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# Systematic Risk and the Cross-Section of Hedge Fund Returns

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# Systematic risk and the cross-section of hedge fund returns*

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Abstract

This paper investigates the extent to which market risk, residual risk, and tail risk explain the cross sectional dispersion in hedge fund returns. The paper introduces a comprehensive measure of systematic risk (*SR*) for individual hedge funds by breaking up total risk into systematic and fund specific or residual risk components. Contrary to the popular understanding that hedge funds are 'market neutral' we find that systematic risk is a highly significant factor explaining the dispersion of cross-sectional returns while at the same time measures of residual risk and tail risk seem to have little explanatory power. Funds in the highest *SR* quintile generate 6% more average annual returns compared to funds in the lowest *SR* quintile. After controlling for a large set of fund characteristics and risk factors, systematic risk remains positive and highly significant, whereas the relation between residual risk and future fund returns continues to be insignificant. Hence, systematic risk is a powerful determinant of the cross-sectional differences in hedge fund returns.

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## 1. Introduction

This paper examines the extent to which aggregate risk measures explain the cross sectional dispersion of hedge fund returns. Despite the fact that hedge funds are marketed as "absolute return" or market neutral investments that generate positive returns in both good and bad market conditions, work by Asness, Krail, and Liu (2001), Patton (2009), and Bali, Brown, and Caglayan (2011) show that hedge fund returns are indeed exposed to market factors. On the other hand, an important recent paper by Titman and Tiu (2011) argues that the low R-squared funds – those that are truly market neutral – are the ones that generate the greatest alpha. In addition, Fung and Hsieh (1997, 2001), Mitchell and Pulvino (2001), Agarwal and Naik (2004), and Fung, Hsieh, Naik, and Ramadorai (2008) have all shown that the dynamic trading and arbitrage strategies implemented by hedge funds generate significant hedge fund tail risk exposure. Brown, Gregoriou, and Pascalau (2011) present results to show that this tail risk exposure may not be diversifiable, which suggests that tail risk may explain hedge fund returns. It is reasonable to believe then that these factors can explain a significant fraction of the observed differences in returns across different hedge funds and hedge fund strategies.

We find that both the portfolio-level analyses and the cross-sectional regressions indicate a positive and significant link between total risk (variance) and expected returns, whereas skewness and kurtosis as measures of tail risk do not have any predictive power for future hedge fund returns. After demonstrating the economic and statistical significance of total variance, we then divide the total variance into its systematic and unsystematic components and explore the relative predictive power of systematic risk versus unsystematic (residual) risk over future fund returns. We find that it is systematic risk rather than residual risk which has the greatest role in explaining the cross section of hedge fund returns.

Earlier studies provide evidence for a wide variety of macroeconomic and financial factors that predict the time-series and cross-sectional variation in asset returns. In this paper, we utilize three different factor model specifications to obtain alternative measures of the systematic and fund specific or residual risk of hedge funds and investigate their performance in predicting the cross-section of future hedge fund returns. First, we use the 4-factor model of Fama-French (1993) and Carhart (1997) to generate systematic and residual risk of individual hedge funds. Second, we extend the 4-factor model of Fama-French-Carhart to the 6-factor model by including two bond factors originally used by Fung and Hsieh (2004). Third, and finally, in order to generate more comprehensive measures of systematic and residual risk, we use a 9-factor model that extends the 6-factor model of Fama-French-Carhart and Fung-Hsieh (2004) by adding the three trend following factors (in currencies, bonds, and commodities) introduced by Fung and Hsieh (2001).

We examine the significance of a cross-sectional relation between alternative measures of systematic risk and individual hedge funds using the Fama-MacBeth (1973) cross-sectional regressions as well as the univariate and bivariate portfolio-level analyses. The univariate Fama-MacBeth regressions of one-month ahead hedge fund returns on systematic risk provide an economically and statistically significant positive link between systematic risk and future fund returns. This result is robust across different sample periods as well as for alternative measures of systematic risk (i.e., whether 4-, 6-, or 9-factor models are utilized). In multivariate Fama-MacBeth regressions, we control for the residual risk, lagged returns, age, size, management fee, incentive fee, redemption period, minimum investment amount, lockup, and leverage structures of individual hedge funds. Even after controlling for the aforementioned fund characteristics, the average slope on systematic risk remains positive and highly significant. On the other hand, the relation between the unsystematic (or residual) risk and future fund returns proves to be insignificant after controlling for the systematic risk. Hence, we conclude that systematic risk is more powerful than residual risk in predicting the cross-sectional variation in hedge fund returns.

As an alternative to the Fama-MacBeth parametric tests we also conduct nonparametric portfolio-level analyses and find that the average raw return on the quintile portfolios of systematic risk increases monotonically as we move from the lowest systematic risk quintile (quintile 1) to the highest systematic risk quintile (quintile 5), with the average return difference between quintiles 5 and 1 being 6% per annum and highly significant. We also check whether the positive and significant performance difference between high systematic risk quintile funds and low systematic risk quintile funds also holds true when the analysis is done in terms of risk-adjusted returns (i.e. 4-, 6-, or 9-factor alphas). The results indicate positive and significant alpha differences between high and low systematic risk quintile funds as well.

A distinct feature of hedge funds is their dynamic management styles. Many fund managers actively vary their exposures to risk factors according to the macroeconomic conditions and the state of the financial markets. Consistent with the factor timing ability of hedge funds, our results suggest that by predicting changes in financial and macroeconomic factors, hedge fund managers can adjust their portfolio exposures up or down in a timely fashion to generate superior returns. Indeed, we find that hedge funds following directional dynamic trading strategies, such as global macro, emerging markets, and managed futures funds, correctly adjust their aggregate exposure to changes in factors, and hence there exists a positive and stronger link between their systematic risk and future returns. However, the cross-sectional relation between systematic risk and future returns is insignificant for the funds following non-directional strategies, such as equity market neutral, fixed income arbitrage, and convertible arbitrage funds. These results are supported and can be explained by our finding that the variation of systematic risk across time is much wider for directional strategies and is much smaller for non-directional strategies, and for this reason there is a stronger link between their future returns and their systematic risk. Lastly, another notable point in our paper is that the cross-sectional spreads in hedge fund returns and alphas are not related to the differences in funds' skewness and kurtosis, and this weak performance of higher moments remains intact across all hedge fund investment styles.

This paper is organized as follows. Section 2 provides a brief literature review. Section 3 describes the data and variables. Section 4 investigates the predictive power of volatility, skewness, and kurtosis for future hedge fund returns. Section 5 presents the factor models utilized in this study to obtain alternative measures of systematic and residual risk. Section 6 examines the relative performance of systematic and residual risk in predicting the cross-section of hedge fund returns. Section 7 concludes the paper.

## 2. Literature Review

The explosive growth of hedge funds, both in numbers and in assets under management over the last two decades, has resulted in a significant number of studies on hedge fund performance. The literature examining the risk-return characteristics of hedge funds has evolved considerably especially in recent years.[1] Sun, Wang, and Zheng (2009) construct a measure of the distinctiveness of a fund's investment strategy (*SDI*) and find that higher *SDI* is associated with better subsequent performance of hedge funds. Sadka (2010) demonstrates that liquidity risk is an important determinant of the cross-sectional differences in hedge fund returns and shows that hedge funds that significantly load on liquidity risk subsequently outperform low-loading funds by an average of 6% annually. Titman and Tiu (2011) regress individual hedge fund returns on a group of risk factors and find that funds with low R-squares of returns on factors have higher Sharpe ratios. Their results also show that the low R-square funds generate higher information ratios, and they charge higher incentive and management fees.[2] Patton and Ramadorai (2010) introduce a new econometric methodology to capture time-series variation in hedge funds' exposures to risk factors using high-frequency data and find that hedge fund risk exposures vary significantly across months. Cao, Chen, Liang, and Lo (2010) investigate how hedge funds manage their liquidity risk by responding to aggregate liquidity shock. Their results indicate that hedge fund managers have the ability to time liquidity by increasing their portfolios' market exposure when the equity market liquidity is high.

Among earlier studies investigating the risk-return characteristics of hedge funds, the closest paper to our work is Bali, Brown, and Caglayan (2011) that examines hedge funds' exposures to various risk factors through alternative measures of factor betas. The main finding in Bali, Brown, and Caglayan (2011) is that hedge funds with a higher (lower) exposure to default spread (inflation) generate statistically and economically higher returns in the following month. Specifically, hedge funds in the highest default spread beta quintile generate about 6% more annual returns compared to funds in the lowest default spread beta quintile. Similarly, the annual average returns of funds in the lowest inflation beta quintile are 5% higher than the annual average returns of funds in the highest inflation beta quintile. In this paper, our focus is not

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[1] A partial list includes Fung and Hsieh (1997, 2000, 2001, 2004), Ackermann, McEnally, and Ravenscraft (1999), Liang (1999,2001), Mitchell and Pulvino (2001), Agarwal and Naik (2000,2004), Kosowski, Naik, and Teo (2007), Bali, Gokcan, and Liang (2007), Liang and Park (2007), Fung et al. (2008), Patton (2009), Agarwal, Bakshi, and Huij (2009), Jagannathan, Malakhov, and Novikov (2010), Aggarwal and Jorion (2010), and Agarwal et al. (2010).

[2] We should note that funds with high systematic risk (SR) are not necessarily high R-square funds. High R-square funds have high systematic risk to total risk ratio (SR/TR). Hence, our finding of the positive relation between SR and future fund returns is not inconsistent with the finding of Titman and Tiu (2011) that funds with low R-squares have higher risk-adjusted returns.

on individual factor betas as in Bali, Brown, and Caglayan (2011). Instead, we introduce an *aggregate* measure of systematic risk for individual hedge funds and find a positive and significant link between the composite measure of systematic risk and the cross-section of hedge fund returns. In our study, we also show that after controlling for a large set of fund characteristics and risk factors, systematic risk remains positive and highly significant, whereas the relation between the unsystematic (or residual) risk and future fund returns proves to be insignificant after controlling for the systematic risk. Hence, this is the first paper to show that systematic risk is more powerful than residual risk in predicting the cross-sectional differences in hedge fund returns. Lastly, in addition to our findings on systematic versus residual risk, in this paper, we also investigate the significance of volatility, skewness, and kurtosis in predicting the cross-sectional variation in hedge fund returns. We find that portfolio level analyses and cross-sectional regressions indicate a positive and significant link between total risk and expected returns, whereas skewness and kurtosis do not have any predictive power for future fund returns.

## 3. Data and Variables

The hedge fund dataset is obtained from Lipper TASS database, and it contains information on a total of 14,228 defunct and live hedge funds with total assets under management, as of June 2010, close to $1.3 trillion. Between January 1994 and June 2010, out of the 14,228 hedge funds that reported monthly returns to TASS, we have 8,201 funds in the defunct / graveyard database and 6,027 funds in the live hedge fund database. The TASS database, in addition to reporting monthly returns (net of fees) and monthly assets under management, it also provides information on certain fund characteristics, including the management fees and incentive fees charged to investors.

