Do Hedge Funds' Exposures to Risk Factors Predict Their Future Returns?*

Turan G. Bali[a], Stephen J. Brown[b], and Mustafa O. Caglayan[c]

ABSTRACT

This paper investigates hedge funds' exposures to various financial and macroeconomic risk factors through alternative measures of factor betas and examines the performance of these factor betas in predicting the cross-sectional variation in hedge fund returns. The results indicate a positive and significant link between default premium beta (*DEF beta*) and future hedge fund returns as well as a negative and significant link between inflation beta (*INF beta*) and future hedge fund returns. Hedge funds in the highest *DEF beta* quintile generate 5.8% more annual raw and risk-adjusted returns compared to funds in the lowest *DEF beta* quintile. Similarly, the annual average raw and risk-adjusted returns of funds in the lowest *INF beta* quintile are 5% higher than the annual average returns of funds in the highest *INF beta* quintile. After controlling for Fama-French-Carhart's four factors of market, size, book-to-market, and momentum as well as Fung-Hsieh's five trend-following factors in stocks, short-term interest rates, currencies, bonds, and commodities, the positive relation between *DEF beta* and future hedge fund returns, as well as the negative relation between *INF beta* and future hedge fund returns remain economically and statistically significant.

This Version: February 2010

Keywords: hedge funds, return predictability, risk factors

JEL Classification: G10, G11, C13.

---

* We thank Vikas Agarwal, Mila Getmansky, Bing Liang, Andrew Lo, and Christian Tiu for helpful comments. All errors remain our responsibility.

[a] David Krell Professor of Finance, Department of Economics and Finance, Zicklin School of Business, Baruch College, One Bernard Baruch Way, Box 10-225, New York, New York 10010. Phone: (646) 312-3506, Fax: (646) 312-3451, E-mail: turan.bali@baruch.cuny.edu

[b] David S. Loeb Professor of Finance, Leonard N. Stern School of Business, New York University, Kaufman Management Center, 44 West Fourth Street, KMC 9-89, New York, New York, 10012. E-mail: sbrown@stern.nyu.edu

[c] Assistant Professor of Finance, Faculty of Economics and Administrative Sciences, Ozyegin University, Kusbakisi Caddesi, No:2, Altunizade, Uskudar, Istanbul, TURKEY. Phone: +90 (216) 559-2315, Fax: +90 (216) 559-2470, E-mail: mustafa.caglayan@ozyegin.edu.tr

Do Hedge Funds' Exposures to Risk Factors Predict Their Future Returns?

ABSTRACT

This paper investigates hedge funds' exposures to various financial and macroeconomic risk factors through alternative measures of factor betas and examines the performance of these factor betas in predicting the cross-sectional variation in hedge fund returns. The results indicate a positive and significant link between default premium beta (*DEF beta*) and future hedge fund returns as well as a negative and significant link between inflation beta (*INF beta*) and future hedge fund returns. Hedge funds in the highest *DEF beta* quintile generate 5.8% more annual raw and risk-adjusted returns compared to funds in the lowest *DEF beta* quintile. Similarly, the annual average raw and risk-adjusted returns of funds in the lowest *INF beta* quintile are 5% higher than the annual average returns of funds in the highest *INF beta* quintile. After controlling for Fama-French-Carhart's four factors of market, size, book-to-market, and momentum as well as Fung-Hsieh's five trend-following factors in stocks, short-term interest rates, currencies, bonds, and commodities, the positive relation between *DEF beta* and future hedge fund returns, as well as the negative relation between *INF beta* and future hedge fund returns remain economically and statistically significant.

Keywords: hedge funds, return predictability, risk factors

JEL Classification: G10, G11, C13.

1. Introduction

Merton (1973) indicates that any variable that affects future investment opportunities could be a priced risk factor in equilibrium. Ross (1976) further documents that securities affected by such systematic risk factors should earn risk premia in a risk-averse economy. Macroeconomic variables are excellent candidates for these systematic risk factors because innovations or unexpected changes in macroeconomic variables can generate global impact on firms' fundamentals, such as their cash flows, risk-adjusted discount factors, and investment opportunities.

Although the theory of finance suggests that asset prices are influenced by economic news, the theory has been silent about which variables are likely to influence all assets.[1] There are several channels by which macroeconomic fundamentals such as inflation, short-term and long-term interest rates, unemployment, and economic growth may have effects on the prices of risky assets such as stocks, bonds, currencies, and their derivatives.

A direct, negative effect on stock returns could emerge if a positive surprise in announced inflation induces investors to raise their level of expected inflation since a number of studies have found that higher expected inflation depresses stock prices. The explanation for this finding is that investors use inflation-swelled nominal interest rates to capitalize corporate earnings. Higher expected inflation leads to higher nominal interest rates. The anticipation of higher rates in the future causes investors to sell Treasury securities immediately, forcing interest rates upward. Higher interest rates then lead to lower stock prices, assuming investors view stocks and bonds as substitutes. A second channel by which inflation surprises may affect stock prices is if investors believe that policymakers react to inflation news. Unexpectedly high inflation may lead to more restrictive policies, which in turn lead to reduced cash flows for firms and lower stock prices. In other words, if a positive inflation surprise causes investors to revise upward their assessment of future money demand, higher interest rates and lower stock prices may result if investors further expect the Federal Reserve to maintain its previous monetary growth objectives.

The positive relation between expected stock returns and real output growth makes economic sense. Announced increases in real economic activity, if greater than expected, may increase investors' expectations of future growth. Forecasts of higher real GDP per capita, higher growth rate of industrial production, and lower unemployment rate should make stocks more attractive and thus cause an immediate jump in share prices.

Through purchasing power parity as well as covered and uncovered interest rate parities, return on currency depends on inflation, spot interest rate, and forward interest rate differences between two

[1] Bodie (1976), Fama (1981), Geske and Roll (1983), Pearce and Roley (1983, 1985) document a negative impact of inflation and money growth on equity values. Chan, Chen, and Hsieh (1985), Chen, Roll, and Ross (1986), and Chen (1991) find that changes in aggregate production, inflation, term spread, and default spread are important economic indicators in determining equilibrium expected returns on securities. In time-series analyses, Fama and Schwert (1977), Keim and Stambaugh (1986), Campbell (1987), Campbell and Shiller (1988), and Fama and French (1988, 1989) find that short-term interest rates, expected inflation, dividend yields, term spread, default spread, and lagged stock returns can predict the expected returns of bonds and stocks.

countries. Capital inflows and outflows that depend on the real interest rate differentials of two countries also affect the relative movements in exchange rates. All of these potential links suggest that the prices of stocks, bonds, currencies, and their derivatives are related to the movements in macroeconomic fundamentals. Thus, we expect the performance of hedge funds investing in these financial securities to be influenced by funds' sensitivity to these macroeconomic factors.

This paper analyzes hedge funds' exposures to various financial and macroeconomic risk factors through univariate, bivariate, and multivariate estimates of factor betas and investigates the performance of these factor betas in predicting the cross-sectional variation in hedge fund returns over the sample period from January 1994 to December 2008. The two most important findings from this study are summarized as follows: (i) hedge funds with higher exposure to default risk premium in the past month generate higher returns in the following month; (ii) hedge funds with lower exposure to inflation in the past month generate higher returns in the following month.

Risk premia on risky assets co-vary negatively with current economic activity, i.e., investors require high expected returns in recessions, and lower expected returns in booms when holding risky financial securities. Since default spread is high in recessions, hedge funds with higher exposure to default premium are expected to generate higher returns. During expansions (contractions), we observe lower (higher) unemployment rate, higher (lower) growth rate of income per capita, and hence increased (reduced) demand for investment and consumption, which leads to an increase (decrease) in inflation, corresponding to lower (higher) expected returns. Hence, hedge funds with lower exposure to inflation are expected to generate higher returns.

The first major finding from this study that shows a positive relationship between exposure to default risk premium (default premium beta) and future hedge fund returns can also be attributed to the opportunistic behaviour of hedge funds in general. In fact, certain hedge fund investment styles such as Event-driven and Global Macro hedge funds take positions or bets in the market on specific areas or companies that are likely to face distressed situations in the future. As these distressed situations become reality and bankruptcies commence with the rising default premium, these hedge funds' returns increase tremendously.

Once the default premium increases for the general economy it stays at elevated levels for an extended period. Funds that had higher exposure to default spread in the past month continue to benefit nicely and generate handsome returns in the following month, outperforming the funds that had low exposure to default spread in the past month. Hence, the higher the exposure to default risk premium (i.e. default premium beta) in the past month, the higher the hedge fund returns in the following month. This result is confirmed in our analyses by both parametric tests of cross-sectional regressions of one-month ahead hedge fund returns on past months' default premium betas, as well as by non-parametric portfolio tests that sort funds into quintiles based on their past month's default premium betas in the first stage and analyze each quintile's next month return performance in the second stage.

Jagannathan and Korajczyk (1986) indicate that hedge funds investing in stocks with little or no risky debt show negative market timing performance (i.e., lower future returns), while funds that invest in small, levered stocks will show positive timing performance (i.e., higher future returns). A portfolio manager can choose to show varying degrees of market timing by choosing options with different exercise prices (or stocks of firms with lower or higher proportions of risky debts). Funds holding assets that are more option-like than the assets in the market proxy should show positive measures of market timing. Goetzmann, Ingersoll, Spiegel, and Welch (2007) indicate that simple dynamic strategies that only relever the portfolio each measurement period or buy very liquid at the money options can produce superior performance measures. Levering is achieved by buying or selling synthetic forward contracts consisting of a long position in calls and a short position in puts that are at-the-money in present value.[2]

We use individual equity options data in OptionMetrics and compute the average spread between at-the-money put and at-the-money call options' implied volatilities, $IV_{ATM}^{put} - IV_{ATM}^{call}$, for the sample period of January 1997 to December 2008. The sample correlation between $IV_{ATM}^{put} - IV_{ATM}^{call}$ and the default spread is found to be positive and large at 45%, implying that the high put-call volatility spread, $IV_{ATM}^{put} - IV_{ATM}^{call}$, corresponds to high default risk premium. We also calculate the difference between out-of-the-money put and at-the-money call options' implied volatilities, $IV_{OTM}^{put} - IV_{ATM}^{call}$, which can be viewed as a risk-neutral measure of negative skewness or options' implied measure of left tail risk. Our findings indicate that the negative skew or left tail risk is also higher during periods of high default spread with high expected returns. These results combined with the findings of Jagannathan and Korajczyk (1986) and Goetzmann, Ingersoll, Spiegel, and Welch (2007) provide an option-based explanation of the positive relation between default premium beta and hedge fund returns.[3]

Agarwal, Bakshi, and Huij (2009) point out that hedge funds often use derivatives, short-selling, and leverage to produce returns during extreme movements of the equity market and this makes funds to be exposed to high-moment risks of the equity market. We should note that if a retail investor invests in equity and derivatives markets using extensive leverage or short positions, there is a possibility that he might lose his entire wealth. However, if he invests in a hedge fund that uses extensive leverage or short positions, the individual investor loses up to his original investment. Thus, part of the default risk premium we observe may be attributed to the value of this implicit put option over and above the fees the hedge funds charge.

[2] Hedge funds have broad scope to invest in a range of instruments, including derivatives. Mitchell and Pulvino (2001) show that merger arbitrage, a common hedge fund strategy, generates returns that resemble a short put-short call payoff. Agarwal and Naik (2000) indicate that option-like payoffs are inherent in the compensation-structure of the typical hedge fund contract.

[3] As indicated by Fama and French (1993), default risk factor has the explanatory power for the cross-section of bond returns. This suggests that another reason for the significance of *DEF beta* in predicting the cross-section of hedge fund returns is the hedge funds' holdings of bond portfolios.

The second major finding from this study that shows a negative relationship between exposure to inflation (inflation beta) and future hedge fund returns can be explained with the uncertainty factor that comes along with inflation. As inflation rises, and the associated uncertainty increases in the economy (as investors form adaptive inflation expectations), it is expected to see a decline not only in hedge fund returns, but also in returns of all financial instruments in the following months. Conversely, when inflation is stable and uncertainty is low, one would expect to see in the following months positive and attractive returns for all financial instruments, including hedge funds.

Once inflation takes root in an economy it stays at an elevated level for an extended period (i.e. inflation and uncertainty lingers). For this reason, funds that had higher exposure to inflation in the past month (i.e. funds that face higher uncertainty) do poorly and generate unattractive returns in the following month, underperforming the funds that had low exposure to inflation. On the other hand, funds that had lower exposure to inflation in the past month (i.e. funds that face lower uncertainty) do well and generate respectable returns in the following month, outperforming the funds that had high exposure to inflation. Hence, the lower the exposure to inflation (i.e., inflation beta) in the past month, the higher the hedge fund returns in the following month, or vice versa. This result is again proven in our analyses by both parametric tests of cross-sectional regressions of one-month ahead hedge fund returns on past months' inflation betas, as well as by non-parametric portfolio tests that sort hedge funds into quintiles based on their past month's inflation betas in the first stage and analyze each quintile's next month return performance in the second stage.

This paper is organized as follows. Section 2 summarizes the relevant hedge fund literature. Section 3 describes the data and variables used in our empirical analyses. Section 4 explains potential data biases. Section 5 presents empirical results. Section 6 provides a battery of robustness checks and Section 7 concludes the paper.

2. Literature Review

The explosive growth of hedge funds both in numbers and in assets under management in the last decade and a half resulted in a significant number of studies on hedge fund performance. Fung and Hsieh (1997) show that hedge funds follow strategies that are highly dynamic and significantly different from mutual funds. Ackermann, McEnally, and Ravenscraft (1999) show that because of their flexible investment strategies, strong managerial incentives, substantial managerial investment, sophisticated investors, and limited government oversight, hedge funds consistently outperform mutual funds, but not standard market indices. Brown, Goetzmann, and Ibbotson (1999) examine the performance of the off-shore hedge fund industry over the period 1989-1995 using a sample of live and defunct funds and find little evidence of differential managerial skills and that the industry contains funds with high attrition rates and low market beta. Agarwal and Naik (2000) investigate persistence in the performance of hedge funds using a multi-period framework in which the likelihood of observing persistence by chance is lower than in the traditional two-period framework. Brown, Goetzmann, and Park (2001) find a relation between past performance and the volatility of hedge funds and CTAs in light of managerial career concerns. They show that survival depends on absolute and relative performance, excess volatility, and fund age. Based on a sample of 77 hedge funds and 13 hedge fund indices for the sample period of 1990 – 2000, Amin and Kat (2003) find that hedge funds do not offer a superior risk-return profile. Baquero, Horst, and Verbeek (2005) analyze liquidation, look-ahead bias, and the performance persistence of hedge funds over the period 1994-2000. Using a robust bootstrap procedure, Kosowski, Naik, and Teo (2007) find that top hedge fund performance cannot be explained by luck, and hedge fund performance persists at annual horizons. Fung, Hsieh, Naik, and Ramadorai (2008) use a comprehensive data set of funds-of-funds and by using a seven-factor model show that a subset of funds-of-funds consistently delivers alpha. The alpha-producing funds are not as likely to liquidate as those that do not deliver alpha, and experience far greater and steadier capital inflows than their less fortunate counterparts. They also find that, compared to the mutual fund literature, look-ahead bias for hedge funds is quite severe. Agarwal, Daniel, and Naik (2009) find that hedge funds with better managerial incentives (higher option deltas, greater managerial ownership, and the presence of a high-water mark provision in the hedge fund contract) are associated with better performance. Choi, Getmansky, Henderson, and Tookes (2009) link the aggregate convertible bond issuance to convertible bond arbitrage hedge fund flows, returns, and a proxy for arbitrageurs' use of leverage. They find that issuance is positively related to increases in all three capital supply measures.

The hedge fund and mutual fund literatures investigate the effects of incentive fees, performance fees, managerial skills, and the risk-appetite of fund managers. Goetzmann, Ingersoll, and Ross (2003) show that hedge fund performance fees are valuable to money managers, and conversely, represent a claim on a significant proportion of investor wealth. Elton, Gruber, and Blake (2003) examine the effect of incentive fees on the behaviour of mutual fund managers, and find that funds with incentive fees exhibit positive stock selection ability, but a beta less than one results in funds not earning positive fees. Goetzmann, Ingersoll, Spiegel, and Welch (2007) show that a manager that seeks to manipulate portfolio performance measures can indeed produce very impressive performance statistics. Against this, they suggest a unique measure that cannot be manipulated and is simultaneously of some value to investors. Hodder and Jackwerth (2007) investigate incentive effects of a typical hedge fund contract for a manager and find that hedge fund managers' risk taking varies dramatically with fund value and is moderated if the fund performs reasonably well. Chen and Liang (2007) examine whether market timing hedge funds have the ability to time the U.S. equity market and find significant evidence of timing ability both at the aggregate level and at the fund level. Griffin and Xu (2009) find that hedge funds are slightly better than mutual funds at stock picking. They also provide weak evidence of differential ability between hedge funds and weak evidence of superior skill of hedge fund managers. Panageas and Westerfield (2009) study the portfolio choice incentives that are implied by high water mark fees for hedge fund managers. They find that even risk-neutral managers do not place unbounded weights on risky assets, despite option-like contracts. Instead, they place a constant fraction of funds in a mean-variance efficient portfolio and the rest in the riskless asset.

