Systematic risk and the cross-section of hedge fund returns

Online Appendix

To save space, we present some of our findings in the Online Appendix. Section I discusses potential data biases. Section II presents results from the univariate regressions of one-month ahead hedge fund returns on the volatility, skewness, and kurtosis for alternative sample periods. Section III provides univariate portfolio level analysis of volatility, skewness, and kurtosis. Section IV presents results from the univariate regressions of one-month ahead hedge fund returns on the 4-factor, 6-factor, and 9-factor systematic risk measures for alternative sample periods. Section V investigates the predictive power of volatility, skewness, and kurtosis for each investment style separately.

I. Potential Data Biases

Hedge fund studies can be subject to potential data biases. Brown, Goetzmann, Ibbotson, and Ross (1992), Fung and Hsieh (2000), Liang (2000), and Edwards and Caglayan (2001) cover these well-known data biases extensively in the hedge fund literature. The most common and easily fixable data bias in a hedge fund study is the survivorship bias. Survivorship bias exists if the database does not include the returns of non-surviving hedge funds, causing reported hedge fund performance in that database to appear higher/better than the true actual hedge fund performance. In our study, for the sample period 1994:01 – 2010:06, we do have monthly return histories of 6,027 funds in the live funds (survivor) database and 8,201 funds in the graveyard (defunct) database. We find that if the returns of non-surviving hedge funds (graveyard database) had not been included in the analyses, there would have been a survivorship bias of 1.91% in average annual hedge funds returns (the difference between the annualized average return of only surviving funds in the sample and the annualized average return of all surviving and non-surviving funds in the sample).[1] The fact that we have defunct funds as well as live funds in our database eliminates the possibility of survivorship bias in our analyses.

In a recent study, Fung and Hsieh (2009) point out the increasing difficulty in measuring true survivorship bias due to funds migrating from one database vendor to another. As a hedge fund industry practice, when funds stop reporting (arbitrarily) to a specific database vendor, those funds are moved by that database vendor to their graveyard database from their live funds database; that is, funds in graveyard database are not necessarily all liquidated funds. Fung and Hsieh (2009) draw attention to the importance of differentiating in between *missing* funds and *liquidated* funds in estimating survivorship bias and conclude that only liquidated funds, rather than all funds in the graveyard database, should be considered in survivorship bias estimations. Our database TASS provides information on why a fund is dropped from the database (i.e., moved from live database to graveyard database). Possible reasons of being dropped from the live database include fund liquidation, fund no longer reporting, fund closed to new investments, and fund merged into another entity. Based on this information, we calculate that only 4,037 of the 8,201 funds in our graveyard database, that is, only 49% of the funds in the graveyard database, are indeed confirmed liquidated funds. This low ratio, which is similar to the estimates of Fung and Hsieh (2009), shows how common that non-reporting and migration are in graveyard hedge fund databases. More importantly, the annual average returns of liquidated funds during our sample period 1994:01 – 2010:06 is 5.45%, compared to 6.99% annual average returns of all funds in the graveyard database (liquidated and non-liquidated). This shows that non-liquidated hedge funds in the graveyard database significantly outperforms the liquidated funds (simply

[1] This finding is comparable to earlier studies of hedge funds. Liang (2000) reports an annual survivorship bias of 2.24%, Edwards and Caglayan (2001) report an annual survivorship bias of 1.85%, and Bali, Brown, and Caglayan (2011) report an annual survivorship bias of 1.74%.

because non-liquidated funds are not dead yet). In return, this suggests, as Fung and Hsieh (2009) also point out, that survivorship bias estimates should be calculated not based on all funds in the graveyard database (as is the case in previous literature), but based on liquidated funds only. We calculate that survivorship bias estimation done using this format (the difference between the annualized average return of combined live and non-liquidated graveyard funds in the sample and the annualized average return of all live, liquidated, and non-liquidated funds in the sample) would actually increase the survivorship bias in our study to 2.15% from an earlier estimate of 1.91%.