Table 1 provides summary statistics on the hedge funds' numbers, returns, assets under management (AUM), and their fee structures. For each year for the period 1994:01 to 2010:06, Panel A of Table 1 reports the number of hedge funds entered to the database, number of hedge funds dissolved, total assets under management (AUM) at the end of each year by all hedge funds (in billion $s), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted hedge fund portfolio. One important item worth noting about this database is the fact that TASS does not include any defunct funds prior to 1994. In an effort to mitigate potential survivorship bias in the data, we select 1994 as the start of our sample period and employ our analyses on hedge fund returns only for the period January 1994 – June 2010. Looking at Panel A in detail, one can easily detect the sharp reversal seen in the growth of hedge funds both in numbers and in assets under management since the end of 2007, the starting point of the sub-prime mortgage financial crisis. Between the years 1994 – 2007, the number of hedge funds performing in the market increased on average 17% per year (see column "Year End"), while the amount of assets under management swelled on average 33% per year (see column "Total AUM"). However, both of these trends reversed course starting in 2008 together with the start of the big financial crisis, as the number of hedge funds performing in the financial industry fell by an average 10.5% per year, while the total assets under management dropped by an average 14.0% per year during the period 2008 – 2010. Just these two sharp reversals in the data simply explain the severity of the financial crisis that the hedge fund industry had to face over the past few years. In addition, the yearly attrition rates in Panel A (the ratio of number of dissolved funds to the total number of funds at the beginning of the year) also paint a similar picture; from 1994 to 2007, on average, the annual attrition rate was only 8.0%, from 2008 to mid-2010 , however, this figure more than doubled to 16.8%.

Panel B of Table 1 reports for the sample period 1994:01 – 2010:06, the cross-sectional mean, median, standard deviation, minimum, and maximum statistics for hedge fund characteristics including returns, size, age, management fee, and incentive fee. An important aspect of hedge funds is their widespread use of asymmetrical incentive fee structures. Incentive fees are typically a percentage of the fund's annual net profits above a designated hurdle rate and are paid to hedge fund portfolio managers to generate superior performance. The median (mean) incentive fee is 20.00% (14.02%) in our database (which reflects the true industry standards), and in some instances, goes up as high as 50.00% for a few hedge funds. Another interesting hedge fund fact that can be drawn from Panel B of Table 1 is the hedge funds' short span of life. The median age (number of months in existence since inception) of a fund is only 51 months, just over 4 years. The existence of a payout schedule, where hedge fund managers are paid only if they exceed the hurdle rate and that they have to first cover all losses from prior years before getting paid on a current year, forces hedge fund managers to dissolve quickly and form a new hedge fund after a bad year (hence the short span of life), instead of trying to cover those losses in the following years. One final interesting observation that can be extracted from this panel is the large size disparity seen among hedge funds, where size of a fund is measured as the average monthly assets under management over the life of the fund. Based on our data, while the mean hedge fund size is $126.7 million, the median hedge fund size is only $28.6 million. This suggests the existence of very few hedge funds with very large assets under management, which again reflects the true hedge fund industry standards.

Earlier studies find significantly positive aggregate alpha in the hedge funds market (e.g., Brown, Goetzmann, and Ibbotson (1999), Ackermann, McEnally, and Ravenscraft (1999), Liang (1999), Agarwal and Naik (2000), Fung and Hsieh (2004), Kosowski, Naik, and Teo (2007), and Fung, Hsieh, Naik, and Ramadorai (2008)). These studies recognize the sample selection bias issues inherent in all hedge fund research and address these issues in various ways. We follow this literature by including both live (6,027 funds) and dead funds (8,201) in our sample to eliminate survivorship bias. 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. In dealing with the back-fill bias, we find that there is a one-year gap between the first performance date and the date that the fund is added to the database. We discover that the average annual return of hedge funds during the first year of existence is, in fact, 1.87% higher than the average annual returns in subsequent years. To avoid back-fill bias, we follow Fung and Hsieh (2000) and delete the first 12-month return histories of all individual hedge funds in our sample. Lastly, to address the multi-period sampling bias and to obtain sensible measures of risk for funds from the time-series regressions, we require that all hedge funds in our study have at least 24 months of return history (see Kosowski, Naik, and Teo (2007)) to mitigate the impact of multi-period sampling bias. These well-known data bias issues related to our work, including the survivorship bias (see Brown et al. (1992)), the back-fill bias, and the multi-period sampling bias are discussed in detail in Section I of the Online Appendix, which is available at the authors' website.

## 4. Predictive Power of Volatility, Skewness, and Kurtosis

Arditti (1967), Kraus and Litzenberger (1976), and Kane (1982) extend the mean-variance portfolio theory of Markowitz (1952) to incorporate the effect of skewness on valuation. They present a three-moment asset pricing model in which investors hold concave preferences and like positive skewness. Their results indicate that assets that decrease a portfolio's skewness (i.e., that make the portfolio returns more left-skewed) are less desirable and should command higher expected returns. Similarly, Harvey and Siddique (2000) propose an asset pricing model with conditional co-skewness, where risk-averse investors prefer positively skewed assets to negatively skewed assets. Following Kimball (1993) and Pratt and Zeckhauser (1987), Dittmar (2002) extends the three-moment asset-pricing model and finds preference for lower kurtosis; i.e., investors are averse to kurtosis, and prefer stocks with lower probability mass in the tails of the distribution to stocks with higher probability mass in the tails of the distribution. According to Dittmar (2002), assets that increase a portfolio's kurtosis (i.e, that make the portfolio returns more leptokurtic) are less desirable and should command higher expected returns.

This is a particular issue for hedge funds. Fung and Hsieh (1997, 2001), Mitchell and Pulvino (2001), Agarwal and Naik (2004), and Fung, Hsieh, Naik, and Ramadorai (2008), have all shown that the dynamic trading and arbitrage strategies implemented by hedge funds generate significant hedge fund tail risk exposure. Brown, Gregoriou, and Pascalau (2011) present results to show that this tail risk exposure may not be diversifiable, which suggests that cross sectional dispersion in measures of skewness and kurtosis may be an important factor explaining differences in hedge fund expected returns.

In this study, we use a 36-month rolling-window estimation period to generate the monthly time-series measures of volatility, skewness, and kurtosis for each fund in our sample:

$$VOL_{i,t} = \frac{1}{n-1}\sum_{t=1}^{n}\left(R_{i,t} - \overline{R}_i\right)^2 ,$$

$$SKEW_{i,t} = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{R_{i,t} - \overline{R}_i}{\sigma_{i,t}}\right)^3 , \tag{1}$$

$$KURT_{i,t} = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{R_{i,t} - \overline{R}_i}{\sigma_{i,t}}\right)^4 - 3\,,$$

where $R_{i,t}$ is the excess return on fund $i$ in month $t$, $\overline{R}_i = \frac{\sum_{t=1}^{n} R_{i,t}}{n}$ is the sample mean of excess returns on fund $i$ over the past 36 months ($n$ = 36), $VOL_{i,t}$, $SKEW_{i,t}$, and $KURT_{i,t}$ are the sample variance, skewness, and kurtosis of excess returns on fund $i$ over the past 36 months, and $\sigma_{i,t} = \sqrt{VOL_{i,t}}$ is the sample standard deviation of excess returns on fund $i$ over the past 36 months, defined as the square root of the variance.

Starting with the first 3 years of monthly data from January 1994 to December 1996, we use individual hedge fund excess returns to estimate the sample variance, skewness, and kurtosis for each fund. Then, in the second stage, starting from January 1997, we run the Fama-MacBeth (1973) cross-sectional regressions of one-month ahead individual fund excess returns on volatility, skewness, and kurtosis to predict the cross-section of hedge fund returns in month $t$+1:

$$\begin{aligned} R_{i,t+1} &= \omega_t + \lambda_t \cdot VOL_{i,t} + \varepsilon_{i,t+1}\,, \\ R_{i,t+1} &= \omega_t + \lambda_t \cdot SKEW_{i,t} + \varepsilon_{i,t+1}\,, \\ R_{i,t+1} &= \omega_t + \lambda_t \cdot KURT_{i,t} + \varepsilon_{i,t+1}\,, \end{aligned} \tag{2}$$

where $R_{i,t+1}$ is the excess return on fund $i$ in month $t$+1, and $VOL_{i,t}$, $SKEW_{i,t}$, and $KURT_{i,t}$ are defined in Eq. (1). $\omega_t$ and $\lambda_t$ are, respectively, the monthly intercepts and slope coefficients from the Fama-MacBeth regressions. If the average slope coefficients in Eq. (2), $\overline{\lambda} = \sum_{t=1}^{n} \lambda_t \big/ n$, indicate statistical significance, then we conclude that the aforementioned variable(s) have a significant predictive power for future returns.

Table 2 (the first three rows) presents the time-series average slope coefficients from Eq. (2) over the sample period January 1997 to June 2010. The corresponding Newey-West (1987) $t$-statistics are reported in parentheses. As shown in the first row of Table 2, we obtain a positive and significant relation between total risk (volatility) and expected returns on hedge funds; the average slope on volatility is 0.0047 with a Newey-West $t$-statistic of 2.74. 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 row of Table 2, the relation between skewness and future returns is statistically insignificant; the average slope on SKEW is –0.0156 with a $t$-statistic of –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 coefficient on KURT is statistically insignificant. The third row of Table 2 shows that the average slope on KURT is 0.0451 with a $t$-statistic of 0.81.

To check the robustness of our results, in the online appendix (Section II), we examine the predictive power of volatility, skewness, and kurtosis for alternative sample periods. The statistically significant, positive average slopes on volatility persist for all sub-period analyses. The univariate regressions produce statistically insignificant *t*-statistics for the average slopes on SKEW and KURT for all sample periods. The results 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.

In the online appendix (Section III), we also form 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. The average raw return difference between High VOL and Low VOL quintiles is 0.472% per month and statistically significant. In addition, the 4-, 6-, and 9-factor alpha differences between quintiles 5 and 1 are found to be positive and highly significant, implying that the well-known hedge fund factors do not explain the positive relation between total risk and the cross-section of hedge fund returns. On the other hand, the same portfolio level analyses provide no evidence for a significant link between skewness, kurtosis, and future fund returns.

We have so far shown that total variance (volatility) is very capable of predicting the cross-sectional variation in hedge fund returns, whereas skewness and kurtosis do not have any power. We now investigate the performance of total risk after controlling for skewness and kurtosis and a large set of individual fund characteristics. Table 2 (starting with the fourth row) reports the time-series average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead returns on volatility, skewness, and kurtosis with the control variables; past-month return, age, size, management fee, incentive fee, redemption period, minimum investment amount, dummy for lockup, and dummy for leverage. Monthly cross-sectional regressions are run for the following multivariate specification and its nested versions:

$$\begin{aligned} R_{i,t+1} = \omega_t &+ \lambda_{1,t} \cdot VOL_{i,t} + \lambda_{2,t} \cdot SKEW_{i,t} + \lambda_{3,t} \cdot KURT_{i,t} + \lambda_{4,t} \cdot R_{i,t} + \lambda_{5,t} \cdot AGE_{i,t} \\ &+ \lambda_{6,t} \cdot SIZE_{i,t} + \lambda_{7,t} \cdot MGMTFEE_i + \lambda_{8,t} \cdot INCENTIVEFEE_i + \lambda_{9,t} \cdot REDEMPTION_i \\ &+ \lambda_{10,t} \cdot MININVEST_i + \lambda_{11,t} \cdot D\_LOCKUP_i + \lambda_{12,t} \cdot D\_LEVERAGE_i + \varepsilon_{i,t+1} \end{aligned} \tag{3}$$

where $R_{i,t+1}$ is the excess return on fund *i* in month *t*+1, and $VOL_{i,t}$, $SKEW_{i,t}$, and $KURT_{i,t}$ are defined in Eq. (1). *SIZE*, *AGE*, *MGMTFEE*, *INCENTIVEFEE*, *REDEMPTION*, *MININVEST*, *D_LOCKUP*, and *D_LEVERAGE* are the fund characteristics: Size is measured as the monthly assets under management in billion dollars; Age is measured as the number of months in existence since inception; Management Fee is a fixed percentage fee on assets under management, typically ranging from 1% to 2%; Incentive Fee is a fixed percentage fee of the fund's annual net profits above a designated hurdle rate; Redemption is the minimum number of days an investor needs to notify a hedge fund before he/she can redeem the invested amount from the fund; MinInvest is the minimum initial investment amount (measured in million dollars in the regression) that the fund requires from its investors to invest in a fund; D_Lockup is the dummy variable for lockup provisions (1 if the fund requires investors not able to withdraw initial investments for a pre-specified term, usually 12 months, 0 otherwise); D_Leverage is the dummy variable for leverage (1 if the fund uses leverage, 0 otherwise). We also include the one-month lagged fund returns ( $R_{i,t}$ ) in the cross-sectional regressions to control for potential momentum or reversal effects in hedge fund returns. In Table 2, the Fama-MacBeth cross-sectional regressions are run for each month and the average slope coefficients are reported for the full sample period January 1997 – June 2010.

