74)	(0.83)	(0.89)	(0.85)	(1.18)	(1.42)	(1.95)	(2.37)
ADJ alpha	−3.24	−1.44	0.36	1.56	1.92	2.28	4.80	7.44**	10.08***	16.32***
	(−0.06)	(0.36)	(0.40)	(0.66)	(0.84)	(0.87)	(1.50)	(1.98)	(2.88)	(3.89)
OLS alpha error	2.28***	2.52***	1.68***	0.96***	0.48***	0.12	−0.72***	−1.80***	−3.00***	−4.68***
	(5.17)	(10.62)	(9.01)	(4.60)	(2.81)	(0.45)	(−3.62)	(−7.20)	(−9.10)	(−6.38)

Note. This table reports the performance measures for individual hedge funds sorted into skewness deciles. The first (last) column reports the decile of funds with the lowest (highest) skewness. The first row reports the mean estimate of skewness for each decile. The second row reports the mean annualized ordinary least squares (OLS) alpha estimate. The third row reports the mean annualized ADJ alpha (alpha adjusted for skewness) for each decile. The fourth row reports the estimated OLS performance rating error. Newey–West (1987) adjusted *t*-statistics are reported in parentheses below coefficient estimates. Results are estimated using all available returns for each fund from January 1994 to April 2015.

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

We find similar results when we repeat this analysis for subsets of funds that use different strategies.[16] OLS consistently overrates managerial performance for negatively skewed funds and consistently underrates managerial performance for hedge funds with positive skewness. Specifically, the OLS performance assessment ranking error is largest for Managed Futures fund style. Here, OLS overstates the performance of the most negatively skewed funds by 6.72% and understates the performance of the most positively skewed funds by 7.44%. Other strategies where the performance of positively skewed funds is heavily understated by OLS are Emerging Markets and Global Macro funds. Performance misrating is greatest for Fixed Income Arbitrage funds with negatively skewed returns.

5 | SKEWNESS IN FUND RETURNS AND SELECTION OF HEDGE FUND MANAGERS

Our results so far provide strong evidence that assessing hedge fund performance based on OLS alphas underrates the skills of hedge fund managers who earn positively skewed returns and overrates the skills of fund managers who earn negatively skewed returns. In this section, we investigate whether managerial selection can be improved ex ante by selecting hedge funds based on historical ADJ alphas instead of historical OLS alphas.

5.1 | ADJ alpha and future hedge fund returns

We first estimate historical ADJ alphas and OLS alphas for the first 2 years of monthly returns (January 1994 to December 1995) and then for a 24-month rolling window. This procedure generates monthly time-series estimates of ADJ and OLS alphas for each fund in the sample. Then, we estimate 12-month-ahead benchmark-adjusted returns for each fund. Finally, we estimate the following Fama and MacBeth (1973) cross-sectional regressions of future benchmark-adjusted returns on historical OLS and ADJ alphas:

$$BAR_{i,t+1:t+12} = \gamma_t + \delta_t ALP_{i,t} + \varepsilon_{i,t}. \tag{8}$$

Here, $BAR_{i,t+1:t+12}$ is the 12-month-ahead benchmark-adjusted fund return, $ALP_{i,t}$ is the ADJ or OLS alpha observed at time t, and γ_t and δ_t are the intercept and slope coefficients, respectively.

We report the results for the full sample as well as crisis and noncrisis subsamples in Table 9. Panel A shows results for the Fung and Hsieh (2004) risk benchmarks and confirms the predictive power of both OLS and ADJ alphas for 12-month-ahead benchmark-adjusted hedge fund returns for the full sample. The t-statistics for $\delta_{\mathrm{OLS}\,\alpha}$ and $\delta_{\mathrm{ADJ}\,\alpha}$ estimates are 5.15 and 7.93, respectively, for the full sample, and 6.51 and 5.58, respectively, for the noncrisis subsample.

In comparison, we find that only $\delta_{\mathrm{ADJ}\,\alpha}$ is statistically significant (t-statistic = 2.89) in the crisis subperiod. Panel B of Table 9 confirms these results for the alternative macroeconomic factor model-based benchmark-adjusted hedge fund returns. Both OLS and ADJ alphas have predictive power during the full sample period and outside of the crisis period. However, only ADJ alpha maintains its statistical significance in the crisis subperiod.