The literature also examines the risk-return characteristics of individual hedge funds. Agarwal and Naik (2004) characterize the linear and nonlinear risks of various hedge fund strategies using buy-and-hold and option-based risk factors. Their results indicate that using the traditional mean-variance framework substantially underestimates the tail losses for hedge funds. Gupta and Liang (2005) use the extreme value approach of Bali (2003) to examine value at risk and capital adequacy of individual hedge funds. Bali, Gokcan, and Liang (2007) and Liang and Park (2007) provide evidence for a significant, positive link between downside risk and the cross-section of hedge fund returns. Brown, Goetzmann, Liang, and Schwarz (2008) examine the value of mandatory disclosure of major hedge funds through the SEC requirement. Brown et al. (2008a,b) are able to establish a link between potential conflicts identified in Form ADV filings and operational risk characteristics of individual funds in the TASS database. Brown et al. (2008a,b) is the first to obtain a time series of operational risk for each fund. Bollen and Whaley (2009) provide evidence that hedge funds' exposures to risk factors change in response to changing market conditions. Billio, Getmansky, and Pelizzon (2009) study the effects of financial crises on hedge fund risk and show that liquidity, credit, equity market, and volatility are common risk factors during crises for various hedge fund strategies. Khandani and Lo (2009) provide evidence for the use of autocorrelation as a measure of illiquidity in hedge funds. They find a significant link between autocorrelation and expected returns; the estimated liquidity spread among hedge funds is 3.96% per year in their sample. 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. Titman and Tiu (2009) regress individual hedge fund returns on a group of risk factors and find that funds with low R-squares of returns on systematic 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. Cao, Chen, Liang, and Lo (2010) examine 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 (decreasing) their portfolios' market exposure when the equity market liquidity is high (low).

While most of these earlier studies focus on the risk-return characteristics of hedge funds, either by estimating alpha (risk-adjusted returns) using multifactor models or by investigating the impact of fund characteristics on returns, none of these studies, so far, has analyzed the economic and statistical significance of factor loadings in predicting future hedge fund performance.[4] This paper contributes to the literature on hedge funds in a significant way by analyzing hedge funds' exposures to numerous financial and macroeconomic risk factors through univariate, bivariate, and multivariate estimates of factor betas, and by investigating the performance of these factor betas in predicting the cross-sectional

[4] The only exception is Titman and Tiu (2009). Although the focus of our paper is quite different from Titman and Tiu (2009), in some ways the papers complement each other and together paint an interesting story.

variation in hedge fund returns. This is the first study to conduct a sensitivity analysis of factor loadings (betas) on future hedge fund returns through both parametric (cross-sectional regressions) and non-parametric (quintile analysis) tests.

3. Data and Description of Variables

This study uses hedge fund data from Lipper TASS database, which contains information, as of December 2008, on a total of 12,980 defunct and live hedge funds with close to $1.8 trillion under management. Between January 1994 and December 2008, out of the 12,980 hedge funds that reported monthly returns to TASS, 6,188 are defunct funds and the remaining 6,792 are live funds. TASS provides information on monthly returns (net of fees) and monthly assets under management for each individual hedge fund as well as specifics on each fund's characteristics such as their management and incentive fees.

Table I provides summary statistics on the hedge funds' numbers, returns, assets under management (AUM), and their fee structures. Panel A of this table reports, for each year from 1994 to 2008, the number of hedge funds, total assets under management at the end of the year (in billion dollars), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on an equal-weighted hedge fund portfolio. One important item worth noting is the fact that TASS did not include any defunct funds in the database 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 – December 2008.[5] The other significant transformation that can be observed in Panel A is the sharp reversal in the growth of hedge funds both in numbers and in assets under management in year 2008, the year when the extreme negative effects of the financial crisis were felt heavily in the hedge fund industry. Analyzing Panel A of Table I in more detail, from 1994 to 2007, the number of hedge funds performing in the market increased on average 17.7% per year (see column "Year End") while the amount of assets under management swelled on average 32% per year (see column "Total AUM"). However, this big surge came to a sudden halt in 2008 (together with the big financial crisis) as the number of hedge funds performing in the financial industry fell by 16.4%, while the total assets under management dropped by 17.8% just in 2008. Even these two significant shifts in the data explain enough about the severity of the financial crisis that the hedge fund industry faced back in 2008. In addition, the yearly attrition rates in Panel A (the ratio of number of dissolved funds to the total

[5] For a robustness check of our results, we employed all statistical work for the period 1984 – 2008 as well, the longest time history available to conduct our tests with the available data. The results from the period 1984 – 2008 are very similar to our findings from the survivorship bias-free period 1994 – 2008. Later in the paper, we will report some results from the full 1984 – 2008 period under the "Robustness Check" section.

number of funds at the beginning of the year) also paint a similar picture; from 1994 to 2007, on average, the attrition rate was only 8.1% per year, in 2008, this figure almost tripled to 22.9%.[6]

Continuing with the descriptive statistics on hedge funds, Panel B of Table I reports for the sample period 1994 – 2008 the cross-sectional mean, median, standard deviation, minimum, and maximum statistics for hedge fund characteristics including returns, size, age, management and incentive fees. One interesting observation 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 $120.4 million, the median hedge fund size is only $32.5 million. This shows the existence of very few hedge funds with very large assets under management in the hedge fund industry. Another characteristic 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% (14.05%) in our database (which reflects the true industry standards), and 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 I is their short span of life. The median age (number of months in existence since inception) of a fund is only 47 months, less than 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 given year forces hedge fund managers to dissolve quickly (hence the short span of life) and form a new hedge fund after a bad year, instead of trying to cover those losses in the following years.

Lastly, Panel C of Table I reports for the whole sample period 1994 – 2008 the time series mean, median, standard deviation, minimum, and maximum monthly percentage returns of the 15 financial and macroeconomic risk factors used in this study. For comparison purposes, the panel also reports the same statistics for an equal-weighted hedge fund portfolio (EWHF). The 15 financial and macroeconomic risk factors included in this analysis are as follows: 1) MKT: Value-weighted NYSE/AMEX/NASDAQ (CRSP) market index return; 2) SMB: Fama-French (1993) size factor; 3) HML: Fama-French (1993) book-to-market factor; 4) MOM: Carhart (1997) momentum factor; 5) DEF: Default spread measured as the difference between yields on BAA-rated and AAA-rated corporate bonds; 6) TERM: Term spread measured as the difference between yields on 10-year and 3-month Treasury securities; 7) DIV: Aggregate dividend yield; 8) INF: Monthly inflation rate based on the US consumer price index; 9) IP: Monthly growth rate of industrial production; 10) PYRL: Monthly percent change in US non-farm payrolls; 11) FXTF: Fung-Hsieh (2001) currency trend-following factor measured as the return of PTFS Currency Lookback Straddle; 12) BDTF: Fung-Hsieh (2001) bond trend-following factor measured as the return of PTFS Bond Lookback Straddle; 13) CMTF: Fung-Hsieh (2001) commodity trend-following

[6] In this study the average attrition rate for the whole sample period 1994 – 2008 is 9.1% and is comparable to the earlier studies of Liang (2000) and Getmansky, Lo, and Makarov (2004) who estimate average attrition rates of 8.3% for the period 1994 – 1998, and 9.11% for the period 1994 – 1999, respectively in their analyses.

factor measured as the return of PTFS Commodity Lookback Straddle; 14) IRTF: Fung-Hsieh (2001) short-term interest rate trend-following factor measured as the return of PTFS Short Term Interest Rate Lookback Straddle; 15) SKTF: Fung-Hsieh (2001) stock index trend-following factor measured as the return of PTFS Stock Index Lookback Straddle.[7]

Analyzing Panel C of Table I in more detail, we see that the average monthly hedge fund return on an equal-weighted portfolio is slightly higher than the average monthly market return during our sample period 1994 – 2008; 0.71% vs. 0.62% per month. Also, the monthly standard deviation of returns is much lower in the equal-weighted hedge fund portfolio relative to the market; 1.72% vs. 4.50%. This big difference in volatility can also be seen in the gap between the minimum and the maximum monthly returns for the market vs. the equal-weighted hedge fund portfolio; the worst monthly hedge fund return on the equal-weighted portfolio is –5.93% vs. market's –18.47%, while the best hedge fund return on the equal-weighted portfolio is 6.38% vs. market's 8.39%.

4. Potential Data Biases

Hedge fund studies in general are subject to certain potential data biases. These data biases are covered, in detail, in some of the earlier hedge fund studies (see Brown, Goetzmann, Ibbotson, and Ross (1992), Fung and Hsieh (2000), Liang (2000), Edwards and Caglayan (2001)). The first potential data bias in a hedge fund study is the survivorship bias if the database does not include the returns of non-surviving hedge funds. In our study, we do have monthly return histories of 6,792 surviving and 6,188 non-surviving hedge funds during our sample period 1994 – 2008. We estimate that if the returns of non-surviving hedge funds had been excluded from the analyses, there would have been a survivorship bias of 1.74% in average annual hedge funds returns (the difference between the annualized average return of only surviving funds in the sample and the annualized average return of all surviving and non-surviving funds in the sample).[8]

The second potential data bias in a hedge fund study is the instant history bias. Once a hedge fund is added to a database, that fund's previous returns are also automatically added to that database (this is called "backfilling"). This practice may create a problem, because only successful hedge funds (until the point of entry to the database) may prefer to be included in a database (there is no incentive for an unsuccessful hedge fund to advertise their past bad performance) and as a result this may generate an upward bias in returns of newly reporting hedge funds during their early (reported) histories. In the TASS database we have information on when a hedge fund was added to the database as well as the fund's first reported performance date. On average, there is a one-year gap between the first performance date and the date that the fund was added to the database (the latter being one year later than the former). We

[7] The five trend-following factors of Fung and Hsieh (2001); FXTF, BDTF, CMTF, IRTF, SKTF are provided by David Hsieh at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

[8] This finding is comparable to earlier studies of hedge funds. Liang (2000) reported an annual survivorship bias of 2.24% and Edwards and Caglayan (2001) reported an annual survivorship bias of 1.85%.

checked whether this one-year gap generates a difference in returns between funds' first year performance vs. rest of period performance (rest of period performance starts from the 13th month until either the fund is deceased or until the end of our sample period December 2008). We find that the average annual return of hedge funds during the first year of existence is 1.68% higher than the average annual returns in subsequent years. Fung and Hsieh (2000) also find a similar 1.4% instant history bias in annual hedge fund returns and delete the first 12-month returns of all individual hedge funds in their sample. Following Fung and Hsieh, in order to avoid instant history bias in our analyses, we also deleted the first 12-month return histories of all individual hedge funds in our database.[9]

The third, and final, potential data bias in a hedge fund study is the multi-period sampling bias. Investors typically require a minimum 24 or 36 months of return history before investing in a hedge fund. Therefore, in a hedge fund study, inclusion of hedge funds with shorter return histories than 24 or 36 months can be misleading to those investors who seek past performance data to make investment decisions. In addition, a minimum 24-month return history requirement (to be included in a hedge fund study) makes sense in order to be able to run regressions and get sensible estimates of factor betas and alphas for each individual hedge fund in the sample. In this study, we require that all hedge funds in the sample have a minimum of 24 months of returns, after excluding the first 12 months of returns for all hedge funds (to correct for any potential instant history bias).[10] This 24-month minimum return history requirement decreases our sample size from 12,277 to 8,801 (i.e. 3,476 funds in the sample had return histories less than 24 months). There is a slight chance, however, that we might introduce a new survivorship bias into the system due to deletion of these 3,476 hedge funds from the sample (funds that had return histories less than 24 months most probably dissolved due to bad performance). In an effort to find the impact of these deleted 3,476 hedge funds on total hedge fund performance, we compare the performance of hedge funds *before* and *after* the 24-month return history requirement and find that the annual average return of hedge funds that pass the 24-month requirement (8,801 funds) is only 0.24% higher than the return of all hedge funds (12,277 funds) in the sample, a small insignificant percentage difference between the two samples in terms of survivorship bias considerations.[11]

[9] Deleting the first 12-month returns resulted in deleting 703 funds from our sample because they had return histories less than 12 months, bringing the total number of hedge funds in our database to 12,277 from 12,980. There is a also a slight chance that we might introduce a new survivorship bias into the system due to deletion of 703 hedge funds from the sample (funds that had return histories less than 12 months most probably dissolved due to bad performance). We find, however, that the average annual return of 12,277 funds is only 0.01% higher than the average annual return of 12,980 funds, suggesting no evidence of inclusion of a new survivorship bias into our analyses.

[10] Fung and Hsieh (2000) require a minimum of 36 months of return history while Ackermann, McEnally, and Ravenscraft (1999) require a minimum of 24 months of return history.

[11] This figure is similar to the estimates from earlier hedge fund studies. Edwards and Caglayan (2001) imposed a 24-month return history requirement and found a small survivorship bias estimate of 0.32%. Fung and Hsieh (2000), on the other hand, imposed a 36-month return history requirement and found the survivorship bias estimate to be around 0.60%.

5. Empirical Results

5.1. Cross-Sectional Regressions of Future Fund Returns on Factor Betas

The literature provides evidence for a variety of macroeconomic and financial risk factors that are capable of explaining the returns of financial assets. The primary objective of this paper is to test the significance of these macroeconomic and financial risk factors' betas on predicting the cross-sectional variation in monthly returns of hedge funds. This can be achieved through both parametric (regression) and non-parametric (quintile portfolios) tests. In this section, we conduct parametric tests to assess the predictive power of factor betas over future hedge fund returns. Basically, in the first stage, for each individual hedge fund, we derive univariate, bivariate, and multivariate monthly time-series beta estimates of 15 different macroeconomic and financial risk factors (factor betas) calculated over a rolling-window period, and in the second stage, for each month in the sample period, we conduct Fama-MacBeth (1973) cross-sectional regressions of one-month ahead individual hedge fund excess returns (individual hedge fund returns over the risk-free rate) on the factor betas. If, for certain macroeconomic and financial risk factors, the slope coefficients from these Fama-MacBeth regressions indicate statistical significance, then we conclude that those factor betas have a significant predictive power over future expected hedge fund returns.

5.1.1. Univariate Factor Betas in Cross-Sectional Regressions

Table II reports the time-series average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead hedge fund returns on the univariate factor betas. In the first stage, univariate monthly factor betas are estimated for each fund from the univariate time-series regressions of hedge fund excess returns on the factor over a 36-month rolling window period. In the second stage, the cross-section of one-month ahead funds' excess returns are regressed on the funds' univariate factor betas (derived from the first stage) each month during the period 1997 – 2008. In other words, we start with the first 3 years of monthly returns from January 1994 to December 1996 to estimate the factor betas for each fund in our sample, and then follow a monthly rolling regression approach with a fixed estimation window of 36 months to generate the time-series monthly factor betas based on the following regression equation:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{F} \cdot F_t + \varepsilon_{i,t} \,, \qquad (1)$$

where $R_{i,t}$ is the excess raw return on fund *i* in month *t* and F_t is the macroeconomic or financial risk factor *F* in month *t*. $\alpha_{i,t}$ and $\beta_{i,t}^{F}$ are, respectively, the alpha and the risk factor *F*'s beta for fund *i* in month *t*. Note that the macroeconomic/financial risk factor *F* in equation (1) represents one of the 15 variables tested in this study, including MKT, SMB, HML, MOM, DEF, TERM, DIV, INF, IP, PYRL, FXTF, BDTF, CMTF, IRTF, and SKTF.[12] In other words, equation (1) is not only one regression, but it is a set of 15 regression equations where each regression equation is run for each macroeconomic and financial risk factor separately.

Then, in the second stage, starting from January 1997, we use the Fama-MacBeth cross-sectional regressions of one-month ahead individual fund excess returns on the factor betas:

$$R_{i,t+1} = \omega_t + \lambda_t \cdot \beta_{i,t}^F + \varepsilon_{i,t+1}, \tag{2}$$

where $R_{i,t+1}$ is the raw excess return on fund i in month t+1 and $\beta_{i,t}^F$ is the risk factor F's beta for fund i in month t estimated using eq. (1). ω_t and λ_t are, respectively, the monthly intercepts and slope coefficients from the Fama-MacBeth regressions. As in equation (1), equation (2) is not only a single regression, but it is a set of 15 regression equations where each regression equation is run for each macroeconomic/financial risk factor beta separately.