The fourth row in Table 2 shows that controlling for the individual fund characteristics and the lagged fund returns does not alter the statistically significant predictive power of total risk over future hedge fund returns; there is still a positive and significant relation between volatility and future returns. The average slope coefficient on volatility is estimated to be 0.0033 with the Newey-West *t*-statistic of 2.98. The fifth and sixth rows in Table 2 provide similar results for the weak performance of skewness and kurtosis. Specifically, after controlling for the individual fund characteristics, the average slope on SKEW is found to be –0.0798 with a *t*-statistic of –0.63, and the average slope on KURT is 0.0496 with a *t*-statistic of 0.88.

Table 2 (seventh row) also tests whether the significantly positive link between volatility and hedge fund returns remains intact in the existence of skewness and kurtosis in the picture. The Fama-MacBeth regressions of one-month ahead returns on volatility, skewness, and kurtosis produce positive and highly significant average slope coefficient on volatility, whereas the average slopes on higher moments remain economically and statistically insignificant. The average slope on VOL is estimated to be 0.0037 with a *t*-statistic of 2.97, while the average slope on SKEW is –0.0158 with *t*-statistic of –0.21, and the average slope on KURT is 0.0340 with *t*-static of 0.67.

The last row of Table 2 examines the performance of total risk after controlling for skewness, kurtosis, and the individual fund characteristics all at the same time. The results provide clear evidence for the strong performance of volatility and the weak performance of higher moments after taking into account fund characteristics and lagged returns. A notable point in Table 2 is that although total risk remains the powerful determinant of the cross-sectional differences in hedge fund returns, there has never been an instance in any of the regression specifications where the average slopes on skewness and kurtosis are observed to be statistically significant. That is, higher moments do not have any predictive power for future fund returns when considered alone and/or in conjunction with total risk and control variables.

Another important point in Table 2 is that the average slope on lagged fund returns is positive and highly significant in all regression specifications without any exception. The average slope on $R_{i,t}$ is in the range of 0.0855 and 0.0982, with the *t*-statistics ranging from 4.01 to 4.46. This result indicates strong momentum effects in individual fund returns, i.e., winner (loser) funds continue to be winners (losers) in one month investment horizon.[3] Based on these results, we can conclude that even the significance of lagged returns, does not reduce or alter the predictive power of total risk over future hedge fund returns.

Another interesting observation in Table 2 is the fact that the incentive fee variable has always a positive and significant coefficient in monthly Fama-MacBeth regressions (regardless of the regression specification) when the fund characteristics are added to the regression equation as well. This suggests that incentive fee has a strong positive explanatory power for future hedge fund returns (i.e., funds that charge higher incentive fees also generate higher future returns), a finding similar to earlier studies of hedge funds (see Brown, Goetzmann, and Ibbotson (1999), Liang (1999), and Edwards and Caglayan (2001)). As in lagged return results, however, the significance of incentive fee does not change the predictive power of total risk on future hedge fund returns. Another notable point in Table 2 is that the redemption period, the minimum investment amount, and the dummy for lockup variables, which are used by Aragon (2007) to measure illiquidity of hedge fund portfolios, also have positive and significant average slope coefficients (although the average slopes on the minimum investment amount are marginally significant in regressions with skewness and kurtosis). This suggests that funds that use lockup and other share restrictions, which enable themselves to invest in illiquid assets, earn higher returns in following months, an outcome that coincides with Aragon's findings. However, even the significance of these variables does not alter or reduce the predictive power of total risk over hedge fund returns.

## 5. Factor Models: Systematic and Residual risk

After presenting the economic and statistical significance of total variance in Section 4, we now move forward and divide total variance into its systematic and unsystematic components. Within total variance, we are interested in seeing whether systematic or unsystematic component has a stronger predictive power over future hedge fund returns. This section describes the different factor models that we utilize to generate systematic and residual risk of individual hedge funds.

In this paper we employ three different factor model specifications to calculate alternative measures of systematic and residual risk. To understand the contribution of systematic risk to the prediction of hedge

[3] A similar result that there is short term (monthly) persistence in hedge fund returns is also found by Agarwal and Naik (2000) and Jagannathan, Malakhov, and Novikov (2010). Jegadeesh and Titman (1993, 2001) find momentum in stock returns for 3-month, 6-month, 9-month, and 12-month horizons although Jegadeesh (1990) and Lehmann (1990) provide strong evidence for the short-term reversal effect in individual stock returns for one-week to one-month horizon. In our empirical results we control for this phenomenon by using the Carhart's (1997) momentum factor.

fund returns, we assume that the excess return of each fund *i* is driven by a set of common factors and fund-specific (or residual) return $\varepsilon_{i,t}$ . To be concrete, assume a single factor return generating process:

$$R_{i,t} = \alpha_i + \beta_i \cdot F_t + \varepsilon_{i,t}\,, \tag{4}$$

where $R_{i,t}$ is the excess return on fund *i* in month *t* and $F_t$ is the macroeconomic or financial risk factor *F* in month *t*. $\alpha_i$ and $\beta_i$ are, respectively, the alpha and the risk factor's beta for fund *i*. Eq. (4) shows that total return on fund *i* is the sum of its systematic and unsystematic (or residual) components. Eq. (4) also indicates that the total variance of hedge fund returns can be broken down into two terms:

$$\sigma_i^2 = \beta_i^2 \sigma_F^2 + \sigma_{\varepsilon,i}^2\,, \tag{5}$$

where $\sigma_i^2$ denotes the total risk of fund *i*. The first term on the right hand side, $\beta_i^2 \sigma_F^2$ , is the fund's systematic risk component, which represents the part of fund's variance that is attributable to overall volatility of the common factor. The second term, $\sigma_{\varepsilon,i}^2$ , is the fund's unsystematic (or residual) risk component, which represents the part of fund's variance that is not attributable to overall volatility of the common factor. The residual risk component is related to the fund's specific volatility.

The econometric representations of the factor models as well as specifications as to how systematic and residual risk measures are calculated for each factor model are described in the section below:

*4-Factor Model of Fama-French (1993) and Carhart (1997)*:

$$R_{i,t} = \alpha_i + \beta_{1,i} \cdot MKT_t + \beta_{2,i} \cdot SMB_t + \beta_{3,i} \cdot HML_t + \beta_{4,i} \cdot MOM_t + \varepsilon_{i,t}\,, \tag{6}$$

where $R_{i,t}$ is the excess return on fund *i*, and $F_t = \left[MKT_t, SMB_t, HML_t, MOM_t\right]$ is a vector containing the Fama-French-Carhart four factors: the excess market return (MKT), size (SMB), book-to-market (HML), and momentum (MOM). Total risk of fund *i* is defined by the variance of $R_{i,t}$ denoted by $\sigma_i^2$ . The unsystematic (or residual) risk of fund *i* is defined by the variance of $\varepsilon_{i,t}$ in Eq. (6), denoted by $\sigma_{\varepsilon,i}^2$ . The systematic risk of fund *i* is defined as the difference between total and unsystematic variance, $SR_i = \sigma_i^2 - \sigma_{\varepsilon,i}^2$ , and it is a function of (i) the variance of the MKT, SMB, HML, and MOM factors; (ii) the cross-covariance of the market, SMB, HML, and MOM factors; and (iii) the exposures of fund's excess returns to the MKT, SMB, HML, and MOM factors. That is, the systematic risk of fund *i* is measured by the fund's variance that is attributable to overall volatility of the Fama-French-Carhart factors as well as the factors' cross-covariances.

*6-Factor Model of Fama-French (1993), Carhart (1997), and Fung and Hsieh (2004)*:

$$R_{i,t} = \alpha_i + \beta_{1,i} \cdot MKT_t + \beta_{2,i} \cdot SMB_t + \beta_{3,i} \cdot HML_t + \beta_{4,i} \cdot MOM_t + \beta_{5,i} \cdot \Delta 10Y_t + \beta_{6,i} \cdot \Delta CredSpr_t + \varepsilon_{i,t} \tag{7}$$

where $F_t = [MKT_t, SMB_t, HML_t, MOM_t, \Delta 10Y_t, \Delta CredSpr_t]$ is a vector containing the four factors of Fama-French-Carhart (MKT, SMB, HML, and MOM) and the two factors of Fung and Hsieh (2004) ($\Delta 10Y$ and $\Delta CredSpr$). $\Delta 10Y$ is the monthly change in the US Federal Reserve 10-year constant-maturity yield. $\Delta CredSpr$ is the monthly change in the difference between Moody's BAA yield and the 10-year constant-maturity yield. The unsystematic (or residual) risk of fund *i* is defined by the variance of $\varepsilon_{i,t}$ in Eq. (7), denoted by $\sigma^2_{\varepsilon,i}$. The 6-factor systematic risk of fund *i* is defined as the difference between total and unsystematic variance, $SR_i = \sigma_i^2 - \sigma^2_{\varepsilon,i}$.

*9-Factor Model of Fama-French (1993), Carhart (1997), and Fung and Hsieh (2001, 2004):*

$$\begin{aligned} R_{i,t} = \alpha_i + \beta_{1,i} \cdot MKT_t + \beta_{2,i} \cdot SMB_t + \beta_{3,i} \cdot HML_t + \beta_{4,i} \cdot MOM_t + \beta_{5,i} \cdot \Delta 10Y_t + \beta_{6,i} \cdot \Delta CredSpr_t \\ + \beta_{7,i} \cdot BDTF_t + \beta_{8,i} \cdot FXTF_t + \beta_{9,i} \cdot CMTF_t + \varepsilon_{i,t} \end{aligned} \tag{8}$$

where $F_t = [MKT_t, SMB_t, HML_t, MOM_t, \Delta 10Y_t, \Delta CredSpr_t, BDTF_t, FXTF_t, CMTF_t]$ is a vector containing the four factors of Fama-French-Carhart, two factors of Fung and Hsieh (2004), and three factors of Fung and Hsieh (2001). BDTF is Fung-Hsieh (2001) bond trend-following factor measured as the return of PTFS Bond Lookback Straddle; FXTF is Fung-Hsieh (2001) currency trend-following factor measured as the return of PTFS Currency Lookback Straddle; and CMTF is Fung-Hsieh (2001) commodity trend-following factor measured as the return of PTFS Commodity Lookback Straddle. The unsystematic (or residual) risk of fund *i* is defined by the variance of $\varepsilon_{i,t}$ in Eq. (8), denoted by $\sigma^2_{\varepsilon,i}$. The 9-factor systematic risk of fund *i* is defined as the difference between total and unsystematic variance, $SR_i = \sigma_i^2 - \sigma^2_{\varepsilon,i}$.

## 6. Predictive Power of Systematic and Residual risk

The literature provides evidence for a variety of risk factor models that are capable of explaining the returns of financial assets. The primary objective of this paper is not to come up with a new risk factor model capable of explaining hedge fund returns, but to test the significance of systematic and residual risk derived from these existing factor models on predicting the cross-sectional variation in monthly returns of hedge funds. In the following sections, we conduct parametric and nonparametric tests to assess the predictive power of systematic and residual risk over future hedge fund returns.