Another important data bias in a hedge fund study is called the back-fill bias. Once a hedge fund is included into a database, that fund's previous returns are automatically added to that database (this process is called "backfilling"). This practice in hedge fund industry seems problematic, because it generates an incentive only for successful hedge funds (at least until the point of entry to the database) to report their past returns to the database vendor (there is no incentive for an unsuccessful hedge fund to advertise their past bad performance) and as a result this may generate an upward bias in returns of newly reporting hedge funds during their early (reported) histories. The TASS database provides information on when a hedge fund was added to the database as well as the fund's first reported performance date. On average, we find a one-year gap between the first performance date and the date that the fund was added to the database. We check whether this one-year gap generates a difference in returns between funds' first year performance vs. the rest of period performance (the rest of period performance starts from the 13th month until either the fund is deceased or until the end of our sample period June 2010). We find that the average annual return of hedge funds during the first year of existence is 1.87% higher than the average annual returns in subsequent years. Similarly, Fung and Hsieh (2000) also find a 1.4% back-fill bias in annual returns and delete the first 12-month returns of all individual hedge funds in the sample to correct for the potential back-fill bias in their analyses. Following Fung and Hsieh, to avoid back-fill bias in our analyses, we also delete the first 12-month return histories of all individual hedge funds in our database. Deleting the first 12-month returns results in deleting 982 funds from our sample because these funds have return histories less than 12 months, bringing the total number of hedge funds in our database to 13,246 from 14,228. There is a also a slight chance that we may introduce a new survivorship bias into the system due to deletion of 982 hedge funds from the sample. We find, however, that the average annual return of 13,246 funds is only 0.03% higher than the average annual return of 14,228 funds, suggesting no evidence of inclusion of a new bias into our analyses.

We also check whether our main finding of a positive link between future hedge fund returns and total risk and systematic risk would remain intact if we do not delete the first 12-month returns of all individual hedge funds in our sample. Using the sample with the full return history for all individual hedge funds, we estimate the average slope coefficient from the monthly univariate Fama-MacBeth (1973) cross-section regressions of future hedge fund returns on total risk (volatility) to be 0.0044 with a Newey-West *t*-

statistic of 2.41. Similarly, using a separate set of cross-section regressions, we obtain an average slope coefficient of 0.0121 with a Newey-West *t*-statistic of 2.24 on the 6-factor systematic risk (*SR*). These results suggest that deleting the first 12-month return history of all individual hedge funds in our sample does not alter or reduce the predictive power of total risk and systematic risk on future hedge fund returns.

As an alternative method to calculate back-fill bias, Aggarwal and Jorion (2010) measure back-fill period as the difference between a fund's inception date and the date the fund is added to the database. They define a fund as "non-back-filled" if the back-fill period (the period between the inception date and date added to database) is below 180 days. In other words, they call hedge funds whose inception date and database entry date are in proximity as non-back-filled funds, and they name the rest of funds in the sample (whose back-fill periods are more than 180 days) as back-filled funds. Then, they calculate the average annual return difference between back-filled funds and non-back-filled funds to measure the back-fill bias. Following Aggarwal and Jorion's (2010) procedure, we identify 2,366 hedge funds as non-back-filled funds in our sample. For the sample period 1994:01 – 2010:06, we estimate the magnitude of back-fill bias to be 2.03% using the aforementioned methodology.

The last possible data bias in a hedge fund study is called the multi-period sampling bias. Investors typically ask for a minimum 24 or 36 months of return history before making a decision whether to invest in a hedge fund or not. Therefore, in a hedge fund study, inclusion of hedge funds with shorter return histories than 24 or 36 months would be misleading to those investors who seek past performance data to make investment decisions. Also, a minimum 24-month return history requirement (to be included in a hedge fund study) would make sense from a statistical perspective to be able to run regressions and get sensible regression estimates for each individual hedge fund in the sample. In this study, we require that all hedge funds in the sample have at least 24 months of return history, after excluding the first 12 months of returns for all hedge funds (to correct for any potential back-fill bias). This 24-month minimum return history requirement, however, decreases our sample size from 13,246 to 9,611 (i.e., 3,635 funds in the sample have return histories less than 24 months), and as a result, it might introduce a new survivorship bias into our analyses, because deleted 3,635 hedge funds that had return histories less than 24 months most probably dissolved due to bad performance. In an effort to find the impact of these deleted 3,635 hedge funds on total hedge fund performance, we compare the performance of hedge funds *before* and *after* the 24-month return history requirement and find that the annual average return of hedge funds that pass the 24-month requirement (9,611 funds) is only 0.34% higher than the return of all hedge funds (13,246 funds) in the sample, a small insignificant percentage difference in annual terms between the two samples in terms of survivorship bias considerations (This figure is similar to the estimates from Fung and Hsieh (2000) and Edwards and Caglayan (2001)).

