Economic Uncertainty and the Cross-Section of Hedge Fund Returns*

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ABSTRACT

This paper estimates hedge funds' exposures to alternative measures of economic uncertainty and examines the performance of these uncertainty betas in predicting the cross-sectional variation in hedge fund returns. The results indicate a positive and significant link between uncertainty beta and future hedge fund returns. Funds in the highest uncertainty beta quintile generate 5.5% to 7.5% more average annual returns compared to funds in the lowest uncertainty beta quintile. After controlling for a large set of fund characteristics and risk factors, the positive relation between uncertainty beta and future returns remains economically and statistically significant. We also use a novel statistical approach to construct a hedge fund related economic uncertainty index and find a significantly positive link between funds' exposures to the broad uncertainty index and future fund returns. Hence, economic uncertainty is a powerful determinant of the cross-sectional differences in hedge fund returns.

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1. Introduction

The standard finance theory generally overlooks the conditions in which investors are unsure about the probability distribution of asset returns. Knight (1921) draws the important distinction between risk, in the sense of a measurable probability, and uncertainty, which cannot be measured and by that fact is uninsurable. While uncertainty of its nature cannot be measured, economic change which he argues is the source of this uncertainty can indeed be measured. We argue that economic uncertainty, as calibrated by the the time-varying conditional volatility of macroeconomic variables, is associated with business cycle fluctuations. The purpose of this paper is to discover whether standard measures of risk or economic uncertainty (more broadly considered) is a more powerful determinant of the cross-sectional differences in hedge fund returns.

The macroeconomic variables we consider that are associated with business cycle fluctuations include the default spread, term spread, TED spread, short-term interest rate changes, aggregate dividend yield, equity market index, inflation rate, unemployment rate, growth rate of real GDP per capita, and the Chicago Fed National Activity Index (CFNAI) – a weighted average of 85 existing monthly indicators of national economic activity. Alternative measures of economic uncertainty are generated by estimating time-varying volatility of the aforementioned 10 economic indicators based on the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. Monthly uncertainty betas are estimated for each fund from the time-series regressions on the basis of 36-month rolling regressions of hedge fund excess returns on these uncertainty factors. Finally, we examine the performance of these uncertainty betas in predicting the cross-sectional variation in hedge fund returns.

Both portfolio level analyses and cross-sectional regressions indicate a positive and significant link between uncertainty beta and future hedge fund returns. Quintile portfolios are formed every month by sorting individual hedge funds according to their uncertainty betas. Out of sample average quintile returns for the following month are used to examine whether exposure to economic uncertainty explains the cross-sectional dispersion in hedge fund returns. Depending on the proxy for economic uncertainty, hedge funds in the highest uncertainty beta quintile generate 5.5% to 7.5% higher average annual returns than do funds in the lowest uncertainty beta quintile. After controlling for Fama-French (1993) and Carhart (1997)'s four factors of market, size, book-to-market, and momentum as well as Fung-Hsieh's (2001) five trend-following factors in stocks, short-term interest rates, currencies, bonds, and commodities, the positive relation between uncertainty beta and risk-adjusted returns (9-factor alpha) remains economically and statistically significant. In multivariate cross-sectional regressions, we also control for a large set of fund characteristics and risk attributes, and find that the average slope on uncertainty beta remains positive and highly significant across alternative regression specifications.

Bali, Brown, and Caglayan (2011) investigate hedge funds' exposures to various risk factors and analyze the predictive power of these exposures on future fund returns. They show that out of 15 factors commonly used in the literature, only default premium and inflation betas predict the cross-section of hedge fund returns. They find no evidence for a significant link between future fund returns and funds' exposures to the remaining 13 factors. In this paper, we replicate the findings of Bali et al. (2011) based on the renowned 11 risk factors: Fama-French (1993) and Carhart (1997)'s four factors of market, size, book-to-market, and momentum; Fung-Hsieh's (2001) five trend-following factors in stocks, short-term interest rates, currencies, bonds, and commodities; and Fung-Hsieh's (2004) two additional factors of the changes in credit spreads and long-term interest rates. Consistent with the findings of Bali et al. (2011), our results from an updated sample provide no evidence for a significant link between risk factor betas and future fund returns. Hence, compared to risk, economic uncertainty is a stronger determinant of the cross-sectional dispersion in hedge fund returns.

In addition to individual measures of economic uncertainty, we use a novel statistical approach to construct two broad indices of hedge fund-related economic uncertainty based on the portfolio returns of 11 hedge fund investment styles and the 10 measures of economic uncertainty. We generate a linear combination of the 11 hedge fund portfolio returns and a linear combination of the 10 economic uncertainty factors which leads to the highest correlation between these two linear combinations. After building the two univariate indices of economic uncertainty, we test their performance in predicting the cross-sectional variation in hedge fund returns. The results indicate a positive and significant relation between exposures to the broad uncertainty index and future hedge fund returns: Funds in the highest economic uncertainty index beta quintile generate 6% higher annual returns and alphas than do funds in the lowest economic uncertainty index beta quintile. Overall, the significant predictive relation between fund returns and the newly proposed uncertainty proxies validate our measures as descriptive quantitative measures of economic uncertainty.

A natural question is why hedge funds with higher exposure to economic uncertainty generate higher returns. Is there a theoretical framework supporting this finding? The positive relation between uncertainty beta and expected returns is justified in Merton's (1973) intertemporal capital asset pricing model (ICAPM), where investors are concerned not only with the terminal wealth that their portfolio produces, but also with the investment and consumption opportunities that they will have in the future.[1] In other words, when choosing a portfolio at time t, ICAPM investors consider how their wealth at time t+1 might vary with future state variables. This implies that like CAPM investors, ICAPM investors prefer high expected return and low return variance, but they are also concerned with the covariances of portfolio returns with state variables that affect future investment opportunities.

There is substantial evidence that economic uncertainty is a relevant state variable affecting future consumption and investment decisions. Bloom (2009) and Bloom, Bond, and Van Reenen (2007) introduce a theoretical model linking economic uncertainty shocks to aggregate output, employment and investment dynamics. Chen (2010) introduces a model that shows how business cycle variation in economic uncertainty and risk premia influences firms' financing decisions. The model also shows that

[1] The unconditional (static) capital asset pricing model (CAPM) is built on an implausible assumption that investors care only about the mean and variance of single-period portfolio returns. However, in practice, investors make decisions for multiple periods and they revise their portfolio and risk management decisions over time based on the expectations about future investment opportunities.

countercyclical fluctuations in risk prices arise through firms' responses to macroeconomic conditions. Stock and Watson (2012) find that the decline in aggregate output and employment during the recent crisis period are driven by financial and economic uncertainty shocks. Allen, Bali, and Tang (2012) show that downside risk in the financial sector predicts future economic downturns, linking financial uncertainty to future investment opportunity set. Hence, our finding that economic uncertainty is priced in the cross-section of risky assets – individual hedge funds – is consistent with the well celebrated intertemporal capital asset pricing model of Merton (1973).

Hedge funds use a wide variety of dynamic trading strategies, and make extensive use of derivatives, short-selling, and leverage. The elements contributing to a hedge fund strategy include the hedge fund's approach to the financial sector that the fund specializes in, the particular financial instruments used, the method used to select financial securities, and the amount of diversification within the fund. Since there are so many elements affecting hedge funds' investment decisions, fund managers have heterogeneous expectations and different reactions to changes in the state of the economy. There is also substantial evidence of disagreement among professional forecasters and investors on expectations about macroeconomic fundamentals (e.g., Kandel and Pearson (1995), Lamont (2002), and Mankiw et al. (2004)). Hence, economic uncertainty plays a critical role in generating cross-sectional differences in fund managers' expectations about the level and volatility of economic indicators.

In fact, many fund managers actively vary their exposures to changes in macroeconomic conditions and to fluctuations in financial markets. Consistent with the market-timing ability of hedge funds, our results suggest that by predicting fluctuations (volatility) of financial and macroeconomic variables, hedge fund managers can adjust their portfolio exposures up or down in a timely fashion to generate superior returns. Indeed, we find that several hedge funds, particularly those that follow directional and semi-directional trading strategies, correctly adjust their aggregate exposure to economic uncertainty, and hence there exists a positive and stronger link between their uncertainty beta and future returns. However, the cross-sectional relation between uncertainty beta and future returns is relatively weaker for the funds following non-directional strategies. These results are supported and can be explained by our finding that the variations in uncertainty betas across time are much wider for directional strategies compared to non-directional strategies.

This paper is organized as follows. Section 2 provides a brief literature review. Section 3 describes the data and variables. Section 4 presents a conditional asset pricing model with economic uncertainty. Section 5 discusses the empirical results and provides a battery of robustness checks. Section 6 concludes the paper.

2. Literature Review

The literature examining the risk-return characteristics of hedge funds has evolved considerably especially in recent years.[2] Sadka (2010) demonstrates that liquidity risk is an important determinant of the cross-sectional differences in hedge fund returns and shows that hedge funds that significantly load on liquidity risk subsequently outperform low-loading funds by an average of 6% annually. Bali, Brown, and Caglayan (2011) find a positive (negative) and significant link between default premium beta (inflation beta) and future hedge fund returns. Funds in the highest default premium beta quintile generate 5.8% more annual returns compared to funds in the lowest default premium beta quintile. Similarly, the annual average return of funds in the lowest inflation beta quintile is 5% higher than the annual average return of funds in the highest inflation beta quintile. Titman and Tiu (2011) regress individual hedge fund returns on a group of risk factors and find that funds with low R-squares of returns on factors have higher Sharpe ratios. Their results also show that the low R-square funds generate higher information ratios, and they charge higher incentive and management fees. Bali, Brown, and Caglayan (2012) introduce a comprehensive measure of systematic risk for individual hedge funds by breaking up total risk into systematic and residual risk components. They find that systematic variance is a highly significant factor explaining the dispersion of cross-sectional returns, while at the same time measures of residual risk and tail risk have little explanatory power. Cao, Chen, Liang, and Lo (2012) investigate how hedge funds manage their liquidity risk by responding to aggregate liquidity shock. Their results indicate that hedge fund managers have the ability to time liquidity by increasing their portfolios' market exposure when the equity market liquidity is high. Patton and Ramadorai (2013) introduce a new econometric methodology to capture time-series variation in hedge funds' exposures to risk factors using high-frequency data, and find that hedge fund risk exposures vary significantly across months. Sun, Wang, and Zheng (2013) 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.

Anderson, Ghysels, and Juergens (2009) introduce a model in which the volatility, skewness and higher order moments of all returns are known exactly, whereas there is uncertainty about mean returns. In their model, asset returns are uncertain only because mean returns are not known, and investors' uncertainty in mean returns is defined as the dispersion of predictions of mean market returns obtained from the forecasts of aggregate corporate profits. They find that the price of uncertainty is significantly positive and explains the cross-sectional variation in stock returns. Bekaert, Engstrom, and Xing (2009) investigate the relative importance of economic uncertainty and changes in risk aversion in the determination of equity prices. Different from Knightian uncertainty or uncertainty originated from disagreement of professional forecasters, Bekaert et al. (2009) focus on economic uncertainty proxied by

[2] A partial list includes Fung and Hsieh (1997, 2000, 2001, 2004), Ackermann, McEnally, and Ravenscraft (1999), Liang (1999, 2001), Mitchell and Pulvino (2001), Agarwal and Naik (2000, 2004), Kosowski, Naik, and Teo (2007), Bali, Gokcan, and Liang (2007), Fung et al. (2008), Patton (2009), Jagannathan, Malakhov, and Novikov (2010), Aggarwal and Jorion (2010), and Brown, Gregoriou, and Pascalau (2012).

the conditional volatility of dividend growth, and find that both the conditional volatility of cash flow growth and time-varying risk aversion are important determinants of equity returns.

Compared to Anderson, Ghysels, and Juergens (2009) and Bekaert, Engstrom, and Xing (2009), we use time-varying conditional volatility of 10 different economic indicators (generated from the GARCH model) as proxies for economic uncertainty. More importantly, however, instead of looking at the direct link between economic uncertainty and future returns on equity, we examine whether hedge funds' exposures to economic uncertainty (i.e. uncertainty beta) have a predictive power over future fund returns. In other words, our focus is on the significance of *uncertainty beta* in predicting the cross-sectional variation in future returns of individual hedge funds.

3. Data and Variables

In this section, we first describe the hedge fund database, fund characteristics and their summary statistics. Second, we provide descriptive statistics and cross correlations of the risk factors. Third, we explain how we generate alternative measures of economic uncertainty and present their summary statistics and the correlation matrix. Finally, we provide descriptive statistics and cross correlations of the uncertainty betas.

3.1. Hedge Fund Database

This study uses monthly hedge fund data from Lipper TASS (Trading Advisor Selection System) database. Our database contains information on a total of 17,534 defunct and live hedge funds with total assets under management around $1.4 trillion. Out of the 17,534 hedge funds that reported monthly returns to TASS during the period January 1994 – March 2012, we have 10,805 funds in the defunct / graveyard database and 6,729 funds in the live hedge fund database. The TASS database, in addition to reporting monthly returns (net of fees) and monthly assets under management, it also provides information on certain fund characteristics, including the management fees, incentive fees, redemption periods, minimum investment amounts, and lockup and leverage provisions.

Table I of the online appendix provides summary statistics on the hedge funds' numbers, returns, assets under management (AUM), and their fee structures.[3] For each year, Panel A of Table I reports the number of funds entered to the database, number of funds dissolved, total assets under management (AUM) at the end of each year (in billion $s), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted hedge fund portfolio. One important item worth noting about TASS is that it does not include any defunct funds prior to 1994. Therefore, 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 for the period January 1994 – March 2012.

Table I, Panel A reports a sharp reversal in the growth of hedge funds both in numbers and in assets under management (AUM) since the end of 2007, the starting point of the big worldwide financial

[3] To save space in the paper, we present some of our findings in the online appendix.

crisis. The AUM in our database increased exponentially from a small \$59.3 billion in 1994 to an eye-opening \$2.1 trillion in 2007, and the number of hedge funds performing in the market increased more than ten-fold to 9,555 in December 2007 from 853 in January 1994. However, both of these figures reversed course beginning in 2008 together with the start of the big financial crisis, as the number of hedge funds performing in the market fell one-fourth, almost to 7,000, while the total assets under management dropped one-third, to \$1.4 trillion by the end of December 2011. In addition, the yearly attrition rates in Panel A of Table I (the ratio of number of dissolved funds to the total number of funds at the beginning of the year) also paint a similar picture; from 1994 to 2007, on average, the annual attrition rate in the database was only 7.4%, between 2008 and 2011, however, this annual figure increased almost by 2.5 times to 17.9%. These statistics drawn from the data simply explain the severity of the financial crisis that the hedge fund industry went through over the past few years. Just during 2008 and during 2011, for example, hedge funds on average lost 1.40% and 0.37% (return) per month, respectively.

Panel B of Table I reports the cross-sectional mean, median, standard deviation, minimum, and maximum figures for certain hedge fund characteristics for the sample period January 1994 – March 2012. One interesting point that can be detected in Panel B is hedge funds' short span of life. The median age (number of months in existence since inception) of a fund is only 54 months, exactly four-and-a-half years. This short span of life is mostly due to the fact that hedge fund managers have to first cover all losses from previous years before getting paid on a current year. This forces hedge fund managers to dissolve quickly and form a new hedge fund after a bad year, instead of trying to cover those losses in the following years. Another remarkable observation that can be extracted from this panel is the large size disparity seen among hedge funds. When we measure the size of a fund as the average monthly assets under management over the life of the fund, we see that the mean hedge fund size is \$149 million, while the median hedge fund size is only \$40 million. This suggests that there are a few hedge funds with very large assets under management in our database, which reflects the true hedge fund industry standards.

Lastly, hedge fund studies could be subject to potential data biases. These well-known data bias issues, including the survivorship bias, the back-fill bias, and the multi-period sampling bias, and how we address them in our study are discussed in detail in Section I of the online appendix.

3.2. Risk Factors

In our empirical analysis, we rely on the standard risk factors commonly used in the hedge fund literature: 1) MKT: Excess return on the value-weighted NYSE/AMEX/NASDAQ (CRSP) equity market index; 2) SMB: Fama-French (1993) size factor; 3) HML: Fama-French (1993) book-to-market factor; 4) MOM: Carhart (1997) momentum factor; 5) Δ10Y: Fung and Hsieh (2004) long-term interest rate factor defined as the monthly change in the 10-year constant maturity Treasury yields; 6) ΔCrdSpr: Fung and Hsieh (2004) credit risk factor defined as the monthly change in the difference between BAA-rated corporate bond yields and 10-year constant maturity Treasury yields; 7) BDTF: Fung-Hsieh (2001) bond trend-following factor measured as the return of PTFS (Primitive Trend Following Strategy) Bond

Lookback Straddle; 8) FXTF: Fung-Hsieh (2001) currency trend-following factor measured as the return of PTFS Currency Lookback Straddle; 9) CMTF: Fung-Hsieh (2001) commodity trend-following factor measured as the return of PTFS Commodity Lookback Straddle; 10) IRTF: Fung-Hsieh (2001) short-term interest rate trend-following factor measured as the return of PTFS Short Term Interest Rate Lookback Straddle; 11) SKTF: Fung-Hsieh (2001) stock index trend-following factor measured as the return of PTFS Stock Index Lookback Straddle.[4]

Panel A of Table II in online appendix reports the time series mean, median, standard deviation, minimum, and maximum monthly percentage returns of the 11 risk factors (identified in the hedge funds literature) for the full sample period January 1994 – March 2012. Panel B of Table II presents the correlation matrix of the 11 risk factors for the same time period. A notable point in Panel B is that the correlation of the equity market factor (MKT) with the other factors is generally negative and low, in the range of –0.17 to –0.31. Out of 10 factors, only SMB and Δ10Y are positively correlated with MKT; 0.25 and 0.09, respectively. Another notable point is that the cross correlations of the Fung-Hsieh trend following factors (BDTF, FXTF, CMTF, IRTF, SKTF) are all positive, but the magnitudes of the correlations are not large, in the range of 0.14 to 0.39, implying that each factor has the potential to capture different attributes of hedge fund returns.

3.3. Economic Uncertainty Factors

In this section, we first come up with a list of state variables that potentially affect investors' consumption and investment opportunities. The state variables utilized in our study are the financial and economic indicators that are widely used in the literature: 1) *DEF*: Default spread measured as the difference between yields on the BAA-rated and AAA-rated corporate bonds; 2) *TERM*: Term spread measured as the difference between yields on the 10-year and 3-month Treasury securities; 3) *TED*: TED spread, an indicator of credit risk and the perceived health of the banking system, defined as the difference between the 1-month LIBOR and 1-month T-bill rate; 4) *RREL*: Relative T-bill rate defined as the difference between the 3-month T-bill rate and its 12-month backward moving average; 5) *DIV*: Aggregate dividend yield on the S&P 500 index; 6) *MKT*: Excess return on the value-weighted NYSE/AMEX/NASDAQ (CRSP) equity market index; 7) *INF*: Monthly inflation rate based on the U.S. consumer price index; 8) *UNEMP*: The U.S. monthly unemployment rate defined as the number of unemployed as a percent of the labor force; 9) *GDP*: The U.S. monthly growth rate of real gross domestic product (GDP) per capita; and 10) *CFNAI*: The Chicago Fed National Activity Index defined as the weighted average of 85 existing monthly indicators of national economic activity. CFNAI is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward

[4] The four factors of Fama-French-Carhart; MKT, SMB, HML, and MOM are obtained from the online data library of Kenneth French: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The five trend-following factors of Fung and Hsieh; FXTF, BDTF, CMTF, IRTF, SKTF are provided by David Hsieh at http://faculty.fuqua.duke.edu/~dah7/HFRFData.htm. The BAA-rated corporate bond yields and the 10-year constant maturity Treasury yields are obtained from H.15 historical database of the Federal Reserve Board: http://www.federalreserve.gov/releases/h15/data.htm.

trend growth rate over time, a positive index reading corresponds to growth above trend and a negative index reading corresponds to growth below trend.[5]

We generate alternative measures of economic uncertainty by estimating the time-varying conditional volatility of the aforementioned state variables based on the following Asymmetric GARCH model with an autoregressive process of order one, AR(1):

$$Z_{t+1} = a_0 + a_1 Z_t + \cdot \varepsilon_{t+1} \tag{1}$$

$$E\left[\varepsilon_{t+1}^2 \mid \Omega_t\right] \equiv \sigma_{t+1}^2 = \gamma_0 + \gamma_1 \cdot \varepsilon_t^2 + \gamma_2 \cdot \sigma_t^2 + \gamma_3 \cdot \varepsilon_t^2 \cdot D_t \tag{2}$$

$$D_t = 1 \text{ for } \varepsilon_t < 0 \text{ and } D_t = 0 \text{ otherwise}$$

where Z_{t+1} is one of the state variables in month t+1; Z = [*DEF*, *TERM*, *TED*, *RREL*, *DIV*, *MKT*, *INF*, *UNEMP*, *GDP*, *CFNAI*]. Eq. (1) follows an AR(1) process to account for the persistence in state variables. Ω_t denotes the information set at time t that investors use to form expectations about the state variables. σ_{t+1}^2 is the time-t expected conditional variance of Z_{t+1} estimated using the Threshold GARCH (TGARCH) model of Glosten, Jagannathan, and Runkle (1993) that allows positive and negative economic shocks to have different impacts on the conditional variance. The dummy variable D_t equals one when ε_t is negative and zero otherwise. If γ_3 is estimated to be positive (negative), the TGARCH model implies that a negative shock causes higher (lower) volatility than a positive shock of the same size.