5.2 | Hedge fund selection: Adjusted versus OLS alphas

In the last set of tests, we investigate whether our ADJ alpha estimates allow us to identify superior fund managers on an ex ante basis. We sort funds into decile portfolios using their OLS alphas estimated over the preceding 24 months and then repeat the process using the ADJ alphas of those funds. We re-sort the portfolios at the beginning of each calendar year and compare the results. Continuously re-sorted top decile portfolios allow us to measure the difference

[16] Results by strategy are not tabulated to save space but are available upon request.

TABLE 9 Historical alpha and future returns: Fama–MacBeth cross-sectional regression estimates

	ADJ Alpha			OLS alpha				
Intercept	**FS**	**Crisis**	**No crisis**	**FS**	**Crisis**	**No crisis**	**Avg. *N***	**Avg. R^2**
Panel A. Fung and Hsieh benchmark-adjusted returns								
0.28***	0.12***						1,501	11.22%
(7.10)	(7.93)							
0.36***		0.12***					1,838	33.31%
(6.71)		(2.89)						
0.27***			0.12***				1,528	8.73%
(5.83)			(6.51)					
0.21***				0.25***			1,501	14.96%
(3.53)				(5.15)				
0.51***					−0.01		1,839	29.93%
(2.83)					(−0.06)			
0.19***						0.28***	1,528	13.20%
(2.98)						(5.58)		
Panel B. Macroeconomic model benchmark-adjusted returns								
0.29***	0.09***						1,612	9.62%
(6.06)	(5.35)							
0.14		0.16***					1,838	31.11%
(1.46)		(6.70)						
0.29***			0.08***				1,622	6.75%
(5.54)			(3.97)					
0.24***				0.15***			1,612	10.98%
(4.88)				(3.44)				
0.20					0.12		1,839	26.51%
(1.60)					(0.72)			
0.23***						0.15***	1,623	8.83%
(4.07)						(3.24)		

Note. This table reports average intercept and slope coefficients from the Fama and MacBeth (1973) cross-sectional regressions of 12-month ahead average benchmark-adjusted fund return on current Fung and Hsieh (2004) model alpha adjusted for fund-specific skewness (ADJ alpha) and ordinary least squares (OLS) alpha. In the first stage, monthly alpha and ADJ alpha are estimated for each fund from the time-series regressions of hedge fund excess returns on the Fung and Hsieh (2004) factors over a 24-month rolling window. In the second stage, the cross-section of 12-month-ahead funds' benchmark-adjusted returns is regressed on the funds' alpha each month from January 1996 to April 2015. Newey–West (1987) adjusted *t*-statistics are reported in parentheses below average coefficient estimates. In Panel A (Panel B), results are reported for Fung and Hsieh (2004) model (macroeconomic model) benchmark-adjusted hedge fund returns. Results are reported for full sample (FS), crisis (Crisis), and noncrisis (No Crisis) periods, classified following Billio et al. (2011).
***Significant at the 0.01 level.

in performance that arises from making forward-looking investment decisions based on historical ADJ alphas instead of OLS alphas.

Full-sample results in Table 10 show that the 1-year-ahead alpha of the top decile portfolio sorted on ADJ alphas exceeds the 1-year-ahead alpha of the top decile portfolio sorted on OLS alphas by 0.84% per year with Fung and Hsieh (2004) risk factors and 0.26% per year with macroeconomic factors. We also report the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measures ($MPPM_3$ and $MPPM_4$) for each portfolio and find that they are both larger for the top-decile ADJ alpha portfolio than for the top-decile OLS portfolio.