### *6.1. Systematic and residual risk in cross-sectional regressions*

We start with the first 3 years of monthly returns from January 1994 to December 1996 to estimate the total risk and residual risk (and hence systematic risk) for each fund in our sample, and then use a 36-month rolling-window estimation period to generate the monthly time-series estimates of systematic and residual risk. Then, in the second stage, starting from January 1997, we run the Fama-MacBeth cross-sectional regressions of one-month ahead individual fund excess returns on the systematic risk:

$$R_{i,t+1} = \omega_t + \lambda_t \cdot SR_{i,t} + \varepsilon_{i,t+1}, \tag{9}$$

where $R_{i,t+1}$ is the excess return on fund $i$ in month $t$+1 and $SR_{i,t}$ is the systematic risk for fund $i$ in month $t$ generated from the first stage analyses. $\omega_t$ and $\lambda_t$ are, respectively, the monthly intercepts and slope coefficients from the Fama-MacBeth regressions.

Although not reported in the paper to save space, the online appendix (Section IV) presents the average slope coefficients from Eq. (9) for the full sample period (January 1997 – June 2010) as well as for alternative sub-sample periods. For all periods and for alternative measures of systematic risk obtained from the 4-, 6-, and 9-factor models, we find a positive and significant link between systematic risk and expected returns on hedge funds. The average slopes on *SR* translate into a monthly return difference of almost 0.8% to 0.9% per month return spread between average funds in the high *SR* and low *SR* quintile portfolios.

In this section we also analyze the interaction between the systematic risk and the unsystematic (residual) risk and check if our earlier results on systematic risk hold true in the existence of residual risk in the picture, after controlling for individual fund characteristics. Table 3 reports the average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead fund excess returns on the 6-factor systematic risk and residual risk with and without the control variables. Monthly cross-sectional regressions are run for the following multivariate specification and its nested versions:

$$\begin{aligned} R_{i,t+1} &= \omega_t + \lambda_{1,t} \cdot SR_{i,t} + \lambda_{2,t} \cdot USR_{i,t} + \lambda_{3,t} \cdot R_{i,t} + \lambda_{4,t} \cdot AGE_{i,t} + \lambda_{5,t} \cdot SIZE_{i,t} + \\ &\lambda_{6,t} \cdot MGMTFEE_i + \lambda_{7,t} \cdot INCENTIVEFEE_i + \lambda_{8,t} \cdot REDEMPTION_i + \\ &\lambda_{9,t} \cdot MININVEST_i + \lambda_{10,t} \cdot D\_LOCKUP_i + \lambda_{11,t} \cdot D\_LEVERAGE_i + \varepsilon_{i,t+1}, \end{aligned} \tag{10}$$

where $R_{i,t+1}$ is the excess return on fund $i$ in month $t$+1, and $SR_{i,t}$ and $USR_{i,t}$ are, respectively, the 6-factor systematic risk and the 6-factor residual risk for fund $i$ in month $t$ generated from the first stage regression analyses. In Table 3, the Fama-MacBeth cross-sectional regressions are run for each month and the average slope coefficients are reported for five different sample periods: January 1997 – June 2010 in Panel A (full sample period); January 1997 – August 1998 in Panel B; September 1998 – February 2000 in Panel C; March 2000 – June 2007 in Panel D; and July 2007 – June 2010 in Panel E (as will be discussed later, subsamples are determined based on a statistical test of structural breakpoints).

As shown in Table 3, controlling for the unsystematic hedge fund risk, as well as the individual fund characteristics and lagged returns, does not alter the statistically significant predictive power of systematic risk over future hedge fund returns; there is a positive and significant link between systematic risk and hedge fund returns whether or not all variables are controlled simultaneously or in different combinations of groupings. The average slope coefficient on the 6-factor systematic risk for the full sample period (in Panel A) is estimated to be between 0.0188 and 0.0211, with the Newey-West *t*-statistics ranging from 3.28 to 3.94.

We also investigate whether the predictive power of systematic risk for future fund returns remains intact during different subsample periods when significant structural breaks are observed in risk and returns of hedge funds. Fung, Hsieh, Naik, and Ramadorai (2008) examine the performance, risk, and capital formation of funds-of-funds for the period 1995–2004 and find that the risk and return characteristics of funds-of-funds are time-varying. They identify breakpoints with major market events, namely, the collapse of LTCM in September 1998 and the peak of the technology bubble in March 2000. The cross-sectional relation between hedge funds' systematic risk and their future returns might be time-varying as well since hedge funds change their trading strategies depending on the market conditions over the sample period that we analyze. Following Fung, Hsieh, Naik, and Ramadorai (2008), we use a version of the Chow (1960) test in which we replace the standard error covariance matrix with a serial-correlation and heteroskedasticity consistent covariance matrix of Newey-West (1987). In our sample (January 1997–June 2010), structural breakpoints are identified as September 1998 (the collapse of LTCM), March 2000 (the peak of the technology bubble), and July 2007 (the beginning of subprime mortgage crisis with the collapse of two Bear-Sterns hedge funds). We investigate the significance of a cross-sectional link between expected returns and systematic risk for four subsample periods; January 1997–August 1998, September 1998–February 2000, March 2000–June 2007, and July 2007–June 2010.

Table 3 provides evidence of a positive and significant relation between *SR* and hedge fund returns for all sub-periods without any exception. The average slopes on *SR* are positive and highly significant after controlling for the residual risk, lagged return, and fund characteristics in all of the four subsample periods despite the structural breaks observed in risk and return characteristics of hedge funds. Among these four subsample periods identified above, we pay particular attention to the last subsample period, which is the recent subprime mortgage and global financial crisis period.

Panel E of Table 3 shows that the average slope on *SR* is positive, in the range of 0.0287 to 0.0359, and highly significant with the Newey-West *t*-statistics ranging from 2.35 to 2.81. A notable point in Panel E is that the average slopes on *SR* are much larger in magnitude (implying higher economic significance) for the period July 2007–June 2010, compared to our full sample period 1997–2010 as well as the remaining three subsamples. Despite the very short sample of only 36 months in Panel E, the average slopes on *SR* are statistically significant as well. These findings suggest that the predictive power of systematic risk for future hedge fund returns is amplified during the recent financial crisis period.

Interestingly, there has never been an instance in any of the panels in Table 3 where the average slope coefficient on the residual risk is observed to be statistically significant. That is, the unsystematic (residual) risk does not have any predictive power over future hedge fund returns when considered in conjunction with systematic risk. Overall, we conclude that systematic risk is a more powerful determinant of the cross-sectional differences in hedge fund returns.

Similar to our regression results with volatility, skewness, and kurtosis (in Table 2), the average slopes on the lagged returns and incentive fee in Table 3 are positive and highly significant in all sample periods (with the exception of the short sample period, 1997:01–1998:08, in Panel B). Similar to our earlier findings, the average slopes on the redemption period and the minimum investment amount are also positive and significant for the full sample (Panel A) and the subsample periods of 1998:09–2000:02 (Panel C) and 2000:03–2007:06 (Panel D). However, for the short sample period 1997:01–1998:08 (Panel B) and the recent crisis period 2007:07 – 2010:06 (Panel E), there is no significant link between hedge fund returns and the liquidity variables (the redemption period and the minimum investment amount). In particular, as shown in Panel E, neither the redemption period, the minimum investment amount, nor the dummy for lockup variable (which are used by Aragon (2007) to measure illiquidity of hedge fund portfolios), have any predictive power over future fund returns. This suggests that funds that use lockup and other share restrictions, which enable themselves to invest in illiquid assets, fail to earn higher returns during financial crises periods.

The fact that liquidity characteristics of funds show up in Panels C and D (post-crises periods), but not in Panels B and E (crises periods) may be consistent with how quickly less liquid strategies capture their returns for risk bearing as a function of the market environment. In particular, the results in Panel C may be driven by the industry's recovery post-LTCM crisis during which distressed assets did very well (i.e., after the 1997 Asian currency crisis and the 1998 Russian Debt Crisis). In contrast, the results in Panel E which includes the liquidity crisis of 2008 may reflect illiquid assets from hedge funds being shifted to side-pockets and removed from the fund's month-to-month returns (side pocket performance is generally not reported to commercial databases and hence is absent from the reported returns during the 2010 recovery period).

### *6.2. Measurement Errors in Factor Loadings and Errors-in-Variables Problem*

Our systematic risk (*SR*) measure is the variance of a mix of different factors and factor loadings, and, therefore, it may potentially be measured with error. Getmansky, Lo, and Makarov (2004) present convincing evidence that return smoothing and illiquidity causes hedge fund returns to be positively autocorrelated. More recently, Brown, Gregoriou and Pascalau (2011) find strong evidence of an MA(2) process in individual fund-of-fund returns. Asness, Krail and Liew (2001) argue that one should address this issue by including lagged factors in the alpha regression, and Lo (2008) suggests that this regression be estimated using the Generalized Least Squares, assuming that the errors follow a moving average process of order equal to the number of lagged factors in this regression. To address this issue, we extend the original 6-factor model by including the current and one-month lagged factors on the right hand side of Eq. (7). Then in the second stage, we run the bivariate Fama-MacBeth regressions using the systematic and residual risk measures generated from this extended 6-factor model. The second row of Table 4 (left panel) shows that the average slope on systematic risk is positive, 0.0194, and significant with a Newey-West *t*-statistic of 2.41. On the other hand, similar to our findings from the original 6-factor model, the average slope on residual risk continues to be economically and statistically insignificant for this extended 6-factor model as well (the average slope coefficient on residual risk is 0.0009 with a Newey-West *t*-statistics of 0.25).

To address the nonsynchroneity induced by return smoothing we follow Scholes and Williams (1977), Dimson (1979), and Fama and French (1992), and extend the 6-factor model further by including the current, one-month lagged, and one-month lead factors on the right hand side of Eq. (7) to generate a new set of systematic and unsystematic (residual) risk measures. As shown in the left panel, third row of Table 4, the positive link between this new systematic risk measure and hedge fund returns remains economically and statistically significant; the average slope on *SR* is positive, 0.0172, with a *t*-statistic of 2.66. However, the relation between residual risk and future hedge fund returns again remains insignificant. Hence, after reducing the measurement error in factor loadings, we conclude that systematic risk still proves to be more powerful than residual risk in predicting the cross-sectional variation in hedge fund returns.

Whenever we use estimated risk measures on the right hand side of a cross sectional regression, there is always a potential errors-in-variables problem. While this problem is mitigated in the Fama-NacBeth procedure by estimating risk measures on the basis of funds and performing the cross-sectional regressions using subsequent monthly return data, Shanken (1992) observes that this Fama-MacBeth methodology mitigates, but does not completely eliminate, the errors-in-variables bias. Hence, we follow Shanken (1992) and re-estimate the standard errors for the average slope coefficients on systematic and residual risk measures. To do this, we first estimate systematic and residual risk measures from the original 6-factor model as well as from the aforementioned two extended versions of the 6-factor model with lag, and lead-and-lag variables. Then, we run the bivariate cross-sectional regressions of one-month ahead returns on the three measures of *SR* and *USR* (residual risk) using the Generalized Least Square (GLS) method and compute Shanken (1992) *t*-statistics. As presented in the right panel of Table 4, the average slope coefficients obtained from the GLS regressions with Shanken *t*-statistics produce similar results: there is a positive and significant link between systematic risk and hedge fund returns, whereas the relation between residual risk and future fund returns is insignificant. Specifically, the average slope coefficients of *SR* lie between 0.0269 and 0.0310, with statistically significant Shanken *t*-statistics ranging between 2.30 and 2.50. The average slope coefficients of residual risk, on the other hand, range from 0.0036 to 0.0072, with insignificant Shanken *t*-statistics varying from 0.46 to 0.73. Hence, we conclude that after fixing the errors-in-variables problem in cross-sectional regressions, systematic risk remains once again the dominant factor in predicting the cross-section of hedge fund returns.