Economic uncertainty is measured by the conditional standard deviation (or volatility) of the aforementioned economic indicators. The monthly data for *DEF*, *TERM*, *RREL*, *DIV*, *MKT*, *INF*, *GDP*, and *UNEMP* cover the period from January 1960 to March 2012. The monthly data for *TED* spread cover the period from Janaury 1971 to March 2012. The monthly data for the *CFNAI* index cover the period from May 1967 to March 2012. When estimating eqs. (1) and (2), we use the longest sample possible until December 1993, and start making one-month predictions of the conditional volatility for January 1994. Then, one-month ahead predictions of conditional volatility are generated by adding monthly observations, i.e., using monthly expanding sample until the sample is exhausted in March 2012. This recursive volatility forecasting procedure generates economic uncertainty factors for the full sample period January 1994 – March 2012.

Figure I of the online appendix displays the monthly time-series plots of the 10 measures of economic uncertainty. A notable point in Figure I is that the uncertainty measures closely follow large

[5] The BAA- and AAA-rated rated corporate bond yields, the 1-month LIBOR rates, 3-month T-bill rates, and 10-year constant maturity Treasury yields are obtained from H.15 historical database of the Federal Reserve Board: http://www.federalreserve.gov/releases/h15/data.htm. The 1-month T-bill rate and the U.S. equity market data are available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The monthly aggregate dividend yields on the S&P500 index and the monthly inflation rate are obtained from Robert Shiller's online data library: http://www.econ.yale.edu/~shiller/data.htm. The monthly unemployment rates are obtained from the Bureau of Labor Statistics: http://www.bls.gov/cps/lfcharacteristics.htm#unemp. The real GDP per capita are obtained from the Federal Reserve Bank of St. Louis: http://research.stlouisfed.org/fred2/. The CFNAI data are available at the Federal Reserve Bank of Chicago: http://www.chicagofed.org/webpages/research/data/cfnai.

falls and rises of financial and macroeconomic activity. Specifically, the uncertainty about default and credit risk (*DEF_U*, *TED_U*) is higher during economic and financial market downturns, especially during the recent crisis period in which we observe a large number of bank failures. Similarly, the uncertainty about the short-term and long-term interest rate changes (*RREL_U*, *TERM_U*) is higher during periods corresponding to high levels of term and default spreads as well as stock market declines. The uncertainty about aggregate dividend yield (*DIV_U*) and the uncertainty about the equity market (*MKT_U*) are significantly higher during stock market crashes as well. Lastly, the uncertainty about inflation (*INF_U*), the uncertainty about output growth (*GDP_U*), the uncertainty about unemployment (*UNEMP_U*), and the uncertainty about macroeconomic activity (*CFNAI_U*) are generally higher during bad states of the economy corresponding to periods of high unemployment, low output growth, and low economic activity.

Panel A of Table 1 reports the time-series mean, median, standard deviation, minimum, and maximum values of our uncertainty measures for the sample period January 1994 – March 2012. Panel B of Table 1 displays the correlation matrix for the 10 uncertainty factors. A notable point in Panel B is that the correlations between the uncertainty factors are all positive without any exception. However, the magnitudes of the correlations vary significantly with the minimum of 0.17 and the maximum of 0.89. The average cross correlation among the uncertainty factors is about 0.54. These results indicate that although the uncertainty factors are associated with the common sources of ambiguity about the state of the economy, each factor has the potential to capture different pieces of perplexity and disagreement about the financial and macroeconomic fundamentals.

Panel C of Table 1 presents the correlations between the risk and uncertainty factors for the common sample period January 1994 – March 2012. Interestingly, the correlations are generally low and they exhibit no clear pattern. Just focusing on the negative correlations in Panel C, the average corrrelation between the risk and uncertainty factors is –0.078, with the minimum of –0.255 and the maximum of –0.001. Among the positive correlations only, the average corrrelation between the risk and uncertainty factors is 0.074, with the minimum of 0.004 and the maximum of 0.220. These results suggest that the risk and uncertainty factors potentially capture different aspects of hedge fund returns.

4. A Conditional Asset Pricing Model with Economic Uncertainty

Merton's (1973) ICAPM implies the following equilibrium relation between expected return and risk for any risky asset *i*:

$$\mu_i = A \cdot \sigma_{im} + B \cdot \sigma_{ix}, \tag{3}$$

where μ_i denotes the unconditional expected excess return on risky asset *i*, σ_{im} denotes the unconditional covariance between the excess returns on the risky asset *i* and the market portfolio *m*, and σ_{ix} denotes a ($1 \times k$) row of unconditional covariances between the excess returns on the risky asset *i* and the k-dimensional state variables x. A is the relative risk aversion of market investors and B measures the market's aggregate reaction to shifts in a k-dimensional state vector that governs the stochastic investment opportunity set. Eq. (3) states that in equilibrium, investors are compensated in terms of expected return for bearing market risk and for bearing the risk of unfavorable shifts in the investment opportunity set.

In the original Merton (1973) model, the parameters of expected returns and covariances are all interpreted as constant, but the ability to model time variation in expected returns and covariances makes it natural to include time-varying parameters directly in the analysis (see Bali (2008) and Bali and Engle (2010)):

$$E\left[R_{i,t+1} \mid \Omega_t\right] = A \cdot \operatorname{cov}\left[R_{i,t+1}, R_{m,t+1} \mid \Omega_t\right] + B \cdot \operatorname{cov}\left[R_{i,t+1}, X_{t+1} \mid \Omega_t\right], \tag{4}$$

where $R_{i,t+1}$ and $R_{m,t+1}$ are, respectively, the return on risky asset i and the market portfolio m in excess of the risk-free interest rate, Ω_t denotes the information set at time t that investors use to form expectations about future returns, $E\left[R_{i,t+1} \mid \Omega_t\right]$ is the expected excess return on the risky asset i at time t+1 conditional on the information set at time t, $\operatorname{cov}\left[R_{i,t+1}, R_{m,t+1} \mid \Omega_t\right]$ measures the time-t expected conditional covariance between the excess returns on risky asset i and the market portfolio m, and $\operatorname{cov}\left[R_{i,t+1}, X_{t+1} \mid \Omega_t\right]$ measures the time-t expected conditional covariance between the excess returns on risky asset i and the state variable X that affects future investment opportunities.

To be consistent with earlier studies in the hedge funds literature (e.g., Bali, Brown, and Caglayan (2011, 2012)), we re-write eq. (4) in terms of conditional betas, instead of conditional covariances:

$$E\left[R_{i,t+1} \mid \Omega_t\right] = \widetilde{A} \cdot E\left[\beta_{im,t+1} \mid \Omega_t\right] + \widetilde{B} \cdot E\left[\beta_{ix,t+1} \mid \Omega_t\right], \tag{5}$$

where $\widetilde{A} = A \cdot \operatorname{var}\left[R_{m,t+1} \mid \Omega_t\right]$, $\widetilde{B} = B \cdot \operatorname{var}\left[X_{t+1} \mid \Omega_t\right]$, and $E\left[\beta_{im,t+1} \mid \Omega_t\right]$ is the conditional market beta of asset i, defined as the ratio of the conditional covariance between $R_{i,t+1}$ and $R_{m,t+1}$ to the conditional variance of $R_{m,t+1}$, and $E\left[\beta_{ix,t+1} \mid \Omega_t\right]$ is the conditional beta of asset i with respect to the state variable X, defined as the ratio of the conditional covariance between $R_{i,t+1}$ and X_{t+1} to the conditional variance of X_{t+1}:

$$E\left[\beta_{im,t+1} \mid \Omega_t\right] = \frac{\operatorname{cov}\left[R_{i,t+1}, R_{m,t+1} \mid \Omega_t\right]}{\operatorname{var}\left[R_{m,t+1} \mid \Omega_t\right]}, \tag{6}$$

$$E\left[\beta_{ix,t+1} \mid \Omega_t\right] = \frac{\operatorname{cov}\left[R_{i,t+1}, X_{t+1} \mid \Omega_t\right]}{\operatorname{var}\left[X_{t+1} \mid \Omega_t\right]}. \tag{7}$$

Earlier studies (e.g., Bloom et al. (2007), Bloom (2009), Chen (2010), Stock and Watson (2012), Allen et al. (2012), and Bali and Zhou (2012)) provide theoretical and empirical evidence that economic uncertainty is a relevant state variable proxying for consumption and investment opportunities in the conditional ICAPM framework. Hence, alternative measures of economic uncertainty generated in this paper can be viewed as a proxy for the state variable X in eq. (5).

In our empirical analyses, before generating the monthly time-series estimates of economic uncertainty betas, we start our analyses first by producing the monthly time-series estimates of risk factor betas. In addition to the market factor, we consider 10 other risk factors and estimate the risk factor betas using monthly rolling regressions. Specifically, we start with the first three 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 risk factor betas based on the following regression equation:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{F} \cdot F_t + \varepsilon_{i,t}, \tag{8}$$

where $R_{i,t}$ is the excess return on fund i in month t, and F_t is the macroeconomic or financial risk factor in month t. $\beta_{i,t}^{F}$ is the risk factor beta for fund i in month t. Note that the risk factor F in eq. (8) represents one of the 11 risk factors tested in this study; MKT, SMB, HML, MOM, Δ10Y, ΔCrdSpr, BDTF, FXTF, CMTF, IRTF, and SKTF.

Similarly, we estimate the monthly uncertainty betas for each fund from the time-series regressions of excess returns on the uncertainty factors over a 36-month rolling window period:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{U} \cdot U_t + \varepsilon_{i,t}, \tag{9}$$

where $R_{i,t}$ is the excess return on fund i in month t, and U_t is the economic uncertainty factor in month t. $\beta_{i,t}^{U}$ is the uncertainty beta for fund i in month t. Note that the economic uncertainty factor U in eq. (9) represents one of the 10 uncertainty measures proposed in this study.

Once we have the risk and uncertainty betas, in the second stage, starting from January 1997, we run the Fama-MacBeth cross-sectional regressions of one-month-ahead individual fund excess returns on the risk factor and uncertainty betas:

$$\begin{gathered}
R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{F} + \varepsilon_{i,t+1}, \\
R_{i,t+1} = \lambda_{0,t} + \lambda_{2,t} \cdot \beta_{i,t}^{U} + \varepsilon_{i,t+1}, \\
R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{F} + \lambda_{2,t} \cdot \beta_{i,t}^{U} + \varepsilon_{i,t+1},
\end{gathered} \tag{10}$$

where $R_{i,t+1}$ is the excess return on fund i in month t+1, $\beta_{i,t}^{F}$ and $\beta_{i,t}^{U}$ are the risk and uncertainty betas for fund i in month t. $\lambda_{0,t}$ is the intercept, and $\lambda_{1,t}$ and $\lambda_{2,t}$ are the monthly slope coefficients from the

Fama-MacBeth regressions. We compute the Newey-West (1987) *t*-statistics of the average slope coefficients ($\overline{\lambda}_1$, $\overline{\lambda}_2$) to determine the significance of a cross-sectional relation betweeen the risk and uncertainty betas and future returns on individual hedge funds.

After we estimate the uncertainty betas for each fund and for each month from January 1997 to March 2012, we compute the mean, median, standard deviation, maximum and minimum values of the uncertainty betas (each month) across all hedge funds. Panel A of Table 2 presents the time-series averages of these five statistics for all of the 10 uncertainty betas generated. Panel A provides clear evidence for the significant cross-sectional and time-series variation in the uncertainty betas.

We also compute the cross correlations of the uncertainty betas for each month and we report in Panel B of Table 2 the time-series averages of the cross correlations for the sample period January 1997 – March 2012. A notable point in Panel B is that the cross correlations between the uncertainty betas are all positive without any exception. However, the magnitudes of the correlations vary significantly, with the minimum of 0.008 and the maximum of 0.731. The average cross correlation among the uncertainty betas is about 0.29. These results indicate that although the uncertainty betas capture hedge funds' common exposures to economic uncertainty, each uncertainty beta has the potential to capture distinct pieces of funds' sensitivity to different measures of economic uncertainty. This is also consistent with the fact that fund managers following directional, semi-directional, or non-directional strategies have heterogeneous expectations and different reactions to changes in the state of the economy.

5. Empirical Results

In this section, we conduct parametric and nonparametric tests to assess the predictive power of risk factor and uncertainty betas over future hedge fund returns. First, we start with the univariate portfolio level analyses. Second, we present the univariate cross-sectional regression results. Third, we run the multivariate cross-sectional regressions to control for the fund characteristics, risk and liquidity attributes. Fourth, we investigate whether the predictive power of uncertainty betas for future fund returns remains intact during subsample periods when significant structural breaks are observed. Fifth, we classify hedge funds into three groups (directional, semi-directional, and non-directional) and test whether the predictive power of uncertainty betas increase as we move from non-directional to directional strategies. Finally, we build a canonical correlation-based measure of economic uncertainty index and a factor of hedge fund index returns, and then investigate the performance of these two new factors in predicting the cross-sectional variation in hedge fund returns.

5.1. Univariate quintile portfolio analysis of risk factor betas

For each month, from January 1997 to March 2012, we form quintile portfolios by sorting hedge funds based on their risk factor betas ($\beta_{i,t}^F$), where quintile 1 contains funds with the lowest $\beta_{i,t}^F$ and quintile 5 contains funds with the highest $\beta_{i,t}^F$. Table III of the online appendix reports the average values of the risk factor betas as well as the next month average returns for each of the five quintiles. The last two rows in Table III display the average raw and risk-adjusted return (i.e., 9-factor alpha) differences between quintiles 5 and 1.

Univariate quintile portfolios in Table III provide no evidence for a significant link between the risk factor betas and future returns. Hedge funds' exposures to the 11 commonly used risk factors do not predict the cross-sectional variation in hedge fund returns, because the average raw return and alpha differences between the highest and lowest $\beta_{i,t}^{F}$ portfolios are economically and statistically insignificant. These results from the updated sample of 1997-2012 are consistent with the findings of Bali, Brown, and Caglayan (2011) using a shorter sample of 1997-2008.

5.2. Univariate quintile portfolio analysis of uncertainty betas

Table 3 provides the univariate portfolio test results for the 10 alternative measures of uncertainty betas introduced in this paper. For each month, we form quintile portfolios by sorting hedge funds based on their uncertainty betas ($\beta_{i,t}^{U}$), where quintile 1 contains funds with the lowest $\beta_{i,t}^{U}$, and quintile 5 contains funds with the highest $\beta_{i,t}^{U}$. As shown in Table 3, when moving from quintile 1 to 5, there is significant cross-sectional variation in the average values of $\beta_{i,t}^{U}$. For example, moving from quintile 1 to 5, the average uncertainty beta for the default risk ($\beta_{i,t}^{DEF-U}$) increases from –40.73 to 53.24. Similar large cross-sectional spreads are observed for the other uncertainty beta measures as well.

Another notable point in Table 3 is that in moving from quintile 1 to 5, we observe that the next-month average raw returns on uncertainty beta portfolios increase monotonically in most cases, except for the uncertainty beta portfolio for the real GDP growth per capita ($\beta_{i,t}^{GDP-U}$) and the uncertainty beta portfolio for the short-term interest rate changes ($\beta_{i,t}^{RREL-U}$). For example, as shown in the first column, moving from the lowest $\beta_{i,t}^{DEF-U}$ quintile to the highest $\beta_{i,t}^{DEF-U}$ quintile, the next-month average raw returns increase from 0.101% to 0.729% per month. This indicates a monthly average raw return difference of 0.628% between quintiles 5 and 1 with a Newey-West *t*-statistic of 2.46, suggesting that this positive return difference is economically and statistically significant. This result indicates that hedge funds in the highest $\beta_{i,t}^{DEF-U}$ quintile generate about 7.5% more annual returns compared to funds in the lowest $\beta_{i,t}^{DEF-U}$ quintile. We also check whether the significant return difference between high $\beta_{i,t}^{DEF-U}$ funds and low $\beta_{i,t}^{DEF-U}$ funds can be explained by Fama-French-Carhart's four factors of market, size, book-to-market, and momentum, as well as Fung-Hsieh's five trend-following factors in stocks, short-term interest rates, currencies, bonds, and commodities. As shown in the last row of Table 3, the 9-factor alpha difference between quintiles 5 and 1 is 0.722% with a *t*-statistic of 2.35. This suggests that after controlling for the well-known factors, the return difference between high $\beta_{i,t}^{DEF\_U}$ and low $\beta_{i,t}^{DEF\_U}$ funds remains positive and significant.

In terms of economic and statistical significance, similar results are obtained from the other measures of uncertainty betas, except for $\beta_{i,t}^{GDP\_U}$ and $\beta_{i,t}^{RREL\_U}$. Specifically, when hedge funds are sorted into the univariate quintile portfolios based on their exposures to the uncertainty about default risk ($\beta_{i,t}^{DEF\_U}$), uncertainty about term spread ($\beta_{i,t}^{TERM\_U}$), uncertainty about credit risk ($\beta_{i,t}^{TED\_U}$), uncertainty about aggregate dividend yield ($\beta_{i,t}^{DIV\_U}$), uncertainty about the equity market ($\beta_{i,t}^{MKT\_U}$), uncertainty about the inflation rate ($\beta_{i,t}^{INF\_U}$), uncertainty about the unemployment rate ($\beta_{i,t}^{UNEMP\_U}$), and uncertainty about macroeconomic activity ($\beta_{i,t}^{CFNAI\_U}$), the average raw return differences between the highest and lowest uncertainty beta quintiles are in the range of 0.46% to 0.63% per month, corresponding to the annualized return differences of 5.5% to 7.5%. The Newey-West *t*-statistics of these return spreads are in the range of 2.06 to 3.06.

Lastly, after controlling for the Fama-French-Carhart four factors and the Fung-Hsieh five trend-following factors, the positive relation between uncertainty betas and risk-adjusted returns (9-factor alpha) still remains strong and highly significant for all uncertainty betas, again except for $\beta_{i,t}^{GDP\_U}$ and $\beta_{i,t}^{RREL\_U}$.[6]

5.3. Uncertainty betas in cross-sectional regressions

This section presents the Fama-MacBeth (1973) cross-sectional regression results with and without the control variables. As presented in eqs. (8)-(10), we start with the first three years of monthly returns from January 1994 to December 1996 to estimate the risk factor and uncertainty betas for each fund in our sample, and then use a 36-month rolling-window estimation period to generate the monthly time-series estimates of the risk factor and uncertainty betas. Then, in the second stage, starting from January 1997, we run the Fama-MacBeth cross-sectional regressions of one-month-ahead individual fund excess returns on the risk factor and uncertainty betas.

Although not reported in the paper to save space, the average slope coefficients on the risk factor betas turn out to be statistically insignificant without any exception. Consistent with our findings from the univariate portfolios, there is no significant link between future returns and hedge funds' exposures to risk factors. This result remains intact when the risk factor betas are included along with the uncertainty betas as presented in eq. (10).

[6] In addition to time-varying conditional volatility of economic indicators generated from GARCH model as proxies for economic uncertainty, we use the cross-sectional dispersion in quarterly forecasts on economic variables as alternative measures of economic uncertainty. The Federal Reserve Bank of Philadelphia releases measures of cross-sectional dispersion in economic forecasts from the Survey of Professional Forecasters, calculating the the degree of disagreement among the expectations of different forecasters. As discussed in the online appendix, our main findings from these model-independent, nonparametric measures of uncertainty turn out to be very similar to those reported in Table 3.