Table II presents the time-series average intercept and slope coefficients from equation (2) over the sample period January 1997 to December 2008, using as the independent variable the *univariate* factor betas that are estimated using a fixed 36-month rolling window period. The corresponding Newey-West (1987) t-statistics are reported in parentheses. As a robustness check, we also estimate the factor betas using a fixed 24-month rolling window period (we do not however report results from the 24-month rolling window period estimates to save space). Using 36-month or 24-month rolling window period in estimating factor betas, we obtain a positive and significant relation between the default premium beta (β^{DEF}) and the expected returns on hedge funds, and a significantly negative link between inflation beta (β^{INF}) and future returns on hedge funds. In particular, using 36-month rolling window estimates of factor betas in Table II, we find the average slope coefficient from the monthly regressions of one-month ahead hedge fund returns on the previous month's default premium beta (*DEF beta*) to be 0.048 with a Newey-West t-statistic of 2.88, and the average slope coefficient from the monthly regression of one-month ahead hedge fund returns on the previous month's inflation beta (*INF beta*) to be –0.042 with a Newey-West t-statistic of –2.42. More importantly, although not reported in the table, we obtain very similar results when 24-month rolling window estimates of factor betas are utilized in the regressions, with the respective average slope coefficient on *DEF beta* being 0.030 with a Newey-West t-statistic of 2.29, and the average slope coefficient on *INF beta* being –0.036 with a Newey-West t-statistic of –2.20. This suggests that the positive and significant link between *DEF beta* and future hedge fund returns, as well as the negative and significant link between *INF beta* and future hedge fund returns is robust to however the factor betas are estimated (i.e., whether 36-month or 24-month rolling windows utilized), making the case stronger for further analyses on these two factor betas and their impact on hedge fund returns. Other than the *DEF beta* and *INF beta* estimates, the remaining 13 macroeconomic/financial risk

[12] The definitions of these macroeconomic and financial risk factors can be found in the previous section "Data and Descriptions of Variables" as well as in Panel B of Table I.

factor betas, including the market beta, do not have any predictive power over expected future hedge fund returns (see the diagonal in Table II).

5.1.2. Bivariate Factor Betas in Cross-Sectional Regressions

Table III reports the time-series average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead hedge fund excess returns on the bivariate factor betas. In the first stage, bivariate time-series monthly factor betas are estimated for each fund from the bivariate time-series regressions of fund excess returns on the market factor (MKT) and one of the other remaining 14 factors (one by one) over a 36-month rolling window period. In the second stage, for each month during the 1997– 2008 period, the cross-section of one-month ahead funds' excess returns are regressed one by one on the funds' 14 factor betas (derived from the first stage) after controlling for the market beta (β^{MKT}). In other words, in the first stage, we run the following regression with a fixed rolling estimation window of 36 months to generate the time-series monthly bivariate factor betas:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{F} \cdot F_t + \varepsilon_{i,t}\,, \tag{3}$$

where $R_{i,t}$ is the raw excess return on fund *i* in month *t*, F_t is the risk factor *F* in month *t*, MKT_t is the market factor in month *t*. The coefficients $\alpha_{i,t}$, $\beta_{i,t}^{MKT}$, and $\beta_{i,t}^{F}$ are, respectively, the alpha, the market beta, and the risk factor *F*'s beta for fund *i* in month *t*. Note that the risk factor *F* in equation (3) represents one by one, other than the market factor, all of the remaining 14 variables tested in this study, including SMB, HML, MOM, DEF, TERM, DIV, INF, IP, PYRL, FXTF, BDTF, CMTF, IRTF, and SKTF. In other words, equation (3) is not only one regression, but it is a set of 14 regression equations, where each regression equation is run for each macroeconomic/financial risk factor separately.

In the second stage, we follow the Fama-MacBeth approach and regress the one-month ahead excess fund returns on the factor betas obtained from the aforementioned bivariate regressions:

$$R_{i,t+1} = \omega_t + \lambda_t \cdot \beta_{i,t}^{MKT} + \theta_t \cdot \beta_{i,t}^{F} + \varepsilon_{i,t+1}\,, \tag{4}$$

where $R_{i,t+1}$ is the raw excess return on fund *i* in month *t*+1, $\beta_{i,t}^{MKT}$ and $\beta_{i,t}^{F}$ are, respectively, the market beta and the risk factor *F*'s beta for fund *i* in month *t* estimated from regression (3) over the past 3 years. ω_t, λ_t and θ_t are the monthly intercept and slope coefficients from the Fama-MacBeth regressions.

Table III presents the time-series average intercept and slope coefficients from equation (4) over the sample period January 1997–December 2008, using as the independent variable the *bivariate* factor betas that are estimated using a fixed 36-month rolling window period. The corresponding Newey-West t-statistics are given in parentheses. As a robustness check, we again estimate the factor betas using a fixed 24-month rolling window period, but we do not present these results to preserve space. As reported in Table III, controlling for market beta (β^{MKT}) does not alter the statistically significant predictive power of default premium beta (*DEF beta*) and inflation beta (*INF beta*) over future hedge fund returns; there is still a positive and significant link between the default premium beta (β^{DEF}) and the cross-section of future hedge fund returns, and there is still a negative and significant link between inflation beta (β^{INF}) and the cross-section of future hedge fund returns. Using 36-month rolling window estimates of factor betas in Table III, we find the average slope coefficient from the monthly regressions of one-month ahead hedge fund returns on the previous month's *DEF beta* to be 0.040 with a Newey-West t-statistic of 2.57, and the average slope coefficient from the monthly regressions of one-month ahead hedge fund returns on the previous month's *INF beta* to be –0.040 with a Newey-West t-statistic of –2.11. Comparing Table III to Table II, the addition of the market beta (β^{MKT}) into Fama-MacBeth regressions seems to only reduce the magnitude of the average slope coefficients for β^{DEF} and β^{INF} very slightly, with somewhat lower t-statistics, but the statistically significant predictive power of these two factor betas for future hedge fund returns remains robust and intact.

Although not reported in Table III, we obtain very similar results when 24-month rolling window estimates of factor betas are utilized in the regressions, with the respective average slope coefficient on *DEF beta* being 0.024 with a Newey-West t-statistic of 2.02, and the average slope coefficient on *INF beta* being –0.029 with a Newey-West t-statistic of –2.01. This suggests that the positive and significant relation between *DEF beta* and future hedge fund returns as well as the negative and significant relation between *INF beta* and future hedge fund returns is robust to both how the factor betas are estimated (i.e., whether 36-month or 24-month rolling windows utilized), and how regression equations are formulated (i.e., whether *univariate* or *bivariate* factor betas used in Fama-MacBeth regressions). It is interesting to note that in Table III, market beta (β^{MKT}) is never statistically significant, no matter what other risk factor beta is combined with in the Fama-MacBeth regressions. Lastly, like in our earlier results, other than the *DEF* and *INF beta* estimates, the remaining macroeconomic/financial risk factor betas, do not seem to have any predictive power over expected future hedge fund returns (see the diagonal in Table III).

5.1.3. Multivariate Factor Betas in Cross-Sectional Regressions

In the previous two sections we have witnessed how strongly and consistently *DEF betas* and *INF betas* (estimated from both univariate and bivariate regressions) are capable of predicting the cross-sectional variation in hedge fund returns. In this section, we now drop the other insignificant risk factors from our analyses and focus only on these two risk factor betas (*DEF* and *INF betas*), analyzing the interaction between the two and the market factor, and check if our earlier results hold true even after controlling for individual hedge fund characteristics, such as size, age, management fee, and incentive fee.

Table IV reports the time-series average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead fund excess returns on the *multivariate* factor betas. In the first stage, market, default premium, and inflation betas (β^{MKT} , β^{DEF} , β^{INF}) are estimated for each fund from the time-series regressions of hedge fund excess returns on the market, default spread, and inflation rate (MKT, DEF, INF) using a 36-month rolling window period. In the second stage, for each month during the January 1997–December 2008 period, the cross-section of one-month ahead funds' excess returns are regressed on the funds' aforementioned three factor betas with and without controlling for individual hedge fund characteristics. In other words, in the first stage, we run the following regression with a fixed rolling estimation window of 36 months to generate the time-series monthly *multivariate* factor betas:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{DEF} \cdot DEF_t + \beta_{i,t}^{INF} \cdot INF_t + \varepsilon_{i,t}, \tag{5}$$

where $R_{i,t}$ is the raw excess return on fund *i* in month *t*; MKT_t , DEF_t , INF_t are, respectively, the market factor, the default spread, and the inflation rate in month *t*. The coefficients $\alpha_{i,t}$, $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{DEF}$, and $\beta_{i,t}^{INF}$ are, respectively, the alpha, the market beta, the default premium beta, and the inflation beta for fund *i* in month *t*.

In the second stage, monthly cross-sectional regressions are run for the following multivariate specification and its nested versions:

$$\begin{aligned} R_{i,t+1} &= \omega_t + \lambda_t \cdot \beta_{i,t}^{MKT} + \theta_{1,t} \cdot \beta_{i,t}^{DEF} + \theta_{2,t} \cdot \beta_{i,t}^{INF} + \theta_{3,t} \cdot SIZE_{i,t} + \\ &\theta_{4,t} \cdot AGE_{i,t} + \theta_{5,t} \cdot MGMTFEE_i + \theta_{6,t} \cdot INCENTIVEFEE_i + \varepsilon_{i,t+1} \end{aligned} \tag{6}$$

where $R_{i,t+1}$ is the raw excess return on fund *i* in month *t*+1, and $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{DEF}$ $\beta_{i,t}^{INF}$ are, respectively, the market beta, the default premium beta, and the inflation beta for fund *i* in month *t* estimated from regression (5) over the past 3 years. *SIZE*, *AGE*, *MGMTFEE*, and *INCENTIVEFEE* are the fund characteristics: Size is measured as the monthly assets under management in million 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%; and Incentive Fee is a fixed percentage fee of the fund's annual net profits above a designated hurdle rate.

As shown in Table IV, controlling for the market beta (β^{MKT}), the other factor beta in question (β^{DEF} and β^{INF}), and the individual hedge fund characteristics, do not alter the statistically significant predictive power of *DEF beta* and *INF beta* over future hedge fund returns; there is still a positive and significant relation between β^{DEF} and future hedge fund returns, and there is still a negative and significant link between β^{INF} and expected returns on hedge funds, no matter whether all variables are controlled simultaneously or in different combinations of groupings. The average slope coefficient on *DEF beta* is estimated to be between 0.031 and 0.049, with the Newey-West t-statistics ranging from 2.83 to 2.90, and the average slope coefficient on *INF beta* is estimated to be between –0.038 and –0.041, with the Newey-West t-statistics ranging from –2.02 to –2.05. All in all, the clear conclusion is that Fama-MacBeth cross-sectional regressions provide strong corroborating evidence for an economically and statistically significant positive (negative) link between default premium beta (inflation beta) and future hedge fund returns.

One final interesting observation in Table IV is the fact that the incentive fee variable has a positive and statistically significant coefficient (0.010 with a Newey-West t-statistic of 3.36) in monthly cross-sectional regressions of one-month ahead funds' excess returns on factor betas when hedge fund characteristics are added to the cross-sectional regression equation as well. This suggests that incentive fee has a strong positive explanatory power over expected hedge fund returns (i.e., funds that charge higher incentive fees also generate higher future hedge fund returns), a finding similar to the earlier studies of hedge funds (see Brown, Goetzmann, and Ibbotson (1999), Liang (1999), Edwards and Caglayan (2001)).

5.2. Univariate Quintile Portfolio Analyses of DEF and INF Betas

In testing the relationship between funds' factor betas and future hedge fund returns, one alternative to parametric tests of Fama-MacBeth regressions, is a non-parametric portfolio analysis, where quintile portfolios are formed every month by sorting hedge funds according to their factor betas and next month returns are observed in each quintile to see if there is a significant pattern (difference) in the performance of high factor beta quintile vs. low factor beta quintile.

5.2.1. Univariate Portfolio Analysis of DEF Betas

We first conduct our non-parametric quintile portfolio analysis for *DEF betas* by sorting hedge funds according to their past month's *DEF betas* (β^{DEF}) and compare the performance of *high DEF beta* portfolio to *low DEF beta* portfolio in the following month. Quintile portfolios are formed every month from January 1997 to December 2008 by sorting hedge funds based on their 36-month β^{DEF}, where Quintile 1 contains the hedge funds with the lowest β^{DEF}, and Quintile 5 contains the hedge funds with the highest β^{DEF}. Table V, Panel A reports the average β^{DEF}, average next month returns, 4-factor and 9-factor alphas for each of these *DEF beta* sorted quintiles. Moving from quintile 1 to quintile 5, we observe that average raw return on the *DEF beta* portfolios increases monotonically from 0.061% to 0.530% per month. Effectively, the average raw return difference between quintiles 5 and 1 (i.e., high β^{DEF} vs. low β^{DEF}) is 0.469% per month with a Newey-West t-statistic of 2.16, suggesting that this positive return difference is statistically and economically significant. In other words, this result indicates that hedge funds in the highest *DEF beta* quintile generate about 5.6% more annual return compared to funds in the lowest *DEF beta* quintile.

In Table V Panel A, we also compute the 4-factor and 9-factor alphas of each *DEF beta* quintile. We regress the monthly excess returns of the *DEF* beta portfolios on the Fama-French-Carhart's 4 factors (MKT, SMB, HML, and MOM) as well as on the Fama-French-Carhart and Fung-Hsieh's combined 9 factors (MKT, SMB, HML, MOM, FXTF, BDTF, CMTF, IRTF, and SKTF) and we check if the intercepts from these two regressions (namely, 4-factor alpha and 9-factor alpha) are statistically significant. As shown in the last two columns of Panel A, Table V, as we move from quintile 1 to quintile 5, the 4-factor and 9-factor alphas on the *DEF beta* portfolios increase monotonically from –0.213% to 0.267% per month for the 4-factor model, and from –0.057% to 0.388% per month for the 9-factor model. Note also that the 4-factor alphas and 9-factor alphas are statistically significant for most of the time for both *high DEF beta* and *low DEF beta* portfolios.

We also check whether the significant raw return difference between *high DEF beta* funds and *low DEF beta* funds can be explained by different factors such as Fama-French (1993) and Carhart's (1997) four factors of market, size, book-to-market, and momentum, as well as Fung and Hsieh's (2001) five trend-following factors on stocks, short-term interest rates, currencies, bonds, and commodities. To do this, we regress the monthly time series of return differences between *high DEF beta* and *low DEF beta* funds on Fama-French-Carhart's 4 factors as well as on Fama-French-Carhart and Fung-Hsieh's combined 9 factors and we check if the intercepts from these two regressions (namely, 4-factor alpha and 9-factor alpha) are statistically significant. Table V, Panel A reports the 4-factor and 9-factor alphas from these regressions. The 4-factor alpha difference between quintiles 5 and 1 is 0.480% with a t-statistic of 2.23. Similarly, the 9-factor alpha difference between quintiles 5 and 1 is 0.445% with a t-statistic of 2.56. This suggests that after controlling for market, size, book-to-market, momentum, and trend-following factors, the return difference between *high DEF beta* and *low DEF beta* funds remains positive and significant. Alternatively, these 4 and 9 factors tested here do not explain the positive relation between β^{DEF} and the cross-section of future hedge fund returns.

Lastly, we investigate the source of this significant return difference between *high DEF beta* funds and *low DEF beta* funds: is it due to outperformance by *high DEF beta* funds, or underperformance by *low DEF beta* funds, or both? For this, we compare the performance of *high DEF beta* quintile to the performance of the rest of quintiles as well as the performance of rest of quintiles to the performance of *low DEF beta* quintile, both in terms of raw returns and risk-adjusted returns (i.e., 4-factor and 9-factor alphas). Analyzing the rows starting with "High β^{DEF} – Rest of Quintiles" and "Rest of Quintiles – Low β^{DEF}" in Panel A of Table V, we find that, on average, *high DEF beta* funds generate 0.319% more monthly raw returns compared to the rest of their peers (with a t-statistic of 2.02), and *low DEF beta* funds produce 0.268% less monthly raw returns compared to the rest of their peers (with a t-statistic of 1.97), suggesting that the positive and significant return difference between *high DEF beta* and *low DEF beta* funds is due to both outperformance by *high DEF beta* funds and underperformance by *low DEF beta* funds. Finally, when 4-factor and 9-factor alpha differences are considered, the outcome remains the same; the *high DEF beta* funds generate significantly higher risk-adjusted returns compared to the rest of the crowd (0.250% 4-factor alpha difference with a t-statistic of 1.99; and 0.237% 9-factor alpha difference with a t-statistic of 2.02), while the *low DEF beta* funds produce significantly smaller risk-adjusted returns compared to the rest of the crowd (0.350% 4-factor alpha difference with a t-statistic of 2.99; and 0.320% 9-factor alpha difference with a t-statistic of 3.18). In sum, all of these estimates confirm our earlier findings for the existence of a positive and significant relation between *DEF betas* and future hedge fund returns.

