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Macroeconomic risk and hedge fund returns ☆

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This paper estimates hedge fund and mutual fund exposure to newly proposed measures of macroeconomic risk that are interpreted as measures of economic uncertainty. We find that the resulting uncertainty betas explain a significant proportion of the cross-sectional dispersion in hedge fund returns. However, the same is not true for mutual funds, for which there is no significant relationship. After controlling for a large set of fund characteristics and risk factors, the positive relation between uncertainty betas and future hedge fund returns remains economically and statistically significant. Hence, we argue that macroeconomic risk is a powerful determinant of cross-sectional differences in hedge fund returns.

1. Introduction

It is widely accepted that unexpected changes in macroeconomic variables can generate global impacts on firm fundamentals, such as cash flows, risk-adjusted discount factors, and investment opportunities. There are several channels by which macroeconomic fundamentals such as inflation, short-term and long-term interest rates, unemployment, and economic growth have significant impact on prices of risky assets such as stocks, bonds, currencies, and their derivatives. To the extent that hedge funds aggressively pursue opportunities arising from changing economic circumstances, we would expect that their performance from investments in these financial securities are influenced by the extent to which they vary their exposure to leading economic indicators.

We argue that these changes can be regarded as a source of macroeconomic risk that is interpreted as economic uncertainty. We quantify this risk using the

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time-varying conditional volatility of macroeconomic variables associated with business cycle fluctuations. This paper attempts to determine the extent to which exposure to this source of risk explains cross-sectional dispersion of hedge fund returns. We find that exposure to macroeconomic risk is a more powerful determinant than is the exposure to financial risk commonly used to explain hedge fund returns.

The macroeconomic variables we consider include default spread, term spread, short-term interest rate changes, aggregate dividend yield, equity market index, inflation rate, unemployment rate, and the growth rate of real Gross Domestic Product (GDP) per capita. Alternative measures of macroeconomic risk are generated by estimating time-varying conditional volatility of the aforementioned economic indicators based on a Vector Autoregressive–Generalized Autoregressive Conditional Heteroskedasticity (VAR–GARCH) model, which allows for asymmetric response of volatility to changes in economic circumstances, and accounts for serial correlation and cross-correlations among the macroeconomic factors. For each fund, we estimate time-varying uncertainty betas via a 36-month rolling regression of excess returns on the measures of macroeconomic risk. Finally, we examine the performance of these uncertainty betas in predicting cross-sectional variation in future fund returns.

Both portfolio-level analyses and cross-sectional regressions indicate a positive and significant link between these uncertainty betas and future hedge fund returns. Quintile portfolios are formed each 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 exposures to macroeconomic risk factors explain the cross-sectional dispersion in hedge fund returns. Depending on the proxy for macroeconomic risk, hedge funds in the highest uncertainty beta quintile generate 6% to 9% higher average annual returns than do funds in the lowest uncertainty beta quintile. After controlling for the Fama-French (1993) and Carhart (1997) four factors of market, size, book-to-market, and momentum, and the five Fung-Hsieh (2001) trend-following factors of stocks, short-term interest rates, currencies, bonds, and commodities, the positive relation between uncertainty betas and risk-adjusted returns (nine-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.

In addition to individual measures of macroeconomic risk, we use a statistical approach to develop a broad index of macroeconomic risk. To sufficiently capture the common variation among the correlated factors of economic uncertainty, we use the principal component analysis that uses orthogonal transformation to convert a set of highly correlated economic indicators into a set of linearly uncorrelated variables called principal components. After building the broad index of macroeconomic risk, we test its 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 uncertainty index beta quintile generate 0.80% to 0.90% higher monthly returns and alphas than do funds in the lowest uncertainty index beta quintile. Overall, the significant predictive relation between fund returns and the newly proposed measure of macroeconomic risk validates our measure as a descriptive quantitative indicator of economic uncertainty.

A natural question is, why do hedge funds with higher exposure to macroeconomic risk generate higher returns? Is there a theoretical framework supporting this finding? The positive relation between uncertainty betas and expected returns is justified in the Merton (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. 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 covariance of portfolio returns with state variables, which affects future investment opportunities.

There is substantial evidence that macroeconomic risk 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 macroeconomic shocks to aggregate output, employment, and investment dynamics. Chen (2010) introduces a model that shows how business cycle variation in economic uncertainty and risk premiums influence firm financing decisions. The Chen model also shows that countercyclical fluctuation in risk prices arises through firm response to macroeconomic conditions. Stock and Watson (2012) find that the decline in aggregate output and employment during the 2008 crisis period are driven by financial and macroeconomic shocks. Allen, Bali, and Tang (2012) show that downside risk in the financial sector predicts future economic downturns, linking economic uncertainty to a future investment opportunity set. Hence, our finding that individual hedge funds that have greater exposure to macroeconomic risk earn commensurately higher returns than other funds is consistent with the ICAPM of Merton (1973), which suggests that such exposure should be rewarded.