II. Volatility, Skewness, and Kurtosis in Univariate Cross-Sectional Regressions

Table I presents the time-series average slope coefficients from the univariate cross-sectional regressions of one-month ahead hedge fund returns on volatility, skewness, and kurtosis separately over the sample period January 1997 to June 2010. For robustness of our results, we also report, for alternative sample periods ending June 2010, average slope coefficients for shorter sample periods, where we reduce the sample size by one year at a time from 1997 to 2007. The corresponding Newey-West *t*-statistics are reported in parentheses. As shown in the first column of Table I, we obtain a positive and significant relation between total risk (volatility) and expected returns on hedge funds. More importantly, the statistically significant, positive average slope coefficients on volatility persist for all sub-period analyses. For the full sample period 1997:01 – 2010:06, the average slope on volatility is 0.0047 with a Newey-West *t*-statistic of 2.74. Given a difference in average total variance of approximately 184 between the high VOL and low VOL quintiles (reported in the first column of Table II), this coefficient estimate (0.0047) translates into a monthly return difference of almost 0.85% per month, implying an economically significant return spread between average funds in the high and low volatility quintile portfolios. Reducing the sample size and conducting the analyses anywhere starting from 1998 or 2007 (with sample periods ending June 2010), generate the same positive and significant link between total risk and hedge fund returns as well. Interestingly, the predictive power of total risk for future returns continues during the most recent financial crisis period 2007:01 – 2010:06 despite a very short period of 42 months; the average slope equals 0.0046 with a Newey-West *t*-statistic of 1.87.

In line with the three-moment asset pricing models in which investors like positive skewness, we find a negative cross-sectional link between the skewness of individual funds and their future returns. However, as shown in the second column of Table I, the average slope coefficients on SKEW are statistically insignificant without any exception. For the full sample period, the average slope on SKEW is –0.0156 with a Newey-West *t*-statistic of –0.14. For all other sample periods, the univariate regressions produce very low *t*-statistics for the average slopes on SKEW; in the range of –0.42 and –0.14. Again consistent with the theoretical findings of earlier studies, the univariate Fama-MacBeth regressions provide a positive relation between the kurtosis and the cross-section of hedge fund returns. However, similar to our results for skewness, the average slope coefficients on KURT are statistically insignificant for all sample periods. The last column of Table I shows that the average slope on KURT is 0.0451 with a Newey-West *t*-statistic of 0.81 for the full sample period. Similarly, for alternative sample periods, the *t*-statistics of the average slopes on KURT range from 0.81 and 1.01.

These extremely low *t*-statistics for SKEW and KURT indicate that although hedge funds exhibit non-normal return distributions with significant skewness and kurtosis, these higher moments do not explain the cross-sectional returns. Instead, the volatility of hedge funds is an important, robust determinant of the cross-sectional differences in hedge fund returns.

III. Univariate Portfolio Analysis of Volatility, Skewness, and Kurtosis

To provide an alternative evidence for the predictive power of volatility, skewness, and kurtosis, we construct univariate portfolios and test whether the second and higher moments of the return distribution can explain the spreads in hedge fund returns and alphas. Specifically, we form quintile portfolios each month from January 1997 to June 2010 by sorting hedge funds based on their variance, skewness, and kurtosis, separately, where Quintile 1 contains the hedge funds with the lowest VOL, SKEW, and KURT, and Quintile 5 contains the hedge funds with the highest VOL, SKEW, and KURT. Table II reports the average VOL, SKEW, and KURT, as well as the next month average returns for each quintile. The last four rows in Table II present the differences between quintile 5 and quintile 1 monthly returns; the Alphas with respect to the 4-Factor model of Fama-French-Carhart; the Alphas with respect to the combined 6-Factor model of Fama-French-Carhart and Fung-Hsieh bond factors; and the Alphas with respect to the combined 9-Factor model of Fama-French-Carhart and Fung-Hsieh bond and trend following factors.