Table IV of the online appendix shows that the average slope coefficients from the univariate regressions of one-month-ahead returns on the uncertainty betas are positive and statistically significant. Consistent with our findings from the univariate portfolios, all measures of uncertainty beta, with the exception of $\beta_{i,t}^{GDP\_U}$ and $\beta_{i,t}^{RREL\_U}$, predict the cross-section of future returns. Specifically, the average slopes on $\beta_{i,t}^{DEF\_U}$, $\beta_{i,t}^{TERM\_U}$, $\beta_{i,t}^{TED\_U}$, $\beta_{i,t}^{DIV\_U}$, $\beta_{i,t}^{MKT\_U}$, $\beta_{i,t}^{INF\_U}$, $\beta_{i,t}^{UNEMP\_U}$ and $\beta_{i,t}^{CFNAI\_U}$ are positive, in the range of 0.0080 and 0.1705, with the *t*-statistics ranging from 1.96 to 3.57.

To provide an economic significance of the average slope coefficients in Table IV, we use the average values of the uncertainty betas in the quintile portfolios reported in Table 3. For example, Table 3 shows that the difference in $\beta_{i,t}^{INF\_U}$ values between average funds in the first and fifth quintiles is 47.09 [= 23.55 – (–23.54)]. If a fund were to move from the first quintile to the fifth quintile of $\beta_{i,t}^{INF\_U}$ what would be the change in that fund's expected return? The average slope coefficient of 0.0148 on $\beta_{i,t}^{INF\_U}$ in Table IV represents an economically significant increase of $0.0148 \times 47.09 = 0.70\%$ per month in the average fund's expected return for moving from the first to the fifth quintile of $\beta_{i,t}^{INF\_U}$.[7]

Our analyses so far have only focused on one-month ahead return predictability of uncertainty betas. However, from a practical standpoint it would make sense to check the return predictability of uncertainty betas for longer-term investment horizons (such as three months), as some investors and hedge fund managers may prefer longer portfolio holding periods, and thus may have investment horizons beyond one month. In addition, registered hedge funds over $100 million are required by the Securities and Exchange Commission (SEC) to file quarterly updates on portfolio holdings. These holdings are filed online through form 13F at SEC. Hedge funds are required to file these holdings no later than 45 days after the end of the calendar quarter. Hence, it is important to find out whether uncertainty betas capture the cross-sectional variation in three-month ahead returns of individual hedge funds as well.

Table V of the online appendix reports the average slope coefficients from the Fama-MacBeth cross-sectional regressions of three-month-ahead hedge fund returns on the current month uncertainty betas. Similar to our findings from the one-month-ahead predictability, the average slopes on the uncertainty betas are positive and statistically significant for all measures of uncertainty beta, with the exception of $\beta_{i,t}^{GDP\_U}$ and $\beta_{i,t}^{RREL\_U}$. Specifically, the average slopes on $\beta_{i,t}^{DEF\_U}$, $\beta_{i,t}^{TERM\_U}$, $\beta_{i,t}^{TED\_U}$, $\beta_{i,t}^{DIV\_U}$, $\beta_{i,t}^{MKT\_U}$, $\beta_{i,t}^{INF\_U}$, $\beta_{i,t}^{UNEMP\_U}$ and $\beta_{i,t}^{CFNAI\_U}$ are positive, in the range of 0.0141 and 0.3942, with the *t*-statistics ranging from 1.98 to 2.28. Overall, the results indicate that the cross-sectional relation

[7] The implied return difference of 70 basis points per month is somewhat larger than the return spread of 0.54% per month that we obtained from the univariate quintile portfolios in Table 3. However, as reported in Table 2, uncertainty betas have strong time-series variation, and the outlier observations of uncertainty betas influence the monthly slope coefficients from the Fama-MacBeth regressions. Hence, in some cases the average slopes on the uncertainty betas translate into larger monthly return differences, as compared to the quintile portfolios.

between uncertainty betas and hedge fund returns remains significantly positive three months into the future.

Bali, Brown, and Caglayan (2011), out of the 15 risk factor betas that they investigate, find that only default premium and inflation betas predict the cross-section of hedge fund returns for the period 1997–2008. We find that the same significantly positive (negative) link between default premium beta (inflation beta) and future fund returns remains intact for the extended sample of 1997–2012 as well. Specifically, funds in the highest default premium beta (highest inflation beta) quintile generate 6.3% more (4% less) annual returns compared to funds in the lowest default premium beta (lowest inflation beta) quintile. In addition, the 9-factor alpha difference between the highest and lowest *DEF_Beta* (*INF_Beta*) quintile is about 7.9% (–5.7%) per annum. More importantly, these average return and alpha differences are all statistically significant. In sum, consistent with Bali et al. (2011), we find that out of many risk factors commonly used in the literature, only default premium beta (*DEF_Beta*) and inflation beta (*INF_Beta*) are significant determinants of the cross-sectional differences in hedge fund returns.

Since *DEF_Beta* and *INF_Beta* are found to be significant in our sample, we test whether the uncertainty betas remain significant predictors of future returns after controlling for default premium and inflation betas. Specifically, we run the Fama-MacBeth cross-sectional regressions of one-month-ahead individual fund excess returns on the uncertainty beta as well as *DEF_Beta* and *INF_Beta* simultaneously:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{DEF} + \lambda_{2,t} \cdot \beta_{i,t}^{INF} + \lambda_{3,t} \cdot \beta_{i,t}^{U} + \varepsilon_{i,t+1}, \tag{11}$$

where $\beta_{i,t}^{DEF}$ is the *DEF_Beta*, $\beta_{i,t}^{INF}$ is the *INF_Beta*, and $\beta_{i,t}^{U}$ is the uncertainty beta for fund *i* in month *t*. Note that eq. (11) is run for each of the economic uncertainty betas separately. Table VI of the online appendix provides evidence for a significantly positive (negative) link between *DEF_beta* (*INF_Beta*) and future fund returns after controlling for the uncertainty betas. Consistent with the findings of Bali et al. (2011), the average slope coefficients on $\beta_{i,t}^{DEF}$ are always positive, in the range of 0.0511 and 0.0699, with statistically significant *t*-statsitics ranging in between 1.85 and 2.23. Likewise, the average slope coefficients on $\beta_{i,t}^{INF}$ are always negative, in the range of –0.0473 and –0.0632, with again statistically significant *t*-statsitics ranging in between –1.92 and –2.29. More importantly, however, the average slope coefficients on alternative measures of uncertainty beta remain positive and significant after controlling for *DEF_Beta* and *INF_Beta* (see the diagonal in Table VI in online appendix). All in all, we can conclude that the significance of *DEF_Beta* and *INF_Beta* does not alter or reduce the predictive power of uncertainty betas over future hedge fund returns.

5.4. Uncertainty betas in cross-sectional regressions with control variables

In this section, we investigate the significance of the uncertainty betas after controlling for individual fund characteristics. Table 4 reports the average intercept and slope coefficients from the

Fama-MacBeth cross-sectional regressions of one-month-ahead fund excess returns on the uncertainty betas with the control variables. Monthly cross-sectional regressions are run for the following multivariate specification:

$$\begin{aligned} R_{i,t+1} &= \lambda_{0,t} + \lambda_{1,t} \cdot \beta^{U}_{i,t} + \lambda_{2,t} \cdot R_{i,t} + \lambda_{3,t} \cdot SIZE_{i,t} + \lambda_{4,t} \cdot AGE_{i,t} + \\ &\lambda_{5,t} \cdot MGMTFEE_{i} + \lambda_{6,t} \cdot INCENTIVEFEE_{i} + \lambda_{7,t} \cdot REDEMPTION_{i} + \\ &\lambda_{8,t} \cdot MININVEST_{i} + \lambda_{9,t} \cdot D\_LOCKUP_{i} + \lambda_{10,t} \cdot D\_LEVERAGE_{i} + \varepsilon_{i,t+1} \end{aligned} \tag{12}$$

where $R_{i,t+1}$ is the excess return on fund *i* in month *t*+1, and $\beta^{U}_{i,t}$ is one of the uncertainty beta measures for fund *i* in month *t* generated from the first stage time-series regression analyses. *SIZE*, *AGE*, *MGMTFEE*, *INCENTIVEFEE*, *REDEMPTION*, *MININVEST*, *D_LOCKUP*, and *D_LEVERAGE* are the fund characteristics: Size is measured as the monthly assets under management in billion dollars; Age is measured as the number of months in existence since inception; Management Fee is a fixed percentage fee on assets under management, typically ranging from 1% to 2%; Incentive Fee is a fixed percentage fee of the fund's annual net profits above a designated hurdle rate; Redemption is the minimum number of days an investor needs to notify a hedge fund before she can redeem the invested amount from the fund; MinInvest is the minimum initial investment amount (measured in million dollars in the regression) that the fund requires from its investors to invest in a fund; D_Lockup is the dummy variable for lockup provisions (1 if the fund requires investors not able to withdraw initial investments for a pre-specified term, usually 12 months, 0 otherwise); D_Leverage is the dummy variable for leverage (1 if the fund uses leverage, 0 otherwise). We also include the one-month lagged fund returns ($R_{i,t}$) in the cross-sectional regressions to control for potential momentum or reversal effects in hedge fund returns.

In Table 4, the Fama-MacBeth cross-sectional regressions are run for each month and the average slope coefficients are reported for the full sample period January 1997 – March 2012.[8] The first 8 regressions in Table 4 examine the predictive power of each uncertainty beta one at a time after controlling for the fund characteristics. The last two regressions investigate the predictive power of all uncertainty betas simultanously with and without the control variables.

The average slope coefficients on uncertainty betas in regressions (1) to (8) are all positive, in the range of 0.0060 to 0.1602, and highly significant with the *t*-statistics ranging from 2.40 to 3.84. A notable point in Table 4 is that after controlling for the fund characteristics, the effect of outlier $\beta^{U}_{i,t}$ observations on future returns diminished significantly. For example, the average slope on $\beta^{INF\_U}_{i,t}$ reduced from 0.0148 without the control variables (see online appendix Table IV) to 0.0118 with the control variables (see column (7) in Table 4). The average slope of 0.0118 translates into a monthly return sperad of 0.56% per month between funds in the high $\beta^{INF\_U}_{i,t}$ and low $\beta^{INF\_U}_{i,t}$ quintile

[8] In Table 4 we do not report multivariate regression results from β^{RREL_U}, β^{GDP_U} and the control variables. Similar to our findings from the univariate regressions, the average slope coefficients on β^{RREL_U} and β^{GDP_U} are insignificant in multivariate regressions.

portfolios, which is similar to the return spread of 0.54% per month that we obtained from the univariate quintile portfolios in Table 3.

When all uncertainty betas are included simultaneously in the same regression (columns (9) and (10) in Table 4), $\beta_{i,t}^{UNEMP\_U}$ and $\beta_{i,t}^{MKT\_U}$ lose predictive power with or without the control variables. Although the average slopes on $\beta_{i,t}^{UNEMP\_U}$ and $\beta_{i,t}^{MKT\_U}$ are still positive, they are no longer statistically significant . However, hedge funds' exposures to the remaining 6 measures of economic uncertainty remain strong predictors of future returns. Hence, we can conclude that after controlling for a large set of fund characteristics, risk and liquidity attributes, the orthogonal components of $\beta_{i,t}^{DEF\_U}$, $\beta_{i,t}^{TERM\_U}$, $\beta_{i,t}^{TED\_U}$, $\beta_{i,t}^{DIV\_U}$, $\beta_{i,t}^{INF\_U}$ and $\beta_{i,t}^{CFNAI\_U}$ are still significant determinants of the cross-sectional differences in hedge fund returns.

One important point in Table 4 is that the average slope on the lagged fund returns is positive and highly significant in all regression specifications without any exception. The average slope on $R_{i,t}$ is in the range of 0.0798 and 0.0922, with the *t*-statistics ranging from 4.93 to 5.43. This result indicates strong momentum effects in individual fund returns, i.e., winner (loser) funds continue to be winners (losers) in one month investment horizon.[9] Based on these results, we can conclude that even the significance of lagged returns does not reduce or alter the predictive power of uncertainty betas over future hedge fund returns.

Another interesting observation in Table 4 is the fact that the incentive fee variable has always a positive and significant coefficient in monthly Fama-MacBeth regressions (regardless of the regression specification) even when the other fund characteristics are added to the regression equation as well. This suggests that incentive fee has a strong positive explanatory power for future hedge fund returns (i.e., funds that charge higher incentive fees also generate higher future returns), a finding similar to earlier studies of hedge funds (see Brown, Goetzmann, and Ibbotson (1999), Liang (1999), and Edwards and Caglayan (2001)). As in lagged return results, however, the significance of incentive fee does not change the predictive power of uncertainty betas on future hedge fund returns. One last noteworthy point in Table 4 is that the minimum investment amount, the dummy for lockup and leverage variables, which are used by Aragon (2007) to measure illiquidity of hedge fund portfolios, also have positive and significant average slope coefficients. This suggests that funds that use lockup, leverage and other share restrictions, which enable themselves to invest in illiquid assets, earn higher returns in following months, an outcome that coincides with Aragon's (2007) findings. However, even the significance of these variables does not alter or reduce the predictive power of uncertainty betas over hedge fund returns.

[9] A similar result that there is short-term (monthly) persistence in hedge fund returns is also found by Agarwal and Naik (2000), Jagannathan, Malakhov, and Novikov (2010), and Bali, Brown, and Caglayan (2011, 2012). Jegadeesh and Titman (1993, 2001) find momentum in stock returns for 3-, 6-, 9-, and 12-month horizons although Jegadeesh (1990) and Lehmann (1990) provide strong evidence for the short-term reversal effect in individual stock returns for one-week to one-month horizon. In addition to accounting for the lagged returns in Fama-MacBeth regressions, we control for this phenomenon using the Carhart's (1997) momentum factor in portfolio level analyses.

5.5. Structural breaks and subsample analysis

We now investigate whether the predictive power of uncertainty betas for future fund returns remains intact during subsample periods when significant structural breaks are observed in financial markets. Fung, Hsieh, Naik, and Ramadorai (2008) examine the performance, risk, and capital formation of funds-of-funds for the period 1995–2004 and find that the risk and return characteristics of funds-of-funds are time-varying. They identify breakpoints with major market events, namely, the collapse of LTCM in September 1998 and the peak of the technology bubble in March 2000. The cross-sectional relation between hedge funds' exposures to economic uncertainty and their future returns might be time-varying as well, since hedge funds have the capacity to change their trading strategies depending on the market conditions during the analyzed sample period. Following Fung et al. (2008), we use a version of the Chow (1960) test in which we replace the standard error covariance matrix with a serial-correlation and heteroskedasticity consistent covariance matrix of Newey-West (1987). In our sample (January 1997–March 2012), structural breakpoints are identified as September 1998 (the collapse of LTCM), March 2000 (the peak of the technology bubble), and September 2008 (the collapse of Lehman Brothers during the recent financial crisis period). We then investigate the significance of the cross-sectional link between expected returns and uncertainty betas for four subsample periods; January 1997–August 1998, September 1998–February 2000, March 2000–September 2008, and October 2008–March 2012.

Despite the structural breaks observed in risk and return characteristics of hedge funds, Table 5 provides evidence of a positive and significant relation between uncertainty betas and hedge fund returns for most of the subsample periods, after controlling for the lagged return and fund characteristics. For instance, the average slopes on $\beta_{i,t}^{DEF\_U}$ and $\beta_{i,t}^{TED\_U}$ are positive and significant for all subsample periods without any exception, implying that hedge funds' exposures to default and credit risk uncertainty are important determinants of the cross-sectional dispersion of hedge fund returns for all states of the economy (contraction or expansion).

In addition, in Table 5, the average slopes on $\beta_{i,t}^{TERM\_U}$, $\beta_{i,t}^{DIV\_U}$, $\beta_{i,t}^{INF\_U}$, $\beta_{i,t}^{UNEMP\_U}$ and $\beta_{i,t}^{CFNAI\_U}$ are positive and significant in at least three out of the four subsample periods analyzed, with the first subsample period January 1997–August 1998 being the outlier in most instances. This period corresponds to a phase of low inflation, low unemployment, high output growth, high economic activity, low term spread, and high earnings with upward trend in the U.S. equity market (except the crash in August 1998). Specifically, during the period January 1997–August 1998, the average inflation rate is around 1.8% per annum, the average unemployment rate is 4.7%, the average GDP growth is close to 5%, the CFNAI index is positive in 17 out of 20 months, the average term spread is below 1% per annum, and the average market return is 2.1% per month excluding August 1998, and 1.2% per month including August 1998.[10] Since this period corresponds to a highly positive state of the economy (where

[10] The U.S. equity market declined by 15.8% in August 1998, corresponding to Russian financial crisis. In August 1998, the Russian government devalues the ruble, defaults on domestic debt, and declares a moratorium on payment

overall economic uncertainty is very low), hedge funds' exposures to uncertainty about the interest rates, earnings, inflation, and economic activity do not seem to explain the cross-sectional differences in fund returns during this short 20-month period.

Another interesting point in Table 5 is that the predictive power of control variables is sensitive to the sample period analyzed. Among the large set of fund characteristics considered in the paper, only lagged returns and lockup turn out to be robust predictors of future fund returns. The average slopes on the lagged returns are positive and significant almost in all subsample periods, with the exception of first subsample period January 1997–August 1998. Similarly, the average slopes on the dummy variable for lockup (which is used by Aragon (2007) to measure illiquidity of hedge fund portfolios) are also positive and significant almost in all subsample periods with the exception of second subsample period September 1998–February 2000.

Analyzing the other fund characteristics during the subsample periods, we find that the average slopes on incentive fee are positive and significant for the last two subsample periods (March 2000–September 2008 and October 2008–March 2012), but insignificant for the first two subsample periods (January 1997–August 1998 and September 1998–February 2000). Also, the average slopes on the minimum initial investment amount are positive and significant for the first and third subsample periods (January 1997–August 1998 and March 2000–September 2008), but insignificant for the second and fourth subsample periods (September 1998–February 2000 and October 2008–March 2012). Lastly, the average slopes on the dummy variable for leverage (1 if the fund uses leverage, 0 otherwise) are positive and significant only for the last subsample period October 2008–March 2012, and the average slopes on the Redemption variable are positive and significant only for the second subsample period September 1998–February 2000.

5.6. Predictive power of uncertainty betas by hedge fund investment styles

In this section, we investigate whether our main findings change if our analysis is applied to homogeneous groups of hedge funds, i.e., hedge fund investment strategies. Hedge funds have various trading strategies; some willingly take direct market exposure and risk (directional strategies, such as Managed Futures, Global Macro, and Emerging Market funds), while some try to minimize the market risk altogether (non-directional strategies, such as Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage funds), and some try to diversify the market risk by taking both long and short, diversified positions (semi-directional strategies, such as Fund-of-Funds, Long-Short Equity Hedge, Event Driven, and Multi Strategy funds).

Given these three broad hedge fund investment strategies, it is not surprising to see varying degrees of exposures to a specific economic uncertainty factor by different investment strategy groups. Even within the same investment strategy group, one can see varying degrees of exposures to the same

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to foreign creditors. So, if we include this extremely low, negative return observation, –15.8%, observed in August 1998, the average market return reduces from 2.1% to 1.2% per month for the period January 1997 – August 1998.

economic uncertainty factor through time, as hedge fund managers adjust their exposures dynamically in response to changing market conditions. In order to understand the variation in uncertainty betas among different investment strategies clearly, Panel A of Table 6 presents, for each of the three broad hedge fund investment strategies separately, the cross-sectional average of individual hedge funds' standard deviation of uncertainty betas. Moreover, in Panel B of Table 6, we also report the cross-sectional average of individual funds' maximum minus minimum (max–min) uncertainty beta differences. We expect a larger variation in uncertainty betas for a given strategy [i.e., bigger standard deviation of uncertainty betas, and larger max–min uncertainty beta spreads] to improve the explanatory power of uncertainty betas over future fund returns for that strategy. Conversely, we expect a smaller variation in uncertainty betas for a given strategy to worsen the cross-sectional relation between uncertainty betas and future returns for that strategy. For comparison purposes, the cross-sectional averages of these two statistics across all hedge funds (irrespective of the hedge fund strategies) are also reported in bold in the last coulumn of each panel. Table 6 clearly demonstrates that the standard deviation and max–min differences of economic uncertainty betas increase monotonically as we move from the non-directional strategy group to the directional strategy group. In other words, directional strategies, which include the Managed Futures, Emerging Market and Global Macro hedge funds, have very high standard deviations and max–min differences of uncertainty betas compared to the non-directional and semi-directional strategies. This finding is consistent across all eight economic uncertainty betas tested. Also, non-directional strategies' standard deviations and max–min differences of uncertainty betas are relatively smaller compared to directional and semi-directional strategies. Finally, semi-directional strategies have standard deviations and max–min differences of economic uncertainty betas that are very similar to the all hedge fund group.

Based on these new set of results on the variation of uncertainty betas among hedge fund investment strategies, we expect our main finding – a positive and significant connection between uncertainty betas and future hedge fund returns – obtained for the all hedge fund category, actually to be stronger for funds following directional and semi-directional strategies (i.e., strategies that exhibit larger variation in uncertainty betas).