In the hedge fund literature, in addition to reporting raw returns and alphas, it is also common to report the appraisal ratios (the ratio of alphas to the standard error of the factor model regressions) because hedge funds' extensive use of leverage can sometimes obscure alpha measures (see Agarwal and Naik (2000)). Although not reported in Panel A of Table V to save space, we also compute the appraisal ratios of the 4-factor and 9-factor models for each of the *DEF beta* quintiles.[13] Moving from quintile 1 to quintile 5, the 4-factor appraisal ratios increase almost monotonically from –0.117 to 0.136, and similarly, the 9-factor appraisal ratios increase again almost monotonically from –0.033 to 0.203 (only quintile 4 has a larger appraisal ratio than quintile 5 in both instances), suggesting that the ranking order of *DEF beta* quintiles is almost identical for both alphas and appraisal ratios.

In a recent paper Goetzmann, Ingersoll, Spiegel, and Welch (2007) point out the vulnerability of traditional performance measures to a number of simple dynamic manipulation strategies, and develop a manipulation-proof performance measure (MPPM):

$$MPPM = \frac{1}{(1-\rho)\Delta t}\ln\left(\frac{1}{T}\sum_{t=1}^{T}\left[\left(1+R_{p,t}\right)/\left(1+r_{f,t}\right)\right]^{1-\rho}\right), \tag{7}$$

where $R_{p,t}$ and $r_{f,t}$ are the monthly portfolio return and risk-free interest rate in month *t*. Goetzmann et al. (2007) transformed the measure so that equation (7) can be interpreted as the annualized continuously compounded excess return certainty equivalent of the portfolio. They relate the MPPM with some benchmark portfolio which is chosen to be the market index. They show that if the benchmark market portfolio has a lognormal return, $1+r_{m,t}$, then the parameter ρ should be selected so that

$$\rho = \frac{\ln\left[E(1+\bar{r}_m)\right]-\ln(1+\bar{r}_f)}{Var\left[\ln(1+\bar{r}_m)\right]}. \tag{8}$$

Goetzmann et al. (2007) find this number to be around 2 to 4 for the CRSP value-weighted market portfolio depending on the time period and frequency of data used. In our sample, ρ is estimated to be close to 2, so in our empirical analysis we set $\rho = 2$.

[13] The Treynor (1965) ratio and the Treynor appraisal ratio were introduced to negate the leverage effect on alpha. The Treynor measure is the ratio of alpha to beta, while the appraisal measure is the ratio of alpha to residual standard deviation from a factor model. In this paper, we report the appraisal ratios from the 4-factor and 9-factor models.

Although not presented in Table V to preserve space, we compute the MPPM measure for each of the *DEF beta* quintiles as well. Moving from quintile 1 to quintile 5, the MPPM measures increase monotonically from –3.78% to 1.78%, with a difference of 5.56% per annum. These results indicate that the *low DEF beta* portfolio, on average, underperforms the market portfolio by 3.78% per annum, whereas the *high DEF beta* portfolio, on average, outperforms the market portfolio by 1.78% per annum. A notable point is that the ranking order of *DEF beta* quintiles is almost identical for raw returns, 4-factor and 9-factor alphas, appraisal ratios, and the MPPM measures. Another notable point is that as shown in Panel A of Table V, the annualized raw return, 4-factor and 9-factor alpha differences between the *high* and *low DEF beta* quintiles are, respectively, 5.63%, 5.76%, and 5.34%, which are very similar to the difference between the MPPM measures of the *high* and *low DEF beta* quintiles, 5.56% per annum. These results indicate that the strong, positive relation between *DEF beta* and future hedge fund returns is not sensitive to the choice of performance measures.

5.2.2. Univariate Portfolio Analysis of INF Betas

We conduct the same non-parametric quintile portfolio analysis this time for *INF betas* by sorting hedge funds according to their past month's *INF betas* (β^{INF}) and compare the performance of *high INF beta* portfolio to *low INF beta* portfolio in the following month. Quintile portfolios are formed every month from January 1997 to December 2008 by sorting hedge funds based on their 36-month β^{INF}, where Quintile 1 contains the hedge funds with the lowest β^{INF}, and Quintile 5 contains the hedge funds with the highest β^{INF}. Table V, Panel B presents the average β^{INF}, average next month returns, and average risk-adjusted returns (4-factor and 9-factor alphas) for each of these *INF beta* sorted quintiles. Moving from quintile 1 to quintile 5, average raw return on the *INF beta* portfolios decreases monotonically from 0.502% to 0.151% per month. In effect, the average raw return difference between quintiles 5 and 1 (i.e., high β^{INF} vs. low β^{INF}) is –0.350% per month with a t-statistic of –2.34, suggesting that this negative return difference is statistically and economically significant. This finding indicates that the average annual raw returns of funds in the lowest *INF beta* quintile are about 4.2% higher than the average returns of funds in the highest *INF beta* quintile.

In Table V Panel B, we also compute the 4-factor and 9-factor alphas of each *INF beta* quintile. We regress the monthly excess returns of the *INF* beta portfolios on the Fama-French-Carhart's 4 factors as well as on the Fama-French-Carhart and Fung-Hsieh's combined 9 factors and we check if the intercepts from these two regressions (namely, 4-factor alpha and 9-factor alpha) are statistically significant. As shown in the last two columns of Panel B, Table V, as we move from quintile 1 to quintile 5, the 4-factor and 9-factor alphas on the *INF beta* portfolios decrease monotonically from 0.271% to –0.114% per month for the 4-factor model, and from 0.455% to 0.042% per month for the 9-factor model.

Note also that the 4-factor alphas and 9-factor alphas are statistically significant for most of the time for both *high INF beta* and *low INF beta* portfolios.

We check whether the significant negative raw return difference between *high INF beta* and *low INF beta* funds can be explained by different factors such as Fama-French-Carhart's four factors and Fung and Hsieh's five trend-following factors. The 4-factor alpha difference between quintiles 5 and 1 is –0.385% with a t-statistic of –2.80. Likewise, the 9-factor alpha difference between quintiles 5 and 1 is –0.413% with a t-statistic of –2.86. This implies that after controlling for the market, size, book-to-market, momentum, and trend-following factors, the risk-adjusted return difference between *high INF* and *low INF beta* funds remains negative and significant. Alternatively, these 4 and 9 factors do not explain the negative relation between β^{INF} and the cross-section of hedge fund returns. In sum, all of these results strengthen our earlier findings of the existence of a negative and significant link between *INF betas* and future hedge fund returns.

Lastly, we look for the source of the negative significant return difference between *high INF beta* funds and *low INF beta* funds: is it due to outperformance by *low INF beta* funds, or underperformance by *high INF beta* funds, or both? In Panel B of Table V, we show that the returns from *high INF beta* funds minus the returns from the rest of all hedge funds in other quintiles is only –0.155% with a t-statistic of –1.32, implying that this return difference between the two groups is statistically insignificant (i.e., there is no statistically significant underperformance by *high INF beta* funds relative to its peers). On the other hand, our analyses show that the returns from the rest of quintiles minus the returns from *low INF beta* funds is –0.283% with a t-statistic of –2.58, suggesting that there is a statistically significant outperformance by *low INF beta* funds relative to its peers. Based on these results, we conclude that the negative significant return difference between *high INF beta* and *low INF beta* funds is primarily due to outperformance by *low INF beta* funds, but not due to underperformance by *high INF beta* funds. Finally, when 4-factor alpha and 9-factor alpha differences are considered, the outcome remains the same; the *low INF beta* funds produce significantly larger risk-adjusted returns compared to the rest of the funds (the 4-factor alpha difference between the rest of quintiles and low β^{INF} quintile is –0.255% with a t-statistic of –2.25; and the 9-factor alpha difference between the rest of quintiles and low β^{INF} quintile is –0.317% with a t-statistic of –2.50). On the other hand, *high INF beta* funds' risk-adjusted returns do not differ much from the rest of the funds (the 4-factor alpha difference between high β^{INF} quintile and the rest of quintiles is –0.226% with a t-statistic of –1.51; and the 9-factor alpha difference between high β^{INF} quintile and the rest of quintiles is –0.199% with a t-statistic of –1.42).

Next, in addition to reporting raw returns and alphas, we look at alternative measures of performance for *INF beta* portfolios as well. Although not reported in Panel B of Table V to save space, we compute the appraisal ratios of the 4-factor and 9-factor models for each of the *INF beta* quintiles. Moving from quintile 1 to quintile 5, the 4-factor appraisal ratios decrease monotonically from 0.132 to

–0.068, and similarly, the 9-factor appraisal ratios decrease again monotonically from 0.236 to 0.027, suggesting that the ranking order of *INF beta* quintiles is identical for both alphas and appraisal ratios.

We calculate the MPPM measure for each of the *INF beta* quintiles as well. Although not shown in Table V to preserve space, moving from quintile 1 to quintile 5, the MPPM measures decrease monotonically from 1.58% to –2.71%, with a difference of 4.29% per annum. These results indicate that the *low INF beta* portfolio, on average, outperforms the CRSP market index by 1.58% per annum, whereas the *high INF beta* portfolio, on average, underperforms the market index by 2.71% per annum. Similar to our earlier findings, the ranking order of *INF beta* portfolios is identical for raw returns, 4-factor and 9-factor alphas, appraisal ratios, and the MPPM measures. Another notable point is that, the annualized raw return, 4-factor and 9-factor alpha differences between the *low* and *high INF beta* quintiles are, respectively, 4.20%, 4.62%, and 4.96%, which are very similar to the difference between the MPPM measures of the *low* and *high INF beta* quintiles, 4.29% per annum. These results indicate that the significantly negative relation between *INF beta* and future hedge fund returns is robust across different measures of performance.

5.3. Bivariate Quintile Portfolio Analyses of DEF and INF Betas

In this section, we conduct a similar non-parametric quintile portfolio analysis, but this time by taking into consideration the interaction between *DEF* and *INF betas*. We first present results from the bivariate quintile portfolios of *DEF* and *INF betas*, then we investigate the robustness of their predictive power after controlling for incentive fee variable.

5.3.1. Bivariate Portfolios of DEF Betas after Controlling for INF Betas

In this section, we test whether there is still a positive relation between *DEF betas* and future hedge fund returns after controlling for *INF betas*. To perform this test, quintile portfolios are formed every month from January 1997 to December 2008 by first sorting hedge funds into 5 quintiles based on their 36-month β^{INF}. Then, within each β^{INF} portfolios, hedge funds are sorted further into 5 sub-quintiles based on their 36-month β^{DEF}. This methodology, under each *INF beta* sorted quintiles, produces sub-quintile portfolios of hedge funds with dispersion in *DEF betas* and with near identical *INF betas* (i.e., these newly generated *DEF beta* quintile portfolios control for differences in *INF betas*). Overall, this procedure generates 25 sub-quintile portfolios, where $Q_{i,j}$ is the j^{th} ranked *DEF beta* portfolio within i^{th} ranked *INF beta* portfolio (i=1,2,…,5; j=1,2,…,5). In Panel A of Table VI, "Quintile DEF,1" represents for the lowest *DEF beta* ranked hedge fund quintiles within each of the 5 *INF beta* ranked quintiles. In other words, "Quintile DEF,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 DEF,5" represents for the highest *DEF beta* ranked hedge fund quintiles within each of the 5 *INF beta* ranked quintiles. Alternatively, "Quintile

DEF,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 VI, Panel A shows the average β^{DEF} and next month returns for the following quintiles: DEF,1; DEF,2; DEF,3; DEF,4, and DEF,5. Moving from quintile DEF,1 to quintile DEF,5, the average return on the *DEF beta* portfolios increases monotonically from 0.087% to 0.497% per month. The average return difference between quintiles DEF,5 and DEF,1 (i.e., high β^{DEF} vs. low β^{DEF}) is 0.411% per month with a t-statistic of 2.28, suggesting that the positive relation between *DEF betas* and future hedge fund returns remains significant after controlling for *INF betas*, a result that is very similar to the results we obtained from our earlier parametric Fama-MacBeth regressions.

We also check whether this significant return difference between DEF,5 quintile and DEF,1 quintile can be explained by Fama-French-Carhart's four factors as well as Fung and Hsieh's five trend-following factors. The 4-factor alpha difference between quintiles DEF,5 and DEF,1 is 0.429% with a t-statistic of 2.42. Similarly, the 9-factor alpha difference between quintiles DEF,5 and DEF,1 is 0.436% with a t-statistic of 2.99. This suggests that after controlling first for *INF betas*, and second for the market, size, book-to-market, momentum, and trend-following factors, the return difference between DEF,5 and DEF,1 quintiles remains positive and significant. Alternatively, these 4 and 9 factors do not explain the positive relation between β^{DEF} and the cross-section of future hedge fund returns.

Lastly, we examine the source of this significant return difference between DEF,5 quintile and DEF,1 quintile: is it due to outperformance by DEF,5 quintile funds, or underperformance by DEF,1 quintile funds, or both? For this, we compare the performance of DEF,5 quintile to the performance of the rest of quintiles as well as the performance of rest of quintiles to the performance of DEF,1 quintile, both in terms of raw returns and risk-adjusted returns (i.e., 4-factor and 9-factor alphas). In Panel A of Table VI, we find that, on average, DEF,5 quintile funds (i.e., *high DEF beta* funds) generate 0.278% more monthly raw returns compared to the rest of their peers (with a t-statistic of 2.25), and DEF,1 quintile funds (i.e., *low DEF beta* funds) produce 0.236% less monthly raw returns compared to the rest of their peers (with a t-statistic of 2.05), suggesting that the positive and significant return difference between *high DEF beta* and *low DEF beta* funds is due to both outperformance by *high DEF beta* funds and underperformance by *low DEF beta* funds. Finally, when 4-factor and 9-factor alpha differences are considered, the outcome remains the same; DEF,5 quintile funds (i.e., *high DEF beta* funds) generate significantly higher risk-adjusted returns compared to the rest of the funds (0.242% 4-factor alpha difference with a t-statistic of 2.04; and 0.247% 9-factor alpha difference with a t-statistic of 2.30), while DEF,1 quintile funds (i.e., *low DEF beta* funds) produce significantly smaller risk-adjusted returns compared to the rest of the funds (0.294% 4-factor alpha difference with a t-statistic of 2.86; and 0.299% 9-factor alpha difference with a t-statistic of 3.28). All in all, these results again reconfirm the positive and significant link between *DEF betas* and future hedge fund returns.

5.3.2. Bivariate Portfolios of INF Betas after Controlling for DEF Betas

We now change the order of sorting between *DEF* and *INF betas*. In other words, we test whether there is still a negative relation between *INF betas* and future hedge fund returns after controlling for *DEF betas*. To perform this test, quintile portfolios are formed every month from January 1997 to December 2008 by first sorting hedge funds into 5 quintiles based on their 36-month β^{DEF}. Then, within each β^{DEF} portfolios, hedge funds are sorted further into 5 sub-quintiles based on their 36-month β^{INF}. This methodology, under each *DEF beta* sorted quintiles, produces sub-quintile portfolios of hedge funds with dispersion in *INF betas* and with near identical *DEF betas* (i.e., these newly generated *INF beta* sub-quintile portfolios control for differences in *DEF betas*). In Panel B of Table VI, "Quintile INF,1" represents for the lowest *INF beta* ranked hedge fund quintiles within each of the 5 *DEF beta* ranked quintiles. Similarly, "Quintile INF,5" represents for the highest *INF beta* ranked hedge fund quintiles within each of the 5 *DEF beta* ranked quintiles. Table VI, Panel B presents the average β^{INF} and next month returns for the following quintiles: INF,1; INF,2; INF,3; INF,4; and INF,5. Moving from quintile INF,1 to quintile INF,5, the average return on the *INF beta* portfolios decreases monotonically from 0.505% to 0.147% per month. The average return difference between quintiles INF,5 and INF,1 is –0.357% per month with a t-statistic of –2.96, suggesting that the negative relation between *INF betas* and future hedge fund returns remains significant after controlling for *DEF betas*, a result that is very similar to the results we obtained from our earlier parametric Fama-MacBeth regressions.