The left panel of Table II shows that moving from the Low VOL to High VOL quintile, the average return on volatility portfolios increases monotonically from 0.203% to 0.675% per month. Effectively, the average raw return difference between quintiles 5 and 1 (i.e., High VOL quintile vs. Low VOL quintile) is 0.472% per month with a Newey-West *t*-statistic of 2.02, suggesting that this positive return difference is statistically and economically significant. This result indicates that hedge funds in the highest volatility quintile generate about 5.7% more annual returns compared to funds in the lowest volatility quintile. We check whether the significant return difference between high-VOL funds and low-VOL funds can be explained by different factors such as Fama-French (1993) and Carhart's (1997) four factors of market, size, book-to-market, and momentum, as well as Fung and Hsieh's (2001, 2004) two bond factors (ΔCredSpr and Δ10Y) and three trend-following factors on currencies, bonds, and commodities. To do this, we regress the monthly time series of return differences between high-VOL and low-VOL funds on Fama-French-Carhart's 4 factors as well as on Fama-French-Carhart and Fung-Hsieh's combined 6 factors (4-factor Fama-French-Carhart plus Fung-Hsieh 2 bond factors) and combined 9 factors (4-factor Fama-French-Carhart plus Fung-Hsieh 2 bond and 3 trend following factors) and we check if the intercepts from these three regressions (namely, 4-factor alpha, 6-factor alpha, and 9-factor alpha) are statistically significant. Table II reports these 4-factor, 6-factor and 9-factor alphas in the last three rows. The 4-factor alpha difference between quintiles 5 and 1 is 0.342% with a *t*-statistic of 2.37. Similarly, the 6-factor and 9-factor alpha differences between quintiles 5 and 1 are, respectively, 0.349% and 0.417%, with the respective *t*-statistics of 2.39 and 2.82. This suggests that after controlling for the market, size, book-to-market, momentum, and Fung-Hsieh's bond and trend-following factors, the return difference between high-VOL and low-VOL funds remains positive and significant. In other words, these 4, 6, and 9 factors tested here do not explain the positive relation between total risk and the cross-section of hedge fund returns. In sum, these new results from the univariate portfolio analysis confirm our earlier findings from the univariate Fama-MacBeth regressions on the existence of a positive and significant link between volatility and hedge fund returns.

The middle panel of Table II shows that the funds in the Low SKEW quintile have on average higher returns than the funds in the High SKEW quintile, implying a negative relation between the skewness and the cross-section of hedge fund returns. However, the average return difference between the High SKEW and Low SKEW quintiles is economically and statistically insignificant; –0.07% per month with a *t*-statistic of –0.68. Similar results are obtained from the risk-adjusted return differences: The 4-factor, 6-factor, and 9-factor alpha differences between the High SKEW and Low SKEW portfolios are in the range of –0.10% to –0.13%, and insignificant with the *t*-statistics ranging from –0.97 to –1.29.

Confirming our findings from the Fama-MacBeth regressions, the right panel of Table II presents a positive but very weak relation between the kurtosis and future returns at the portfolio level. The funds in the High KURT quintile generate only 6.5 basis points more average monthly returns compared to the funds in the Low KURT quintile. Not surprisingly, this economically small return spread is statistically insignificant as well (*t*-stat. = 0.75). The weak performance of kurtosis is also reflected in the alpha spreads. The 4-factor, 6-factor, and 9-factor alpha differences between the High KURT and Low KURT portfolios are in the range of 0.075% to 0.089%, and insignificant with the *t*-statistics ranging from 0.97 to 1.21.

Overall, the portfolio-level analyses echo the Fama-MacBeth regression results, indicating that the asymmetric and leptokurtic behaviour of hedge funds' return distributions do not predict the cross-sectional variation in hedge fund returns.