We now investigate the predictive power of uncertainty betas over future hedge fund returns for the three aforementioned investment strategies separately, and check if indeed a larger variation in betas through time is associated with a stronger predictive power of the uncertainty betas. We perform this test by forming univariate quintile portfolios of uncertainty betas for each investment strategy separately and by analyzing the next month return and alpha differences between the high and low uncertainty beta quintiles.

Table 7 reports, for each of the three investment strategies separately, the next month average return spreads as well as the 9-factor alpha differences between the high and low uncertainty beta quintiles for each of the eight uncertainty beta portfolios analyzed. The statistically significant average return and alpha spreads in Table 7, particularly for the semi-directional and directional strategies, confirm our conjecture. As can be seen clearly in the table, for all eight uncertainty factor beta portfolios tested, (i.e., $\beta_{i,t}^{DEF\_U}$, $\beta_{i,t}^{TERM\_U}$, $\beta_{i,t}^{TED\_U}$, $\beta_{i,t}^{DIV\_U}$, $\beta_{i,t}^{MKT\_U}$, $\beta_{i,t}^{INF\_U}$, $\beta_{i,t}^{UNEMP\_U}$ and $\beta_{i,t}^{CFNAI\_U}$ portfolios), the return and 9-factor alpha spreads between high uncertainty beta (quintile 5) and low uncertainty beta (quintile 1) funds increase monotonically as we move from non-directional strategies to directional strategies. For instance, while the return spreads between high uncertainty beta funds and low uncertainty beta funds range in between 0.234% and 0.514% per month (among the eight uncertainty beta portfolios) for the non-directional strategies, it ranges in between 0.422% and 0.565% per month for the semi-directional strategies, and in between 0.656% and 0.848% per month for the directional strategies. The 9-factor alpha spreads follow a similar pattern among the three investment strategies as well: it ranges in between 0.230% and 0.506% per month for the non-directional strategies, in between 0.377% and 0.635% per month for the semi-directional strategies, and in between 0.711% and 1.066% per month for the directional strategies. More importantly, the statistical significance of these return and alpha spreads between high and low uncertainty beta funds are quite high (statistically significant at the 5% level) for the semi-directional and directional strategies in all of the eight uncertainty beta portfolios analyzed. On the other hand, the statistical significance of the return and alpha spreads between quintile 5 and quintile 1 are somewhat weaker for the non-directional strategies; significant only in five out of the eight uncertainty beta portfolios tested. In Table VII of the online appendix, we test statistical significance of the differences between 9-factor alphas for directional and non-directional funds. For five out of the eight uncertainty beta portfolios, the alphas are economically and statistically higher for directional funds compared to non-directional funds.

Combining these new set of results with the results we obtained earlier on the variation of uncertainty betas through time across different investment strategies, we see an economically and statistically stronger relation between uncertainty betas and future returns for funds with sizeable and greater variation in uncertainty betas. One possible explanation for this could be the market-timing ability of hedge fund managers. Many fund managers, especially those that pursue directional and semi-directional strategies, actively vary their exposures to economic uncertainty variables up or down in a timely fashion according to the macroeconomic conditions and the state of the financial markets, and as a result, can generate superior returns. Hence, our results suggest that some hedge funds (particularly directional and semi-directional strategy funds) correctly adjust their exposures to changes in financial and macroeconomic conditions and, therefore, there exists a positive and stronger link between their uncertainty betas and future returns. On the other hand, the cross-sectional relation between uncertainty betas and future returns is relatively weaker for the funds following non-directional strategies, because the variation in betas through time for these strategies are quite low in comparison to directional and semi-directional strategies.[11]

[11] In Table 6, in addition to reporting the time-series variation of uncertainty betas among the three broad hedge fund investment strategies, we also report the number of hedge funds for each strategy and the percentage of funds in total sample. A notable point in the first two rows of Table 6 is that the total number of funds in the non-directional category is only 921 (out of 11,779 funds), corresponding to 7.82% of the hedge fund sample. On the

5.7. Canonical correlation analysis

In this section, we use a novel statistical approach to construct unique hedge fund-related economic uncertainty indices and check the performance of these indices in predicting the cross-sectional variation in hedge fund returns. Canonical correlation analysis, originally introduced by Hotelling (1936), is a way of grasping the meaning of cross-covariance matrices. If we have two sets of variables, $X_1,...,X_n$ and $Y_1,...,Y_m$, and there are correlations among the variables, then canonical correlation analysis will enable us to find linear combinations of the X's and the Y's which have maximum correlation with each other.[12]

We construct univariate measures of hedge fund-related economic uncertainty by considering, on the one hand, vectors of portfolio returns of 11 hedge fund investment styles, and on the other hand, the 10 measures of economic uncertainty introduced in this paper. We then generate a linear combination of the 11 hedge fund portfolio investment style returns and a linear combination of the 10 economic uncertainty factors which leads to the highest correlation between these two linear combinations. In this way, we construct two univariate indices of economic uncertainty:

- *Economic Uncertainty Index*: A univariate index of hedge fund-related economic uncertainy (the linear combination of economic uncertainty factors)
- *Hedge Fund Index*: A univariate index of economic uncertainty-related hedge fund investment style portfolio returns (the linear combination of hedge fund style index returns).

We use two sets of variables to construct the Economic Uncertainty Index and the Hedge Fund Index. The first set of variables are the 10 measures of economic uncertainty defined as the time-varying conditional volatility of the 10 state variables; *DEF*, *TERM*, *TED*, *RREL*, *DIV*, *MKT*, *INF*, *UNEMP*, *GDP*, and *CFNAI*. As discussed earlier, descriptive statistics of these uncertainty factors are presented in Table 1. The second set of variables are the 11 hedge fund style portfolio returns. Hedge funds in TASS database have various trading strategies. We generate 11 hedge fund portfolios based on the equal-weighted returns of individual hedge funds that belong to one of the 11 investment styles; Convertible Arbitrage, Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Long-Short Equity Hedge, Managed Futures, and Multi Strategy. Table VIII of the online appendix presents the descriptive statistics for the 11 hedge fund portfolio returns.

In Table 8 (of this paper) we report the results from the canonical correlation analysis. The first column in the top panel shows positive and highly significant correlations between the Economic Uncertainty Index and the 10 measures of economic uncertainty. The correlations between the univariate index of hedge fund-related economic uncertainy and the 10 measures of economic uncertainty are

other hand, the total number of funds following semi-directional and directional strategies is 10,858, corresponding to 92.18% of the hedge fund universe. These results indicate that the significantly positive link between uncertainty betas and future returns holds for more than 92% of the overall hedge fund sample.

[12] Brown, Goetzmann, Liang, and Schwarz (2009, 2012) use canonical correlation analysis to construct a measure of operational risk in the hedge fund industry.

statistically significant at the 1% level without any exception. The uncertainty about aggregate dividend yield (DIV_U), the uncertainty about default spread (DEF_U), and the uncertainty about the stock market (MKT_U) have the highest correlations with the Economic Uncertainty Index (0.86, 0.75, and 0.72, respectively). The uncertainty measures for the TED spread (TED_U) and the relative T-bill rate (RREL_U) have the lowest correlations with the Economic Uncertainty Index (0.17 and 0.21, respectively).

The second column in the top panel displays positive and highly strong correlations between the Hedge Fund Index and the 10 measures of economic uncertainty. The correlations between the univariate index of economic uncertainty-related hedge fund portfolio returns and the 10 measures of economic uncertainty are statistically significant at the 1% level, with only two exceptions (RREL_U and TED_U). Similar to our earlier findings, DIV_U, DEF_U, and MKT_U have the largest correlations with the Hedge Fund Index (0.58, 0.51, and 0.48, respectively). Again, TED_U and RREL_U have the lowest correlations with the Hedge Fund Index; 0.11 (p-value = 9.86%) and 0.14 (p-value = 3.81%). Overall, the results in the top panel of Table 8 provide clear evidence for the robustness of the canonical correlation analysis, which leads to the highest correlation between the linear combination of hedge fund portfolio returns and the linear combination of the economic uncertainty factors. Hence, the two univariate indices of economic uncertainty are similarly associated with the same set of variables.

The bottom panel in Table 8 reports the correlations between the hedge fund portfolio returns (aggregate investment style returns) and the two univariate indices of economic uncertainty. The first column shows that only four investment styles (out of 11) are significantly correlated with the Economic Uncertainty Index: Equity Market Neutral, Fund of Funds, Event Driven, and Short Bias. Although not as strong, the correlation between Fixed Income Arbitrage and the Economic Uncertainty Index is marginally significant with a p-value of 5.9%. The second column provides similar findings: Equity Market Neutral, Fund of Funds, Event Driven, Short Bias, Fixed Income Arbitrage and Multi Strategy are significantly correlated with the Hedge Fund Index.

The last row of Table 8 shows that the maximal correlation between a linear combination of the 10 economic uncertainty factors and a linear combination of the 11 hedge fund portfolio returns is 0.67 and highly significant. These results indicate that the canonical correlation analysis enabled us to obtain two univariate indices of economic uncertainty based on the linear combinations of the economic uncertainty factors and the hedge fund portfolios which have maximum correlation with each other. Figure 1 presents time-series plots of the Economic Uncertainty and Hedge Fund Indices obtained from canonical analysis. Panel A of Figure 1 (Economic Uncertainty Index) provides a clear interpretation of the economic cycles over the past 19-year period, while Panel B of Figure 1 (Hedge Fund Index) seems to be a much more noisy measure of the same phenomena.

The next step is to test whether funds' exposures to the newly proposed economic uncertainty indices capture the cross-sectional variation in hedge fund returns. First, we estimate monthly uncertainty betas for each fund based on the 36-month rolling regressions of hedge fund excess returns on the

Economic Uncertainty Index and the Hedge Fund Index separetely. Then, we form quintile portfolios every month by sorting individual hedge funds according to these two new uncertainty betas. We use out of sample average quintile returns for the following month to examine whether exposures to these two new indices of economic uncertainty explain the cross-sectional dispersion in hedge fund returns.

Although not reported in the paper to save space, the results indicate a positive and significant relation between exposures to the Economic Uncertainty Index and future hedge fund returns. Specifically, funds in the highest Economic Uncertainty Index beta quintile generate 5.6% higher average annual returns than do funds in the lowest Economic Uncertainty Index beta quintile. This average return difference between quintiles 5 and 1 is also highly significant with the Newey-West *t*-statistic of 2.74. After controlling for Fama-French-Carhart's four factors as well as Fung-Hsieh's five trend-following factors, the positive relation between the Economic Uncertainty Index beta and risk-adjusted returns (9-factor alpha) remains economically and statistically significant as well; 0.50% per month (*t*-stat. = 2.41).

The results from the Hedge Fund Index beta, however, turn out to be much weaker. We find a positive but economically and statistically insignificant relation between exposures to the Hedge Fund Index and future fund returns. Specifically, funds in the highest Hedge Fund Index beta quintile generate 3.3% higher average annual returns than do funds in the lowest Hedge Fund Index beta quintile. However, this average return difference is statistically insignificant with a *t*-statistic of 1.15. Especially after controlling for the 9 factors, the positive relation between the Hedge Fund Index beta and risk-adjusted returns becomes practically zero: 0.07% per month with a *t*-statistic of 0.30. Hence, compared to the Hedge Fund Index, the Economic Uncertainty Index is a stronger determinant of the cross-sectional differences in hedge fund returns.

6. Conclusion

Earlier studies have so far paid no attention to the distinction between risk and uncertainty in the cross-sectional pricing of individual hedge funds. This paper contributes to the literature in a significant way by examining the relative performance of hedge funds' exposures to risk and uncertainty factors in terms of their ability to explain cross-sectional differences in hedge fund returns. In this study, we first introduce alternative measures of economic uncertainty based on the time-varying conditional volatility of macroeconomic variables associated with business cycle fluctuations. Then, we generate monthly time-series estimates of uncertainty betas for each fund from rolling-window time-series regressions of hedge fund returns on the uncertainty factors. Finally, we investigate the performance of these uncertainty betas in predicting the cross-sectional variation in hedge fund returns. In the literature, this is the first sensitivity analysis of expected future hedge fund returns to loadings on economic uncertainty. Both portfolio level analyses and cross-sectional regressions reveal clear, robust and corroborating results, showing a positive and significant relation between alternative measures of uncertainty betas and expected future returns of individual hedge funds.

Depending on the proxy for economic uncertainty, hedge funds in the highest uncertainty beta quintile generate 5.5% to 7.5% more average annual returns compared to funds in the lowest uncertainty beta quintile. After controlling for Fama-French (1993) and Carhart (1997)'s four factors and Fung-Hsieh's (2001) five trend-following factors, the positive relation between uncertainty beta and risk-adjusted returns (9-factor alpha) remains economically and statistically significant. In multivariate cross-sectional regressions, we also control for a large set of fund characteristics and risk attributes, and find that the average slopes on uncertainty beta measures remain positive and highly significant across alternative regression specifications. In addition, in our subsample analyses, despite the structural breaks observed in risk and return characteristics of hedge funds during the sample period analyzed, we find evidence of a continuing positive and significant relation between uncertainty betas and hedge fund returns in most of the subsample periods examined.

We also test the performance of hedge funds' exposures to various risk factors in predicting their future returns. The results provide no evidence for a significant link between risk factor betas and future fund returns. We find for the first time that economic uncertainty explains the cross-section of hedge fund returns after controlling for every kind or classification of market risk discussed in the literature. Hence, we conclude that compared to risk, economic uncertainty is a stronger determinant of the cross-sectional dispersion in hedge fund returns.

In addition, we investigate whether the predictive power of uncertainty betas for future fund returns changes across specific hedge fund categories. The empirical analyses indicate that the economic and statistical significance of the uncertainty betas gradually increases as we move from the least directional strategies to the most directional strategies, implying a stronger relation between uncertainty betas and future returns for funds with sizeable time-series variation in uncertainty betas. Our results suggest that the predictive power of uncertainty betas emanates from hedge funds' competence in detecting fluctuations in financial markets and their ability to timely adjust their positions to the changes in financial and macroeconomic conditions.

Finally, we use canonical correlation analysis to construct a broad hedge fund related economic uncertainty index and test its performance in predicting the cross-sectional variation in hedge fund returns. The results indicate a positive and significant link between funds' exposures to the broad uncertainty index and future hedge fund returns. Overall, the significant correlations between fund returns and the newly proposed uncertainty proxies validate our measures as descriptive quantitative measures of economic uncertainty.

References

Ackermann, C., McEnally, R., Ravenscraft, D., 1999. The performance of hedge funds: risk, return, and incentives. Journal of Finance 54, 833–874.

Agarwal, V., Naik, N.Y., 2000. Multi-period performance persistence analysis of hedge funds. Journal of Financial and Quantitative Analysis 35, 327–342.

Agarwal, V., Naik, N.Y., 2004. Risks and portfolio decisions involving hedge funds. Review of Financial Studies 17, 63–98.

Aggarwal, R.K., Jorion, P., 2010. The performance of emerging hedge funds and managers. Journal of Financial Economics 96, 238–256.

Allen, L., Bali, T.G., Tang, Y., 2012. Does systemic risk in the financial sector predict future economic downturns? Review of Financial Studies 25, 3000–3036.

Anderson, E.W., Ghysels, E., Juergens, J.L., 2009. The impact of risk and uncertainty on expected returns. Journal of Financial Economics 94, 233–263.

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

Bali, T.G., 2008. The intertemporal relation between expected returns and risk, Journal of Financial Economics 87, 101–131.

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

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

Bali, T.G., Engle, R.F., 2010. The intertemporal capital asset pricing model with dynamic conditional correlations, Journal of Monetary Economics 57, 377–390.

Bali, T.G., Gokcan, S., Liang, B., 2007. Value at risk and the cross-section of hedge fund returns. Journal of Banking and Finance 31, 1135–1166.

Bali, T.G., Zhou, H., 2012. Risk, uncertainty, and expected returns. Working Paper, SSRN Library.

Bekaert, G., Engstrom, E., Xing, Y., 2009. Risk, uncertainty, and asset prices. Journal of Financial Economics 91, 59–82.

Bloom, N., 2009. The impact of uncertainty shocks, Econometrica 77, 623–685.

Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics, Review of Economic Studies 74, 391–415.

Brown, S.J., Goetzmann, W.N., Ibbotson, R.G., 1999. Offshore hedge funds: survival and performance 1989-95. Journal of Business 72, 91–117.

Brown, S.J., Goetzmann, W.N., Liang, B., Schwarz, C., 2009. Estimating operational risk for hedge funds: The ω-score, Financial Analysts Journal 65, 43–53.

Brown, S.J., Goetzmann, W.N., Liang, B., Schwarz, C., 2012. Trust and delegation, Journal of Financial Economics 103, 221–234.

Brown, S.J., Gregoriou, G., Pascalau, R., 2012. Is it possible to overdiversify? The case of funds of hedge funds. Review of Asset Pricing Studies 2, 89–110.

Cao, C., Chen, Y., Liang, B., Lo, A.W., 2012. Can hedge funds time market liquidity? Journal of Financial Economics, forthcoming.

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

Chen, H., 2010. Macroeconomic conditions and the puzzles of credit spreads and capital structure. Journal of Finance 65, 2171–2212.

Chow, G., 1960. Test of equality between sets of coefficients in two linear regressions. Econometrica 28, 591–605.

Edwards, F.R., Caglayan, M.O., 2001. Hedge fund performance and manager skill. Journal of Futures Markets 21, 1003–1028.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., MacBeth, J.D., 1973. Risk and return: some empirical tests. Journal of Political Economy 81, 607–636.

Fung, W.H., Hsieh, D.A., 1997. Empirical characteristics of dynamic trading strategies: the case of hedge funds. Review of Financial Studies 10, 275–302.

Fung, W.H., Hsieh, D.A., 2000. Performance characteristics of hedge funds and CTA funds: natural versus spurious biases. Journal of Financial and Quantitative Analysis 35, 291–307.

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

Fung, W.H., Hsieh, D.A., 2004. Hedge fund benchmarks: a risk-based approach. Financial Analysts Journal 60, 65–80.

Fung, W.H., Hsieh, D.A., Naik, N.Y., Ramadorai, T., 2008. Hedge funds: performance, risk, and capital formation. Journal of Finance 63, 1777–1803.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance 48, 1779–1801.

Hotelling, H., 1936. Relations between two sets of variates. Biometrika 28, 321–377.

Jagannathan, R., Malakhov, A., Novikov, D., 2010. Do hot hands exist among hedge fund managers? An empirical evaluation. Journal of Finance 65, 217–255.

Jegadeesh, N., 1990. Evidence of predictable behaviour of security returns. Journal of Finance 45, 881–898.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65–91.

Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: an evaluation of alternative explanations. Journal of Finance 56, 699–720.

Kandel, E., Pearson, N.D., 1995. Differential interpretation of public signals and trade in speculative markets, Journal of Political Economy 103, 831–872.

Knight, F.H., 1921. Risk, uncertainty and profit. New York: Harper.

Kosowski, R., Naik, N., Teo, M., 2007. Do hedge funds deliver alpha? A Bayesian and bootstrap analysis. Journal of Financial Economics 84, 229–264.

Lamont, O.A., 2002. Macroeconomic forecasts and microeconomic forecasters. Journal of Economic Behavior and Organization 48, 265–280.

Lehmann, B., 1990. Fads, martingales, and market efficiency. Quarterly Journal of Economics 105, 1–28.

Liang, B., 1999. On the performance of hedge funds. Financial Analysts Journal 55, 72–85.

Liang, B., 2001. Hedge fund performance: 1990-1999. Financial Analysts Journal 57, 11–18.

Mankiw, G.N., Reis, R., Wolfers, J., 2004. Disagreement about inflation expectations, in NBER Macroeconomics Annual 2003, Volume 18, NBER Chapters, pp. 209–270.

Merton, R.C., 1973. An intertemporal capital asset pricing model. Econometrica 41, 867–887.

Mitchell, M., Pulvino, T., 2001. Characteristics of risk and return in risk arbitrage. Journal of Finance 56, 2135–2175.

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

Patton, A.J., 2009. Are "market neutral" hedge funds really market neutral? Review of Financial Studies 22, 2495–2530.

Patton, A.J., Ramadorai, T., 2013. On the high-frequency dynamics of hedge fund risk exposures. Journal of Finance, forthcoming.

Sadka, R., 2010. Liquidity risk and the cross-section of hedge fund returns. Journal of Financial Economics 98, 54–71.

Stock, J.H., Watson, M.W., 2012. Disentangling the channels of the 2007-2009 recession. Brookings Papers on Economic Activity, forthcoming.

Sun, Z., Wang, A., Zheng, L., 2013. The road less traveled: Strategy distinctiveness and hedge fund performance. Review of Financial Studies, forthcoming.