Following the same sequence of analyses, we check whether this significant return difference between INF,5 quintile and INF,1 quintile can be explained by Fama-French-Carhart's four factors and Fung and Hsieh's five trend-following factors. The 4-factor alpha from the difference between quintiles INF,5 and INF,1 is –0.364% with a t-statistic of –3.01. Similarly, the 9-factor alpha from the difference between quintiles INF,5 and INF,1 is –0.451% with a t-statistic of –3.20. This suggests that after controlling first for *DEF betas*, and second for the market, size, book-to-market, momentum, and trend-following factors, the return difference between INF,5 and INF,1 quintiles remains negative and significant.

Lastly, we investigate the source of the negative significant return difference between INF,5 quintile and INF,1 quintile. In Panel B of Table VI, we show that the returns from INF,5 quintile funds (i.e., *high INF beta* funds) minus the returns from the rest of all hedge funds in other quintiles is –0.160% with a t-statistic of –2.03. On the same token, we find that the returns from the rest of quintiles minus the returns from INF,1 quintile funds (i.e. *low INF beta* funds) is –0.287% with a t-statistic of –3.05. Both of these results suggest that there is a statistically significant outperformance by *low INF beta* funds as well as a statistically significant underperformance by *high INF beta* funds relative to their peers.[14] Finally, when 4-factor and 9-factor alpha differences are considered, the outcome remains the same; INF,1 quintile funds (i.e., *low INF beta* funds) produce significantly larger risk-adjusted returns compared to the rest of the funds (the 4-factor alpha difference between the rest of quintiles and INF,1 quintile is –0.268% with a t-statistic of –2.68; and the 9-factor alpha difference between the rest of quintiles and INF,1 quintile is –0.356% with a t-statistic of –3.03), while INF,5 quintile funds (i.e., *high INF beta* funds) produce significantly smaller risk-adjusted returns compared to the rest of the funds (the 4-factor alpha difference between INF,5 quintile and the rest of quintiles is –0.186% with a t-statistic of –2.62; and the 9-factor alpha difference between INF,5 quintile and the rest of quintiles is –0.208% with a t-statistic of –2.42). In sum, all of these estimates confirm and strengthen our earlier findings (from parametric tests of Fama-MacBeth cross-sectional regressions) for the existence of a negative and significant link between *INF betas* and future hedge fund returns.

5.3.3. Bivariate Portfolios of DEF Betas after Controlling for Incentive Fee

In our earlier analyses, we find that among hedge fund characteristics, only incentive fee variable has a statistically significant coefficient in monthly cross-sectional regressions of one-month ahead funds' excess returns on factor betas, when hedge fund characteristics are added to the regression equation as well. However, the significance of the incentive fee variable does not affect the predictive power of *DEF betas* and *INF betas* over future hedge fund returns. In an effort to validate this finding, we repeat our non-parametric bivariate quintile portfolio analysis, but this time by taking into consideration *DEF betas*' and *INF betas*' interaction with funds' incentive fees.

We first test whether there is a positive relation between *DEF betas* and future hedge fund returns after controlling for incentive fees. To perform this test, quintile portfolios are formed every month from January 1997 to December 2008 by first sorting hedge funds into 5 quintiles based on their incentive fees. Then, within each incentive fee sorted quintile portfolios, hedge funds are sorted further into 5 sub-quintiles based on their 36-month β^{DEF}. Table VII, Panel A shows the average β^{DEF} and next month returns for the *DEF beta* quintiles. Moving from quintile DEF,1 to quintile DEF,5, average return on *DEF beta* portfolios increases monotonically from 0.020% to 0.554% per month. The average return difference between high β^{DEF} and low β^{DEF} is 0.534% per month with a t-statistic of 2.90, suggesting that the positive relation between *DEF betas* and future hedge fund returns remains significant even after controlling for incentive fees, an outcome that coincides with our earlier results from parametric Fama-MacBeth regressions.

---

[14] In the previous univariate portfolio analysis, we had found that this was primarily due to outperformance by *low INF beta* funds, rather than underperformance by *high INF beta* funds. The interaction of *DEF* and *INF betas* in bivariate portfolio analysis seems to improve the results for the underperformance of *high INF beta* funds, although both the size of difference and the t-statistic still suggest a much stronger outperformance by *low INF beta* funds compared to the underperformance by *high INF beta* funds.

The 4-factor alpha difference between quintiles DEF,5 and DEF,1 is 0.561% with a t-statistic of 3.06. Similarly, the 9-factor alpha difference between quintiles DEF,5 and DEF,1 is 0.579% with a t-statistic of 3.89. This suggests that after controlling first for incentive fees, and second for the market, size, book-to-market, momentum, and trend-following factors, the return difference between DEF,5 and DEF,1 quintiles remains positive and significant.

Following the same sequence of analyses, lastly, we examine the source of the significant positive return difference between DEF,5 quintile and DEF,1 quintile. In Panel A of Table VII, we find that, on average, DEF,5 quintile funds (i.e., *high DEF beta* funds) generate 0.348% more monthly raw returns compared to the rest of their peers (with a t-statistic of 2.59), and DEF,1 quintile funds (i.e., *low DEF beta* funds) produce 0.319% less monthly raw returns compared to the rest of their peers (with a t-statistic of 2.60), suggesting that the positive and significant return difference between *high DEF beta* and *low DEF beta* funds is due to both outperformance by *high DEF beta* funds and underperformance by *low DEF beta* funds. Finally, when 4-factor and 9-factor alpha differences are considered, the result remains the same; DEF,5 quintile funds generate significantly higher risk-adjusted returns compared to the rest of the funds (0.306% 4-factor alpha difference with a t-statistic of 2.25; and 0.325% 9-factor alpha difference with a t-statistic of 2.95), while DEF,1 quintile funds produce significantly smaller risk-adjusted returns compared to the rest of the crowd (0.395% 4-factor alpha difference with a t-statistic of 3.59; and 0.398% 9-factor alpha difference with a t-statistic of 4.02). All in all, these results again reconfirm the positive and significant link between *DEF betas* and future hedge fund returns.

5.3.4. Bivariate Portfolios of INF Betas after Controlling for Incentive Fee

We test whether the significantly negative relation between *INF betas* and future hedge fund returns remains intact after controlling for incentive fees. To perform this test, we form sub-quintile portfolios of *INF betas* within each quintile portfolio of incentive fees. Panel B of Table VII shows the average β^{INF} and next month returns for the *INF beta* quintiles. The average return difference between quintiles INF,5 and INF,1 is –0.460% per month with a t-statistic of –4.13, suggesting that the negative relation between *INF betas* and future hedge fund returns remains significant after controlling for incentive fees, a result that goes in hand with the results obtained from our earlier parametric Fama-MacBeth regressions. The 4-factor alpha difference between quintiles INF,5 and INF,1 is –0.474% with a t-statistic of –4.49. Similarly, the 9-factor alpha difference between quintiles INF,5 and INF,1 is –0.521% with a t-statistic of –4.51. This suggests that after controlling first for incentive fees, and second for the market, size, book-to-market, momentum, and trend-following factors, the return difference between INF,5 and INF,1 quintiles remains negative and significant.

As a final step, we check whether the source of this finding is due to outperformance by INF,1 quintile funds or underperformance by INF,5 quintile funds, or both. In Panel B of Table VII, we show that the returns from INF,5 quintile funds (i.e. *high INF beta* funds) minus the returns from the rest of all hedge funds in other quintiles is –0.258% with a t-statistic of –3.54. On the same token, we find that the returns from the rest of quintiles minus the returns from INF,1 quintile funds (i.e. *low INF beta* funds) is –0.317% with a t-statistic of –3.81. Both of these results suggest that there is a statistically significant outperformance by *low INF beta* funds as well as a statistically significant underperformance by *high INF beta* funds relative to their peers. Similar results are obtained from the 4-factor and 9-factor alpha differences as well, confirming and strengthening our earlier findings for the existence of a negative and significant link between *INF betas* and future hedge fund returns.

6. Robustness Check

6.1. Predictive Power of DEF and INF Betas by Hedge Fund Investment Style

We have so far provided strong, robust evidence for a significantly positive (negative) relation between *DEF beta* (*INF beta*) and the cross-section of *all* hedge fund returns in the TASS database. However, our results might potentially be driven by one particular hedge fund style. In this section, we investigate this issue by focusing on the predictive power of *DEF* and *INF betas* for each fund style separately.

Table VIII reports the average slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead fund excess returns on the univariate factor betas for each investment style: (1) convertible arbitrage, (2) emerging markets, (3) equity market neutral, (4) event driven, (5) fixed income arbitrage, (6) fund-of-funds, (7) global macro, (8) long-short equity hedge, (9) managed futures, and (10) multi strategy. In the first stage, default and inflation betas (β^{DEF}, β^{INF}) are estimated for each fund in a given investment style from the time-series regressions of hedge fund excess returns on default spread and inflation rate separately using a 36-month rolling window period. In the second stage, the cross-section of funds' excess returns are regressed on the funds' two factor betas (β^{DEF}, β^{INF}) separately each month for the period January 1997–December 2008. In short, regression equations (1) and (2) from our earlier analyses are re-estimated (for *DEF betas* and *INF betas*) for each hedge fund investment style separately.

As presented in the first column of Table VIII, the cross-sectional relation between *DEF beta* and future fund returns is positive and significant for all fund styles, except for the fixed income arbitrage. Similar to our earlier findings for *all* funds, the average slopes on *DEF beta* are in the range of 0.028 to 0.069 with strong statistical significance. The second column of Table VIII shows that, for 7 out of 10 fund styles, there is a negative and significant link between *INF beta* and expected fund returns. The average slopes on *INF beta* range from –0.032 to –0.070 and have strong statistical significance. The relation between *INF beta* and future fund returns turns out to be negative but insignificant for only three styles (convertible arbitrage, equity market neutral, and fixed income arbitrage). These results indicate that the predictive power of *DEF* and *INF betas* over future hedge fund returns is not an artefact of one or a few particular investment styles.

6.2. Results from Longer Sample Period: 1984-2008

As discussed in Section 3, TASS do not include defunct funds prior to 1994 and for that reason we chose 1994 as the start date of our analysis to mitigate survivorship bias, although we had individual hedge fund returns data going back to 1984. As a robustness check, we now expand our sample period to 1984 – 2008, the longest time history available to conduct our tests with the available data.

Using 1984 as the start of our sample period, Table IX reports the time-series average intercepts and slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead individual hedge fund excess returns on the *multivariate* factor betas. In the first stage, monthly market, default premium, and inflation betas ($\beta^{MKT}, \beta^{DEF}, \beta^{INF}$) are estimated for each fund from the time-series regressions of hedge fund excess returns on the market, default premium, and inflation rate (MKT, DEF, INF) using a 36-month rolling window period. In the second stage, for each month during the 1987–2008 period, the cross-section of one-month ahead funds' excess returns are regressed on the funds' aforementioned three factor betas with and without controlling for individual hedge fund characteristics, such as size, age, management fee, and incentive fee. In short, regression equations (5) and (6) from our earlier analyses are re-estimated for the full sample period 1984 – 2008.

As reported in Table IX, the same conclusions remain intact for the broadened sample period; there is a positive and significant link between the default premium beta (β^{DEF}) and future hedge returns, and there is a negative and significant link between inflation beta (β^{INF}) and future hedge returns, no matter whether all variables are controlled simultaneously or in different combinations of groupings. Among alternative combinations of regression equation (6), the average slope coefficient on *DEF beta* is estimated to be between 0.036 and 0.050, with the Newey-West t-statistics ranging from 2.96 to 3.44, and the average slope coefficient on *INF beta* is estimated to be between –0.044 and –0.055, with the Newey-West t-statistics ranging from –2.06 to –2.15. The only difference between these results and previous results for the period 1994 – 2008 is the fact that the broadened sample period 1984 – 2008 has larger (in absolute terms) average slope coefficients for *DEF betas* and *INF betas* with correspondingly larger (again in absolute terms) Newey-West t-statistics, which is expected. Other than that, the results for the two sample periods are almost identical.

In addition to the Fama-MacBeth cross-sectional regressions, we report average raw return and risk-adjusted return differences between high factor beta fund and low factor beta fund quintiles for the longest sample period 1987 – 2008 (conducting both univariate and bivariate portfolio analyses).[15] As presented in Panel A of Table X, for univariate portfolios, the average raw return difference and the 4-

[15] For the period 1987 – 2008, we cannot estimate the combined 9-Factor Fama-French-Carhart and Fung-Hsieh model alpha differences between the quintiles, because the earliest data on 5 Fung-Hsieh trend-following factors goes back to only 1994. For this reason, in this section, we only report the 4-factor Fama-French-Carhart alpha differences between the quintiles as the risk-adjusted return differences.

factor alpha difference between the high and low *DEF beta* portfolios are significantly positive, 0.594% and 0.729% per month, respectively, with corresponding t-statistics of 2.63 and 2.67. The last column of Panel A, Table X indicates a negative and significant relation between *INF beta* and the cross-section of hedge fund returns; the average raw return difference and the 4-factor alpha difference between the high and low *INF beta* portfolios are, respectively, –0.551% and –0.658% per month, with the t-statistics of –2.55 and –2.86. As shown in Panel B of Table X, similar results are obtained from the bivariate portfolios of *DEF* and *INF betas* as well.

Overall, the Fama-MacBeth cross-sectional regressions and portfolio level analyses provide strong, robust, and corroborating evidence for an economically and statistically significant positive (negative) relation between default premium beta (inflation beta) and future hedge fund returns, regardless of the sample period chosen (1997–2008 vs. 1987–2008), and regardless of how the portfolios are formed (univariate vs. bivariate), and how the cross-sectional regression equations are formulated (whether control for the market and controls for hedge fund characteristics are utilized simultaneously or separately).

6.3. Predictive Power of DEF and INF Betas During the Recent Crisis Period

The recent subprime mortgage crisis is an ongoing real estate and financial crisis triggered by a dramatic rise in mortgage delinquencies and foreclosures in the United States, with major adverse consequences for banks and financial markets around the globe. The crisis, which has its roots in the closing years of the 20th century, became apparent in 2007 and has exposed pervasive weaknesses in financial industry regulation and the global financial system. Approximately 80% of U.S. mortgages issued in recent years to subprime borrowers were adjustable-rate mortgages. After U.S. house prices peaked in mid-2006 and began their steep decline thereafter, refinancing became more difficult. As adjustable-rate mortgages began to reset at higher rates, mortgage delinquencies soared. Securities backed with subprime mortgages, widely held by financial firms, lost most of their value. The result has been a large decline in the capital of many banks and U.S. government sponsored enterprises, with tightening credit all around the world.

Between June 2007 and November 2008, Americans lost more than a quarter of their net worth. By early November 2008, a broad U.S. stock index, the S&P 500, was down 45% from its 2007 high. Housing prices had dropped 20% from their 2006 peak, with futures markets signaling a 30-35% potential drop. Total home equity in the United States, which was valued at $13 trillion at its peak in 2006, had dropped to $8.8 trillion by mid-2008 and was still falling in late 2008. Total retirement assets, Americans' second-largest household asset, dropped by 22%, from $10.3 trillion in 2006 to $8 trillion in mid-2008. During the same period, savings and investment assets (apart from retirement savings) lost $1.2 trillion and pension assets lost $1.3 trillion. Taken together, these losses total a staggering $8.3 trillion.

During 2008, three of the largest U.S. investment banks either went bankrupt (Lehman Brothers) or were sold at fire sale prices to other banks (Bear Stearns and Merrill Lynch). These failures augmented the instability in the global financial system. The remaining two investment banks, Morgan Stanley and Goldman Sachs, opted to become commercial banks, thereby subjecting themselves to more stringent regulation. The headline grabbing collapse of two Bear Stearns hedge funds in July 2007 offers fascinating insight into the world of hedge fund strategies and their associated risks. Therefore, we investigate the predictive power of *DEF* and *INF betas* during the recent crisis period from July 2007 to December 2008.

Table XI shows that the average return difference between high β^{DEF} and low β^{DEF} quintiles is positive and extremely large for the period July 2007–December 2008, as compared to our earlier results from the periods of 1987–2008 and 1997–2008; 1.795% per month with a Newey-West t-statistic of 2.03, implying a strong positive link between *DEF beta* and future hedge fund returns. The 4-factor Fama-French-Carhart alpha difference between high β^{DEF} and low β^{DEF} portfolios is also positive and highly significant, both economically and statistically; 0.837% per month with a t-statistic of 2.14. These results indicate that during the recent crisis period of July 2007–December 2008, hedge funds in the highest *DEF beta* quintile generated 21.5% more annual raw and 10.0% more annual risk-adjusted returns compared to funds in the lowest *DEF beta* quintile.