IV. Systematic Risk in Cross-Sectional Regressions

Table III presents the time-series average slope coefficients from the univariate cross-sectional regressions of one-month ahead hedge fund returns on systematic risk (*SR*) derived from three alternative factor models over the sample period January 1997 to June 2010. For robustness of our results, we also report, for alternative sample periods ending June 2010, average slope coefficients for shorter sample periods, where we reduce the sample size by one year at a time from 1997 to 2007. The corresponding Newey-West *t*-statistics are reported in parentheses. For the period 1997:01 – 2010:06, we obtain a positive and significant relation between systematic risk and expected returns on hedge funds. In particular, we find the average slope coefficient from the monthly regressions of one-month ahead hedge fund returns on the previous month's 4-factor systematic risk to be 0.0128 with a *t*-statistic of 2.18. More importantly, using 6-factor and 9-factor systematic risk estimates in the same cross-sectional regressions generate similar significant results for the same full sample period: the average slope coefficients are, respectively, 0.0125 and 0.0083 on these two alternative systematic risk measures, with the respective Newey West *t*-statistics of 2.26 and 2.18. Given a difference in the average 6-factor systematic variance of approximately 70.62 between the high *SR* and low

SR quintiles (reported in the first column of Table 5 in the paper), the average slope on *SR* (0.0125) translates into a monthly return difference of almost 0.88% per month, implying an economically significant return spread between average funds in the high *SR* and low *SR* quintile portfolios.

Another notable point in Table III is that reducing the sample size and conducting the analyses anywhere starting from 1998 or 2007 (with sample periods ending June 2010), generate the same positive and significant relation between systematic risk and future hedge fund returns. Analyzing the average slope coefficients on the 4-factor systematic risk in Table III, for example, we see that they range in between 0.0128 and 0.0267, and they are all statistically significant, with the Newey West *t*-statistics ranging from 1.96 to 2.90. Interestingly, the predictive power of 4-factor systematic risk over future hedge fund returns continues during the most recent financial crisis period of 2007:01 – 2010:06 (average slope coefficient of 0.0204 with a Newey West *t*-statistics of 1.96), despite a very short sample period. Most importantly, however, the statistically significant positive Fama-MacBeth average slope coefficients persist for all sub-period analyses when the 6-factor and the 9-factor systematic risk estimates are used in the cross-sectional regressions. For different sample periods, the average slope coefficients on the 6-factor systematic risk range in between 0.0125 and 0.0260 and the average slopes on the 9-factor systematic risk range from 0.0083 to 0.0186, and they are all statistically significant. This suggests that the positive and significant link between systematic risk and hedge fund returns is robust across different sample periods as well as for alternative estimates of systematic risk (i.e., whether 4-factor, 6-factor, or 9-factor models are utilized).

Lastly, we check whether the results in Table 3 in the paper generated with the use of 6-factor systematic risk and 6-factor unsystematic risk together in multivariate cross-section regressions can actually be replicated instead by using the 9-factor systematic risk and 9-factor unsystematic risk. Table IV reports the average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead returns on the 9-factor systematic risk and 9-factor unsystematic risk together with the control variables; size, age, management fee, incentive fee, past month returns, redemption period, minimum investment amount, dummy for lockup, and dummy for leverage. In line with our previous results, the predictive power of systematic risk over future fund returns persists even when the 9-factor systematic risk and the 9-factor unsystematic risk estimates are utilized in the cross-sectional regressions. To be more specific, among the same full and four sub-sample periods, we find the average slope coefficient on the 9-factor systematic risk to be in between 0.0111 and 0.0273, with the statistically significant *t*-statistics ranging from 2.17 to 3.79, while the average slope coefficient on the 9-factor unsystematic risk still continuing to be insignificant. These findings suggest that our earlier results are not dependent on the factor model utilized to generate the systematic and unsystematic risk. That is, our results, which show a positive link between systematic risk and future hedge fund returns, are robust across alternative factor model specifications.

V. Predictive Power of Volatility, Skewness, and Kurtosis by Fund Investment Style

We investigate the predictive power of volatility, skewness, and kurtosis for each investment style separately. Based on our results from the paper, we expect the relative performance of total risk to improve gradually as we move from the least directional strategies to the most directional strategies, whereas the higher moments (skewness and kurtosis) may not have significant power in predicting future hedge fund returns for any hedge fund style. Table V confirms our conjecture. As shown in the first three rows of Table V, the next month average return spreads between High VOL and Low VOL quintiles are found to be statistically insignificant for the three non-directional styles, Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage funds. However, for the semi-directional and directional strategies, the average raw return differences between the High VOL and Low VOL quintiles are positive and highly significant. Similar to our findings for systematic risk, we obtain the highest predictive power of total risk for the directional strategies, Managed Futures, Global Macro, and Emerging Markets funds. Overall, the results in Table V indicate an economically and statistically stronger relation between total risk and future returns for funds with larger variation in total risk. Another notable point in Table V is that we do not find a significant link between hedge fund returns and higher moments (skewness and kurtosis) for any of the 10 investment styles.