Titman, S., Tiu, C., 2011. Do the best hedge funds hedge? Review of Financial Studies 24, 123–168.

Table 1. Summary Statistics for Alternative Measures of Economic Uncertainty

Panel A presents the time-series mean, median, standard deviation, minimum, and maximum values for alternative measures of economic uncertainty for the sample period January 1994 – March 2012. Economic uncertainty measures are defined as the time-varying conditional volatility of the state variables; *DEF*, *TERM*, *TED*, *RREL*, *DIV*, *MKT*, *INF*, *UNEMP*, *GDP*, and *CFNAI*. As presented in eqs. (1)-(2), they are estimated using the Threshold GARCH model of Glosten et al. (1993) with an AR(1) process.

Panel A. Economic Uncertainty Factors: January 1994 – March 2012

	N	Mean	Median	Std. Dev.	Minimum	Maximum
DEF_U: Uncertainty about default premium	219	0.11	0.07	0.10	0.02	0.59
TERM_U: Uncertainty about term spread	219	0.26	0.25	0.08	0.13	0.56
TED_U: Uncertainty about credit risk	219	0.41	0.37	0.26	0.07	1.63
RREL_U: Uncertainty about short-term interest changes	219	0.18	0.15	0.11	0.05	0.56
DIV_U: Uncertainty about aggregate dividend yield	219	0.08	0.06	0.05	0.05	0.41
MKT_U: Uncertainty about the equity market	219	4.54	4.03	1.43	3.12	11.35
INF_U: Uncertainty about the inflation rate	219	0.29	0.27	0.09	0.18	0.71
UNEMP_U: Uncertainty about the unemployment rate	219	0.16	0.14	0.05	0.13	0.39
GDP_U: Uncertainty about real GDP per capita	219	0.14	0.13	0.04	0.10	0.26
CFNAI_U: Uncertainty about macroeconomic activity	219	0.24	0.22	0.09	0.16	0.70

Table 1 (continued)

Panel B. Correlation Matrix of the Economic Uncertainty Factors: January 1994 – March 2012

	DEF_U	DIV_U	CFNAI_U	UNEMP_U	TERM_U	MKT_U	INF_U	TED_U	GDP_U	RREL_U
DEF_U	1.000									
DIV_U	0.885	1.000								
CFNAI_U	0.837	0.794	1.000							
UNEMP_U	0.824	0.749	0.875	1.000						
TERM_U	0.575	0.572	0.517	0.581	1.000					
MKT_U	0.619	0.746	0.557	0.475	0.506	1.000				
INF_U	0.642	0.620	0.671	0.549	0.368	0.370	1.000			
TED_U	0.351	0.496	0.465	0.390	0.280	0.530	0.296	1.000		
GDP_U	0.615	0.567	0.646	0.656	0.589	0.618	0.496	0.542	1.000	
RREL_U	0.171	0.307	0.253	0.288	0.460	0.488	0.229	0.658	0.449	1.000

Panel C. Correlations between the Risk and Economic Uncertainty Factors: January 1994 – March 2012

	DEF_U	DIV_U	CFNAI_U	UNEMP_U	TERM_U	MKT_U	INF_U	TED_U	GDP_U	RREL_U
MKT	–0.020	–0.016	–0.017	–0.022	–0.112	–0.028	–0.098	–0.129	–0.196	–0.171
SMB	0.074	0.040	0.053	0.063	0.092	0.035	0.071	–0.021	0.080	0.053
HML	–0.069	–0.153	–0.055	0.018	0.087	–0.154	0.026	–0.045	0.109	–0.010
MOM	–0.192	–0.242	–0.255	–0.200	–0.067	–0.163	-0.198	–0.013	–0.082	0.055
Δ10Y	–0.042	–0.112	0.010	0.021	–0.013	–0.166	0.004	–0.045	–0.085	0.020
ΔCRDSPR	–0.138	–0.018	–0.071	–0.167	–0.083	0.186	–0.068	0.113	0.097	0.130
BDTF	–0.026	0.103	0.012	–0.016	–0.078	0.173	–0.087	0.109	0.030	0.103
FXTF	–0.081	–0.024	–0.009	–0.036	–0.018	–0.001	–0.005	0.013	0.037	0.071
CMTF	–0.124	–0.062	–0.044	–0.054	–0.094	–0.078	–0.030	–0.008	–0.056	0.051
IRTF	–0.036	0.032	0.086	0.116	0.019	0.094	0.069	0.164	0.207	0.220
SKTF	–0.086	–0.014	0.035	0.054	–0.123	–0.033	–0.005	0.074	0.000	0.019

Table 2. Time-series and Cross-sectional Statistics of the Uncertainty Betas

First, the uncertainty betas are estimated for each fund and for each month from January 1997 to March 2012. Then, the mean, median, standard deviation, maximum and minimum values of the uncertainty betas are computed cross-sectionally for each uncertainty beta separately. Panel A presents the time-series averages of these five statistics. After computing the cross correlations of the uncertainty betas for each month, Panel B reports the time-series averages of these cross correlations for the sample period January 1997 – March 2012.

Panel A. Descriptive Statistics of the Uncertainty Betas: January 1994 – March 2012

	β^{DEF_U}	β^{DIV_U}	β^{CFNAI_U}	β^{UNEMP_U}	β^{TERM_U}	β^{MKT_U}	β^{INF_U}	β^{TED_U}	β^{GDP_U}	β^{RREL_U}
Mean	3.433	16.095	0.444	–19.391	1.166	–0.173	0.097	–0.723	–0.370	–0.344
Median	1.379	9.343	–0.465	–13.475	1.149	–0.184	0.303	–0.414	–1.327	–0.238
Std. Deviation	38.195	59.870	22.424	62.049	17.218	1.034	18.838	5.727	44.904	10.804
Max	344.175	504.967	181.489	365.898	131.380	8.439	126.635	43.515	331.229	87.905
Min	–315.893	–490.215	–173.664	–523.375	–118.015	–10.048	–139.369	–47.436	–322.580	–86.608

Panel B. Cross Correlations of the Uncertainty Betas: January 1994 – March 2012

	β^{DEF_U}	β^{DIV_U}	β^{CFNAI_U}	β^{UNEMP_U}	β^{TERM_U}	β^{MKT_U}	β^{INF_U}	β^{TED_U}	β^{GDP_U}	β^{RREL_U}
β^{DEF_U}	1.000									
β^{DIV_U}	0.489	1.000								
β^{CFNAI_U}	0.313	0.302	1.000							
β^{UNEMP_U}	0.254	0.207	0.321	1.000						
β^{TERM_U}	0.362	0.211	0.252	0.483	1.000					
β^{MKT_U}	0.336	0.731	0.260	0.185	0.188	1.000				
β^{INF_U}	0.281	0.094	0.492	0.113	0.296	0.008	1.000			
β^{TED_U}	0.231	0.167	0.211	0.134	0.314	0.314	0.272	1.000		
β^{GDP_U}	0.232	0.158	0.225	0.277	0.459	0.285	0.335	0.426	1.000	
β^{RREL_U}	0.317	0.297	0.120	0.090	0.391	0.367	0.128	0.594	0.312	1.000

Table 3. Univariate Portfolios of the Uncertainty Betas

Quintile portfolios are formed every month from January 1997 to March 2012 by sorting hedge funds based on their uncertainty betas. Quintile 1 is the portfolio of hedge funds with the lowest uncertainty betas, and quintile 5 is the portfolio of hedge funds with the highest uncertainty betas. In each column, the table reports the average uncertainty betas in each quintile as well as all quintiles' next month average returns. The last two rows show the monthly average raw return differences and the 9-factor Alpha differences between quintile 5 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.

	Average Size of β^{DEF_U}	Average Size of β^{DIV_U}	Average Size of β^{CFNAI_U}	Average Size of β^{UNEMP_U}	Average Size of β^{TERM_U}	Average Size of β^{MKT_U}	Average Size of β^{INF_U}	Average Size of β^{TED_U}	Average Size of β^{GDP_U}	Average Size of β^{RREL_U}
Q1	–40.733	–51.722	–26.521	–103.528	–19.928	–1.467	–23.535	–8.334	–54.542	–14.105
Q2	–9.640	–6.630	–6.866	–34.730	–3.929	–0.488	–5.531	–2.212	–15.105	–3.526
Q3	1.349	9.570	–0.474	–13.662	1.137	–0.183	0.282	–0.414	–1.377	–0.239
Q4	12.952	31.413	6.468	4.133	5.981	0.144	5.719	1.264	12.245	2.921
Q5	53.235	97.833	29.615	50.848	22.569	1.127	23.553	6.083	56.929	13.139
	Next-month returns of β^{DEF_U} Quintiles	Next-month returns of β^{DIV_U} Quintiles	Next-month returns of β^{CFNAI_U} Quintiles	Next-month returns of β^{UNEMP_U} Quintiles	Next-month returns of β^{TERM_U} Quintiles	Next-month returns of β^{MKT_U} Quintiles	Next-month returns of β^{INF_U} Quintiles	Next-month returns of β^{TED_U} Quintiles	Next-month returns of β^{GDP_U} Quintiles	Next-month returns of β^{RREL_U} Quintiles
Q1	0.101	0.135	0.081	0.075	0.075	0.164	0.108	0.177	0.297	0.316
Q2	0.246	0.210	0.212	0.287	0.284	0.243	0.258	0.239	0.270	0.257
Q3	0.240	0.265	0.304	0.297	0.302	0.248	0.302	0.241	0.292	0.253
Q4	0.377	0.394	0.424	0.351	0.397	0.413	0.382	0.368	0.376	0.360
Q5	0.729	0.688	0.671	0.682	0.633	0.624	0.642	0.667	0.456	0.505
Q5 – Q1 Return Diff.	**0.628** **(2.46)**	**0.552** **(2.27)**	**0.589** **(3.06)**	**0.606** **(2.36)**	**0.558** **(2.64)**	**0.461** **(2.07)**	**0.535** **(2.77)**	**0.490** **(2.06)**	0.159 (0.72)	0.189 (0.72)
Q5 – Q1 9-factor Alpha Diff.	**0.722** **(2.35)**	**0.473** **(2.05)**	**0.605** **(3.06)**	**0.677** **(2.26)**	**0.500** **(2.16)**	**0.504** **(2.80)**	**0.530** **(2.83)**	**0.668** **(3.83)**	0.243 (1.45)	0.366 (1.57)

Table 4. Multivariate Fama-MacBeth Regressions of One-month ahead Hedge Fund Returns on the Uncertainty Betas with Control Variables

This table reports the average intercept and average slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month-ahead hedge fund excess returns on the uncertainty betas with control variables. The Fama-MacBeth cross-sectional regressions are run each month for the sample period January 1997 – March 2012. Each column represents a cross-sectional regression equation tested in the analyses. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.1129 (0.83)	0.0999 (0.74)	0.1131 (0.83)	0.1191 (0.90)	0.1129 (0.83)	0.1392 (0.97)	0.1136 (0.88)	0.1048 (0.78)	0.2825 (3.63)	0.0235 (0.27)
β^{DEF_U}	**0.0123** **(2.91)**								**0.0521** **(2.08)**	**0.0452** **(2.49)**
β^{DIV_U}		**0.0060** **(3.25)**							**0.0308** **(2.27)**	**0.0311** **(2.34)**
β^{CFNAI_U}			**0.0122** **(2.81)**						**0.0321** **(2.18)**	**0.0301** **(2.21)**
β^{UNEMP_U}				**0.0083** **(2.83)**					0.0082 (1.25)	0.0082 (1.38)
β^{TERM_U}					**0.0152** **(3.84)**				**0.0232** **(3.58)**	**0.0188** **(3.38)**
β^{MKT_U}						**0.1602** **(2.40)**			0.1686 (0.46)	0.2156 (0.66)
β^{INF_U}							**0.0118** **(3.44)**		**0.0218** **(3.16)**	**0.0211** **(3.30)**
β^{TED_U}								**0.0478** **(3.23)**	**0.0540** **(1.75)**	**0.0612** **(1.72)**
LagRet	**0.0897** **(5.43)**	**0.0831** **(4.97)**	**0.0922** **(5.24)**	**0.0798** **(5.16)**	**0.0918** **(5.34)**	**0.0861** **(4.93)**	**0.0912** **(5.27)**	**0.0893** **(4.96)**		**0.0794** **(5.08)**
Size	0.0255 (0.83)	0.0302 (1.05)	0.0148 (0.50)	0.0137 (0.50)	0.0105 (0.37)	0.0222 (0.80)	0.0099 (0.35)	0.0064 (0.21)		0.0206 (0.73)
Age	0.0001 (0.18)	–0.0001 (–0.04)	–0.0001 (–0.12)	0.0001 (0.05)	0.0001 (0.20)	–0.0001 (–0.13)	–0.0001 (–0.12)	–0.0001 (–0.09)		0.0002 (0.56)
MgmtFee	0.0380 (1.05)	0.0372 (1.03)	0.0449 (1.22)	0.0453 (1.31)	0.0422 (1.16)	0.0367 (0.99)	0.0386 (1.09)	0.0424 (1.21)		0.0459 (1.62)
IncentFee	**0.0054** **(2.40)**	**0.0052** **(2.09)**	**0.0052** **(2.21)**	**0.0061** **(2.62)**	**0.0065** **(2.71)**	**0.0052** **(2.16)**	**0.0065** **(2.74)**	**0.0059** **(2.50)**		**0.0059** **(2.71)**
Redemption	**0.0014** **(1.77)**	**0.0014** **(1.68)**	0.0010 (1.27)	0.0011 (1.48)	0.0009 (1.16)	**0.0015** **(1.86)**	0.0010 (1.31)	0.0008 (1.06)		0.0010 (1.50)
MinInvest	**0.0072** **(2.65)**	**0.0076** **(2.77)**	**0.0068** **(2.67)**	**0.0072** **(2.72)**	**0.0073** **(2.88)**	**0.0069** **(2.48)**	**0.0076** **(2.97)**	**0.0074** **(2.65)**		**0.0085** **(3.33)**
D_Lockup	**0.1450** **(3.73)**	**0.1439** **(3.51)**	**0.1038** **(2.52)**	**0.1318** **(3.46)**	**0.1251** **(3.04)**	**0.1351** **(3.35)**	**0.1245** **(2.97)**	**0.1292** **(3.13)**		**0.1075** **(3.21)**
D_Lever	**0.0371** **(1.96)**	**0.0389** **(2.06)**	**0.0428** **(2.22)**	**0.0433** **(2.30)**	**0.0458** **(2.54)**	**0.0458** **(2.44)**	**0.0467** **(2.49)**	**0.0360** **(1.94)**		**0.0482** **(3.12)**

Table 5. Subsample Analysis

This table reports the average intercept and average slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month-ahead hedge fund excess returns on the uncertainty betas with control variables for four different subsample periods. The Fama-MacBeth cross-sectional regressions are run each month for the period January 1997–March 2012, and the average slope coefficients are calculated for the four subsample periods separately. 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.

Panel A. Results for β^{DEF_U}

	Intercept	$\beta^{\mathrm{DEF\_U}}$	*LagRet*	*Size*	*Age*	*MgmtFee*	*IncentFee*	*Redemption*	*MinInvest*	*D_Lockup*	*D_Lever*
1997:01 – 1998:08	–0.4649	**0.0028**	0.0599	**0.3367**	**0.0041**	0.0599	0.0035	0.0052	**0.0282**	**0.4052**	0.0406
	(–0.54)	**(2.73)**	(1.25)	**(3.05)**	**(2.08)**	(0.33)	(0.29)	(1.34)	**(2.18)**	**(2.96)**	(0.52)
1998:09 – 2000:02	1.1653	**0.0155**	**0.1087**	–0.0343	–0.0019	**–0.2129**	0.0012	**0.0053**	0.0103	0.0206	0.0192
	(3.65)	**(2.13)**	**(2.07)**	(–0.16)	(–1.26)	**(–2.09)**	(0.17)	**(3.20)**	(0.70)	(0.14)	(0.17)
2000:03 – 2008:09	0.0457	**0.0056**	**0.0983**	–0.0140	–0.0004	**0.0921**	**0.0051**	0.0006	**0.0056**	**0.1147**	0.0009
	(0.38)	**(2.10)**	**(4.87)**	(–1.34)	(–1.03)	**(1.82)**	**(2.66)**	(0.73)	**(2.15)**	**(2.61)**	(0.06)
2008:10 – 2012:03	0.1018	**0.0320**	**0.0745**	–0.0004	0.0002	0.0026	**0.0088**	–0.0001	0.0001	**0.1486**	**0.1319**
	(1.13)	**(2.12)**	**(1.90)**	(–0.10)	(0.48)	(0.12)	**(2.04)**	(–0.13)	(0.34)	**(1.85)**	**(4.24)**

Panel B. Results for β^{DIV_U}

	Intercept	$\beta^{\mathrm{DIV\_U}}$	*LagRet*	*Size*	*Age*	*MgmtFee*	*IncentFee*	*Redemption*	*MinInvest*	*D_Lockup*	*D_Lever*
1997:01 – 1998:08	–0.4178	0.0003	0.0331	**0.3252**	**0.0043**	0.0749	0.0054	0.0040	**0.0238**	**0.4224**	0.0652
	(–0.52)	(0.12)	(0.64)	**(2.66)**	**(2.11)**	(0.36)	(0.40)	(0.90)	**(2.27)**	**(3.23)**	(0.76)
1998:09 – 2000:02	1.1850	**0.0077**	**0.1016**	0.0159	**–0.0029**	**–0.2541**	–0.0066	**0.0071**	0.0174	–0.0382	0.0278
	(3.54)	**(3.30)**	**(1.66)**	(0.09)	**(–1.95)**	**(–2.38)**	(–0.88)	**(4.01)**	(1.18)	(–0.26)	(0.25)
2000:03 – 2008:09	0.0054	**0.0035**	**0.0921**	–0.0122	–0.0005	**0.0951**	**0.0056**	0.0004	**0.0058**	**0.1179**	–0.0005
	(0.05)	**(2.15)**	**(4.91)**	(–1.30)	(–1.22)	**(2.06)**	**(2.71)**	(0.57)	**(2.03)**	**(2.57)**	(–0.03)
2008:10 – 2012:03	0.1128	**0.0139**	**0.0769**	–0.0002	0.0003	0.0018	**0.0090**	0.0001	0.0001	**0.1529**	**0.1278**
	(1.04)	**(2.33)**	**(1.89)**	(–0.05)	(0.54)	(0.09)	**(2.00)**	(0.01)	(0.50)	**(1.82)**	**(4.23)**

Table 5 (continued)

Panel C. Results for β^{CFNAI_U}

	Intercept	β^{CFNAI_U}	*LagRet*	*Size*	*Age*	*MgmtFee*	*IncentFee*	*Redemption*	*MinInvest*	*D_Lockup*	*D_Lever*
1997:01 – 1998:08	–0.4686 (–0.64)	0.0013 (0.13)	0.0420 (0.87)	**0.2867** **(2.42)**	**0.0038** **(2.24)**	0.0720 (0.43)	0.0084 (0.65)	0.0035 (0.82)	**0.0240** **(2.49)**	**0.3708** **(2.74)**	0.0618 (0.80)
1998:09 – 2000:02	1.5381 (4.05)	**0.0084** **(2.29)**	**0.1290** **(1.94)**	–0.0954 (–0.51)	**–0.0028** **(–1.77)**	**–0.2941** **(–3.09)**	–0.0021 (–0.30)	**0.0064** **(3.57)**	0.0053 (0.35)	–0.0243 (–0.17)	0.0083 (0.08)
2000:03 – 2008:09	–0.0106 (–0.09)	**0.0064** **(2.85)**	**0.0966** **(4.80)**	–0.0126 (–1.32)	–0.0004 (–1.11)	**0.1178** **(2.43)**	**0.0043** **(2.40)**	0.0002 (0.29)	**0.0064** **(2.23)**	0.0635 (1.30)	0.0077 (0.43)
2008:10 – 2012:03	0.0825 (0.74)	**0.0330** **(2.18)**	**0.0893** **(2.11)**	–0.0001 (–0.03)	0.0002 (0.51)	–0.0016 (–0.08)	**0.0091** **(1.99)**	–0.0004 (–0.45)	0.0001 (0.44)	**0.1301** **(1.66)**	**0.1346** **(4.33)**