Table XI also presents results for the *INF beta* quintiles for the same period July 2007 – December 2008. The average return difference between high β^{INF} and low β^{INF} quintiles is negative, economically large at –1.186% per month, and statistically significant with a t-statistic of –2.12, confirming a strong negative link between *INF beta* and future hedge fund returns. The 4-factor Fama-French-Carhart alpha difference between high β^{INF} and low β^{INF} portfolios is also negative and significant; –1.028% per month with a t-statistic of –2.40. These findings provide evidence that during the recent crisis period of July 2007–December 2008, the average raw and risk-adjusted returns of funds in the lowest *INF beta* quintile were, respectively, 14.2% and 12.3% higher than the average returns of funds in the highest *INF beta* quintile.

Interestingly, the results for the July 2007–December 2008 period are even stronger than the full sample estimates. Despite the very short sample of only 18 months, the average return differences are statistically significant as well. Clearly the recent financial crisis has not reduced the predictive ability of *DEF* and *INF betas* on future hedge fund returns.

6.4. Predictive Power of DEF and INF Betas during High and Low Economic Activity

In this section, we investigate the significance of a positive (negative) relation between *DEF beta* (*INF beta*) and future hedge fund returns during high and low economic activity. We determine increases and decreases in economic activity by relying on the Chicago Fed National Activity Index (CFNAI index), which is a monthly index designed to assess overall economic activity and related inflationary pressure. The CFNAI is a weighted average of 85 existing monthly indicators of national economic activity. It is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward trend growth rate over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.[16]

Panel A of Table XII shows results for the univariate β^{DEF} quintile portfolios during low economic activity periods. Monthly quintile portfolios are formed by sorting hedge funds based on their 36-month β^{DEF} only for those months when the CFNAI Index was down on a given month during the period January 1987–December 2008. In Panel A of Table XII, the average raw return difference between high β^{DEF} and low β^{DEF} quintiles is positive, 0.525% per month, and statistically significant with a t-statistic of 2.02, implying a positive, significant link between *DEF beta* and hedge fund returns during low economic activity. The 4-factor Fama-French-Carhart alpha difference between high β^{DEF} and low β^{DEF} portfolios is also positive and highly significant; 0.524% per month with a t-statistic of 2.00.

Panel A of Table XII also shows results for the univariate β^{INF} quintile portfolios during low economic activity. The average raw return difference between high β^{INF} and low β^{INF} quintiles is negative and large, –0.981% per month, and highly significant with a t-statistic of –3.28, implying even a stronger negative relation between *INF betas* and expected hedge fund returns during downturns of the markets. The 4-factor Fama-French-Carhart alpha difference between high β^{INF} and low β^{INF} portfolios is also negative and large, and highly significant; –0.940% per month with a t-statistic of –2.98. Comparing in absolute terms the magnitude of raw return and risk-adjusted return differences as well as the corresponding t-statistics, between *DEF betas* and *INF betas*, these results suggest that the predictive power of *INF betas* on future hedge fund returns is stronger compared to *DEF betas* during downturns of the market.

Panel B of Table XII examines the performance of *DEF* and *INF betas* during high economic activity periods. The average raw and risk-adjusted return differences between high β^{DEF} and low β^{DEF} quintiles are 0.656% and 1.051% per month, respectively, implying stronger positive link between *DEF betas* and expected hedge fund returns during upturns of the market (as compared to 0.525% per month raw return difference and 0.524% per month risk-adjusted return difference during downturns of the market).

[16] The 85 economic indicators that are included in the CFNAI are drawn from four broad categories of data: production and income; employment, unemployment, and hours; personal consumption and housing; and sales, orders, and inventories. Each of these data series measures some aspect of overall macroeconomic activity. The derived index provides a single, summary measure of a factor common to these national economic data.

Panel B of Table XII also presents results for the univariate β^{INF} quintile portfolios during expansionary periods. The average return difference between high β^{INF} and low β^{INF} quintiles is negative, but lower than the full sample estimates, at –0.387% per month, and marginally significant with a t-statistic of –1.88. Similarly, the 4-factor Fama-French-Carhart alpha difference between high β^{INF} and low β^{INF} portfolios is also negative, –0.658% per month with a t-statistic of –1.94. Although these results point to a still negative link between *INF beta* and future hedge fund returns during high economic activity, the same relation is much stronger during large falls of the market. Alternatively, these results suggest that the predictive power of *INF betas* on future hedge fund returns is weaker compared to *DEF betas* during upturns of the market.

7. Conclusion

This study contributes to the literature on hedge funds in a significant way by analyzing hedge funds' exposures to various financial and macroeconomic risk factors through univariate, bivariate, and multivariate estimates of factor betas, and by investigating the performance of these factor betas in predicting the cross-sectional variation in hedge fund returns over the sample period January 1994 – December 2008. In hedge fund literature, this is the first sensitivity analysis of expected future hedge fund returns to factor loadings (betas).

Two separate tests are conducted in this paper to determine the significance of factor loadings on future hedge fund returns: parametric tests of Fama-MacBeth cross-sectional regressions of one-month ahead hedge fund returns on past months' factor betas, and non-parametric portfolio tests that sort hedge funds into quintiles based on their past month's factor betas in the first stage and analyze each quintile's next month return performance in the second stage. Both tests reveal clear, robust and corroborating results, showing a positive and significant relation between default premium betas and expected future hedge fund returns, as well as a negative and significant relation between inflation betas and expected future hedge fund returns.

The results from univariate and bivariate portfolio analyses of default premium betas and inflation betas suggest that, on average, between the period 1997 – 2008, hedge funds in the highest *DEF beta* quintile generate 5.6% more annual raw returns compared to funds in the lowest *DEF beta* quintile. Similarly, the average annual raw returns of funds in the lowest *INF beta* quintile are 4.7% higher than the average annual raw returns of funds in the highest *INF beta* quintile. After controlling for Fama-French-Carhart's four factors of market, size, book-to-market, and momentum, as well as Fung-Hsieh's five trend-following factors, the positive relation between default premium beta and future hedge fund returns and the negative relation between inflation beta and future hedge fund returns remain economically and statistically significant. In fact, in terms of risk-adjusted returns, conducting the same aforementioned portfolio comparisons between high factor beta and low factor beta funds result in an annual average of 5.9% 4-factor alpha difference and 5.8% 9-factor alpha difference for the *DEF beta* portfolios, and an annual average of 4.9% 4-factor alpha difference and 5.5% 9-factor alpha difference for the *INF beta* portfolios.

To check whether our main findings are driven by one particular hedge fund style, we examine the predictive power of *DEF* and *INF betas* for each hedge fund style separately. The cross-sectional relation between *DEF beta* and future fund returns is found to be positive and significant for 9 out of 10 hedge fund investment styles. Similarly, we find strong evidence for a negative and significant link between *INF beta* and future fund returns for 7 out of 10 fund styles. Our results point out that the predictive power of *DEF* and *INF betas* is not an artefact of one or a few particular investment styles.

The same robust conclusions for default premium betas, inflation betas and future hedge fund returns hold true for the expanded sample period 1987 – 2008, as well as for alternative estimates of *DEF* and *INF betas* (univariate, bivariate, multivariate estimates of *DEF* and *INF betas* using both 36-month and 24-month rolling window periods), suggesting that our results are not sensitive either to the sample period selected or the way the factor betas are estimated. Also, in addition to computing 4-factor and 9-factor alpha differences between high and low factor beta funds, we find that utilizing alternative measures of risk-adjusted returns (appraisal ratios and manipulation-proof performance measures (MPPM)) yield similar results, indicating that our results are not sensitive to the choice of performance measures selected either.

Finally, we examine the predictive ability of *DEF* and *INF betas* during the recent financial crisis and also during falls and rises of the market. During the recent crisis period July 2007 – December 2008, the positive (negative) link between *DEF beta* (*INF beta*) and expected returns on hedge fund is found to be even stronger than that for the original sample (1997 – 2008) and extended sample (1987 – 2008) periods. Moreover, the cross-sectional predictive power of *DEF* and *INF betas* remains strong and robust during both recessionary and expansionary periods.

References

Ackermann, Carl, Richard McEnally, and David Ravenscraft, D., 1999, The performance of hedge funds: Risk, return, and incentives, *Journal of Finance* 54, 833-874.

Agarwal, Vikas, Gurdip Bakshi, and Joop Huij, 2009, Do higher-moment equity risks explain hedge fund returns? Working Paper, Georgia State University, University of Maryland, and Erasmus University.

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2009, Role of managerial incentives and discretion in hedge fund performance, *Journal of Finance* 64, 2221-2256.

Agarwal, Vikas, and Narayan Y. Naik, 2000, Multi-period performance persistence analysis of hedge funds, *Journal of Financial and Quantitative Analysis* 35, 327-342.

Agarwal, Vikas, and Narayan Y. Naik, 2004, Risks and portfolio decisions involving hedge funds, *Review of Financial Studies* 17, 63-98.

Amin, Gaurav S., and Harry M. Kat, 2003 Hedge fund performance 1990-2000: Do the money machines really add value? *Journal of Financial and Quantitative Analysis* 38, 251-274.

Bali, Turan G., 2003, An extreme value approach to estimating volatility and value at risk, *Journal of Business* 76, 83-108.

Bali, Turan G., Suleyman Gokcan, and Bing Liang, 2007, Value at risk and the cross-section of hedge fund returns, *Journal of Banking and Finance* 31, 1135-1166.

Baquero, Guillermo, Jenke ter Horst, and Marno Verbeek, 2005, Survival, look-ahead biases and the persistence in hedge fund performance, *Journal of Financial and Quantitative Analysis* 40, 493-517.

Billio, Monica, Mila Getmansky, and Loriana Pelizzon, 2009, Crises and hedge fund risk, Working Paper, University of Venice and University of Massachusetts.

Bodie, Zvi, 1976, Common stocks as a hedge against inflation, *Journal of Finance* 31, 459-470.

Bollen, Nicolas P. B., and Robert E. Whaley, 2009, Hedge fund risk dynamics: Implications for performance appraisal, *Journal of Finance*, 64, 985-1035.

Brown, Stephen. J., William N. Goetzmann, and Roger G. Ibbotson, R., 1999, Offshore hedge funds: Survival and performance 1989-95, *Journal of Business* 72, 91-117.

Brown, Stephen. J., William N. Goetzmann, Roger G. Ibbotson, and Stephen A. Ross, 1992, Survivorship bias in performance studies, *Review of Financial Studies* 5, 553-580.

Brown, Stephen. J., William N. Goetzmann, Bing Liang, and Christopher Schwarz, 2008a, Mandatory disclosure and operational risk: Evidence from hedge fund registration, *Journal of Finance* 63, 2785-2815.

Brown, Stephen. J., William N. Goetzmann, Bing Liang, and Christopher Schwarz, 2008b, Estimating operational risk for hedge funds: The ω score, *Financial Analysts Journal* 65, 43-53.

Brown, Stephen. J., William N. Goetzmann, and James Park, 2001, Careers and survival: Competition and risk in the hedge fund and CTA industry, *Journal of Finance* 56, 1869-1886.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373-399.

Campbell, John Y., and Robert Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195-228.

Cao, Charles, Yong Chen, Bing Liang, and Andrew W. Lo, 2010, "Can hedge funds time market liquidity? Working Paper, Penn State University, Virginia Tech, University of Massachusetts at Amherst, MIT Sloan School of Management.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82

Chan, K. C., Nai-fu Chen, and David A. Hsieh, 1985, An exploratory investigation of the firm size effect, *Journal of Financial Economics* 14, 451-471.

Chen, Nai-Fu, 1991, Financial investment opportunities and the macroeconomy, *Journal of Finance* 46, 529-554.

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross, 1986, Economic forces and the stock market, *Journal of Business* 59, 383-403.

Chen, Yong, and Bing Liang, 2007, Do market-timing funds time the market? *Journal of Financial and Quantitative Analysis* 42, 827-856.

Choi, Darwin, Mila Getmansky, Brian Henderson, and Heather Tookes, 2009, Convertible bond arbitrageurs as suppliers of capital, *Review of Financial Studies*, forthcoming.

Edwards, Franklin R., and Mustafa Onur Caglayan, 2001, Hedge fund performance and manager skill, *Journal of Futures Markets* 21, 1003-1028.

Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake, 2003, Incentive fees and mutual funds, *Journal of Finance* 58, 779-804.

Fama, Eugene F., 1981, Stock returns, real activity, inflation, and money, *American Economic Review* 71, 545-565.

Fama, Eugene F., and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics* 22, 3-25.

Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23-49.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns of stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk and return: Some empirical tests, *Journal of Political Economy* 81, 607-636.

Fama, Eugene F., and G. William Schwert, 1977, Asset returns and inflation, *Journal of Financial Economics* 5, 115-146.

Fung, William, and David A. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: The case of hedge funds, *Review of Financial Studies* 10, 275-302.

Fung, William, and David A. Hsieh, 2000, Performance characteristics of hedge funds and CTA funds: Natural versus spurious biases, *Journal of Financial and Quantitative Analysis* 35, 291-307.

Fung, William, and David A. Hsieh, 2001, The risk in hedge fund strategies: Theory and evidence from trend followers, *Review of Financial Studies* 14, 313-341.

Fung, William, David A. Hsieh, Narayan Y. Naik, and Tarun Ramadorai, 2008, Hedge funds: Performance, risk, and capital formation, *Journal of Finance* 63, 1777-1803.

Geske, Robert, and Richard Roll, 1983, The fiscal and monetary linkage between stock returns and inflation, *Journal of Finance* 38, 1-34.

Getmansky, Mila, Andrew W. Lo, and Igor Makarov, 2004, An econometric model of serial correlation and illiquidity in hedge fund returns, *Journal of Financial Economics* 74, 529-610.

Goetzmann, William N., Jonathan E. Ingersoll, and Stephen A. Ross, 2003, High-water marks and hedge fund management contracts, *Journal of Finance* 58, 1685-1718.

Goetzmann, William N., Jonathan E. Ingersoll, Matthew Spiegel, and Ivo Welch, I., 2007, Portfolio performance manipulation and manipulation-proof performance measures, *Review of Financial Studies* 20, 1503-1546.

Griffin, John M., and Jin Xu, 2009, How smart are the smart guys? A unique view from hedge fund stock holdings, *Review of Financial Studies* 22, 2531-2570.

Gupta, Anurag, and Bing Liang, 2005, Do hedge funds have enough capital? A value at risk approach, *Journal of Financial Economics* 77, 219-253.

Hodder, James E., and Jens Carsten Jackwerth, 2007, Incentive contracts and hedge fund management, *Journal of Financial and Quantitative Analysis* 42, 811-826.

Jagannathan, Ravi, and Robert A. Korajczyk, 1986, Assessing the market timing performance of managed portfolios, *Journal of Business* 59, 217-235.

Keim, Donald B., and Robert F. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357-390.

Khandani, Amir E., and Andrew W. Lo, 2009, Illiquidity premia in asset returns: An empirical analysis of hedge funds, mutual funds, and U.S. equity portfolios, Working Paper, MIT Sloan School of Management.

Kosowski, Robert, Narayan Y. Naik, and Melvyn Teo, 2007, Do hedge funds deliver alpha? A Bayesian and bootstrap analysis, *Journal of Financial Economics* 84, 229-264.

Liang, Bing, 1999, On the performance of hedge funds, *Financial Analysts Journal* 55, 72-85.

Liang, Bing, 2000, Hedge fund: The living and the dead, *Journal of Financial and Quantitative Analysis* 35, 309-326.

Liang, Bing, and Hyuna Park, 2007, Risk measures for hedge funds: A cross-sectional approach, *European Financial Management* 13, 333-370.

Merton, Robert C., 1973, An intertemporal asset pricing model, *Econometrica* 41, 867-887.

Mitchell, Mark, and Todd Pulvino, 2001, Characteristics of risk and return in risk arbitrage, *Journal of Finance* 56, 2135-2175.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708

Panageas, Stavros, and Mark M. Westerfield, M., 2009, High water-marks: High risk appetites? Convex compensation, long horizons and portfolio choice, *Journal of Finance* 64, 1-36.

Pearce, Douglas K., and V. Vance Roley, 1983, The reaction of stock prices to unanticipated changes in money: A note, *Journal of Finance* 38, 1323-1333.

Pearce, Douglas K., and V. Vance Roley, 1985, Stock price and economic news, *Journal of Business* 58, 49-67.

Ross, Stephen A., 1976, The arbitrage theory of capital asset pricing, *Journal of Economic Theory* 13, 341-360.

Sun, Zheng, Ashley Wang, and Lu Zheng, 2009, The road less traveled: Strategy distinctiveness and hedge fund performance, Working Paper, University of California, Irvine.