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Table I. Univariate Fama-MacBeth Cross-Sectional Regressions of 1-month ahead Hedge Fund Excess Returns on Volatility, Skewness, and Kurtosis

Each month during the period 1997:01 – 2010:06 hedge fund excess returns are regressed on funds' past 36-month volatility (total variance), past 36-month skewness, and past 36-month kurtosis separately. The numbers in each column show the average slope coefficients from univariate Fama-MacBeth regressions. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

Period	Volatility Slopes	Skewness Slopes	Kurtosis Slopes
1997:01 – 2010:06	**0.0047** **(2.74)**	–0.0156 (–0.14)	0.0451 (0.81)
1998:01 – 2010:06	**0.0048** **(2.92)**	–0.0178 (–0.15)	0.0511 (0.86)
1999:01 – 2010:06	**0.0044** **(3.15)**	–0.0380 (–0.31)	0.0619 (0.96)
2000:01 – 2010:06	**0.0042** **(2.83)**	–0.0347 (–0.26)	0.0708 (1.01)
2001:01 – 2010:06	**0.0047** **(3.21)**	–0.0406 (–0.27)	0.0750 (0.96)
2002:01 – 2010:06	**0.0052** **(3.34)**	–0.0343 (–0.21)	0.0812 (0.94)
2003:01 – 2010:06	**0.0059** **(3.45)**	–0.0262 (–0.14)	0.0924 (0.93)
2004:01 – 2010:06	**0.0057** **(2.96)**	–0.0561 (–0.26)	0.1118 (0.98)
2005:01 – 2010:06	**0.0055** **(2.68)**	–0.0722 (–0.28)	0.1318 (0.99)
2006:01 – 2010:06	**0.0050** **(2.11)**	–0.1064 (–0.34)	0.1625 (1.00)
2007:01 – 2010:06	**0.0046** **(1.87)**	–0.1697 (–0.42)	0.2047 (0.99)

Table II. Univariate Quintile Portfolios of Hedge Funds Sorted by Volatility, Skewness, and Kurtosis

Quintile portfolios are formed every month from January 1997 to June 2010 by sorting hedge funds based on their volatility (VOL), skewness (SKEW), and kurtosis (KURT). Quintile 1 is the portfolio of hedge funds with the lowest VOL, SKEW, and KURT and Quintile 5 is the portfolio of hedge funds with the highest VOL, SKEW, and KURT. The table reports the average VOL, average SKEW, average KURT, and the average next month returns for each quintile. The last four rows represent the differences between Quintile 5 and Quintile 1 the monthly returns; the alphas with respect to the 4-factor model of Fama-French-Carhart; the alphas with respect to the combined 6-factor model of Fama-French-Carhart and Fung-Hsieh bond factors; and the alphas with respect to the combined 9-factor model of Fama-French-Carhart and Fung-Hsieh bond and trend following factors. Average returns and Alphas are defined in monthly percentage terms. Newey-West *t*-statistics are reported in parentheses. Numbers in bold denote statistical significance.