Panel D. Results for β^{UNEMP_U}

	Intercept	β^{UNEMP_U}	*LagRet*	*Size*	*Age*	*MgmtFee*	*IncentFee*	*Redemption*	*MinInvest*	*D_Lockup*	*D_Lever*
1997:01 – 1998:08	–0.6033 (–0.75)	**0.0127** **(2.09)**	0.0430 (0.86)	**0.2865** **(2.61)**	**0.0044** **(2.39)**	0.0693 (0.42)	0.0079 (0.63)	0.0044 (1.18)	**0.0294** **(2.44)**	**0.3603** **(2.59)**	0.0465 (0.66)
1998:09 – 2000:02	1.1749 (2.94)	0.0004 (0.17)	**0.0972** **(1.78)**	–0.1163 (–0.66)	–0.0023 (–1.35)	–0.1582 (–1.53)	0.0002 (0.02)	**0.0045** **(2.62)**	0.0101 (0.66)	–0.0317 (–0.21)	0.0384 (0.34)
2000:03 – 2008:09	0.0902 (0.82)	**0.0044** **(1.82)**	**0.0825** **(4.31)**	–0.0110 (–1.37)	–0.0005 (–1.18)	**0.0937** **(1.89)**	**0.0055** **(2.85)**	0.0005 (0.70)	**0.0053** **(2.19)**	**0.1188** **(2.64)**	0.0053 (0.31)
2008:10 – 2012:03	0.0817 (0.75)	**0.0191** **(2.05)**	**0.0831** **(2.12)**	–0.0003 (–0.07)	0.0002 (0.35)	0.0021 (0.09)	**0.0092** **(2.04)**	–0.0006 (–0.61)	0.0001 (0.26)	**0.1248** **(1.78)**	**0.1371** **(4.37)**

Panel E. Results for β^{TERM_U}

	Intercept	β^{TERM_U}	*LagRet*	*Size*	*Age*	*MgmtFee*	*IncentFee*	*Redemption*	*MinInvest*	*D_Lockup*	*D_Lever*
1997:01 – 1998:08	–0.5172 (–0.62)	0.0007 (0.09)	0.0344 (0.71)	**0.2997** **(2.61)**	**0.0040** **(2.15)**	0.0746 (0.41)	0.0068 (0.53)	0.0042 (1.09)	**0.0257** **(2.43)**	**0.3967** **(3.01)**	0.0614 (0.89)
1998:09 – 2000:02	1.2251 (3.90)	**0.0107** **(2.04)**	**0.1311** **(2.03)**	–0.1619 (–0.99)	–0.0024 (–1.64)	**–0.2392** **(–2.16)**	0.0039 (0.51)	**0.0046** **(2.52)**	0.0124 (1.01)	–0.0395 (–0.25)	0.0316 (0.30)
2000:03 – 2008:09	0.0509 (0.44)	**0.0184** **(3.48)**	**0.0976** **(5.02)**	–0.0113 (–1.40)	–0.0003 (–0.82)	**0.1030** **(2.08)**	**0.0056** **(2.86)**	0.0001 (0.06)	**0.0059** **(2.06)**	**0.0954** **(2.10)**	0.0093 (0.56)
2008:10 – 2012:03	0.0886 (0.79)	**0.0162** **(2.01)**	**0.0879** **(2.03)**	0.0002 (0.04)	0.0003 (0.57)	–0.0017 (–0.09)	**0.0095** **(2.06)**	–0.0003 (–0.33)	0.0001 (0.26)	**0.1393** **(1.70)**	**0.1339** **(4.60)**

Table 5 (continued)

Panel F. Results for β^{MKT_U}

	Intercept	$\beta^{\mathrm{MKT\_U}}$	*LagRet*	*Size*	*Age*	*MgmtFee*	*IncentFee*	*Redemption*	*MinInvest*	*D_Lockup*	*D_Lever*
1997:01 – 1998:08	–0.5380 (–0.61)	0.0336 (0.53)	0.0450 (0.89)	**0.3109** **(2.74)**	**0.0043** **(2.11)**	0.0673 (0.35)	0.0059 (0.47)	0.0044 (1.04)	**0.0262** **(2.14)**	**0.4132** **(3.18)**	0.0798 (0.96)
1998:09 – 2000:02	1.5877 (4.29)	**0.5641** **(4.30)**	0.1073 (1.60)	–0.0412 (–0.23)	**–0.0035** **(–2.43)**	**–0.2864** **(–2.75)**	–0.0068 (–0.97)	**0.0074** **(4.51)**	0.0063 (0.41)	0.0028 (0.02)	0.0374 (0.35)
2000:03 – 2008:09	0.0357 (0.31)	0.0493 (0.61)	**0.0926** **(4.44)**	–0.0139 (–1.34)	–0.0004 (–1.11)	**0.1030** **(2.08)**	**0.0053** **(2.65)**	0.0006 (0.82)	**0.0061** **(2.02)**	**0.1000** **(2.14)**	0.0035 (0.21)
2008:10 – 2012:03	0.0946 (0.89)	**0.3196** **(1.92)**	**0.0809** **(1.87)**	0.0004 (0.10)	0.0003 (0.62)	–0.0019 (–0.10)	**0.0097** **(2.01)**	–0.0004 (–0.39)	0.0001 (0.01)	**0.1455** **(1.83)**	**0.1367** **(5.42)**

Panel G. Results for β^{INF_U}

	Intercept	$\beta^{\mathrm{INF\_U}}$	*LagRet*	*Size*	*Age*	*MgmtFee*	*IncentFee*	*Redemption*	*MinInvest*	*D_Lockup*	*D_Lever*
1997:01 – 1998:08	–0.3251 (–0.44)	0.0006 (0.07)	0.0324 (0.69)	0.2301 (1.62)	**0.0034** **(1.95)**	0.0287 (0.17)	0.0066 (0.51)	0.0043 (1.06)	**0.0242** **(2.23)**	**0.3570** **(2.39)**	0.0655 (0.81)
1998:09 – 2000:02	1.0430 (2.87)	**0.0199** **(2.14)**	**0.1157** **(2.06)**	–0.0843 (–0.53)	–0.0023 (–1.29)	**–0.2173** **(–2.22)**	0.0046 (0.58)	**0.0049** **(2.76)**	0.0186 (1.38)	–0.0085 (–0.06)	0.0615 (0.50)
2000:03 – 2008:09	0.0412 (0.35)	**0.0093** **(2.11)**	**0.1023** **(5.20)**	–0.0124 (–1.37)	–0.0005 (–1.17)	**0.1010** **(2.11)**	**0.0058** **(2.89)**	0.0001 (0.18)	**0.0056** **(2.21)**	**0.0929** **(1.98)**	0.0079 (0.52)
2008:10 – 2012:03	0.1020 (0.92)	**0.0196** **(2.18)**	**0.0813** **(1.92)**	–0.0001 (–0.03)	0.0003 (0.63)	0.0001 (0.01)	**0.0091** **(1.99)**	–0.0001 (–0.02)	0.0001 (0.26)	**0.1481** **(1.70)**	**0.1266** **(4.47)**

Panel H. Results for β^{TED_U}

	Intercept	$\beta^{\mathrm{TED\_U}}$	*LagRet*	*Size*	*Age*	*MgmtFee*	*IncentFee*	*Redemption*	*MinInvest*	*D_Lockup*	*D_Lever*
1997:01 – 1998:08	–0.5286 (–0.61)	**0.0441** **(2.03)**	0.0368 (0.65)	**0.3039** **(2.37)**	**0.0041** **(2.08)**	0.1030 (0.59)	0.0059 (0.46)	0.0033 (0.78)	**0.0284** **(2.38)**	**0.4161** **(2.97)**	0.0576 (0.74)
1998:09 – 2000:02	1.1628 (3.75)	**0.0947** **(2.72)**	**0.1283** **(2.11)**	–0.2129 (–1.29)	**–0.0028** **(–1.89)**	**–0.1900** **(–1.97)**	0.0015 (0.24)	**0.0036** **(2.05)**	0.0114 (0.78)	–0.1009 (–0.61)	–0.0261 (–0.25)
2000:03 – 2008:09	0.0514 (0.45)	**0.0324** **(1.86)**	**0.0974** **(4.63)**	–0.0106 (–1.27)	–0.0005 (–1.31)	**0.0912** **(1.86)**	**0.0051** **(2.59)**	0.0004 (0.53)	**0.0056** **(1.87)**	**0.1093** **(2.38)**	0.0004 (0.02)
2008:10 – 2012:03	0.0841 (0.87)	**0.0674** **(1.79)**	**0.0778** **(1.86)**	0.0004 (0.12)	0.0003 (0.59)	–0.0062 (–0.32)	**0.0099** **(2.02)**	–0.0006 (–0.80)	0.0001 (0.01)	**0.1400** **(1.94)**	**0.1396** **(6.36)**

Table 6. Dynamics of Hedge Funds' Uncertainty Betas by Three Broad Hedge Fund Style Categories

Panel A reports the cross-sectional average of individual funds' time-series standard deviations of the uncertainty betas, and Panel B reports the cross-sectional average of individual funds' Max minus Min time-series differences of uncertainty betas for each of the three broad hedge fund investment style categories separately. For comparison purposes, the cross-sectional averages of these two statistics across all hedge funds (irrespective of the hedge fund categories) are also reported in bold in the last column of each Panel. As can be noticed by reading Panels A and B from left to right, Non-directional category, which includes the Equity Market Neutral, Fixed Income Arbitrage, and Convertible Arbitrage hedge fund investment styles have low standard deviations and Max – Min differences of the uncertainty betas compared to Directional category, which includes the Managed Futures, Global Macro, and Emerging Markets hedge fund investment styles. Also, Non-directional strategies' standard deviations and Max – Min differences of the uncertainty betas are considerably smaller compared to the all hedge fund group, while Directional strategies' standard deviations and Max – Min differences of the uncertainty betas are noticeably bigger compared to the all hedge fund group. Finally, Semi-directional category, which includes the Fund of Funds, Multi Strategy, Long-short Equity Hedge, and Event Driven hedge fund investment styles have standard deviations and Max – Min differences of the uncertainty betas that are very similar to the all hedge fund group.

	Panel A. Standard deviation of Uncertainty Betas				Panel B. Max – Min Uncertainty Beta Differences			
	Non-directional Category	Semi-directional Category	Directional Category	All Hedge Funds	Non-directional Category	Semi-directional Category	Directional Category	All Hedge Funds
Number of Funds	921	9,039	1,819	11,779	921	9,039	1,819	11,779
% of Funds in Total Sample	7.82%	76.74%	15.44%	100.00%	7.82%	76.74%	15.44%	100.00%
β^{DEF_U}	12.90	14.97	30.62	**17.05**	62.89	66.91	141.53	**77.30**
β^{DIV_U}	21.73	25.56	44.31	**27.98**	92.95	109.20	191.00	**119.64**
β^{CFNAI_U}	7.95	9.32	14.95	**10.02**	34.55	37.35	61.05	**40.56**
β^{UNEMP_U}	23.17	27.11	48.56	**29.94**	96.34	113.09	203.93	**125.04**
β^{TERM_U}	5.68	6.02	11.39	**6.77**	23.54	24.87	46.91	**27.98**
β^{MKT_U}	0.55	0.57	0.90	**0.61**	2.36	2.43	4.12	**2.67**
β^{INF_U}	5.46	5.92	10.70	**6.58**	22.95	24.82	47.79	**28.03**
β^{TED_U}	2.99	3.00	4.88	**3.28**	13.75	14.29	23.72	**15.62**

Table 7. Portfolios of Uncertainty Betas for Three Broad Hedge Fund Style Categories

For each of the three broad hedge fund investment style categories (Non-directional, Semi-directional, and Directional), univariate quintile portfolios are formed every month from January 1997 to March 2012 by sorting hedge funds based on their uncertainty betas. Quintile 1 (5) is the portfolio of hedge funds with the lowest (highest) uncertainty betas in each hedge fund category. The table reports the differences in next month returns and 9-factor alphas between quintiles 5 and 1. Newey-West *t*-statistics are given in parantheses. Numbers in bold denote statistical significance.

		Q5 – Q1 Return Difference	Q5 – Q1 9-factor Alpha Difference
β^{DEF_U} Portfolios	Non-directional	**0.514** (**2.31**)	**0.506** (**2.15**)
	Semi-directional	**0.547** (**2.36**)	**0.594** (**2.28**)
	Directional	**0.790** (**2.03**)	**0.750** (**2.05**)
β^{DIV_U} Portfolios	Non-directional	**0.426** (**2.27**)	**0.402** (**2.21**)
	Semi-directional	**0.477** (**2.22**)	**0.470** (**2.07**)
	Directional	**0.846** (**2.00**)	**0.839** (**2.09**)
β^{CFNAI_U} Portfolios	Non-directional	**0.362** (**2.12**)	**0.288** (**1.98**)
	Semi-directional	**0.565** (**3.06**)	**0.483** (**2.47**)
	Directional	**0.726** (**2.04**)	**0.844** (**2.31**)
β^{UNEMP_U} Portfolios	Non-directional	0.253 (1.14)	0.270 (1.40)
	Semi-directional	**0.531** (**2.14**)	**0.523** (**2.04**)
	Directional	**0.848** (**1.98**)	**0.941** (**2.05**)
β^{TERM_U} Portfolios	Non-directional	**0.369** (**2.03**)	**0.310** (**1.84**)
	Semi-directional	**0.518** (**2.62**)	**0.513** (**2.77**)
	Directional	**0.752** (**2.10**)	**0.711** (**2.12**)
β^{MKT_U} Portfolios	Non-directional	**0.349** (**2.19**)	**0.289** (**1.86**)
	Semi-directional	**0.434** (**2.20**)	**0.392** (**2.36**)
	Directional	**0.743** (**2.01**)	**0.941** (**2.97**)
β^{INF_U} Portfolios	Non-directional	0.267 (1.55)	0.230 (1.23)
	Semi-directional	**0.422** (**2.23**)	**0.377** (**2.21**)
	Directional	**0.656** (**2.19**)	**0.784** (**2.66**)
β^{TED_U} Portfolios	Non-directional	0.234 (1.38)	0.344 (1.56)
	Semi-directional	**0.478** (**2.23**)	**0.635** (**3.74**)
	Directional	**0.762** (**2.00**)	**1.066** (**4.06**)

Table 8. Canonical Correlation Analysis of Economic Uncertainty Factors and Hedge Fund Portfolio Returns

This table presents the results of the canonical correlation analysis that produces two univariate indices of economic uncertainty. The first one, Economic Uncertainty Index, is a univariate index of hedge fund-related economic uncertainy (the linear combination of economic uncertainty factors). The second one, Hedge Fund Index, is a univariate index of economic uncertainty-related hedge fund investment style portfolio returns (the linear combination of hedge fund style index returns). We use two sets of variables to construct the two univariate indices of economic uncertainty. The first set of variables are the 10 measures of economic uncertainty defined as the time-varying conditional volatility of the 10 state variables; *DEF*, *TERM*, *TED*, *RREL*, *DIV*, *MKT*, *INF*, *UNEMP*, *GDP*, and *CFNAI*. The second set of variables are the 11 hedge fund style portfolio returns. Hedge funds in TASS database have various trading strategies. The 11 hedge fund portfolios are generated based on the equal-weighted returns of individual hedge funds that belong to one of the 11 investment styles; Convertible Arbitrage, Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Long-Short Equity Hedge, Managed Futures, and Multi Strategy. The top panel reports the correlations between the 10 measures of economic uncertainty and the two univariate indices (Economic Uncertainty and Hedge Fund). The bottom panel presents the correlations between the 10 hedge fund investment style portfolios and the two univariate indices. The last row shows the maximal correlation between the Economic Uncertainty Index and the Hedge Fund Index. **, * denotes statistical significance at the 1% and 5% level, respectively.

Economic Uncertainty covariates	Correlation with Economic Uncertainty Index	Correlation with Hedge Fund Index
DEF_U	0.752**	0.506**
DIV_U	0.863**	0.580**
CFNAI_U	0.696**	0.468**
UNEMP_U	0.615**	0.413**
TERM_U	0.352**	0.236**
MKT_U	0.715**	0.481**
INF_U	0.583**	0.392**
TED_U	0.166**	0.112
GDP_U	0.345**	0.232**
RREL_U	0.208**	0.140*

Hedge Fund Index covariates	Correlation with Economic Uncertainty Index	Correlation with Hedge Fund Index
Convertible Arbitrage	0.020	0.030
Short Bias	–0.145*	–0.216**
Emerging Markets	–0.004	–0.006
Equity Market Neutral	–0.388**	–0.578**
Event Driven	–0.155*	–0.231**
Fixed Income Arbitrage	–0.127	–0.189**
Fund of Funds	–0.162*	–0.241**
Global Macro	–0.020	–0.030
Long-Short Equity Hedge	–0.070	–0.105
Managed Futures	–0.016	–0.024
Multi Strategy	–0.091	–0.135*

Correlation between Hedge Fund Index and Economic Uncertainty Index	0.672**

Figure 1. Two Univariate Indices of Economic Uncertainty

This figure presents the two univariate indices of economic uncertainty obtained from the canonical correlation analysis for the sample period January 1994 – March 2012. The first one, Economic Uncertainty Index (Panel A), is a univariate index of hedge fund-related economic uncertainy (the linear combination of economic uncertainty factors). The second one, Hedge Fund Index (Panel B), is a univariate index of economic uncertainty-related hedge fund investment style portfolio returns (the linear combination of hedge fund style index returns).

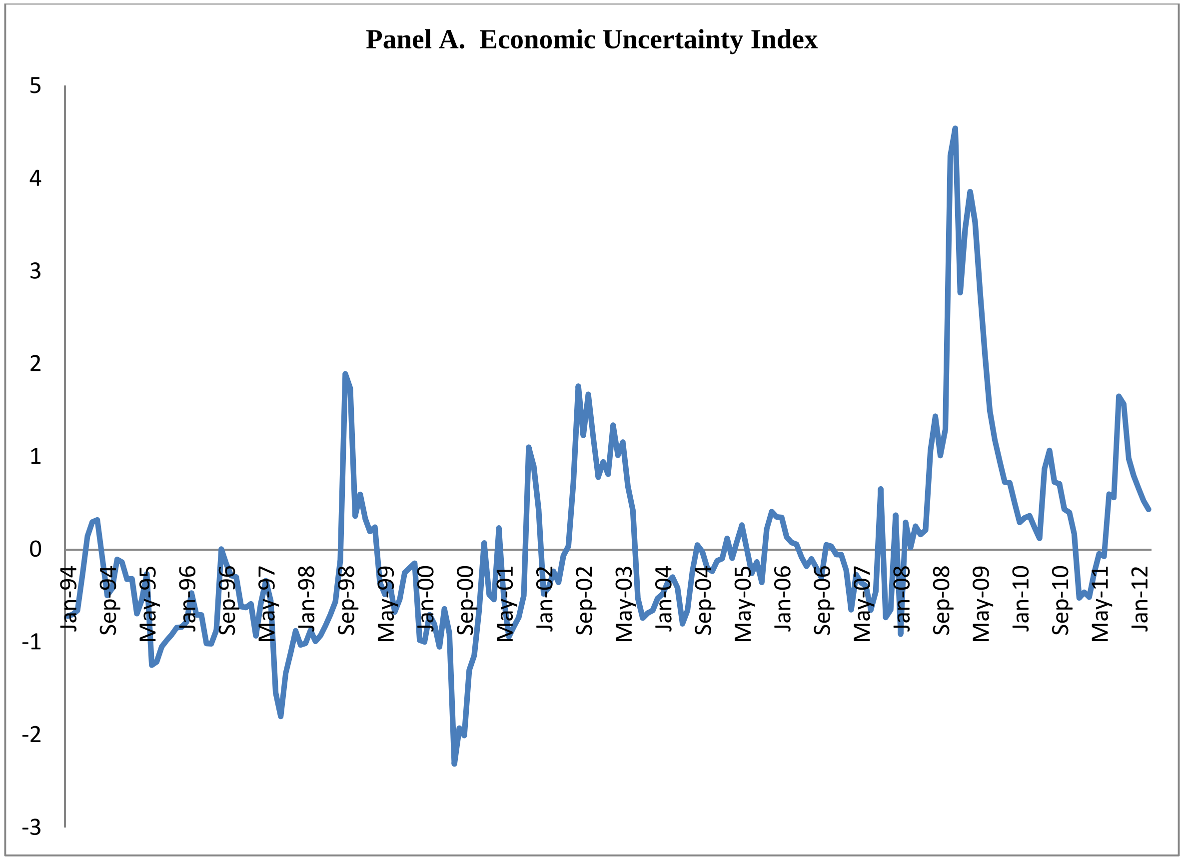
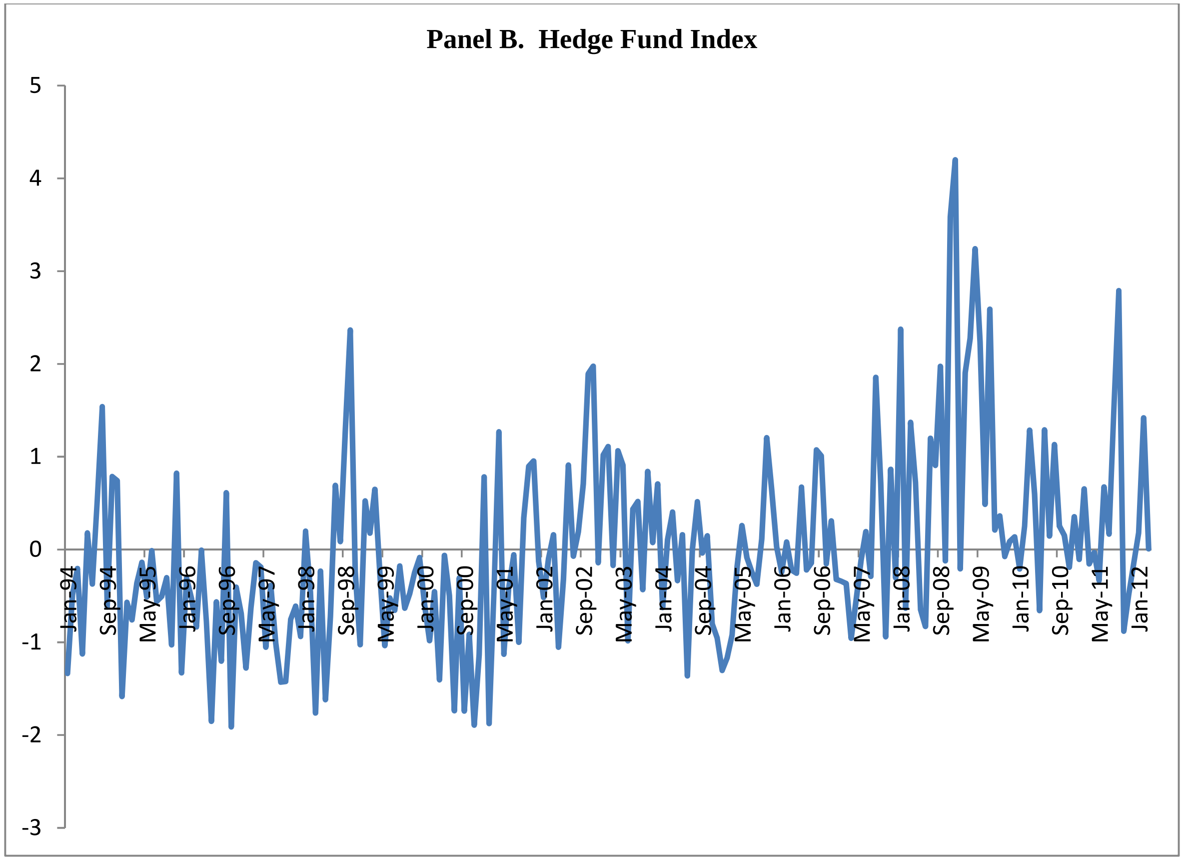