### *6.3. Univariate quintile portfolio analysis of systematic risk*

For each month, from January 1997 to June 2010, we form quintile portfolios by sorting hedge funds based on their 6-factor systematic risk (*SR*), where Quintile 1 contains funds with the lowest 6-factor *SR*, and Quintile 5 contains funds with the highest 6-factor *SR*. Table 5 shows the average *SR*s, the next month average returns, and the 4-, 6-, and 9-factor alphas for each quintile. The last three rows in Table 5 display the differences between quintile 5 and 1, the differences between quintile 5 and the rest of quintiles, and the differences between the rest of quintiles and quintile 1, the monthly returns, and the 4-, 6-, and 9-factor alphas.

Moving from quintile 1 to quintile 5, we observe that average raw return on the 6-factor *SR* portfolios increases monotonically from 0.223% to 0.705% per month. This indicates a monthly average raw return difference of 0.481% between quintiles 5 and 1 (i.e., high *SR* quintile vs. low *SR* quintile) with a Newey-West *t*-statistic of 2.31, suggesting that this positive return difference is statistically and economically significant. This result indicates that hedge funds in the highest *SR* quintile generate about 5.8% more annual returns compared to funds in the lowest *SR* quintile. We also check whether the significant return difference between *high SR* funds and *low SR* funds can be explained by Fama-French-Carhart's four factors of market, size, book-to-market, and momentum, as well as Fung-Hsieh's two bond factors, and three trend-following factors on currencies, bonds, and commodities. As shown in Table 5, the 4-factor alpha difference between quintiles 5 and 1 is 0.336% with a *t*-statistic of 2.69. Similarly, the 6- and 9-factor alpha differences between quintiles 5 and 1 are, respectively, 0.342% and 0.382%, with the respective *t*-statistics of 2.71 and 2.83. This suggests that after controlling for the well-known factors, the return difference between *high SR* and *low SR* funds remains positive and significant.

Another notable point in Table 5 is that the 4-, 6-, and 9-factor alphas are positive for all quintiles, but some of these alphas for intermediate quintile portfolios are not statistically significant. The 4-, 6-, and 9-factor alphas are statistically significant for the extreme portfolios (High SR and Low SR quintiles) without any exception. To investigate whether the alphas are internally consistent, we first compute the averages of these five quintile alphas for each factor model. We then estimate the 4-, 6-, and 9-factor alphas of the equal-weighted average hedge fund index. Finally, we check whether the alphas for the overall hedge fund index are equal to the averages of the 4-, 6-, and 9-factor alphas from five quintiles.

As shown in Table 5, moving from Low SR to High SR quintile, the 4-factor alpha increases from 0.169% to 0.505% per month (although not monotonically). The average of these 4-factor alphas equals 0.235% per month which is very close to the 4-factor alpha of the overall hedge fund index = 0.254% per month with a *t*-statistic of 2.46. Similarly, moving from quintile 1 to 5, the 6-factor alpha increases from 0.189% to 0.530% per month with an average of 0.261% per month which is again very close to the 6-factor alpha of the overall hedge fund index = 0.284% per month with a *t*-statistic of 3.18. Finally, as shown in the last column of Table 5, the 9-factor alpha increases from 0.172% to 0.554% per month with an average of

0.262% per month which is very similar to the 9-factor alpha of the overall hedge fund index = 0.281% per month with a *t*-statistic of 3.04. These results show that the quintile alphas computed based on the factor models generate reasonable estimates when compared to the overall hedge fund market index that consists of all funds available at TASS database.

Lastly, we investigate the source of significant return and alpha differences between High SR and Low SR funds: Is it due to outperformance by High SR funds, or underperformance by Low SR funds, or both? For this, we compare the performance of High SR quintile to the performance of the rest of quintiles as well as the performance of rest of quintiles to the performance of Low SR quintile, both in terms of raw returns and risk-adjusted returns (i.e., 4-factor, 6-factor, and 9-factor alphas).

As shown in the row "High SR–Rest of Quintiles" of Table 5, we find that, on average, High SR funds generate 0.429% more monthly raw returns compared to the rest of their peers (with a *t*-statistic of 2.74), indicating that there is a statistically significant outperformance by High SR funds relative to its peers. However, as shown in the last row "Rest of Quintiles–Low SR", we find that Low SR funds produce only 0.173% less average monthly returns compared to the rest of their peers (with a *t*-statistic of 1.50), implying that this return difference between the two groups is statistically insignificant (i.e., there is no statistically significant underperformance by Low SR funds relative to its peers). Based on these results, we conclude that the significantly positive return difference between High SR and Low SR funds is due to outperformance by High SR funds, but not due to underperformance by Low SR funds.

When the 4-factor, 6-factor, and 9-factor alpha differences are considered, the outcome remains the same: The High SR funds generate significantly higher risk-adjusted returns compared to the rest of the crowd (0.337% 4-factor alpha difference with a *t*-statistic of 3.01; 0.337% 6-factor alpha difference with a *t*-statistic of 3.06; and 0.365% 9-factor alpha difference with a *t*-statistic of 3.00), while Low SR funds' risk adjusted returns are not statistically and significantly smaller compared to their peers (0.082% 4-factor alpha difference with a *t*-statistic of 1.31; 0.090% 6-factor alpha difference with a *t*-statistic of 1.45; and 0.112% 9-factor alpha difference with a *t*-statistic of 1.77). Based on these alpha estimates, we again find that the significantly positive alpha difference between the High SR and Low SR funds is due to outperformance by High SR funds, but not due to underperformance by Low SR funds.

### *6.4. Bivariate portfolio analyses of systematic and residual risk*

We conduct a similar nonparametric portfolio analysis in this part of our study, however, this time we take into account the interaction between the systematic risk and the unsystematic (residual) risk. In short, we perform a bivariate quintile portfolio test for the systematic risk by controlling for the residual risk, and then we carry out the same test for the residual risk by controlling for the systematic risk.

### 6.4.1. Bivariate portfolios of systematic risk after controlling for residual risk

We first test whether there is still a positive relation between systematic risk and future hedge fund returns after controlling for residual risk. To perform this test, quintile portfolios are formed every month from January 1997 to June 2010 by first sorting hedge funds into 5 quintiles based on their 6-factor residual risk (*USR*). Then, within each *USR* sorted portfolios, hedge funds are sorted further into 5 sub-quintiles based on their 6-factor systematic risk (*SR*). This methodology, under each *USR* sorted quintiles, produces sub-quintile portfolios of hedge funds with dispersion in *SR* and with near identical *USR* values (i.e., these newly generated *SR* sub-quintile portfolios control for differences in *USR*). Overall, this procedure generates 25 sub-quintile portfolios, where $Q_{i,j}$ is the $j^{th}$ ranked *SR* portfolio within $i^{th}$ ranked *USR* portfolio ($i$=1,2,…,5; $j$=1,2,…,5). In Panel A of Table 6, "Quintile SR,1" represents for the lowest *SR* ranked hedge fund quintiles within each of the five *USR* ranked quintiles. In other words, "Quintile SR,1" is the average of the following 5 sub-quintile portfolios: $Q_{1,1}$, $Q_{2,1}$, $Q_{3,1}$, $Q_{4,1}$, $Q_{5,1}$. Similarly, "Quintile SR,5" represents for the highest *SR* ranked hedge fund quintiles within each of the five *USR* ranked quintiles. Alternatively, "Quintile SR,5" is the average of the following 5 sub-quintile portfolios: $Q_{1,5}$, $Q_{2,5}$, $Q_{3,5}$, $Q_{4,5}$, $Q_{5,5}$. Table 6, Panel A shows the average *SR* values and the next month average returns for the following quintiles: SR,1; SR,2; SR,3; SR,4; and SR,5. Moving from quintile SR,1 to quintile SR,5, the average return on the *SR* portfolios increases almost monotonically from 0.258% to 0.628% per month. The average return difference between quintiles SR,5 and SR,1 (i.e., *high SR* funds vs. *low SR* funds) is 0.370% per month with a Newey-West *t*-statistic of 2.13, suggesting that the positive relation between the systematic risk and future hedge fund returns remains significant after controlling for the residual risk, a result that is very similar to the findings obtained from our earlier Fama-MacBeth regressions.

We also check whether this significant return difference between SR,5 quintile and SR,1 quintile can be explained by Fama-French-Carhart's four factors of market, size, book-to-market, and momentum, as well as Fung-Hsieh's two bond factors and three trend-following factors on currencies, bonds, and commodities. The 4-factor alpha difference between quintiles SR,5 and SR,1 is 0.298% with a *t*-statistic of 3.89. Similarly, the 6-factor and 9-factor alpha differences between quintiles SR,5 and SR,1 are, respectively, 0.308% and 0.326%, with respective *t*-statistics of 3.87 and 3.74. This suggests that after controlling first for the residual risk, and second for the market, size, book-to-market, momentum, and Fung-Hsieh's bond and trend-following factors, the return difference between SR,5 and SR,1 quintiles remains positive and significant. Alternatively, these 4, 6, and 9 factors do not explain the positive link between systematic risk and the cross-section of hedge fund returns.

### 6.4.2. Bivariate portfolios of residual risk after controlling for systematic risk

By changing the order of sorting between systematic risk and residual risk, this time we check the relationship between residual risk and future fund returns after controlling for systematic risk. To perform this test, quintile portfolios are formed every month from January 1997 to June 2010 by first sorting hedge funds into 5 quintiles based on their 6-factor systematic risk (*SR*). Then, within each *SR* sorted portfolios, hedge funds are sorted further into 5 sub-quintiles based on their 6-factor residual risk (*USR*). Table 6, Panel B shows the average *USR* values and the next month average returns for the quintiles USR,1; USR,2; USR,3; USR,4; and USR,5, as well as the next month average return difference between USR,5 and USR,1 quintiles. Interestingly, we find the average return difference between quintiles USR,5 and USR,1 (i.e., *high USR* funds vs. *low USR* funds) to be 0.207% per month, but statistically insignificant, with a *t*-statistic of only 1.32, suggesting that the relation between the residual risk and future hedge fund returns is positive, but not significant after controlling for the systematic risk. This result exactly matches with our previous findings where we obtain positive, but insignificant average slope coefficients on the residual risk from the Fama-MacBeth regressions when systematic and residual risk variables are included simultaneously in the regression equation. Finally, looking at the risk-adjusted return differences between quintiles USR,5 and USR,1 in Panel B of Table 6, we see that, in addition to the raw return difference, the 4-, 6-, and 9-factor alpha differences are also not statistically significant.

Lastly, after conducting the conditional (sequentially) sorted *SR* and *USR* bivariate portfolio analysis (as explained above), we perform an independently (simultaneously) *SR* and *USR* sorted bivariate portfolio analysis as well (we do not however report results from simultaneously *SR* and *USR* sorted portfolios in the paper to save space). The results from independently sorted *SR* and *USR* bivariate portfolio analyses exactly match and strengthen our earlier findings from sequentially sorted *SR* and *USR* bivariate portfolio tests: the relation between the systematic risk and future fund returns is positive and significant after controlling for the residual risk; however, the relation between the residual risk and future returns is positive, but not significant after controlling for the systematic risk. Overall, the multivariate cross-sectional regressions and bivariate portfolio-level analyses indicate that compared to the residual risk, systematic risk is a much more important determinant of the cross-sectional variation in hedge fund returns.