Quintiles	Average VOL	Next Month Average Returns	Quintiles	Average SKEW	Next Month Average Returns	Quintiles	Average KURT	Next Month Average Returns
Low VOL	1.205	0.203	Low SKEW	–1.511	0.420	Low KURT	–0.445	0.326
2	3.961	0.287	2	–0.573	0.316	2	0.229	0.371
3	9.045	0.303	3	–0.168	0.325	3	0.929	0.366
4	20.23	0.340	4	0.225	0.398	4	2.066	0.353
High VOL	184.08	0.675	High SKEW	1.083	0.350	High KURT	6.808	0.391
High VOL–Low VOL Return Diff.		**0.472** **(2.02)**	High SKEW–Low SKEW Return Diff.		–0.070 (–0.68)	High KURT–Low KURT Return Diff.		0.065 (0.75)
High VOL–Low VOL 4-Factor Alpha Diff.		**0.342** **(2.37)**	High SKEW–Low SKEW 4-Factor Alpha Diff.		–0.099 (–0.97)	High KURT–Low KURT 4-Factor Alpha Diff.		0.087 (1.21)
High VOL–Low VOL 6-Factor Alpha Diff.		**0.349** **(2.39)**	High SKEW–Low SKEW 6-Factor Alpha Diff.		–0.128 (–1.29)	High KURT–Low KURT 6-Factor Alpha Diff.		0.089 (1.20)
High VOL–Low VOL 9-Factor Alpha Diff.		**0.417** **(2.82)**	High SKEW–Low SKEW 9-Factor Alpha Diff.		–0.102 (–1.01)	High KURT–Low KURT 9-Factor Alpha Diff.		0.075 (0.97)

Table III. Univariate Fama-MacBeth Cross-Sectional Regressions of 1-month ahead Hedge Fund Excess Returns on Systematic Risk (SR)

Each month during the period 1997:01 – 2010:06 hedge fund excess returns are regressed on various factor model SRs separately. The numbers in each column show the average slope coefficients on alternative factor model SRs from Fama-MacBeth regressions. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

Period	Average 4-Factor SR Slopes	Average 6-Factor SR Slopes	Average 9-Factor SR Slopes
1997:01 – 2010:06	**0.0128** **(2.18)**	**0.0125** **(2.26)**	**0.0083** **(2.18)**
1998:01 – 2010:06	**0.0133** **(2.13)**	**0.0134** **(2.29)**	**0.0090** **(2.20)**
1999:01 – 2010:06	**0.0154** **(2.36)**	**0.0152** **(2.43)**	**0.0101** **(2.32)**
2000:01 – 2010:06	**0.0161** **(2.30)**	**0.0159** **(2.36)**	**0.0106** **(2.27)**
2001:01 – 2010:06	**0.0188** **(2.56)**	**0.0185** **(2.61)**	**0.0128** **(2.62)**
2002:01 – 2010:06	**0.0215** **(2.70)**	**0.0210** **(2.72)**	**0.0145** **(2.68)**
2003:01 – 2010:06	**0.0254** **(2.90)**	**0.0247** **(2.91)**	**0.0172** **(2.92)**
2004:01 – 2010:06	**0.0240** **(2.41)**	**0.0237** **(2.45)**	**0.0163** **(2.44)**
2005:01 – 2010:06	**0.0267** **(2.34)**	**0.0260** **(2.36)**	**0.0175** **(2.32)**
2006:01 – 2010:06	**0.0264** **(2.01)**	**0.0255** **(2.03)**	**0.0186** **(2.03)**
2007:01 – 2010:06	**0.0204** **(1.96)**	**0.0206** **(1.89)**	**0.0161** **(1.81)**

Table IV. Multivariate Fama-MacBeth Cross-Sectional Regressions of 1-month ahead Hedge Fund Excess Returns on 9-Factor Systematic Risk (SR) and 9-Factor Unsystematic Risk (USR) with Control Variables

This appendix reports the average intercept and slope coefficients from the Fama-MacBeth (1973) cross-sectional regressions of one-month ahead hedge fund excess returns on the 9-factor SR and 9-factor USR with control variables (size, age, management fee, incentive fee, past month returns, redemption period, minimum investment amount, dummy for lockup and dummy for leverage). The Fama-MacBeth cross-section regressions are run each month for the full sample period (January 1997 – June 2010) and we report average slope coefficients for each variable for the full-sample period as well as for four sub-sample periods: January 1997 – August 1998 (first sub-sample period), September 1998 – February 2000 (second sub-sample period), March 2000 – June 2007 (third sub-sample period), and July 2007 – June 2010 (fourth sub-sample period). Newey-West *t*-statistics are given in parentheses to determine the statistical significance of the average intercept and slope coefficients. Numbers in bold denote statistical significance of the average slope coefficients.