Figure 1 (continued)



Economic Uncertainty and the Cross-Section of Hedge Fund Returns

Online Appendix

To save space in the paper, we present some of our findings in the Online Appendix. Section I examines potential data biases related to our study as discussed in the hedge fund literature. Section II presents results from model-independent, nonparametric measures of economic uncertainty proxied by the degree of disagreement among the expectations of a large number of professional forecasters. Table I describes the hedge fund database, fund characteristics, and their summary statistics. Table II reports descriptive statistics of the risk factors commonly used in the hedge funds literature. Table III shows results from quintile portfolios of hedge funds sorted based on their risk factor betas. Table IV provides univariate Fama-MacBeth regression results of one-month ahead hedge fund excess returns on the uncertainty betas. Table V presents results from univariate Fama-MacBeth regressions of three-month-ahead returns on the uncertainty betas. Table VI examines the predictive power of uncertainty betas after controlling for default premium beta and inflation beta. Table VII tests the statistical significance of the differences between 9-factor alphas for directional and non-directional funds. Table VIII reports descriptive statistics of hedge fund style index returns. Table IX shows results from univariate portfolios of hedge funds sorted based on uncertainty betas generated from nonparametric measures of economic uncertainty proxied from dispersion in economic forecasts.

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I. Potential Hedge Fund Data Biases

Hedge fund studies can be subject to potential data biases. Brown, Goetzmann, Ibbotson, and Ross (1992), Fung and Hsieh (2000), Liang (2000), and Edwards and Caglayan (2001) cover these well-known data biases extensively in the hedge funds literature. 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, for the sample period January 1994 – March 2012, we do have monthly return histories of 6,729 funds in the live funds (survivor) database and 10,805 funds in the graveyard (defunct) database. We estimate that if the returns of non-surviving hedge funds (graveyard database) had been excluded from the analyses, there would have been a survivorship bias of 2.49% in average annual hedge fund returns (the difference between the annualized average return of only surviving funds in the sample and the annualized average return of all surviving and non-surviving funds in the sample).[1]

Another important data bias in a hedge fund study is called the back-fill bias. Once a hedge fund is included into a database, that fund's previous returns are automatically added to that database as well (this process is called "backfilling"). This practice in the hedge fund industry is problematic, however, because it generates an incentive only for successful hedge funds to report their initial returns to the database vendor, and as a result, it may generate an upward bias in returns of newly reporting hedge funds during their early histories. The TASS database provides information on when a hedge fund was added to the database as well as the fund's inception date. Aggarwal and Jorion (2010) measure the back-fill period as the difference between a fund's inception date and the date the fund is added to the database. They identify a fund as "non-back-filled" if the back-fill period is below 180 days. In other words, they divide the hedge fund sample into two, and hedge funds whose inception date and database entry date are in proximity are classified as non-back-filled funds, and the rest of funds in the sample (whose back-fill periods are more than 180 days) are classified as back-filled funds. Then, they calculate the average annual return difference between back-filled funds and non-back-filled funds to measure the back-fill bias. Following Aggarwal and Jorion's (2010) procedure, we identify 12,499 hedge funds as back-filled funds in our sample, and estimate a back-fill bias of 2.24% for the sample period January 1994 – March 2012.[2] Note that, in our study, the median back-fill period (i.e, the number of days between the inception date and the date the fund is added to the database) is 560 days (around 18 months) across all hedge funds. In order to check whether the back-fill bias has any significant impact on our main findings, we delete the first 18 months of returns of all individual hedge funds, and re-run our analyses on the predictability of uncertainty betas on future fund returns for this modified sample of hedge funds as well. The results from the portfolio tests and Fama-MacBeth cross-

[1] This finding is comparable to earlier studies of hedge funds. Liang (2000) reports an annual survivorship bias of 2.24% and Edwards and Caglayan (2001) report an annual survivorship bias of 1.85%.
[2] This finding is comparable to earlier studies of hedge funds. Bali, Brown, and Caglayan (2011, 2012), for example, report a back-fill bias estimate of 2.09% and 2.03%, respectively.

sectional regressions turn out to be very similar to those reported in our tables. In other words, the positive and significant link between uncertainty betas and future hedge fund returns persist after taking care of the back-fill bias.[3]

The last possible data bias in a hedge fund study is called the multi-period sampling bias. Investors generally ask for a minimum of 36 months of return history before making a decision whether to invest in a hedge fund or not. Therefore, in a hedge fund study, inclusion of hedge funds with shorter return histories than 36 months would be misleading to those investors who seek past performance data to make investment decisions. Also, a minimum 36-month return history requirement makes sense from a statistical perspective to be able to run regressions and get sensible estimates of alphas and betas for individual hedge funds in the sample. Therefore, we require that all hedge funds in the sample to have at least 36 months of return history in our study. This 36-month minimum return history requirement, however, decreases our sample size from 17,534 to 12,127 (i.e., 5,407 funds in the sample have return histories less than 36 months). There is a slight chance that we might introduce a new survivorship bias into the system due to deletion of these 5,407 hedge funds from the sample (funds that had return histories less than 36 months most probably dissolved due to bad performance). In an effort to find the impact of these deleted 5,407 hedge funds on total hedge fund performance, we compare the performance of hedge funds *before* and *after* the 36-month return history requirement and find that the annual average return of hedge funds that pass the 36-month requirement (12,127 funds) is only 0.39% higher than the annual average return of all hedge funds (17,534 funds) in the sample, a small insignificant percentage difference between the two samples in terms of survivorship bias considerations.[4]

II. Cross-Sectional Dispersion in Economic Forecasts

In this section we check whether hedge funds' exposures to alternative measures of economic uncertainty generate similar results obtained from the GARCH-based parametric measures of economic uncertainty. The Federal Reserve Bank of Philadelphia releases measures of cross-sectional dispersion in economic forecasts from the Survey of Professional Forecasters, calculating the the degree of disagreement among the expectations of different forecasters.[5] Specifically, in this section, we use the cross-sectional dispersion in quarterly forecasts for the U.S. gross domestic product (GDP), industrial production (IP), and inflation rate (INF) as alternative measures of economic uncertainty. Different from the GARCH-based parametric measures of economic uncertainty, these dispersion measures are model-independent, nonparametric measures obtained from disagreements among professional

[3] The empirical results from the modified sample of hedge funds can be obtained from the authors upon request.
[4] This figure is similar to the estimates from earlier studies. Edwards and Caglayan (2001) impose a 24-month return history requirement and find a small survivorship bias estimate of 0.32%. Fung and Hsieh (2000), on the other hand, impose a 36-month return history requirement and find the survivorship bias estimate to be 0.60%.
[5] The Survey of Professional Forecasters is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990.

forecasters. The cross-sectional dispersion measures are defined as the percent difference between the 75th percentile and the 25th percentile (the interquartile range) of the projections for the quarterly level:

$$\text{Dispersion Measure} = 100 \times \log(\text{75th Level/25th Level}) \tag{1}$$

The original data provided by the Federal Reserve Bank of Philadelphia are quarterly. We use a linear interpolation to convert the quarterly data to monthly frequency. Figure II of the online appendix presents monthly time-series plots of the cross-sectional dispersion measures for the sample period January 1994 – March 2012. A visual depiction of the cross-sectional dispersion measures in Figure II and the Economic Uncertainty Index in Figure 1, Panel A of the main text suggests that the model-independent, nonparametric measures of economic uncertainty are closely related to the GARCH-based parametric measures of economic uncertainty. The correlations between the Economic Uncertainty Index obtained from canonical analysis and the cross-sectional dispersion measures for the GDP, IP, and INF are 0.54, 0.53, and 0.64, respectively. These positive and high correlations suggest that hedge funds' exposures to the nonparametric measures of economic uncertainty may potentially capture the cross-sectional differences in hedge fund returns.

To test the cross-sectional predictive power of model-independent, nonparametric measures of economic uncertainty, we first estimate uncertainty betas for each measure of cross-sectional dispersion in economic forecasts, then we form quintile portfolios by sorting hedge funds based on their uncertainty betas. Table IX of this online appendix shows that when moving from quintile 1 to 5, there is significant cross-sectional variation in the average values of uncertainty betas (β^{GDP_F}, β^{IP_F}, and β^{INF_F}). For example, the hedge funds' average uncertainty beta for the disagreement among the expectations of different forecasters about GDP (β^{GDP_F}) increases from –11.01 to 27.12. Similar large cross-sectional spreads are observed for β^{IP_F} and β^{INF_F} as well.

Another notable point in Table IX is that when moving from quintile 1 to 5, the next-month average returns on β^{GDP_F} portfolios increase monotonically from 0.14% to 0.69% per month, generating a monthly average return difference of 0.55% between quintiles 5 and 1 with a Newey-West *t*-statistic of 2.16. When hedge funds are sorted into portfolios based on the uncertainty betas for the professional forecasters' disagreement about industrial production and inflation rate, the average return differences are 0.41% per month for β^{IP_F} (*t*-stat. = 2.07) and 0.40% per month for β^{INF_F} (*t*-stat. = 1.95).

In the paper, we present results from uncertainty measures generated with a GARCH-based parametric model. In this online appendix, we rely on nonparametric measures of economic uncertainty proxied by the degree of disagreement among the expectations of a large number of professional forecasters. Our main findings from the nonparametric measures turn out to be similar to those reported for the GARCH-based parametric measures of uncertainty. Hence, we conclude that economic uncertainty, measured in different ways, is a powerful and robust determinant of the cross-sectional differences in hegde fund returns.

References

Aggarwal, R.K., Jorion, P., 2010. The performance of emerging hedge funds and managers. Journal of Financial Economics 96, 238–256.

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

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

Brown, S.J., Goetzmann, W.N., Ibbotson, R.G., Ross, S.A., 1992. Survivorship bias in performance studies. Review of Financial Studies 5, 553–580.

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

Edwards, F.R., Caglayan, M.O., 2001. Hedge fund performance and manager skill. Journal of Futures Markets 21, 1003–1028.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., MacBeth, J.D., 1973. Risk and return: some empirical tests. Journal of Political Economy 81, 607–636.

Fung, W.H., Hsieh, D.A., 2000. Performance characteristics of hedge funds and CTA funds: natural versus spurious biases. Journal of Financial and Quantitative Analysis 35, 291–307.

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

Fung, W.H., Hsieh, D.A., 2004. Hedge fund benchmarks: a risk-based approach. Financial Analysts Journal 60, 65–80.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. Journal of Finance 48, 1779–1801.

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

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

Table I. Descriptive Statistics of Hedge Funds

There are total of 17,534 hedge funds that reported monthly returns to TASS for the years between 1994 and 2011 in this database, of which 10,805 are defunct funds and 6,729 are live funds. For each year from 1994 to 2011, 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 B reports for the sample period January 1994 – March 2012 the cross-sectional mean, median, standard deviation, minimum, and maximum statistics for hedge fund characteristics including returns, size, age, management fee, incentive fee, redemption period, and minimum investment amount.

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	853	304	21	1,136	59.3	-0.05	0.10	0.94	–1.63	1.00
1995	1,136	332	67	1,401	71.2	1.22	1.32	1.06	–0.92	2.80
1996	1,401	396	127	1,670	96.6	1.40	1.43	1.53	–1.69	3.90
1997	1,670	443	112	2,001	180.1	1.44	1.72	1.99	–1.63	4.70
1998	2,001	439	171	2,269	273.9	0.39	0.23	2.15	–4.94	3.12
1999	2,269	569	190	2,648	619.1	2.01	1.30	2.12	–0.27	6.32
2000	2,648	644	231	3,061	702.4	0.86	0.51	2.12	–1.90	5.38
2001	3,061	897	241	3,717	824.6	0.56	0.63	1.09	–1.38	2.50
2002	3,717	1,048	276	4,489	839.3	0.30	0.56	0.77	–1.16	1.35
2003	4,489	1,318	273	5,534	966.7	1.26	1.12	0.83	–0.13	3.00
2004	5,534	1,605	333	6,806	1,425.4	0.67	0.73	1.09	–1.07	2.60
2005	6,806	1,581	504	7,883	1,943.1	0.76	1.26	1.27	–1.37	1.99
2006	7,883	1,620	604	8,899	1,987.1	0.92	1.20	1.33	–1.68	3.12
2007	8,899	1,617	961	9,555	2,143.9	0.83	0.82	1.37	–1.89	2.75
2008	9,555	1,259	1,797	9,017	1,943.2	-1.40	-1.53	2.35	–5.60	1.69
2009	9,017	1,237	1,707	8,547	1,840.0	1.10	0.92	1.10	–0.51	3.46
2010	8,547	863	1,265	8,145	1,556.1	0.61	0.65	1.34	–2.28	2.31
2011	8,145	443	1,545	7,043	1,405.1	-0.37	-0.23	1.18	–2.36	1.28

Table I (continued)

Panel B. Cross-Sectional Statistics of Hedge Fund Characteristics: January 1994 – March 2012

	N	Mean	Median	Std. Dev.	Minimum	Maximum
Average Monthly Return over the life of the Fund (%)	17,534	0.40	0.40	1.22	–39.50	47.68
Average Monthly AUM over the life of the Fund (million $)	17,534	149.0	40.0	1,747.2	0.5	92,165.0
Age of the Fund (# of months in existence)	17,534	63.9	54.0	45.0	1.0	219.0
Management Fee (%)	17,304	1.46	1.50	0.71	0.00	10.00
Incentive Fee (%)	16,451	13.83	20.00	8.42	0.00	50.00
Redemption Period (# of days)	17,534	30.93	30.03	33.12	0.00	365.0
Minimum Investment Amount (million $)	17,408	3.52	0.15	95.97	0.00	5,000.0

Table II. Descriptive Statistics of the Risk Factors

Panel A reports the time-series mean, median, standard deviation, minimum, and maximum monthly percentage returns of the 11 risk factors for the sample period January 1994 – March 2012. MKT is the excess return on the value-weighted NYSE/AMEX/NASDAQ (CRSP) market index; SMB is the Fama-French (1993) size factor; HML is the Fama-French (1993) book-to-market factor; MOM is the Carhart (1997) momentum factor; Δ10Y is the Fung and Hsieh (2004) long-term interest rate factor defined as the monthly change in the 10-year constant maturity Treasury yields; ΔCrdSpr is the Fung and Hsieh (2004) credit risk factor defined as the monthly change in the difference between BAA-rated corporate bond yields and 10-year constant maturity Treasury yields; BDTF is the Fung-Hsieh (2001) bond trend-following factor measured as the return of PTFS Bond Lookback Straddle; FXTF is the Fung-Hsieh (2001) currency trend-following factor measured as the return of PTFS Currency Lookback Straddle; CMTF is the Fung-Hsieh (2001) commodity trend-following factor measured as the return of PTFS Commodity Lookback Straddle; IRTF is the Fung-Hsieh (2001) short-term interest rate trend-following factor measured as the return of PTFS Short Term Interest Rate Lookback Straddle; SKTF is the Fung-Hsieh (2001) stock index trend-following factor measured as the return of PTFS Stock Index Lookback Straddle. Panel B presents the correlation matrix for the 11 risk factors given in Panel A.

Panel A. Risk Factors: January 1994 – March 2012

	N	Mean	Median	Std. Dev.	Minimum	Maximum
MKT: Excess return on the value-weighted market index	219	0.53	1.24	4.70	–18.55	11.53
SMB: Fama-French size factor	219	0.21	–0.15	3.58	–16.62	22.06
HML: Fama-French book-to-market factor	219	0.22	0.21	3.40	–12.87	13.88
MOM: Carhart momentum factor	219	0.45	0.66	5.50	–34.75	18.40
Δ**10Y**: Fung-Hsieh long-term interest rate factor	219	–0.02	–0.04	0.24	–1.11	0.65
Δ**CrdSpr**: Fung-Hsieh credit spread factor	219	0.01	–0.01	0.20	–0.99	1.45
BDTF: Fung-Hsieh bond trend-following factor	219	–1.42	–5.04	15.07	–25.36	68.86
FXTF: Fung-Hsieh currency trend-following factor	219	–0.40	–4.64	19.19	–30.13	90.27
CMTF: Fung-Hsieh commodity trend-following factor	219	–0.51	–3.01	13.85	–23.04	64.75
IRTF: Fung-Hsieh short-term interest rate trend-following factor	219	1.72	–4.48	27.80	–34.64	221.92
SKTF: Fung-Hsieh stock index trend-following factor	219	–5.07	–6.51	12.93	–30.19	46.15

Table II (continued)

Panel B. Correlation Matrix of the Risk Factors: January 1994 – March 2012

	MKT	SMB	HML	MOM	Δ10Y	ΔCRDSPR	BDTF	FXTF	CMTF	IRTF	SKTF
MKT	1.000										
SMB	0.250	1.000									
HML	–0.232	–0.363	1.000								
MOM	–0.277	0.087	–0.151	1.000							
Δ10Y	0.094	0.088	–0.033	–0.075	1.000						
ΔCRDSPR	–0.310	–0.207	–0.017	0.136	–0.518	1.000					
BDTF	–0.238	–0.086	–0.058	–0.011	–0.184	0.182	1.000				
FXTF	–0.193	–0.017	0.017	0.117	–0.178	0.270	0.235	1.000			
CMTF	–0.167	–0.052	–0.026	0.210	–0.117	0.185	0.207	0.394	1.000		
IRTF	–0.298	–0.105	–0.006	–0.005	–0.175	0.395	0.198	0.306	0.297	1.000	
SKTF	–0.216	–0.117	0.093	0.018	–0.250	0.274	0.195	0.234	0.142	0.306	1.000

Table III. Univariate Portfolios of the Risk Factor Betas

Quintile portfolios are formed every month from January 1997 to March 2012 by sorting hedge funds based on their risk factor betas. Quintile 1 is the portfolio of hedge funds with the lowest risk factor betas, and quintile 5 is the portfolio of hedge funds with the highest risk factor betas. In each column, the table reports the average risk factor betas in each quintile as well as all quintiles' next month average returns. The last two rows show the average monthly raw return differences and the 9-factor Alpha differences between quintile 5 and 1uintile 1. Average returns and Alphas are defined in monthly percentage terms. Newey-West (1987) adjusted *t*-statistics are given in parentheses.