### *6.5. Predictive Power of Systematic Risk by Hedge Fund Investment Style*

We now check whether our main findings would change (and how) if our analysis is applied to homogeneous groups of hedge funds, i.e., hedge fund investment styles. Hedge funds have various trading strategies; some willingly take direct factor exposure and have high systematic risk (directional strategies, such as Managed Futures, Global Macro, and Emerging Markets funds), while some try to minimize the market risk altogether (non-directional strategies, such as Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage funds), and some try to diversify the market risk by taking both long and short, diversified positions (semi-directional strategies, such as Fund-of-Funds, Long-Short Equity Hedge, Event Driven and Multi Strategy funds). Given these various trading strategies and styles, one would expect to see varying degrees of systematic risk by different hedge fund investment styles. Even within each investment style, one may also see varying degrees of systematic risk at different times, as hedge fund managers dynamically adjust their exposures to factors in response to changing market conditions.

To check the validity of these propositions, and to understand the time-series and cross-sectional variation in systematic risk by investment styles more clearly, we report in Table 7, for each style separately, the cross-sectional average of individual funds' standard deviation of systematic risk as well as the cross-sectional average of individual funds' max minus min (max – min) systematic risk differences. We expect a smaller variation in *SR* for a given style [i.e., smaller standard deviation of *SR* and smaller (max – min) *SR* spreads] to decrease the explanatory power of *SR* over future fund returns for that style. Conversely, we expect a larger variation in *SR* for a given style to improve the cross-sectional relation between *SR* and future returns for that style. In Table 7, in each cell, the first number before the slash is the cross-sectional average of individual funds' standard deviation of *SR* for that style, and the second number after the slash is the cross-sectional average of individual funds' (max – min) *SR* differences for the same style. For comparison purposes, we also report in bold the cross-sectional average of these two statistics across all hedge funds as a separate category in the last row of Table 7. In line with our expectations, non-directional strategies, such as Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage funds have considerably lower variation in systematic risk – lower standard deviation and lower (max – min) *SR* differences – compared to directional strategies, such as Managed Futures, Global Macro and Emerging Markets funds. Also, non-directional strategies' standard deviation of *SR* and (max – min) *SR* differences are considerably smaller compared to the all hedge funds category, while directional strategies' variation in *SR* are noticeably larger compared to the all hedge funds category.

Combining these new set of results on the variation of systematic risk among hedge fund investment styles, we expect our main finding – a significantly positive link between *SR* and hedge fund returns – obtained for all hedge funds to be stronger for funds following directional and semi-directional strategies (i.e., strategies that exhibit larger variation in systematic risk). We now investigate whether our conjecture that a large variation in systematic risk can actually translate into a large variation in hedge fund returns, and that the large variation in hedge fund returns improves the predictive power of *SR* over future hedge fund returns.

We perform this test by forming univariate quintile portfolios of *SR* for each hedge fund investment style separately and by analyzing the next month return and alpha differences between the High *SR* and Low *SR* quintiles. If a large variation in *SR* also implies an economically large variation in hedge fund returns, one would expect to see larger return and alpha spreads between the High *SR* and Low *SR* quintiles (i.e., larger economic significance) for funds following semi-directional and directional trading strategies.

Table 8 reports, for each investment style separately, the next month average return spreads as well as the 4-, 6-, and 9-factor alpha differences between the High *SR* and Low *SR* quintiles. The statistically significant average return and alpha spreads in this table for the semi-directional and directional strategies confirm our conjecture. As can be seen clearly in the table, the predictive power of systematic risk gradually increases as we move from the least directional strategies to the most directional strategies. As presented in the first three rows of Table 8, the next month average return and alpha spreads are found to be statistically insignificant for the three non-directional styles (Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage). However, for the semi-directional strategies (Fund-of-Funds, Multi Strategy, Long-short Equity Hedge, and Event Driven), the average return difference between High *SR* and Low *SR* quintiles are positive, in the range of 0.271% to 0.699% per month, and highly significant with the *t*-statistics ranging from 2.19 to 3.02. Most importantly, we obtain the highest predictive power of *SR* for the directional strategies (Managed Futures, Global Macro, and Emerging Markets funds): the average return spreads between High *SR* and Low *SR* quintiles are in the range of 0.716% to 1.094% per month with the *t*-statistics ranging from 3.05 to 3.79. In sum, these results indicate an economically and statistically stronger relation between systematic risk and future returns for funds with sizeable and stronger variation in systematic risk (i.e., stronger relation between systematic risk and future returns for funds with larger variation in *SR*).

Table 8 also reports the number of hedge funds for each investment style and the percentage of funds in total sample. A notable point in the first two columns of Table 8 is that the total number of funds in the non-directional category is only 638 (out of 7,523 funds), corresponding to 8.48% of the hedge fund sample. On the other hand, the total number of funds following semi-directional and directional strategies is 6,885, corresponding to 91.52% of the hedge fund universe. These results indicate that the significantly positive link between systematic risk and future returns holds for about 92% of the overall hedge fund sample.

Finally, we investigate the predictive power of volatility, skewness, and kurtosis for each investment style separately as well. Based on our earlier results, 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. The online appendix (Section V) confirms our conjecture. Although not reported here to preserve space, 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. 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. Overall, the results indicate an economically and statistically stronger relation between total risk and future returns for funds with larger variation in total risk, whereas there is no significant link between hedge fund returns and higher moments (skewess and kurtosis) for any of the 10 investment styles.

## 7. Conclusion

This paper investigates whether the cross-sectional variation in hedge fund returns are related to the differences in funds' aggregate risk measures – market risk, residual risk, and measures of tail risk. Portfolio level analyses and cross-sectional regressions with and without controlling for the funds' characteristics indicate a positive and significant link between volatility (total risk) and future fund returns. However, the results provide no evidence for a significant link between higher moments (skewness and kurtosis) and the cross-section of hedge fund returns. In addition to analyzing the cross-sectional predictive power of volatility and tail risk, this study contributes to the literature in a significant way by examining individual funds' aggregate exposure to financial and macroeconomic factors through alternative factor models' systematic risk estimates, and by investigating the performance of these systematic risk measures in predicting the cross-sectional variation in hedge fund returns. This is the first study to test the relative performance of systematic and residual risk in terms of their ability to explain differences in hedge fund returns.

We utilize three different factor model specifications (4-, 6-, and 9-factor models) to obtain alternative measures of systematic risk, where we measure individual hedge fund systematic risk as the difference between total risk and residual risk. After controlling for residual risk, lagged returns, age, size, management fee, incentive fee, redemption period, minimum investment amount, lockup, and leverage structures of individual hedge funds, all parametric and nonparametric tests reveal clear, robust and corroborating results for a positive and significant relation between systematic risk and future hedge fund returns. More importantly, similar positive and significant links between systematic risk and future hedge fund returns are found both when hedge fund systematic risk is derived from alternative factor model specifications, as well as when alternative sample periods are used, suggesting that our findings are neither sensitive to the factor model utilized, nor the sample period selected.

The results from univariate portfolio analysis of systematic risk suggest that hedge funds in the highest systematic risk quintile generate 6% more annual returns compared to funds in the lowest systematic risk quintile. After controlling for Fama-French-Carhart's four factors of market, size, book-to-market, and momentum, as well as Fung-Hsieh's two bond and three trend-following factors in currencies, bonds, and commodities, the positive relation between systematic risk and hedge fund returns remains significant. In addition, bivariate portfolio tests of systematic and residual risk generate similar statistically significant raw and risk-adjusted return differences between high systematic risk and low systematic risk funds, after controlling for residual risk. However, the relation between the residual risk and future fund returns is insignificant after controlling for the systematic risk. Hence, systematic risk proves to be more powerful than residual risk in predicting the cross-sectional variation in hedge fund returns.

Finally, this study investigates whether the predictive power of systematic risk for future fund returns changes across specific hedge fund categories. The empirical analyses indicate that the economic and statistical significance of systematic risk gradually increases as we move from the least directional strategies to the most directional strategies, implying a much stronger relation between systematic risk and future returns for funds with sizeable time-series variation in systematic risk. In sum, our results suggest that the predictive power of systematic risk emanates from hedge funds' competence in detecting shifts in financial markets and their ability to timely adjust their positions to those changes in financial and economic conditions.

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**Table 1**

Descriptive statistics

There are a total of 14,228 hedge funds that reported monthly returns to TASS at some period between January 1994 and June 2010 in this database, of which 8,201 are defunct funds and 6,027 are live funds. For each year from 1994 to 2010, Panel A reports the number of hedge funds entered to the database, number of hedge funds dissolved, total assets under management (AUM) at the end of each year by all hedge funds (in billion $s), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted hedge fund portfolio. Panel B reports for the sample period 1994:01 – 2010:06 the cross-sectional mean, median, standard deviation, minimum, and maximum statistics for hedge fund characteristics including returns, size, age, management fee and incentive fee.

*Panel A: Summary statistics year by year (1994 – 2010)*

| | | | | | | Equal-Weighted Hedge Fund (EWHF) Portfolio Monthly Returns (%) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Year | Year Start | Entries | Dissolved | Year End | Total AUM (billion $s) | Mean | Median | Std. Dev. | Minimum | Maximum |
| 1994 | 840 | 310 | 31 | 1119 | 56.0 | -0.05 | 0.08 | 0.95 | -1.64 | 1.00 |
| 1995 | 1119 | 329 | 71 | 1377 | 67.8 | 1.25 | 1.39 | 1.04 | -0.94 | 2.76 |
| 1996 | 1377 | 391 | 136 | 1632 | 91.6 | 1.41 | 1.50 | 1.55 | -1.73 | 3.93 |
| 1997 | 1632 | 427 | 111 | 1948 | 140.2 | 1.42 | 1.70 | 2.01 | -1.64 | 4.73 |
| 1998 | 1948 | 428 | 173 | 2203 | 156.9 | 0.37 | 0.20 | 2.14 | -4.88 | 3.12 |
| 1999 | 2203 | 538 | 193 | 2548 | 201.7 | 2.00 | 1.26 | 2.14 | -0.30 | 6.37 |
| 2000 | 2548 | 623 | 238 | 2933 | 253.0 | 0.83 | 0.47 | 2.16 | -1.94 | 5.41 |
| 2001 | 2933 | 876 | 264 | 3545 | 380.7 | 0.53 | 0.62 | 1.11 | -1.45 | 2.46 |
| 2002 | 3545 | 971 | 251 | 4265 | 438.9 | 0.35 | 0.55 | 0.75 | -1.24 | 1.36 |
| 2003 | 4265 | 1240 | 274 | 5231 | 636.4 | 1.24 | 1.10 | 0.85 | -0.18 | 3.01 |
| 2004 | 5231 | 1502 | 334 | 6399 | 930.8 | 0.65 | 0.72 | 1.13 | -1.15 | 2.63 |
| 2005 | 6399 | 1475 | 539 | 7335 | 1,378.0 | 0.74 | 1.25 | 1.30 | -1.44 | 1.98 |
| 2006 | 7335 | 1434 | 622 | 8147 | 1,415.8 | 0.90 | 1.18 | 1.37 | -1.78 | 3.19 |
| 2007 | 8147 | 1334 | 1027 | 8454 | 2,092.6 | 0.80 | 0.79 | 1.43 | -2.02 | 2.85 |
| 2008 | 8454 | 1001 | 1953 | 7502 | 1,587.1 | -1.53 | -1.70 | 2.40 | -5.69 | 1.67 |
| 2009 | 7502 | 360 | 1659 | 6203 | 1,354.8 | 1.01 | 0.87 | 1.15 | -0.64 | 3.50 |
| 2010 | 6203 | 149 | 325 | 6027 | 1,311.8 | -0.03 | -0.02 | 1.62 | -2.65 | 2.15 |