	Intercept	9-Factor SR	9-Factor USR	Lagged Return	Age	Size	Mgmt Fee	Incentive Fee	Redemption Period	Minimum Investment	Dummy Lockup	Dummy Leverage
1997:01 – 2010:06	0.0034	**0.0167**	0.0029	**0.0913**	0.0001	0.0134	0.0588	**0.0091**	**0.0032**	**0.0074**	**0.1279**	0.0309
	(0.02)	**(3.79)**	(1.37)	**(4.54)**	(0.16)	(0.37)	(1.14)	**(3.29)**	**(3.25)**	**(2.58)**	**(2.19)**	(0.94)
1997:01 – 1998:08	–0.6799	**0.0229**	0.0092	0.0032	**0.0057**	**0.3601**	0.0926	0.0077	0.0054	0.0114	**0.4259**	0.0222
	(–0.74)	**(2.26)**	(0.60)	(0.09)	**(2.56)**	**(3.45)**	(0.46)	(0.60)	(1.14)	(0.67)	**(3.17)**	(0.26)
1998:09 – 2000:02	1.3574	**0.0182**	–0.0012	**0.1228**	**–0.0035**	–0.1008	**–0.2597**	**0.0163**	**0.0082**	**0.0247**	–0.2063	0.1456
	(3.74)	**(2.20)**	(–0.20)	**(1.96)**	**(–1.92)**	(–0.49)	**(–2.99)**	**(2.91)**	**(3.62)**	**(1.88)**	(–1.08)	(1.37)
2000:03 – 2007:06	0.0244	**0.0111**	0.0035	**0.0768**	–0.0001	–0.0344	0.0979	**0.0047**	**0.0029**	**0.0058**	**0.1904**	–0.0171
	(0.17)	**(2.17)**	(1.57)	**(3.38)**	(–0.35)	(–1.32)	(1.55)	**(2.16)**	**(3.10)**	**(1.99)**	**(4.03)**	(–0.70)
2007:07 – 2010:06	–0.3771	**0.0273**	–0.0004	**0.1662**	–0.0007	**–0.0071**	0.1077	**0.0179**	0.0001	0.0000	–0.0371	0.1015
	(–1.28)	**(2.63)**	(–0.17)	**(2.97)**	(–0.45)	**(–2.07)**	(0.89)	**(3.19)**	(0.06)	(0.34)	(–0.22)	(0.81)

Table V. Univariate Quintile Portfolios of Hedge Investment Styles Sorted by Skewness and Kurtosis

For each investment style separately, univariate portfolios are formed every month from January 1997 to June 2010 by sorting hedge funds based on their volatility (VOL), Skewness (SKEW), and Kurtosis (KURT). Quintile 1 (5) is the portfolio of funds with the lowest (highest) VOL, SKEW, and KURT within each style. Table reports the differences in next month returns between quintiles 5 and 1. Newey-West *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

Hedge Fund Investment Styles	# of Hedge Funds	% of Funds in Total Sample	VOL 5 – VOL 1 Return Diff.	SKEW 5 – SKEW 1 Return Diff.	KURT 5 – KURT 1 Return Diff.
Equity Mkt. Neutral	257	3.42%	0.050 (0.32)	0.029 (0.15)	0.084 (0.52)
Fixed Income Arbitrage	210	2.79%	0.021 (0.08)	0.180 (0.84)	0.014 (0.09)
Convertible Arbitrage	171	2.27%	0.043 (0.12)	–0.027 (–0.11)	0.122 (0.74)
Fund-of-Funds	2991	39.76%	**0.261** **(2.36)**	–0.062 (–1.25)	0.079 (1.18)
Multi Strategy	398	5.29%	**0.419** **(2.07)**	–0.141 (–1.09)	0.046 (0.42)
Long-Short Equity Hedge	1890	25.12%	**0.678** **(3.00)**	–0.108 (–0.60)	0.136 (0.79)
Event Driven	434	5.77%	**0.585** **(2.66)**	–0.018 (–0.23)	–0.055 (–0.67)
Managed Futures	517	6.87%	**0.792** **(3.40)**	–0.122 (–0.54)	–0.069 (–0.40)
Global Macro	250	3.32%	**0.739** **(3.60)**	–0.043 (–0.31)	0.118 (0.58)
Emerging Markets	405	5.39%	**1.103** **(3.10)**	–0.103 (–0.40)	–0.087 (–0.31)