	Average Size of β^{MKT}	Average Size of β^{SMB}	Average Size of β^{HML}	Average Size of β^{MOM}	Average Size of $\beta^{\Delta 10Y}$	Average Size of $\beta^{\Delta CrdSp}$	Average Size of β^{BDTF}	Average Size of β^{FXTF}	Average Size of β^{CMTF}	Average Size of β^{IRTF}	Average Size of β^{SKTF}
Q1	–0.168	–0.214	–0.606	–0.292	–4.036	–14.038	–0.104	–0.068	–0.087	–0.080	–0.116
Q2	0.084	0.035	–0.181	–0.043	–0.474	–5.140	–0.037	–0.021	–0.024	–0.032	–0.035
Q3	0.206	0.130	–0.042	0.026	0.651	–2.353	–0.017	–0.006	–0.004	–0.016	–0.010
Q4	0.381	0.265	0.059	0.097	1.768	–0.061	0.004	0.009	0.015	–0.005	0.013
Q5	0.904	0.719	0.411	0.344	5.683	5.819	0.079	0.067	0.097	0.030	0.084
	Next-month returns of β^{MKT} Quintiles	Next-month returns of β^{SMB} Quintiles	Next-month returns of β^{HML} Quintiles	Next-month returns of β^{MOM} Quintiles	Next-month returns of $\beta^{\Delta 10Y}$ Quintiles	Next-month returns of $\beta^{\Delta CrdSp}$ Quintiles	Next-month returns of β^{BDTF} Quintiles	Next-month returns of β^{FXTF} Quintiles	Next-month returns of β^{CMTF} Quintiles	Next-month returns of β^{IRTF} Quintiles	Next-month returns of β^{SKTF} Quintiles
Q1	0.288	0.225	0.334	0.550	0.483	0.397	0.414	0.464	0.571	0.470	0.511
Q2	0.260	0.304	0.299	0.379	0.340	0.264	0.356	0.305	0.347	0.355	0.286
Q3	0.260	0.276	0.255	0.226	0.284	0.251	0.277	0.243	0.249	0.276	0.292
Q4	0.356	0.341	0.295	0.220	0.257	0.355	0.308	0.322	0.229	0.294	0.339
Q5	0.528	0.545	0.508	0.317	0.328	0.424	0.337	0.357	0.295	0.297	0.264
Q5 – Q1 Return Diff.	0.240 (0.58)	0.320 (0.95)	0.174 (0.48)	–0.233 (–1.05)	–0.155 (–0.59)	0.027 (0.08)	–0.077 (–0.25)	–0.106 (–0.39)	–0.275 (–1.15)	–0.172 (–0.49)	–0.247 (–0.82)
Q5 – Q1 9-factor Alpha Diff.	–0.054 (–0.32)	0.068 (0.35)	0.258 (0.70)	0.134 (0.62)	–0.294 (–1.42)	0.327 (1.43)	0.105 (0.37)	0.198 (1.13)	0.059 (0.31)	0.084 (0.45)	–0.122 (–0.30)

Table IV. Univariate Fama-MacBeth Cross-Sectional Regressions of One-month-ahead Hedge Fund Returns on the Uncertainty Betas

This table reports the average intercept and average slope coefficients from the Fama-MacBeth (1973) cross-sectional regressions of one-month-ahead hedge fund excess returns on the uncertainty betas. The cross-section of one-month-ahead funds' excess returns are regressed on the funds' uncertainty betas each month for the period January 1997–March 2012. 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^{DEF_U}	β^{DIV_U}	β^{CFNAI_U}	β^{UNEMP_U}	β^{TERM_U}	β^{MKT_U}	β^{INF_U}	β^{TED_U}	β^{GDP_U}	β^{RREL_U}
0.3659	**0.0185**									
(2.93)	**(3.03)**									
0.3443		**0.0080**								
(2.74)		**(2.88)**								
0.3570			**0.0158**							
(2.82)			**(3.09)**							
0.4134				**0.0116**						
(3.47)				**(2.97)**						
0.3892					**0.0209**					
(3.12)					**(3.00)**					
0.3865						**0.1705**				
(3.00)						**(1.96)**				
0.3362							**0.0148**			
(2.38)							**(3.57)**			
0.3200								**0.0581**		
(2.53)								**(2.98)**		
0.3463									0.0045	
(3.20)									(1.49)	
0.3095										0.0186
(2.54)										(1.24)

Table V. Three-month-ahead Predictive Power of the Uncertainty Betas over Hedge Fund Returns Using Fama-MacBeth Cross-Sectional Regressions

This appendix reports the average intercept and average slope coefficients from the Fama-MacBeth (1973) cross-sectional regressions of three-month-ahead hedge fund excess returns on the current month uncertainty betas. The cross-section of three-month-ahead funds' excess returns are regressed on the funds' current month uncertainty betas each month for the period January 1997–March 2012. 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^{DEF_U}	β^{DIV_U}	β^{CFNAI_U}	β^{UNEMP_U}	β^{TERM_U}	β^{MKT_U}	β^{INF_U}	β^{TED_U}	β^{GDP_U}	β^{RREL_U}
1.1567 (3.25)	**0.0335** **(2.19)**									
1.0414 (2.87)		**0.0141** **(2.17)**								
1.0533 (2.88)			**0.0278** **(2.12)**							
1.2662 (3.64)				**0.0194** **(2.02)**						
1.1294 (3.22)					**0.0404** **(2.28)**					
1.1771 (3.22)						**0.3942** **(1.99)**				
1.0861 (2.84)							**0.0250** **(1.98)**			
1.0175 (2.97)								**0.1082** **(2.03)**		
1.0371 (3.32)									0.0084 (1.14)	
0.9978 (2.90)										0.0427 (1.21)

Table VI. Predictive Power of Uncertainty Betas after Controlling for DEF_Beta and INF_Beta

This appendix reports the average intercept and average slope coefficients from the Fama-MacBeth (1973) cross-sectional regressions of one-month-ahead hedge fund excess returns on the uncertainty betas with DEF_Beta and INF_Beta. The cross-section of one-month-ahead funds' excess returns are regressed on the funds' uncertainty betas as well as DEF and INF_Betas each month for the period January 1997–March 2012. 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^{DEF}	β^{IINF}	β^{DEF_U}	β^{DIV_U}	β^{CFNAI_U}	β^{UNEMP_U}	β^{TERM_U}	β^{MKT_U}	β^{INF_U}	β^{TED_U}
0.3125	**0.0538**	**–0.0539**	**0.0270**							
(3.02)	**(1.85)**	**(–2.29)**	**(2.15)**							
0.2914	**0.0650**	**–0.0581**		**0.0219**						
(2.88)	**(2.03)**	**(–2.11)**		**(2.03)**						
0.3022	**0.0657**	**–0.0510**			**0.0215**					
(3.07)	**(1.99)**	**(–1.98)**			**(2.11)**					
0.3473	**0.0511**	**–0.0473**				**0.0121**				
(3.41)	**(2.08)**	**(–1.97)**				**(2.40)**				
0.3437	**0.0699**	**–0.0632**					**0.0117**			
(3.32)	**(2.01)**	**(–1.92)**					**(2.31)**			
0.3213	**0.0575**	**–0.0567**						**0.2234**		
(3.05)	**(2.23)**	**(–2.12)**						**(1.91)**		
0.3186	**0.0583**	**–0.0541**							**0.0230**	
(3.12)	**(1.97)**	**(–2.02)**							**(2.06)**	
0.3226	**0.0681**	**–0.0584**								**0.0598**
(3.05)	**(1.92)**	**(–2.00)**								**(2.27)**

Table VII. Statistical Significance of the Differences between 9-factor Alphas for Directional and Non-directional Hedge Funds

For non-directional, semi-directional, and directional hedge funds, univariate quintile portfolios are formed in the paper by sorting hedge funds based on their uncertainty betas. Table 7 in the paper shows that the 9-factor alphas between quintiles 5 and 1 are larger (economically more significant) for directional funds compared to non-directional funds. This table tests the statistical significance of the differences between 9-factor alphas for directional and non-directional funds. Newey-West *t*-statistics are given in parantheses. Numbers in bold denote statistical significance.

	Differences between 9-Factor alphas for directional and non-directional funds
β^{DEF_U} Portfolios	0.244 (0.78)
β^{DIV_U} Portfolios	0.437 (0.56)
β^{CFNAI_U} Portfolios	**0.555** **(2.02)**
β^{UNEMP_U} Portfolios	**0.671** **(2.11)**
β^{TERM_U} Portfolios	0.401 (1.38)
β^{MKT_U} Portfolios	**0.652** **(2.38)**
β^{INF_U} Portfolios	**0.554** **(1.96)**
β^{TED_U} Portfolios	**0.722** **(3.04)**

Table VIII. Descriptive Statistics of Hedge Fund Investment Style Portfolio Returns

Hedge funds in TASS database have various trading strategies. We generate 11 hedge fund portfolios based on the equal-weighted returns of individual hedge funds that belong to one of the 11 investment styles; Convertible Arbitrage, Short Bias, Emerging Markets, Equity Market Neutral, Event Driven, Fixed Income Arbitrage, Fund of Funds, Global Macro, Long-Short Equity Hedge, Managed Futures, and Multi Strategy. This appendix presents the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted hedge fund portfolios for the sample period January 1994 to March 2012. The last column reports the number of hedge funds in each investment style.

Investment Style	Mean	Median	Stdev	Minimum	Maximum	# of Hedge Funds
Convertible Arbitrage	0.65	0.87	2.17	–17.46	8.41	199
Short Bias	0.24	–0.14	4.06	–9.69	22.09	46
Emerging Markets	1.00	1.51	4.25	–21.97	14.30	684
Equity Market Neutral	0.71	0.71	0.91	–4.54	2.54	429
Event Driven	0.82	1.18	1.63	–7.65	4.21	570
Fixed Income Arbitrage	0.69	0.85	1.13	–7.15	2.83	293
Fund of Funds	0.49	0.56	1.54	–5.52	5.65	4,587
Global Macro	0.73	0.74	1.61	–3.72	6.32	397
Long-Short Equity Hedge	1.01	1.10	2.52	–8.43	10.19	2,658
Managed Futures	0.76	0.55	2.61	–5.10	7.46	738
Multi Strategy	0.87	0.90	1.18	–4.40	4.16	1,224

Table IX. Univariate Portfolios of Uncertainty Betas derived from the Cross-Sectional Dispersion in Economic Forecasts

Quintile portfolios are formed every month from January 1997 to March 2012 by sorting hedge funds based on their uncertainty betas derived from the cross-sectional dispersion in economic forecasts. We use measures of cross-sectional dispersion for quarterly forecasts for the U.S. gross domestic product (GDP), industrial production (IP), and inflation rate (INF). These measures are the percent difference between the 75th percentile and the 25th percentile (the interquartile range) of the projections for the quarterly level. Quintile 1 is the portfolio of hedge funds with the lowest uncertainty betas, and quintile 5 is the portfolio of hedge funds with the highest uncertainty betas. In each column, the table reports the average uncertainty betas (β^{GDP_F}, β^{IP_F}, β^{INF_F}) in each quintile as well as all quintiles' next month average returns. The last row shows the monthly average raw return differences between quintile 5 and 1. Newey-West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance.

	Average Size of β^{GDP_F}	Average Size of β^{IP_F}	Average Size of β^{INF_F}
Q1	–11.009	–7.191	–18.773
Q2	0.089	–2.353	–4.564
Q3	3.978	–0.709	0.047
Q4	9.062	0.875	5.578
Q5	27.124	6.123	23.404
	Next-month returns of β^{GDP_F} Quintiles	**Next-month returns of β^{IP_F} Quintiles**	**Next-month returns of β^{INF_F} Quintiles**
Q1	0.141	0.162	0.192
Q2	0.207	0.300	0.284
Q3	0.274	0.297	0.282
Q4	0.382	0.360	0.344
Q5	0.688	0.572	0.589
Q5 – Q1 Return Diff.	**0.547** **(2.16)**	**0.411** **(2.07)**	**0.396** **(1.95)**

Figure I. Alternative Measures of Economic Uncertainty

This figure presents alternative measures of economic uncertainty for the sample period January 1994 – March 2012. Economic uncertainty measures are defined as the time-varying conditional volatility of the state variables; *DEF*, *TERM*, *TED*, *RREL*, *DIV*, *MKT*, *INF*, *UNEMP*, *GDP*, and *CFNAI*. As presented in eqs. (1)-(2), they are estimated using the Threshold GARCH model of Glosten et al. (1993) with an AR(1) process.

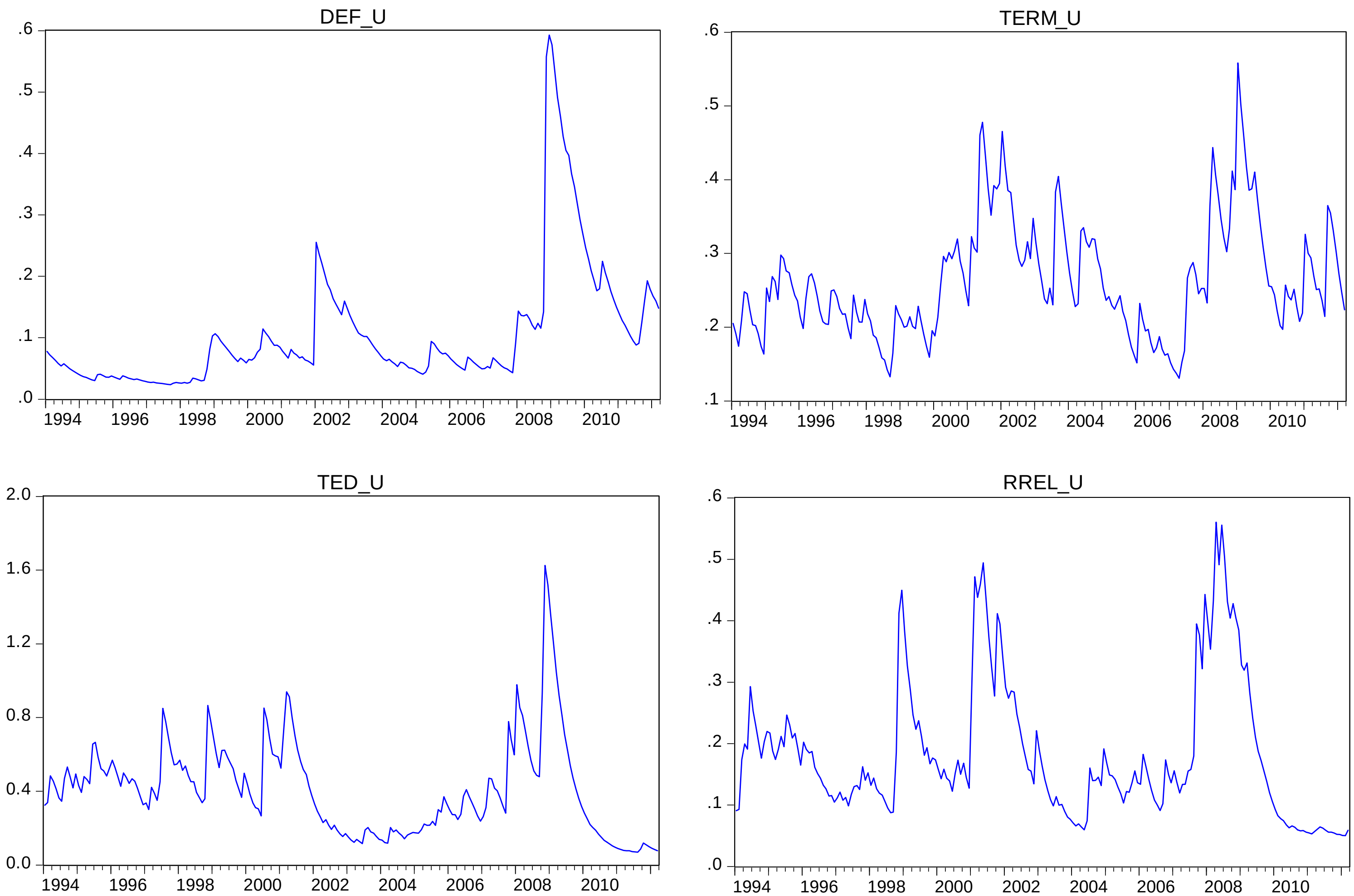

Figure I (continued)

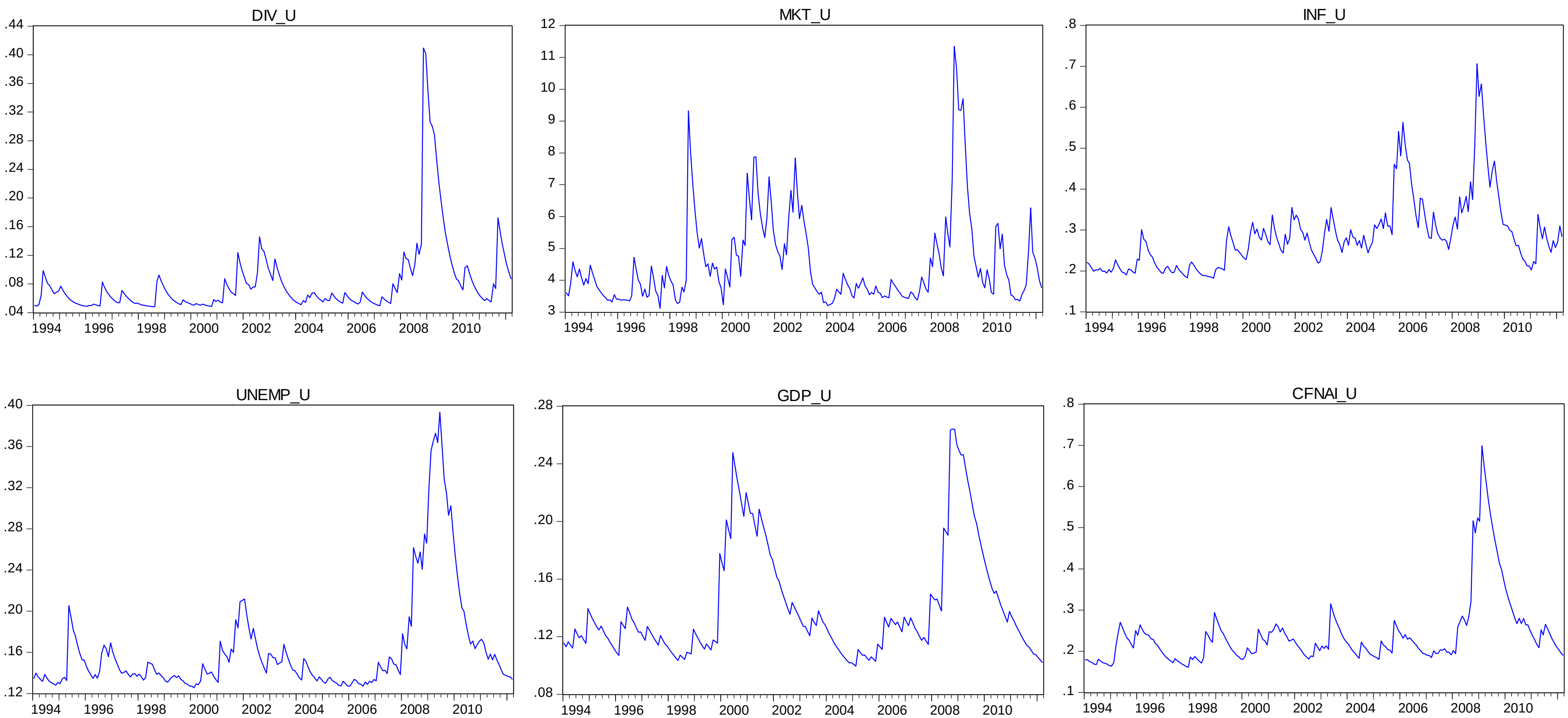

Figure II. The Cross-Sectional Dispersion in Economic Forecasts

This figure presents measures of cross-sectional dispersion for quarterly forecasts for the U.S. gross domestic product (GDP), industrial production (IP), and inflation rate (INF). These measures are the percent difference between the 75th percentile and the 25th percentile (the interquartile range) of the projections for the quarterly level: Dispersion Measure = $100 \times \log$(75th Level/25th Level). The original data provided by the Federal Reserve Bank of Philadelphia are quarterly. We use a linear interpolation to convert the quarterly data on the cross-sectional dispersion measures to monthly frequency. The sample period is from January 1994 to March 2012.