TABLE 10 Performance of fund portfolios formed using OLS and ADJ alphas

	Mean	$MPPM_3$	$MPPM_4$	FH alpha	Macro alpha
Panel A. Full sample					
ADJ full sample	11.57	0.07	0.07	6.71***	7.84***
OLS full sample	10.78	0.05	0.06	5.87***	7.59***
ADJ–OLS full sample	0.79	0.02	0.01	0.84	0.26
ADJ no crisis	13.92	0.10	0.09	8.01***	8.24***
OLS no crisis	13.68	0.09	0.09	7.96***	8.28***
ADJ–OLS no crisis	0.24	0.01	0.00	0.05	–0.04
ADJ crisis	2.74	–0.02	–0.03	–0.10	7.28
OLS crisis	–0.12	–0.06	–0.07	–5.67**	5.77
ADJ–OLS crisis	2.86	0.04	0.04	5.57**	1.51
Panel B. Unsmoothed returns					
ADJ full sample	9.67	0.07	0.07	3.48	3.46
OLS full sample	8.23	0.05	0.06	2.40	2.57
ADJ–OLS full sample	1.44	0.02	0.01	1.08	0.89
ADJ no crisis	11.62	0.10	0.09	3.04	2.93
OLS no crisis	10.49	0.09	0.09	2.82	2.52
ADJ–OLS no crisis	1.13	0.01	0.00	0.22	0.41
ADJ crisis	2.33	–0.02	–0.03	8.95	5.59
OLS crisis	–0.27	–0.06	–0.07	2.52	2.60
ADJ–OLS crisis	2.60	0.04	0.04	6.43	2.99
Panel C. No backfill					
ADJ full sample	9.44	0.05	0.05	5.09**	5.31**
OLS full sample	7.48	0.03	0.02	3.38	3.99*
ADJ–OLS full sample	1.96	0.02	0.03	1.71	1.32
ADJ no crisis	11.58	0.08	0.07	5.85***	5.39**
OLS no crisis	10.69	0.07	0.06	5.85**	4.59*
ADJ–OLS no crisis	0.89	0.01	0.01	0.00	0.80
ADJ crisis	1.92	–0.04	–0.05	5.77	4.96
OLS crisis	–3.78	–0.10	–0.12	–10.94**	1.33
ADJ–OLS crisis	5.70	0.06	0.07	16.71***	3.63

Note. This table reports estimated performance measures for ordinary least squares (OLS) alpha and skewness-adjusted (ADJ) alpha portfolios. Hedge funds are sorted on January 1 each year into decile portfolios, based on their ADJ alpha and OLS alpha estimated over the previous 24 months. Funds with the highest past performance measure are allocated into the ADJ alpha and OLS alpha portfolios. Panels A, B, and C show the mean return (Mean), manipulation-proof performance measures ($MPPM_3$ and $MPPM_4$), Fung and Hsieh (2004) alpha (FH Alpha) and macroeconomic alpha (Macro Alpha) for portfolios formed based on Fung and Hsieh (2004) alphas, alphas corrected for return serial correlation, and backfill bias-corrected alphas, respectively. We perform a means test for differences in FH Alpha and Macro Alpha for the ADJ alpha and OLS alpha portfolios. Results are estimated using annually re-sorted returns from January 1996 to April 2015. Crisis and noncrisis periods are classified following Billio et al. (2011).

***Significant at the 0.01 level.

**Significant at the 0.05 level.

*Significant at the 0.10 level.

When we split the estimation period into crisis and noncrisis subperiods, we find that during noncrisis subperiods, the annualized alpha of the portfolio formed from ADJ alphas is similar to the OLS alpha portfolio. But the differences are striking during crisis subperiods. During these subperiods, the alpha performance differential between the two decile portfolios is 5.5% per year, significant at the 5% level. For robustness, when we consider the macroeconomic factor model, the difference between the intercepts of the OLS and ADJ alpha portfolios during crisis subperiods narrows to 1.51%.

In Panel B of Table 10, we repeat the portfolio sorts using the Getmansky, Lo, and Makarov (2004) specification to unsmooth hedge fund returns, and in Panel C we control for the effects of backfill bias by removing the first 24 months of returns for each fund. These results are generally consistent with those reported in Panel A and confirm that ADJ alphas allow us to select better performing hedge funds ex ante despite these two well-known hedge fund data biases.

6 | SUMMARY AND CONCLUSIONS

Most hedge fund returns exhibit significant skewness, especially during periods of economic uncertainty. In this article, we show that fund-specific skewness is positively associated with future hedge fund performance. In particular, managerial skill in reducing exposure to large losses and the consequent drawdowns generate positive fund-specific skewness at the fund level. We introduce the ADJ alpha measure, which allows us to better assess and predict the performance of hedge fund managers, to quantify this skill. Our new performance measure rates fund managers as superior if they deliver both high traditional alpha and positive fund-specific skewness.

Using the Lipper/TASS hedge fund database, we show that standard performance measures are unlikely to capture the skill of hedge fund managers who introduce positive fund-specific skewness through hedging, risk management, or dynamic trading. We find considerable differences between the ADJ and OLS alpha ratings. Although both performance measures produce similar results for funds with nonskewed returns, the OLS alpha overrates performance (i.e., $\alpha_{OLS} > \alpha_{ADJ}$) when returns are negatively skewed and underrates performance (i.e., $\alpha_{OLS} < \alpha_{ADJ}$) when returns are positively skewed.