Titman, Sheridan, and Cristian Tiu, 2009, Do the best hedge funds hedge? Working Paper, University of Texas-Austin and SUNY-Buffalo.

Treynor, Jack L., 1965, How to rate management of investment funds? *Harvard Business Review* 43, 63-75.

Table I. Descriptive Statistics

There are total of 12,980 hedge funds that reported monthly returns to TASS for the years between 1994 and 2008 in this database, of which 6,188 are defunct funds and 6,792 are live funds. For each year from 1994 to 2008, Panel A reports the number of hedge funds, 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 A. Summary Statistics Year by Year

						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	846	302	31	1117	56.7	-0.06	0.06	0.95	-1.64	1.01
1995	1117	332	71	1378	68.5	1.21	1.32	1.06	-0.96	2.73
1996	1378	396	136	1638	93.2	1.39	1.44	1.54	-1.75	3.89
1997	1638	428	112	1954	142.0	1.41	1.69	2.01	-1.66	4.72
1998	1954	430	175	2209	157.0	0.34	0.16	2.19	-5.11	3.11
1999	2209	537	193	2553	204.0	2.00	1.25	2.14	-0.29	6.38
2000	2553	620	240	2933	254.0	0.82	0.44	2.16	-1.95	5.42
2001	2933	897	264	3566	381.9	0.53	0.61	1.11	-1.46	2.44
2002	3566	989	256	4299	451.4	0.26	0.55	0.81	-1.26	1.39
2003	4299	1204	276	5227	666.4	1.23	1.10	0.85	-0.20	3.00
2004	5227	1480	337	6370	1,039.6	0.64	0.70	1.13	-1.15	2.63
2005	6370	1451	546	7275	1,433.4	0.73	1.26	1.30	-1.46	1.98
2006	7275	1366	635	8006	1,393.3	0.89	1.18	1.37	-1.80	3.11
2007	8006	1173	1055	8124	2,128.1	0.78	0.77	1.42	-2.04	2.81
2008	8124	529	1861	6792	1,749.5	-1.59	-1.73	2.43	-5.93	1.62

Table I (continued)

Panel B reports for the sample period 1994–2008 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 C reports for the same sample period the time-series mean, median, standard deviation, minimum, and maximum monthly percentage returns of the 15 financial and macroeconomic risk factors used in this study. For comparison purposes, the same monthly percentage return statistics are provided for an equal-weighted hedge fund portfolio as well.

Panel B. Cross-Sectional Statistics (Overall Sample Period: 1994 - 2008)

	N	Mean	Median	Std. Dev.	Minimum	Maximum
Average Monthly Return over the life of the Fund (%)	12,980	0.29	0.37	1.38	-25.14	22.10
Average Monthly AUM over the life of the Fund (million $s)	12,955	120.4	32.5	818.4	0.5	36,446.6
Age of the Fund (# of months in existence)	12,980	56.78	47.00	40.51	1.00	180.00
Management Fee (%)	12,768	1.48	1.50	0.67	0.00	10.00
Incentive Fee (%)	12,660	14.05	20.00	8.30	0.00	50.00

Panel C. Time-Series Statistics (Overall Sample Period: 1994 - 2008)

	N	Mean	Median	Std. Dev.	Minimum	Maximum
EWHF: Equal-weighted hedge fund portfolio	180	0.71	0.74	1.72	-5.93	6.38
MKT: CRSP value-weighted market index	180	0.62	1.39	4.50	-18.47	8.39
SMB: Fama-French (1993) size factor	180	-0.08	-0.19	3.78	-21.96	13.78
HML: Fama-French (1993) book-to-market factor	180	0.47	0.33	3.41	-9.86	13.85
MOM: Carhart (1997) momentum factor	180	0.87	0.77	5.06	-25.06	18.39
DEF: Default spread	180	0.89	0.81	0.37	0.55	3.38
TERM: Term spread	180	1.49	1.34	1.26	-1.29	3.94
DIV: Aggregate dividend yield	180	1.74	1.72	0.41	1.05	3.20
INF: Monthly inflation rate based on US CPI	180	0.20	0.20	0.37	-1.92	1.22
IP: Monthly growth rate of industrial production	180	0.21	0.21	2.14	-4.79	5.65
PYRL: Monthly percent change in US non-farm payrolls	180	0.11	0.39	0.81	-2.27	0.96
FXTF: Fung-Hsieh currency trend-following factor	180	0.01	-0.03	0.20	-0.30	0.90
BDTF: Fung-Hsieh bond trend-following factor	180	-0.01	-0.04	0.15	-0.25	0.69
CMTF: Fung-Hsieh commodity trend-following factor	180	0.00	-0.03	0.14	-0.23	0.65
IRTF: Fung-Hsieh short-term interest rate trend-following factor	180	0.03	-0.02	0.30	-0.31	2.22
SKTF: Fung-Hsieh stock index trend-following factor	180	-0.05	-0.06	0.13	-0.30	0.46

Table II. Univariate Fama-MacBeth Cross-Sectional Regressions of One-Month ahead Hedge Fund Returns on the Univariate Factor Betas

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 univariate factor betas. In the first stage, monthly factor betas are estimated for each fund from the univariate time-series regressions of hedge fund excess returns on the factor over a 36-month rolling window period. In the second stage, the cross-section of one-month ahead funds' excess returns are regressed on the funds' factor betas each month for the period 1997–2008. Newey-West (1987) t-statistics are reported 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	β^{MKT}	β^{SMB}	β^{HML}	β^{MOM}	β^{DEF}	β^{TERM}	β^{DIV}	β^{INF}	β^{IP}	β^{PYRL}	β^{FXTF}	β^{BDTF}	β^{CMTF}	β^{IRTF}	β^{SKTF}
0.290	0.106														
(3.14)	(0.32)														
0.193		0.223													
(1.53)		(0.55)													
0.298			0.046												
(2.26)			(0.15)												
0.293				–0.338											
(1.94)				(–1.04)											
0.315					**0.048**										
(2.47)					**(2.88)**										
0.334						0.009									
(2.48)						(0.09)									
0.346							–0.009								
(2.92)							(–0.37)								
0.269								**–0.042**							
(1.76)								**(–2.42)**							
0.250									–0.247						
(1.77)									(–1.15)						
0.285										–0.001					
(1.83)										(–0.01)					
0.288											0.023				
(1.63)											(0.96)				
0.305												0.014			
(1.87)												(0.82)			
0.232													0.002		
(1.26)													(0.13)		
0.331														0.027	
(2.87)														(0.56)	
0.290															0.001
(1.89)															(0.05)

Table III. Bivariate Fama-MacBeth Cross-Sectional Regressions of One-Month ahead Hedge Fund Returns on the Bivariate Factor Betas

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 bivariate factor betas after controlling for market beta β^{MKT}. In the first stage, monthly factor betas are estimated for each fund from the bivariate time-series regressions of hedge fund excess returns on the market factor and the other 14 factors over a 36-month rolling window period. In the second stage, the cross-section of one-month ahead funds' excess returns are regressed on the funds' factor betas each month for the period 1997–2008. Newey-West t-statistics are reported 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	β^{MKT}	β^{SMB}	β^{HML}	β^{MOM}	β^{DEF}	β^{TERM}	β^{DIV}	β^{INF}	β^{IP}	β^{PYRL}	β^{FXTF}	β^{BDTF}	β^{CMTF}	β^{IRTF}	β^{SKTF}
0.287	0.001	0.430													
(3.27)	(0.01)	(1.35)													
0.301	0.080		0.053												
(3.18)	(0.25)		(0.20)												
0.295	0.122			–0.137											
(3.24)	(0.36)			(–0.49)											
0.311	0.122				**0.040**										
(3.42)	(0.40)				**(2.57)**										
0.286	0.163					–0.032									
(3.09)	(0.52)					(–0.44)									
0.303	0.099						–0.005								
(3.41)	(0.32)						(–0.24)								
0.289	0.154							**–0.040**							
(3.32)	(0.47)							**(–2.11)**							
0.279	0.091								–0.108						
(3.17)	(0.27)								(–0.60)						
0.289	0.110									0.030					
(3.29)	(0.34)									(0.58)					
0.272	0.086										0.023				
(2.80)	(0.22)										(1.39)				
0.272	0.064											0.011			
(2.52)	(0.16)											(0.87)			
0.303	0.002												0.003		
(2.87)	(0.01)												(0.21)		
0.305	0.131													0.024	
(3.36)	(0.34)													(0.94)	
0.274	0.085														0.001
(2.90)	(0.21)														(0.13)

Table IV

<u>Multivariate</u> Fama-MacBeth Cross-Sectional Regressions of One-Month ahead Hedge Fund Returns on the <u>Multivariate</u> Factor Betas

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 multivariate factor betas. In the first stage, the market, default, and inflation factor betas (β^{MKT}, β^{DEF}, β^{INF}) are estimated for each fund from the time-series regressions of hedge fund excess returns on the market, default spread, and inflation rate (MKT, DEF, INF) using a 36-month rolling window period. In the second stage, the cross-section of one-month ahead funds' excess returns are regressed on the funds' factor betas each month for the period 1997 – 2008 with and without controlling for individual hedge fund characteristics (size, age, management fee, and incentive fee). 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	β^{MKT}	β^{DEF}	β^{INF}	SIZE	AGE	MGMT FEE	INCENTIVE FEE
0.313	0.117	**0.034**					
(3.42)	(0.38)	**(2.83)**					
0.290	0.147		**–0.040**				
(3.31)	(0.45)		**(–2.03)**				
0.315		**0.049**	**–0.039**				
(2.28)		**(2.84)**	**(–2.02)**				
0.306	0.154	**0.032**	**–0.038**				
(3.48)	(0.50)	**(2.90)**	**(–2.04)**				
0.128	0.139	**0.031**	**–0.041**	0.045	0.001	0.017	**0.010**
(0.83)	(0.45)	**(2.87)**	**(–2.05)**	(1.20)	(0.70)	(0.36)	**(3.36)**

Table V. Univariate Portfolios of Hedge Funds Sorted by β^{DEF} and β^{INF}

Panel A. Quintile Portfolios of Hedge Funds Sorted by β^{DEF}

Quintile portfolios are formed every month from January 1997 to December 2008 by sorting hedge funds based on their 36-month β^{DEF}. Quintile 1 is the portfolio of hedge funds with the lowest β^{DEF} and Quintile 5 is the portfolio of hedge funds with the highest β^{DEF}. The table reports average β^{DEF} in each quintile, the next month average raw returns, 4-Factor and 9-Factor Alphas for each quintile. The last three rows show the differences in monthly returns, the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model, and the differences in Alphas with respect to the combined 9-Factor Fama-French-Carhart and Fung-Hsieh model between quintiles 5 and 1; between quintile 5 and the rest of the quintiles; and between the rest of quintiles and quintile 1. Average returns and Alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. Numbers in bold denote statistical significance.

Quintiles	Average β^{DEF} in each Quintile	Next Month Average Raw Returns	Next Month 4-Factor Alphas	Next Month 9-Factor Alphas
Low β^{DEF}	–8.404	0.061 (0.26)	–0.213 (–1.93)	–0.057 (–0.42)
2	–1.491	0.182 (1.20)	–0.006 (–0.06)	0.109 (1.18)
3	0.792	0.247 (1.81)	0.081 (0.89)	0.200 (2.50)
4	3.295	0.357 (2.75)	0.205 (2.88)	0.353 (5.33)
High β^{DEF}	11.292	0.530 (2.25)	0.267 (2.18)	0.388 (2.15)
High β^{DEF} – Low β^{DEF} Return/Alpha Diff.		**0.469** **(2.16)**	**0.480** **(2.23)**	**0.445** **(2.56)**
High β^{DEF} – Rest of Quintiles Return/Alpha Diff.		**0.319** **(2.02)**	**0.250** **(1.99)**	**0.237** **(2.02)**
Rest of Quintiles – Low β^{DEF} Return/Alpha Diff.		**0.268** **(1.97)**	**0.350** **(2.99)**	**0.320** **(3.18)**

Table V (continued)

Panel B. Quintile Portfolios of Hedge Funds Sorted by β^{INF}

Quintile portfolios are formed every month from January 1997 to December 2008 by sorting hedge funds based on their 36-month β^{INF}. Quintile 1 is the portfolio of hedge funds with the lowest β^{INF} and Quintile 5 is the portfolio of hedge funds with the highest β^{INF}. The table reports average β^{INF} in each quintile, the next month average raw returns, 4-Factor and 9-Factor Alphas for each quintile. The last three rows show the differences in monthly returns, the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model, and the differences in Alphas with respect to the combined 9-Factor Fama-French-Carhart and Fung-Hsieh model between quintiles 5 and 1; between quintile 5 and the rest of the quintiles; and between the rest of quintiles and quintile 1. Average returns and Alphas are defined in monthly percentage terms. Newey-West adjusted t-statistics are given in parentheses. Numbers in bold denote statistical significance.

Quintiles	Average β^{INF} in each Quintile	Next Month Average Raw Returns	Next Month 4-Factor Alphas	Next Month 9-Factor Alphas
Low β^{INF}	–4.148	0.502 (2.67)	0.271 (1.92)	0.455 (2.99)
2	–0.746	0.269 (2.03)	0.110 (1.48)	0.208 (2.99)
3	0.278	0.223 (1.54)	0.041 (0.46)	0.163 (1.72)
4	1.309	0.232 (1.44)	0.028 (0.29)	0.140 (1.41)
High β^{INF}	4.694	0.151 (0.63)	–0.114 (–1.88)	0.042 (0.31)
High β^{INF} – Low β^{INF} Return/Alpha Diff.		**–0.350** **(–2.34)**	**–0.385** **(–2.80)**	**–0.413** **(–2.86)**
High β^{INF} – Rest of Quintiles Return/Alpha Diff.		–0.155 (–1.32)	–0.226 (–1.51)	–0.199 (–1.42)
Rest of Quintiles – Low β^{INF} Return/Alpha Diff.		**–0.283** **(–2.58)**	**–0.255** **(–2.25)**	**–0.317** **(–2.50)**

Table VI. Bivariate Portfolios of Hedge Funds Sorted by β^{DEF} and β^{INF}

Panel A. Quintile Portfolios of Hedge Funds Sorted by β^{DEF} after controlling for β^{INF}

Quintile portfolios are formed every month from January 1997 to December 2008 by first sorting hedge funds based on their 36-month β^{INF}. Then, within each β^{INF} portfolios, hedge funds are sorted into sub-quintiles based on their 36-month β^{DEF}. "Quintile DEF,1" is the portfolio of hedge funds with the lowest β^{DEF} within each β^{INF} quintile portfolio and "Quintile DEF,5" is the portfolio of hedge funds with the highest β^{DEF} within each β^{INF} quintile portfolio. The table reports the average β^{DEF} within each β^{INF} quintile as well as the next month average returns of hedge funds for each β^{DEF} category under each β^{INF} quintile. The last nine rows represent the differences in monthly returns, the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model, and the differences in Alphas with respect to the combined 9-Factor Fama-French-Carhart and Fung-Hsieh model between Quintile DEF,5 and Quintile DEF,1; between Quintile DEF,5 and the rest of DEF quintiles; and between the rest of DEF quintiles and Quintile DEF,1. 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.

β^{DEF} Quintiles After Controlling for β^{INF}	Average β^{DEF} in each β^{INF} Quintile	Next Month Average Returns
DEF,1	–7.866	0.087
DEF,2	–1.682	0.171
DEF,3	0.835	0.288
DEF,4	3.538	0.333
DEF,5	10.652	0.497
DEF,5 – DEF,1 Return Diff.		**0.411** **(2.28)**
DEF,5 – DEF,1 4-Factor Alpha Diff.		**0.429** **(2.42)**
DEF,5 – DEF,1 9-Factor Alpha Diff.		**0.436** **(2.99)**
DEF,5 – Rest of DEF Quintiles Return Diff.		**0.278** **(2.25)**
DEF,5 – Rest of DEF Quintiles 4-Factor Alpha Diff.		**0.242** **(2.04)**
DEF,5 – Rest of DEF Quintiles 9-Factor Alpha Diff.		**0.247** **(2.30)**
Rest of DEF Quintiles – DEF,1 Return Diff.		**0.236** **(2.05)**
Rest of DEF Quintiles – DEF,1 4-Factor Alpha Diff.		**0.294** **(2.86)**
Rest of DEF Quintiles – DEF,1 9-Factor Alpha Diff.		**0.299** **(3.28)**

Table VI (continued)

Panel B. Quintile Portfolios of Hedge Funds Sorted by β^{INF} after controlling for β^{DEF}

Quintile portfolios are formed every month from January 1997 to December 2008 by first sorting hedge funds based on their 36-month β^{DEF}. Then, within each β^{DEF} portfolios, hedge funds are sorted into sub-quintiles based on their 36-month β^{INF}. "Quintile INF,1" is the portfolio of hedge funds with the lowest β^{INF} within each β^{DEF} quintile portfolio and "Quintile INF,5" is the portfolio of hedge funds with the highest β^{INF} within each β^{DEF} quintile portfolio. The table reports the average β^{INF} within each β^{DEF} quintile as well as the next month average returns of hedge funds for each β^{INF} category under each β^{DEF} quintile. The last nine rows represent the differences in monthly returns, the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model, and the differences in Alphas with respect to the combined 9-Factor Fama-French-Carhart and Fung-Hsieh model between Quintile INF,5 and Quintile INF,1; between Quintile INF,5 and the rest of INF quintiles; and between the rest of INF quintiles and Quintile INF,1. 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.