*Panel B: Cross-Sectional Statistics (Overall Sample Period: 1994:01 – 2010:06)*

| | N | Mean | Median | Std. Dev. | Minimum | Maximum |
|---|---|---|---|---|---|---|
| Average Monthly Return over the life of the Fund (%) | 14,228 | 0.41 | 0.40 | 1.24 | -27.17 | 22.10 |
| Average Monthly AUM over the life of the Fund (million $s) | 14,228 | 126.7 | 28.6 | 1,303.4 | 0.5 | 92,483.4 |
| Age of the Fund (# of months in existence) | 14,228 | 60.52 | 51.00 | 42.42 | 1.00 | 198.00 |
| Management Fee (%) | 14,033 | 1.47 | 1.50 | 0.66 | 0.00 | 10.00 |
| Incentive Fee (%) | 13,931 | 14.02 | 20.00 | 8.23 | 0.00 | 50.00 |

**Table 2**

Fama-MacBeth cross-sectional regressions of one-month ahead hedge fund returns on volatility, skewness, kurtosis and control variables

This table 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 funds' total variance or volatility (VOL), skewness (SKEW), and kurtosis (KURT) 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-sectional regressions are run each month for the full sample period January 1997 – June 2010. Average slope coefficients are reported in separate columns for each variable. Each row represents a cross-section regressional equation specification tested in the analyses. 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* | VOL | SKEW | KURT | Lagged Return | Age | Size | Mgmt Fee | Incentive Fee | Redemption Period | Minimum Investment | Dummy Lockup | Dummy Leverage |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.3088 | **0.0047** | | | | | | | | | | | |
| (1.85) | **(2.74)** | | | | | | | | | | | |
| 0.3353 | | –0.0156 | | | | | | | | | | |
| (2.08) | | (–0.14) | | | | | | | | | | |
| 0.2808 | | | 0.0451 | | | | | | | | | |
| (1.48) | | | (0.81) | | | | | | | | | |
| –0.0081 | **0.0033** | | | **0.0889** | 0.0001 | 0.0129 | 0.0663 | **0.0072** | **0.0032** | **0.0071** | **0.1330** | 0.0266 |
| (–0.04) | **(2.98)** | | | **(4.46)** | (0.08) | (0.35) | (1.24) | **(2.55)** | **(3.24)** | **(2.39)** | **(2.29)** | (0.81) |
| –0.0646 | | –0.0798 | | **0.0910** | 0.0004 | 0.0078 | 0.0824 | **0.0101** | **0.0024** | **0.0057** | **0.1745** | 0.0333 |
| (–0.30) | | (–0.63) | | **(4.01)** | (0.73) | (0.21) | (1.39) | **(2.27)** | **(2.42)** | **(1.68)** | **(3.43)** | (1.17) |
| –0.0594 | | | 0.0496 | **0.0855** | 0.0004 | 0.0082 | 0.0829 | **0.0079** | **0.0021** | **0.0059** | **0.1648** | 0.0215 |
| (–0.27) | | | (0.88) | **(4.26)** | (0.74) | (0.22) | (1.37) | **(2.66)** | **(1.81)** | **(1.78)** | **(3.07)** | (0.92) |
| 0.2568 | **0.0037** | –0.0158 | 0.0340 | | | | | | | | | |
| (1.41) | **(2.97)** | (–0.21) | (0.67) | | | | | | | | | |
| –0.1188 | **0.0034** | –0.0780 | 0.0341 | **0.0982** | 0.0003 | 0.0123 | 0.0807 | **0.0091** | **0.0024** | **0.0074** | **0.1456** | 0.0087 |
| (–0.50) | **(2.99)** | (–0.89) | (0.67) | **(4.10)** | (0.58) | (0.33) | (1.32) | **(2.30)** | **(2.07)** | **(2.47)** | **(2.83)** | (0.39) |

**Table 3**

Multivariate Fama-MacBeth cross-sectional regressions of one-month ahead hedge fund returns on the 6-factor systematic risk (SR) and residual risk (USR) with and without control variables

This table 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 6-factor SR and USR with and without 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-sectional regressions are run each month during the full sample period January 1997 – June 2010 (Panel A), as well as for four sub-sample periods: January 1997 – August 1998 (Panel B), September 1998 – February 2000 (Panel C), March 2000 – June 2007 (Panel D), and July 2007 – June 2010 (Panel E). Average slope coefficients are reported in separate columns for each variable. Each row represents a cross-sectional regression equation specification tested in the analyses. 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.

*Panel A: 1997:01 – 2010:06*

| *Intercept* | 6-Factor SR | 6-Factor USR | Lagged Return | Age | Size | Mgmt Fee | Incentive Fee | Redemption Period | Minimum Investment | Dummy Lockup | Dummy Leverage |
|---|---|---|---|---|---|---|---|---|---|---|---|
| –0.0840 | **0.0201** | | **0.0914** | –0.0001 | 0.0066 | 0.0740 | **0.0108** | **0.0034** | **0.0093** | **0.1091** | 0.0315 |
| (–0.45) | **(3.94)** | | **(4.67)** | (–0.19) | (0.19) | (1.42) | **(4.03)** | **(3.43)** | **(2.81)** | **(1.97)** | (1.02) |
| 0.2248 | **0.0211** | 0.0023 | | | | | | | | | |
| (1.46) | **(3.28)** | (1.07) | | | | | | | | | |
| –0.0671 | **0.0188** | 0.0013 | **0.0909** | –0.0001 | 0.0049 | 0.0625 | **0.0091** | **0.0033** | **0.0094** | **0.1121** | 0.0275 |
| (–0.39) | **(3.69)** | (0.70) | **(4.73)** | (–0.17) | (0.14) | (1.28) | **(3.29)** | **(3.48)** | **(2.75)** | **(1.98)** | (0.89) |

*Panel B: 1997:01 – 1998:08*

| *Intercept* | 6-Factor SR | 6-Factor USR | Lagged Return | Age | Size | Mgmt Fee | Incentive Fee | Redemption Period | Minimum Investment | Dummy Lockup | Dummy Leverage |
|---|---|---|---|---|---|---|---|---|---|---|---|
| –0.8327 | **0.0217** | | 0.0358 | **0.0046** | **0.3113** | 0.1351 | 0.0112 | 0.0065 | 0.0093 | **0.2626** | –0.0176 |
| (–0.85) | **(2.02)** | | (0.69) | **(1.99)** | **(3.33)** | (0.59) | (0.89) | (1.55) | (0.67) | **(1.77)** | (–0.23) |
| 0.1158 | **0.0250** | 0.0100 | | | | | | | | | |
| (0.24) | **(2.09)** | (0.72) | | | | | | | | | |
| –0.6547 | **0.0224** | 0.0081 | –0.0002 | **0.0047** | **0.3350** | 0.0575 | 0.0099 | 0.0061 | 0.0092 | **0.3308** | –0.0130 |
| (–0.76) | **(2.06)** | (0.62) | (–0.01) | **(2.16)** | **(3.79)** | (0.32) | (0.84) | (1.44) | (0.67) | **(2.45)** | (–0.16) |

**Table 3 (continued)**

*Panel C: 1998:09 – 2000:02*

| *Intercept* | 6-Factor SR | 6-Factor USR | Lagged Return | Age | Size | Mgmt Fee | Incentive Fee | Redemption Period | Minimum Investment | Dummy Lockup | Dummy Leverage |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1.2402 | **0.0159** | | **0.1333** | **–0.0034** | –0.1161 | **–0.2567** | **0.0163** | **0.0084** | **0.0329** | –0.2535 | 0.1365 |
| (3.30) | **(2.12)** | | **(2.31)** | **(–1.88)** | (–0.56) | **(–2.79)** | **(2.91)** | **(3.43)** | **(2.17)** | (–1.31) | (1.31) |
| 1.0708 | **0.0301** | –0.0031 | | | | | | | | | |
| (2.88) | **(2.09)** | (–0.52) | | | | | | | | | |
| 1.1862 | **0.0244** | –0.0074 | **0.1364** | **–0.0038** | –0.1451 | **–0.2279** | **0.0136** | **0.0080** | **0.0355** | –0.2572 | 0.1262 |
| (3.25) | **(2.43)** | (–1.22) | **(2.26)** | **(–2.10)** | (–0.75) | **(–2.63)** | **(2.66)** | **(3.92)** | **(2.37)** | (–1.34) | (1.22) |

*Panel D: 2000:03 – 2007:06*

| *Intercept* | 6-Factor SR | 6-Factor USR | Lagged Return | Age | Size | Mgmt Fee | Incentive Fee | Redemption Period | Minimum Investment | Dummy Lockup | Dummy Leverage |
|---|---|---|---|---|---|---|---|---|---|---|---|
| –0.0420 | **0.0153** | | **0.0721** | –0.0003 | –0.0322 | 0.1103 | **0.0064** | **0.0029** | **0.0083** | **0.1827** | –0.0010 |
| (–0.27) | **(2.37)** | | **(3.19)** | (–0.75) | (–1.14) | (1.71) | **(2.75)** | **(2.88)** | **(2.20)** | **(4.26)** | (–0.04) |
| 0.2944 | **0.0123** | 0.0027 | | | | | | | | | |
| (2.31) | **(2.07)** | (1.31) | | | | | | | | | |
| –0.0367 | **0.0128** | 0.0025 | **0.0781** | –0.0003 | –0.0349 | 0.1019 | **0.0053** | **0.0029** | **0.0080** | **0.1765** | –0.0068 |
| (–0.24) | **(2.70)** | (1.34) | **(3.59)** | (–0.66) | (–1.33) | (1.62) | **(2.41)** | **(3.03)** | **(2.13)** | **(4.14)** | (–0.29) |

**Table 3 (continued)**

*Panel E: 2007:07 – 2010:06*

| *Intercept* | 6-Factor SR | 6-Factor USR | Lagged Return | Age | Size | Mgmt Fee | Incentive Fee | Redemption Period | Minimum Investment | Dummy Lockup | Dummy Leverage |
|---|---|---|---|---|---|---|---|---|---|---|---|
| –0.4330 | **0.0329** | | **0.1484** | –0.0006 | **–0.0064** | 0.1167 | **0.0185** | 0.0005 | 0.0000 | 0.0254 | 0.0857 |
| (–1.60) | **(2.44)** | | **(2.87)** | (–0.43) | **(–2.03)** | (1.09) | **(3.20)** | (0.36) | (0.96) | (0.16) | (0.76) |
| –0.3080 | **0.0359** | –0.0004 | | | | | | | | | |
| (–0.67) | **(2.35)** | (–0.23) | | | | | | | | | |
| –0.4414 | **0.0287** | –0.0009 | **0.1501** | –0.0006 | **–0.0064** | 0.1141 | **0.0156** | 0.0005 | 0.0000 | 0.0178 | 0.0845 |
| (–1.66) | **(2.81)** | (–0.90) | **(2.89)** | (–0.42) | **(–2.04)** | (1.08) | **(3.20)** | (0.38) | (1.30) | (0.11) | (0.75) |

**Table 4**

OLS and GLS cross-sectional regressions with Newey-West and Shanken t-statistics

Systematic risk (SR) and residual risk (USR) measures are obtained from three alternative specifications of the 6-factor model. Models 1, 2, and 3 are presented below. This table presents the average intercepts and average slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead hedge fund excess returns on the 6-factor systematic and residual risk measures for the sample period January 1997 – June 2010. In left panel, the cross-sectional regressions are run using the Ordinary Least Square (OLS) method and Newey-West (1987) t-statistics are given in parentheses. In right panel, the cross-sectional regressions are run using the Generalized Least Square (GLS) method and Shanken (1992) t-statistics are given in parentheses. Numbers in bold denote statistical significance.