We also examine whether our new ADJ alpha is better able to select fund managers based on historical return characteristics. When we sort funds into deciles based on rolling 2-year estimates of ADJ alphas, we find that the performance assessment error is significant. Furthermore, funds with superior prior ADJ alphas outperform funds with high prior OLS alphas, which suggests that our new performance measure is able to select managers who deliver superior future performance more effectively than OLS.

When we compare these performance differences during periods of economic uncertainty, we find that performance differences are relatively small during periods of low economic uncertainty. However, portfolios formed using historical estimates of ADJ alphas outperform portfolios formed using historical OLS alphas by an impressive amount during crisis periods.

Collectively, these results argue in favor of adjusting for fund-specific skewness to identify skilled hedge fund managers, especially during periods of greater market uncertainty. Standard estimation methods err in a systematic fashion when rating the performance of hedge fund managers when portfolio returns exhibit fund-specific skewness, and this performance difference is amplified during crisis periods.

In future work, it may be useful to investigate the effectiveness of other fund return attributes that are easier to quantify (e.g., intraday return spread) and have the same predictive power as fund-specific skewness. It would also be interesting to examine whether incorporating higher order return moments in traditional performance measures further improves their predictive power.

ACKNOWLEDGMENTS

We are grateful to an anonymous referee, Vikas Agarwal, Sandro Andrade, Brad Barber, Indraneel Chakraborty, Liam Gallagher, Mila Getmansky-Sherman, Bing Han (Editor), Kyung-So Im, Bing Liang, Narayan Naik, and Richard Taffler for helpful comments. Mark Hutchinson is grateful for financial support from the Science Foundation Ireland under grant number 18/SPP/3459. All remaining errors and omissions are ours.

REFERENCES

Agarwal, V., Bakshi, G., & Huij, J. (2009). *Do higher-moment equity risks explain hedge fund returns?* Georgia State University Working Paper.

Agarwal, V., Daniel, N. D., & Naik, N. Y. (2009). Role of managerial incentives and discretion in hedge fund performance. *Journal of Finance*, *64*, 2221–2256.

Agarwal, V., Daniel, N. D., & Naik, N. Y. (2011). Do hedge funds manage their reported returns? *Review of Financial Studies*, *24*, 3281–3320.

Amin, G. S., & Kat, H. M. (2003). Hedge fund performance 1990 to 2000: Do the money machines really add value? *Journal of Financial and Quantitative Analysis*, *38*, 251–274.

Aragon, G. O. (2007). Share restrictions and asset pricing: Evidence from the hedge fund industry. *Journal of Financial Economics*, *83*, 33–58.

Avramov, D., Barras, L., & Kosowski, R. (2013). Hedge fund return predictability under the magnifying glass. *Journal of Financial and Quantitative Analysis*, *48*, 1057–1083.

Avramov, D., Kosowski, R., Naik, N. Y., & Teo, M. (2011). Hedge funds, managerial skill, and macroeconomic variables. *Journal of Financial Economics*, *99*, 672–692.

Back, K., Crane, A. D., & Crotty, K. (2018). Skewness consequences of seeking alpha. *Review of Financial Studies*, *31*, 4720–4761.

Bali, T. G., Brown, S. J., & Caglayan, M. O. (2011). Do hedge funds' exposures to risk factors predict their future returns? *Journal of Financial Economics*, *101*, 36–68.

Bali, T. G., Brown, S. J., & Caglayan, M. O. (2012). Systematic risk and the cross section of hedge fund returns. *Journal of Financial Economics*, *106*, 114–131.

Bali, T. G., Brown, S. J., & Caglayan, M. O. (2014). Macroeconomic risk and hedge fund returns. *Journal of Financial Economics*, *114*, 1–19.

Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics*, *43*, 341–372.

Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, *116*, 111–120.

Billio, M., Getmansky, M., & Pelizzon, L. (2011). *Crises and hedge fund risk*. University of Massachusetts at Amherst Working Paper.

Bollen, N. P. B., & Pool, V. K. (2009). Do hedge fund managers misreport returns? Evidence from the pooled distribution. *Journal of Finance*, *64*, 2257–2288.

Boyer, B., Mitton, T., & Vorkink, K. (2009). Expected idiosyncratic skewness. *Review of Financial Studies*, *23*, 169–202.

Brown, S., Goetzmann, W., & Ibbotson, R. G. (1999). Offshore hedge funds: Survival and performance 1989–95. *Journal of Business*, *72*, 91–117.