β^{INF} Quintiles After Controlling for β^{DEF}	Average β^{INF} in each β^{DEF} Quintile	Next Month Average Returns
INF,1	–3.911	0.505
INF,2	–0.815	0.278
INF,3	0.286	0.234
INF,4	1.400	0.213
INF,5	4.431	0.147
INF,5 – INF,1 Return Diff.		**–0.357** **(–2.96)**
INF,5 – INF,1 4-Factor Alpha Diff.		**–0.364** **(–3.01)**
INF,5 – INF,1 9-Factor Alpha Diff.		**–0.451** **(–3.20)**
INF,5 – Rest of INF Quintiles Return Diff.		**–0.160** **(–2.03)**
INF,5 – Rest of INF Quintiles 4-Factor Alpha Diff.		**–0.186** **(–2.62)**
INF,5 – Rest of INF Quintiles 9-Factor Alpha Diff.		**–0.208** **(–2.42)**
Rest of INF Quintiles – INF,1 Return Diff.		**–0.287** **(–3.05)**
Rest of INF Quintiles – INF,1 4-Factor Alpha Diff.		**–0.268** **(–2.68)**
Rest of INF Quintiles – INF,1 9-Factor Alpha Diff.		**–0.356** **(–3.03)**

Table VII

Bivariate Portfolios of Hedge Funds Sorted by β^{DEF} and β^{INF}: Controlling for Incentive Fee

Panel A. Quintile Portfolios of Hedge Funds Sorted by β^{DEF} after Controlling for Incentive Fee

Quintile portfolios are formed every month from January 1997 to December 2008 by first sorting hedge funds based on their *incentive fees*. Then, within each incentive fee sorted portfolio, hedge funds are sorted into sub-quintiles based on their 36-month β^{DEF}. "Quintile DEF,1" is the portfolio of hedge funds with the lowest β^{DEF} within each incentive fee quintile portfolio and "Quintile DEF,5" is the portfolio of hedge funds with the highest β^{DEF} within each incentive fee quintile portfolio. The table reports the average β^{DEF} within each incentive fee quintile as well as the next month average returns of hedge funds for each β^{DEF} category under each incentive fee quintile. The last nine rows represent the differences in monthly returns, the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model, and the differences in Alphas with respect to the combined 9-Factor Fama-French-Carhart and Fung-Hsieh model between Quintile DEF,5 and Quintile DEF,1; between Quintile DEF,5 and the rest of DEF quintiles; and between the rest of DEF quintiles and Quintile DEF,1. 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.

β^{DEF} Quintiles After Controlling for Incentive Fee	Average β^{DEF} in each Incentive Fee Quintile	Next Month Average Returns
DEF,1	–7.962	0.020
DEF,2	–1.636	0.177
DEF,3	0.793	0.262
DEF,4	3.395	0.364
DEF,5	10.886	0.554
DEF,5 – DEF,1 Return Diff.		**0.534** **(2.90)**
DEF,5 – DEF,1 4-Factor Alpha Diff.		**0.561** **(3.06)**
DEF,5 – DEF,1 9-Factor Alpha Diff.		**0.579** **(3.89)**
DEF,5 – Rest of DEF Quintiles Return Diff.		**0.348** **(2.59)**
DEF,5 – Rest of DEF Quintiles 4-Factor Alpha Diff.		**0.306** **(2.25)**
DEF,5 – Rest of DEF Quintiles 9-Factor Alpha Diff.		**0.325** **(2.95)**
Rest of DEF Quintiles – DEF,1 Return Diff.		**0.319** **(2.60)**
Rest of DEF Quintiles – DEF,1 4-Factor Alpha Diff.		**0.395** **(3.59)**
Rest of DEF Quintiles – DEF,1 9-Factor Alpha Diff.		**0.398** **(4.02)**

Table VII (continued)

Panel B. Quintile Portfolios of Hedge Funds Sorted by β^{INF} after Controlling for Incentive Fee

Quintile portfolios are formed every month from January 1997 to December 2008 by first sorting hedge funds based on their *incentive fees*. Then, within each incentive fee sorted portfolio, hedge funds are sorted into sub-quintiles based on their 36-month β^{INF}. "Quintile INF,1" is the portfolio of hedge funds with the lowest β^{INF} within each incentive fee quintile portfolio and "Quintile INF,5" is the portfolio of hedge funds with the highest β^{INF} within each incentive fee quintile portfolio. The table reports the average β^{INF} within each incentive fee quintile as well as the next month average returns of hedge funds for each β^{INF} category under each incentive fee quintile. The last nine rows represent the differences in monthly returns, the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model, and the differences in Alphas with respect to the combined 9-Factor Fama-French-Carhart and Fung-Hsieh model between Quintile INF,5 and Quintile INF,1; between Quintile INF,5 and the rest of INF quintiles; and between the rest of INF quintiles and Quintile INF,1. 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.

β^{INF} Quintiles After Controlling for Incentive Fee	Average β^{INF} in each Incentive Fee Quintile	Next Month Average Returns
INF,1	–3.448	0.529
INF,2	–0.567	0.315
INF,3	0.343	0.250
INF,4	1.269	0.215
INF,5	3.795	0.069
INF,5 – INF,1 Return Diff.		**–0.460** **(–4.13)**
INF,5 – INF,1 4-Factor Alpha Diff.		**–0.474** **(–4.49)**
INF,5 – INF,1 9-Factor Alpha Diff.		**–0.521** **(–4.51)**
INF,5 – Rest of INF Quintiles Return Diff.		**–0.258** **(–3.54)**
INF,5 – Rest of INF Quintiles 4-Factor Alpha Diff.		**–0.266** **(–3.95)**
INF,5 – Rest of INF Quintiles 9-Factor Alpha Diff.		**–0.251** **(–3.46)**
Rest of INF Quintiles – INF,1 Return Diff.		**–0.317** **(–3.81)**
Rest of INF Quintiles – INF,1 4-Factor Alpha Diff.		**–0.327** **(–3.84)**
Rest of INF Quintiles – INF,1 9-Factor Alpha Diff.		**–0.400** **(–4.25)**

Table VIII
Cross-Sectional Regressions of Future Hedge Fund Returns on the Factor Betas For Each Hedge Fund Investment Style

This table reports the average slope coefficients from the Fama-MacBeth (1973) cross-sectional regressions of one-month ahead hedge fund excess returns on the univariate factor betas for each hedge fund investment style. In the first stage, default and inflation factor betas (β^{DEF}, β^{INF}) are estimated separately for each fund in a given investment style from the time-series regressions of hedge fund excess returns on default spread and inflation rate (DEF, INF) separately using a 36-month rolling window period. In the second stage, the cross-section of one-month ahead funds' excess returns are regressed on the funds' two aforementioned factor betas (β^{DEF}, β^{INF}) separately each month for the period January 1997 – December 2008. Newey-West t-statistics are reported in parentheses to determine the statistical significance of the average slope coefficients. Numbers in bold denote for statistical significance.

Hedge Fund Investment Styles	Number of Hedge Funds	β^{DEF}	β^{INF}
Convertible Arbitrage	205	**0.038** **(2.09)**	–0.009 (–0.16)
Emerging Markets	411	**0.046** **(2.17)**	**–0.032** **(–2.02)**
Equity Market Neutral	397	**0.039** **(1.84)**	–0.024 (–1.17)
Event Driven	557	**0.055** **(2.41)**	**–0.068** **(–2.55)**
Fixed Income Arbitrage	332	0.016 (0.29)	–0.017 (–0.27)
Fund-of-Funds	2686	**0.064** **(2.63)**	**–0.046** **(–2.46)**
Global Macro	356	**0.052** **(3.37)**	**–0.070** **(–2.65)**
Long-Short Equity Hedge	2476	**0.033** **(2.06)**	**–0.034** **(–2.29)**
Managed Futures	625	**0.028** **(1.94)**	**–0.060** **(–2.31)**
Multi Strategy	684	**0.069** **(2.37)**	**–0.044** **(–2.03)**

Table IX (Period: 1987 – 2008)

Multivariate Fama-MacBeth Cross-Sectional Regressions of One-Month ahead Hedge Fund Returns on the Multivariate Factor Betas

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 multivariate factor betas. In the first stage, the market, default, and inflation factor betas (β^{MKT}, β^{DEF}, β^{INF}) are estimated for each fund from the time-series regressions of hedge fund excess returns on the market, default spread, and inflation rate (MKT, DEF, INF) using a 36-month rolling window period. In the second stage, the cross-section of one-month ahead funds' excess returns are regressed on the funds' factor betas each month for the period 1987–2008 with and without controlling for individual hedge fund characteristics (size, age, management fee, and incentive fee). 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	β^{MKT}	β^{DEF}	β^{INF}	SIZE	AGE	MGMT FEE	INCENTIVE FEE
0.527	0.128	**0.036**					
(3.96)	(0.49)	**(2.96)**					
0.540	0.103		**–0.055**				
(4.77)	(0.40)		**(–2.15)**				
0.544		**0.050**	**–0.049**				
(4.11)		**(3.44)**	**(–2.06)**				
0.512	0.166	**0.039**	**–0.044**				
(4.64)	(0.64)	**(3.25)**	**(–2.14)**				
0.338	0.163	**0.036**	**–0.047**	0.450	–0.001	–0.004	**0.015**
(2.14)	(0.60)	**(3.18)**	**(–2.14)**	(1.00)	(–0.81)	(–0.11)	**(3.35)**

Table X (Period: 1987 – 2008)

Panel A. Univariate Quintile Portfolios of Hedge Funds Sorted by β^{DEF}, β^{INF}

Univariate quintile portfolios are formed every month from January 1987 to December 2008 by sorting hedge funds based on their 36-month β^{DEF} (β^{INF}). Quintile 1 is the portfolio of hedge funds with the lowest β^{DEF} (β^{INF}) and Quintile 5 is the portfolio of hedge funds with the highest β^{DEF} (β^{INF}). The table reports the differences in monthly raw returns and the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model between quintiles 5 and 1. Newey-West adjusted t-statistics are given in parentheses. Numbers in bold denote statistical significance.

β^{DEF} Portfolios	Next Month Return/Alpha Diff.	β^{INF} Portfolios	Next Month Return/Alpha Diff.
High β^{DEF} – Low β^{DEF} Return Diff.	**0.594** **(2.63)**	High β^{INF} – Low β^{INF} Return Diff.	**–0.551** **(–2.55)**
High β^{DEF} – Low β^{DEF} 4-Factor Alpha Diff.	**0.729** **(2.67)**	High β^{INF} – Low β^{INF} 4-Factor Alpha Diff.	**–0.658** **(–2.86)**

Panel B. Bivariate Portfolios of Hedge Funds Sorted by β^{DEF} (β^{INF}) after controlling for β^{INF} (β^{DEF})

Quintile portfolios are formed every month from October 1987 to December 2008 by first sorting hedge funds based on their 36-month β^{INF} (β^{DEF}). Then, within each β^{INF} (β^{DEF}) portfolios, hedge funds are sorted into sub-quintiles based on their 36-month β^{DEF} (β^{INF}). "Quintile DEF,1" is the portfolio of hedge funds with the lowest β^{DEF} within each β^{INF} quintile portfolio and "Quintile DEF,5" is the portfolio of hedge funds with the highest β^{DEF} within each β^{INF} quintile portfolio. "Quintile INF,1" is the portfolio of hedge funds with the lowest β^{INF} within each β^{DEF} quintile portfolio and "Quintile INF,5" is the portfolio of hedge funds with the highest β^{INF} within each β^{DEF} quintile portfolio. The table reports the differences in monthly raw returns and the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model between Quintile DEF,5 and Quintile DEF,1, and Quintile INF,5 and Quintile INF,1. Newey-West t-statistics are reported in parentheses. Numbers in bold denote statistical significance.

β^{DEF} Quintiles After Controlling for β^{INF}	Next Month Return/Alpha Diff.	β^{INF} Quintiles After Controlling for β^{DEF}	Next Month Return/Alpha Diff.
DEF,5 – DEF,1 Return Diff.	**0.484** **(2.78)**	INF,5 – INF,1 Return Diff.	**–0.634** **(–3.41)**
DEF,5 – DEF,1 4-Factor Alpha Diff.	**0.576** **(2.98)**	INF,5 – INF,1 4-Factor Alpha Diff.	**–0.735** **(–3.39)**

Table XI. Univariate Quintile Portfolios of Hedge Funds Sorted by β^{DEF}, β^{INF}
Recent Crisis Period: July 2007–December 2008

Univariate quintile portfolios are formed every month from July 2007 to December 2008 by sorting hedge funds based on their 36-month β^{DEF} (β^{INF}). Quintile 1 is the portfolio of hedge funds with the lowest β^{DEF} (β^{INF}) and Quintile 5 is the portfolio of hedge funds with the highest β^{DEF} (β^{INF}). The table reports the differences in monthly raw returns and the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model between quintiles 5 and 1. Newey-West adjusted t-statistics are given in parentheses. Numbers in bold denote statistical significance.

β^{DEF} Portfolios	Next Month Return/Alpha Diff.	β^{INF} Portfolios	Next Month Return/Alpha Diff.
High β^{DEF} – Low β^{DEF} Return Diff.	**1.795** **(2.03)**	High β^{INF} – Low β^{INF} Return Diff.	**–1.186** **(–2.12)**
High β^{DEF} – Low β^{DEF} 4-Factor Alpha Diff.	**0.837** **(2.14)**	High β^{INF} – Low β^{INF} 4-Factor Alpha Diff.	**–1.028** **(–2.40)**

Table XII. Univariate Quintile Portfolios of Hedge Funds Sorted by β^{DEF}, β^{INF}

Panel A. Low Economic Activity

Monthly univariate quintile portfolios are formed by sorting hedge funds based on their 36-month β^{DEF} (β^{INF}) only for those months when the Chicago Fed National Activity Index was down on a given month during the period 1987 – 2008. Quintile 1 is the portfolio of hedge funds with the lowest β^{DEF} (β^{INF}) and Quintile 5 is the portfolio of hedge funds with the highest β^{DEF} (β^{INF}). The table reports the differences in monthly raw returns and the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model between quintiles 5 and 1. Newey-West adjusted t-statistics are given in parentheses. Numbers in bold denote statistical significance.

β^{DEF} Portfolios	Next Month Return/Alpha Diff.	β^{INF} Portfolios	Next Month Return/Alpha Diff.
High β^{DEF} – Low β^{DEF} Return Diff.	**0.525** **(2.02)**	High β^{INF} – Low β^{INF} Return Diff.	**–0.981** **(–3.28)**
High β^{DEF} – Low β^{DEF} 4-Factor Alpha Diff.	**0.524** **(2.00)**	High β^{INF} – Low β^{INF} 4-Factor Alpha Diff.	**–0.940** **(–2.98)**

Panel B. High Economic Activity

Monthly univariate quintile portfolios are formed by sorting hedge funds based on their 36-month β^{DEF} (β^{INF}) only for those months when the Chicago Fed National Activity Index was up on a given month during the period 1987 – 2008. Quintile 1 is the portfolio of hedge funds with the lowest β^{DEF} (β^{INF}) and Quintile 5 is the portfolio of hedge funds with the highest β^{DEF} (β^{INF}). The table reports the differences in monthly raw returns and the differences in Alphas with respect to the 4-Factor Fama-French-Carhart model between quintiles 5 and 1. Newey-West adjusted t-statistics are given in parentheses. Numbers in bold denote statistical significance.

β^{DEF} Portfolios	Next Month Return/Alpha Diff.	β^{INF} Portfolios	Next Month Return/Alpha Diff.
High β^{DEF} – Low β^{DEF} Return Diff.	**0.656** **(1.94)**	High β^{INF} – Low β^{INF} Return Diff.	**–0.387** **(–1.88)**
High β^{DEF} – Low β^{DEF} 4-Factor Alpha Diff.	**1.051** **(1.96)**	High β^{INF} – Low β^{INF} 4-Factor Alpha Diff.	**–0.658** **(–1.94)**