Model 1: $R_{i,t} = \alpha_i + \beta_i \cdot F_t + \varepsilon_{i,t}$

Model 2: $R_{i,t} = \alpha_i + \beta_{1,i} \cdot F_t + \beta_{2,i} \cdot F_{t-1} + \varepsilon_{i,t}$

Model 3: $R_{i,t} = \alpha_i + \beta_{1,i} \cdot F_t + \beta_{2,i} \cdot F_{t-1} + \beta_{3,i} \cdot F_{t+1} + \varepsilon_{i,t}$

where $F_t = \left[MKT_t, SMB_t, HML_t, MOM_t, \Delta 10Y_t, \Delta CredSpr_t\right]$ is a vector containing the four factors of Fama-French-Carhart (MKT, SMB, HML, and MOM) and the two factors of Fung and Hsieh (2004) ( $\Delta 10Y$ and $\Delta CredSpr$ ). $\Delta 10Y$ is the monthly change in the US Federal Reserve 10-year constant-maturity yield. $\Delta CredSpr$ is the monthly change in the difference between Moody's BAA yield and the 10-year constant-maturity yield.

| | *OLS Cross-Sectional Regressions with Newey-West t-statistics* | | | *GLS Cross-Sectional Regressions with Shanken t-statistics* | | |
|---|---|---|---|---|---|---|
| | Intercept | 6-Factor SR | 6-Factor USR | Intercept | 6-Factor SR | 6-Factor USR |
| Model 1 | 0.2248 | **0.0211** | 0.0023 | 0.0537 | **0.0310** | 0.0036 |
| | (1.46) | **(3.28)** | (1.07) | (0.51) | **(2.50)** | (0.73) |
| Model 2 | 0.2556 | **0.0194** | 0.0009 | 0.0447 | **0.0307** | 0.0037 |
| | (1.66) | **(2.41)** | (0.25) | (0.42) | **(2.30)** | (0.46) |
| Model 3 | 0.2228 | **0.0172** | –0.0145 | 0.0441 | **0.0269** | 0.0072 |
| | (1.31) | **(2.66)** | (–0.74) | (0.43) | **(2.43)** | (0.58) |

**Table 5**

Univariate quintile portfolios of hedge funds sorted by 6-factor systematic risk (SR)

Quintile portfolios are formed every month from January 1997 to June 2010 by sorting hedge funds based on their 6-factor Systematic Risk (SR). Quintile 1 is the portfolio of hedge funds with the lowest SR and Quintile 5 is the portfolio of hedge funds with the highest SR. The table reports the average SR as well as the next month average returns for each quintile. The last three columns also report the alphas for each quintile with respect to the 4-factor model of Fama-French-Carhart; the combined 6-factor model of Fama-French-Carhart and Fung-Hsieh bond factors; and the combined 9-factor model of Fama-French-Carhart and Fung-Hsieh bond and trend following factors. The last three rows represent the average monthly return and 4-factor, 6-factor, and 9-factor alpha differences between Quintile 5 and Quintile 1; between Quintile 5 and the Rest of Quintiles; and between Quintile 1and the Rest of Quintiles. 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 SR in each Quintile | Next Month Average Returns | 4-factor Alpha | 6-factor Alpha | 9-factor Alpha |
|---|---|---|---|---|---|
| Low SR | 0.392 | 0.223 | 0.169 | 0.189 | 0.172 |
| | | (2.88) | (2.68) | (3.47) | (2.87) |
| 2 | 1.529 | 0.247 | 0.150 | 0.177 | 0.171 |
| | | (2.03) | (1.67) | (2.38) | (2.13) |
| 3 | 3.730 | 0.290 | 0.158 | 0.187 | 0.183 |
| | | (1.78) | (1.37) | (1.87) | (1.69) |
| 4 | 8.806 | 0.342 | 0.193 | 0.222 | 0.229 |
| | | (1.79) | (1.79) | (2.29) | (2.37) |
| High SR | 71.008 | 0.705 | 0.505 | 0.530 | 0.554 |
| | | (2.73) | (3.79) | (3.96) | (4.12) |
| High SR – Low SR Return/Alpha Diff. | | **0.481** | **0.336** | **0.342** | **0.382** |
| | | **(2.31)** | **(2.69)** | **(2.71)** | **(2.83)** |
| High SR – Rest of Quintiles Return/Alpha Diff. | | **0.429** | **0.337** | **0.337** | **0.365** |
| | | **(2.74)** | **(3.01)** | **(3.06)** | **(3.00)** |
| Rest of Quintiles – Low SR Return/Alpha Diff. | | 0.173 | 0.082 | 0.090 | 0.112 |
| | | (1.50) | (1.31) | (1.45) | (1.77) |

**Table 6**

Bivariate portfolios of hedge funds sorted by SR and USR

In Panel A, quintile portfolios are formed every month from January 1997 to June 2010 by first sorting hedge funds based on their 6-factor Residual risk (USR). Then, within each USR portfolios, hedge funds are sorted into sub-quintiles based on their 6-factor Systematic Risk (SR). "Quintile SR,1" is the portfolio of hedge funds with the lowest SR within each USR quintile portfolio and "Quintile SR,5" is the portfolio of hedge funds with the highest SR within each USR quintile portfolio. Panel A reports the average SRs within each USR quintile as well as the next month average returns of hedge funds for the corresponding quintile. The last four rows represent the differences between Quintile SR,5 and Quintile SR,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 adjusted *t*-statistics are reported in parentheses. Numbers in bold denote statistical significance. Panel B replicates the same procedure for quintile portfolios of hedge funds sorted by USR after controlling for SR.

| *Panel A: Hedge Funds Sorted by SR after controlling for USR* | | | *Panel B: Hedge Funds Sorted by USR after controlling for SR* | | |
|---|---|---|---|---|---|
| SR Quintiles After Controlling for USR | Average SR in each USR Quintile | Next Month Average Returns | USR Quintiles After Controlling for SR | Average USR in each SR Quintile | Next Month Average Returns |
| SR,1 | 1.569 | 0.258 | USR,1 | 1.911 | 0.297 |
| SR,2 | 3.629 | 0.251 | USR,2 | 4.138 | 0.353 |
| SR,3 | 6.531 | 0.320 | USR,3 | 7.166 | 0.324 |
| SR,4 | 11.432 | 0.350 | USR,4 | 12.457 | 0.330 |
| SR,5 | 62.304 | 0.628 | USR,5 | 107.378 | 0.504 |
| SR,5 – SR,1 Return Difference | | **0.370** **(2.13)** | USR,5 – USR,1 Return Difference | | 0.207 (1.32) |
| SR,5 – SR,1 4-Factor Alpha Difference | | **0.298** **(3.89)** | USR,5 – USR,1 4-Factor Alpha Difference | | 0.223 (1.63) |
| SR,5 – SR,1 6-Factor Alpha Difference | | **0.308** **(3.87)** | USR,5 – USR,1 6-Factor Alpha Difference | | 0.196 (1.48) |
| SR,5 – SR,1 9-Factor Alpha Difference | | **0.326** **(3.74)** | USR,5 – USR,1 9-Factor Alpha Difference | | 0.273 (1.66) |

**Table 7**

Dynamics of hedge funds' systematic risk by hedge fund investment style

This table reports the cross-sectional average of individual funds' time-series standard deviations of SR as well as the cross-sectional average of individual funds' max minus min SR differences for each of the fund investment styles separately. In each cell, the first number before the slash is the cross-sectional average of individual hedge funds' standard deviations of SR for that style. The second number after the slash is the cross-sectional average of individual hedge funds' max minus min SR differences for that style. For comparison purposes, the cross-sectional averages of these two statistics across all hedge funds (irrespective of investment styles) are also reported in the last row in bold as a separate category. As can be noticed easily reading the last column from top to bottom, non-directional strategies, such as Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage, have low standard deviations and max – min differences of SR compared to directional strategies, such as Managed Futures, Global Macro and Emerging Markets funds. Also, non-directional strategies' standard deviations and max – min differences of SR are considerably smaller compared to the all hedge fund category, while directional strategies' standard deviations and max – min differences of SR are noticeably bigger compared to the all hedge fund category.

| Hedge Fund Investment Styles | Standard Dev. / Max – Min Spread |
|---|---|
| Equity Mkt. Neutral | 1.82 / 8.46 |
| Fixed Income Arbitrage | 2.58 / 8.49 |
| Convertible Arbitrage | 2.96 / 8.92 |
| Fund-of-Funds | 3.55 / 12.73 |
| Multi Strategy | 3.11 / 10.67 |
| Long-Short Equity Hedge | 3.16 / 10.55 |
| Event Driven | 4.28 / 13.91 |
| Managed Futures | 3.95 / 14.39 |
| Global Macro | 6.07 / 19.92 |
| Emerging Markets | 12.07 / 37.34 |
| **All Hedge Funds** | **3.95 / 12.70** |

**Table 8**

Univariate quintile portfolios of hedge fund investment styles sorted by systematic risk

For each investment style separately, univariate quintile portfolios are formed every month from January 1997 to June 2010 by sorting funds based on their 6-factor SR. Quintile 1 (5) is the portfolio of hedge funds with the lowest (highest) SR in each investment style. Table reports the number of funds, percentage of funds in total sample, differences in next month returns and alphas 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 | Q5 – Q1 Return Diff. | Q5 – Q1 4-Factor Alpha Diff. | Q5 – Q1 6-Factor Alpha Diff. | Q5 – Q1 9-Factor Alpha Diff. |
|---|---|---|---|---|---|---|
| Equity Mkt. Neutral | 257 | 3.42% | 0.053<br>(0.30) | –0.113<br>(–0.54) | –0.104<br>(–0.54) | –0.119<br>(–0.57) |
| Fixed Income Arbitrage | 210 | 2.79% | 0.022<br>(0.08) | –0.091<br>(–0.34) | –0.017<br>(–0.09) | 0.006<br>(0.03) |
| Convertible Arbitrage | 171 | 2.27% | 0.044<br>(0.11) | –0.086<br>(–0.36) | 0.012<br>(0.07) | –0.018<br>(–0.09) |
| Fund-of-Funds | 2991 | 39.76% | **0.271**<br>**(2.63)** | **0.225**<br>**(2.68)** | **0.221**<br>**(2.70)** | **0.236**<br>**(2.97)** |
| Multi Strategy | 398 | 5.29% | **0.444**<br>**(2.19)** | **0.347**<br>**(2.68)** | **0.361**<br>**(2.78)** | **0.380**<br>**(2.83)** |
| Long-Short Equity Hedge | 1890 | 25.12% | **0.699**<br>**(2.97)** | **0.591**<br>**(3.43)** | **0.581**<br>**(3.23)** | **0.579**<br>**(3.16)** |
| Event Driven | 434 | 5.77% | **0.521**<br>**(3.02)** | **0.468**<br>**(3.86)** | **0.497**<br>**(4.32)** | **0.482**<br>**(4.14)** |
| Managed Futures | 517 | 6.87% | **0.846**<br>**(3.48)** | **0.772**<br>**(3.44)** | **0.741**<br>**(3.42)** | **0.784**<br>**(3.44)** |
| Global Macro | 250 | 3.32% | **0.716**<br>**(3.79)** | **0.613**<br>**(3.82)** | **0.612**<br>**(3.90)** | **0.593**<br>**(4.04)** |
| Emerging Markets | 405 | 5.39% | **1.094**<br>**(3.05)** | **0.930**<br>**(3.36)** | **0.945**<br>**(3.36)** | **0.969**<br>**(3.36)** |