Buraschi, A., Kosowski, R., & Sritrakul, W. (2014). Incentives and endogenous risk taking: A structural view on hedge fund alphas. *Journal of Finance*, *69*, 2819–2870.

Caglayan, M. O., & Ulutas, S. (2014). Emerging market exposures and the predictability of hedge fund returns. *Financial Management*, *43*, 149–180.

Chan, L. K. C., & Lakonishok, J. (1992). Robust measurement of beta risk. *Journal of Financial and Quantitative Analysis*, *27*, 265–282.

Conrad, J., Dittmar, R. F., & Ghysels, E. (2013). Ex ante skewness and expected stock returns. *Journal of Finance*, *68*, 85–124.

Dell'Aquila, R., Ronchetti, E., & Trojani, F. (2003). Robust GMM analysis of models for the short rate process. *Journal of Empirical Finance*, *10*, 373–397.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*, 607–636.

Fung, W., & Hsieh, D. A. (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *Review of Financial Studies*, *14*, 313–341.

Fung, W., & Hsieh, D. A. (2004). Hedge fund benchmarks: A risk based approach. *Financial Analyst Journal*, *60*, 65–80.

Fung, W., Hsieh, D. A., Naik, N. Y., & Ramadorai, T. (2008). Hedge funds: Performance, risk, and capital formation. *Journal of Finance*, *63*, 1777–1803.

Gallagher, L. A., & Taylor, M. P. (2000). Measuring the temporary component of stock prices: Robust multivariate analysis. *Economics Letters*, *67*, 193–200.

Garino, G., & Sarno, L. (2004). "Speculative bubbles in U.K. house prices: Some new evidence. *Southern Economic Journal*, *70*, 777–795.

Getmansky, M., Lo, A. W., & Makarov, I. (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics*, *74*, 529–609.
Glode, V. (2011). Why mutual funds underperform. *Journal of Financial Economics*, *99*, 546–559.
Goetzmann, W., Ingersoll, J., Spiegel, M., & Welch, I. (2007). Portfolio performance manipulation and manipulation-proof performance measures. *Review of Financial Studies*, *20*, 1503–1546.
Gupta, A., & Liang, B. (2005). "Do hedge funds have enough capital? A value at risk approach. *Journal of Financial Economics*, *77*, 219–253.
Huber, P. J., & Ronchetti, E. (2009). *Robust statistics*. Hoboken, NJ: Wiley.
Im, K. S., & Schmidt, P. (2008). More efficient estimation under non-normality when higher moments do not depend on the regressors, using residual augmented least squares. *Journal of Econometrics*, *144*, 219–233.
Jagannathan, R., Malakhov, A., & Novikov, D. (2010). Do hot hands exist among hedge fund managers? An empirical evaluation. *Journal of Finance*, *65*, 217–255.
Kadan, O., & Liu, F. (2014). Performance evaluation with high moments and disaster risk. *Journal of Financial Economics*, *113*, 131–155.
Knez, P. J., & Ready, M. J. (1997). On the robustness of size and book-to-market in cross-sectional regressions. *Journal of Finance*, *52*, 1355–1382.
Kosowski, R., Naik, N. Y., & Teo, M. (2007). Do hedge funds deliver alpha? A bayesian and bootstrap analysis. *Journal of Financial Economics*, *84*, 229–264.
Kosowski, R., Timmermann, A., Wermers, R., & White, H. (2005). Can mutual fund stars really pick stocks? New evidence from a bootstrap analysis. *Journal of Finance*, *61*, 2551–2595.
Leland, H. E. (1999). Beyond mean-variance: Performance measurement in a nonsymmetrical world. *Financial Analysts Journal*, *55*, 27–36.
Liang, B., & Park, H. (2010). Predicting hedge fund failure: A comparison of risk measures. *Journal of Financial and Quantitative Analysis*, *45*, 199–222.
MaCurdy, T. E. (2001). Using information on the moments of disturbances to increase the efficiency of estimation. In C. Hsiao, K. Morimune, & J. Powell (Eds.), *Nonlinear statistical modeling, proceedings of the thirteenth international symposium in economic theory and econometrics: Essays in honor of Takeshi Amemiya* (pp. 281–320). New York, NY: Cambridge University Press.
Newey, W. K. (1988). Adaptive estimation of regression models via moment restrictions. *Journal of Econometrics*, *38*, 301–339.
Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*, 703–708.
Sarno, L., & Taylor, M. P. (1999). Moral hazard, asset price bubbles, capital flows, and the east asian crisis: The first tests. *Journal of International Money and Finance*, *18*, 637–657.
Taylor, M. P., & Peel, D. A. (1998). Periodically collapsing stock price bubbles: A robust test. *Economics Letters*, *61*, 221–228.

How to cite this article: Heuson AJ, Hutchinson MC, Kumar A. Predicting hedge fund performance when fund returns are skewed. *Financial Management*. 2020;49:877–896. https://doi.org/10.1111/fima.12304

APPENDIX

RESIDUAL AUGMENTED LEAST SQUARES METHODOLOGY

Im and Schmidt's (2008) residual augmented least square improves estimation efficiency when the error term is non-normal. The procedure augments an ordinary least square (OLS) linear regression with functions of the residuals. This method extends Newey (1988) and MaCurdy (2001), who show that parameter estimation can be improved when higher moments of the errors are assumed to be unrelated to the explanatory variables.

Im and Schmidt (2008) start with a multivariate linear regression model:

$$y_i = \alpha + \beta x_i' + \varepsilon_i. \tag{A1}$$

Here, x_i is a $k \times 1$ vector of explanatory variables.

Then, they develop a simple two-stage approach that can be estimated by first estimating Equation (A1) and then reestimating Equation (A1) augmented with (A2), again with OLS:

$$\hat{w}_i = \left[\left(\hat{\varepsilon}_i^2 - \hat{\sigma}^2\right)\left(\hat{\varepsilon}_i^3 - \hat{m}_3 - 3\hat{\sigma}^2\hat{\varepsilon}_i\right)\right]'. \tag{A2}$$

Here, $\hat{\varepsilon}_i$ denotes the residual, $\hat{m}_3$ denotes the third sample moment of the residuals, and $\hat{\sigma}^2$ denotes the standard residual variance estimate obtained from OLS applied to Equation (A1). The resulting estimates are the RALS estimates of α and β, that is, α^* and β^*.

Im and Schmidt (2008) make two key assumptions. First, the error term, ε, is assumed to be uncorrelated with the explanatory variables, x:

$$E[\varepsilon|x] = 0. \tag{A3}$$

Second, the functions of the error term, $h(\varepsilon)$, are also uncorrelated with x:

$$E[h(\varepsilon)|x] \equiv H(x) = H. \tag{A4}$$

These two assumptions allow Im and Schmidt (2008) to augment the regression model (A1) with additional functions of the residuals to improve estimation efficiency, when residuals are nonnormal.

Im and Schmidt (2008) show that if there is residual skewness, the standardized third central moment is nonzero,

$$E\left(\varepsilon_i^3 - \sigma^3\right) \neq 0, \tag{A5}$$

which implies that $(\varepsilon_i^2 - \sigma^2)$ is correlated with ε_i but not with the explanatory variables (as ε_i and x_i are independent by assumption):

$$E\left[\varepsilon_i\left(\varepsilon_i^2 - \sigma^2\right)\right] \neq 0. \tag{A6}$$

Hence, augmenting the regression model (A1) with $(\hat{\varepsilon}_i^2 - \hat{\sigma}^2)$ improves estimation efficiency.

Similarly, when the standardized fourth central moment of the series exceeds 3, Im and Schmidt (2008) show that augmenting the regression model with $(\hat{\varepsilon}_i^3 - m_3 - 3\hat{\sigma}^2\hat{\varepsilon}_i)$ again improves estimation efficiency, as it is correlated with ε_i but not with x_i.

Im and Schmidt (2008) also derive ρ^*, a measure of the asymptotic gain in efficiency from employing RALS as opposed to OLS. ρ^* is constructed as $(1-\sigma_A^2/\sigma^2)$, 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:

$$\sigma_A^2 = \sigma^2 - \frac{\mu_3^2\left(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2\right) - 2\mu_3\left(\mu_4 - 3\sigma^4\right)\left(\mu_5 - 4\mu_3\sigma^2\right) + \left(\mu_4 - 3\sigma^4\right)^2\left(\mu_4 - \sigma^4\right)}{\left(\mu_4 - \sigma^4\right)\left(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2\right) - \left(\mu_5 - 4\mu_3\sigma^2\right)^2}. \tag{A7}$$

Here, μ_j is the jth central moment of ε_i. 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 OLS error term is nonnormal. For normally distributed first-stage errors, OLS is efficient and the ratio equals 0.