Hedge funds use a wide variety of dynamic trading strategies, and make extensive use of derivatives, short-selling, and leverage. The elements that contribute to a hedge fund's strategy include the fund's approach to the particular financial sector that the fund specializes in, the specific 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 fund 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; Mankiw, Reis, and Wolfers, 2004). Hence, macroeconomic risk plays a critical role in generating cross-sectional differences in fund managers' expectations about the level and volatility of economic indicators.

In fact, many hedge fund managers actively vary their exposure 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 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 macroeconomic risk, and hence there exists a positive and strong link between their uncertainty betas and future returns. However, the cross-sectional relation between uncertainty betas and future returns is relatively weaker for funds that follow non-directional strategies. These results are also supported by our finding that time-series variations in uncertainty betas are much higher for directional funds compared to non-directional funds.[3]

We provide an explanation for the superior performance of directional and semi-directional hedge funds by replicating our main analyses for the mutual fund industry as well. We first investigate whether mutual fund exposure to macroeconomic risk factors predicts their future returns. Then, we analyze whether mutual funds have the ability to time macroeconomic changes. Since mutual funds do not use dynamic trading strategies and tend to invest primarily on the long side without extensively using other tools (e.g., options, leverage, and short-selling), the results provide no evidence for a significant link between mutual fund exposure to macroeconomic risk and their future returns. We also show that while directional and semi-directional hedge fund managers have the ability to time macroeconomic changes by increasing (decreasing) portfolio exposure to macroeconomic risk factors when macroeconomic uncertainty is high (low), mutual funds, as in the case of non-directional hedge funds, do not have significant macro-timing ability.

This paper proceeds as follows. Section 2 provides a literature review. Section 3 describes the data and variables. Section 4 presents a conditional asset pricing model with macroeconomic risk. Section 5 discusses the empirical results and provides a battery of robustness checks. Section 6 examines the predictive power of uncertainty betas for directional, semi-directional, and non-directional hedge funds as well as for mutual funds, and sets forth macro-timing tests for both hedge funds and mutual funds. Section 7 concludes the paper.

2. Literature review

The literature examining the risk-return characteristics of hedge funds has evolved considerably, especially in recent years.[4] 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% higher 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 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 in 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 (2013) investigate how hedge funds manage their liquidity risk by responding to aggregate liquidity shocks. Their results indicate that hedge fund managers have the ability to time liquidity by increasing portfolio market exposure when equity market liquidity is high. Patton and Ramadorai (2013) introduce a new econometric methodology, using high-frequency data, to capture time-series variation in hedge fund exposure to risk factors, and find that hedge fund risk exposure varies significantly across months. Sun, Wang, and Zheng (2012) 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 exactly known, whereas there is uncertainty about mean returns. In this model, asset returns are uncertain only because mean returns are not known, and investor uncertainty in mean returns is defined as the dispersion of predictions of mean market returns obtained from 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 uncertainty and changes in risk aversion in the determination of equity prices. Distinct from the uncertainty that arises from

[3] Cao, Chen, Liang, and Lo (2013) show that hedge fund managers have the ability to time aggregate liquidity by increasing their portfolios' market exposure when equity market liquidity is high. In this paper, we test macro-timing ability of hedge funds and mutual funds, so this particular analysis can be viewed as a generalization of the Cao, Chen, Liang, and Lo (2013) results using a broader set of newly proposed macroeconomic risk factors.

[4] 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, Hsieh, Naik, and Ramadorai (2008), Patton (2009), Jagannathan, Malakhov, and Novikov (2010), Aggarwal and Jorion (2010), and Brown, Gregoriou, and Pascalau (2012).

disagreement among professional forecasters, Bekaert, Engstrom, and Xing (2009) focus on economic uncertainty proxied by 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.

In contrast to Anderson, Ghysels, and Juergens (2009) and Bekaert, Engstrom, and Xing (2009), we use time-varying conditional volatility of eight different economic indicators (generated from the Multivariate Asymmetric VAR–GARCH model) as proxies for macroeconomic risk. More importantly, however, instead of looking at the direct link between economic uncertainty and future returns on equity, our focus is on the significance of *uncertainty beta* in predicting the cross-sectional variation in future returns of individual hedge funds and mutual 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 standard risk factors. Third, we explain how we generate alternative measures of macroeconomic risk and present their summary statistics and the correlation matrix. Finally, we introduce an economic uncertainty index obtained from the principal component analysis.

3.1. Hedge fund database

This study uses monthly hedge fund data from the Lipper TASS (Trading Advisor Selection System) database. In the database, originally we have information on a total of 17,534 defunct and live hedge funds. However, among these 17,534 funds, there are many funds that are listed multiple times in the TASS database as these funds report returns in different currencies, such as USD, Euro, Sterling, and Swiss Franc. These funds are essentially not separate funds, but just one fund with returns reported on a currency converted basis. In addition, typically a hedge fund has an off-shore fund and an on-shore fund, following the exact same strategy. Therefore, naturally, for all these funds their returns are highly correlated. However, the TASS database assigns a separate fund reference number to each on-shore and off-shore fund, and to each of the funds reporting in different currencies, treating these funds as separate individual funds. In order to distinguish between different share classes (of the same fund) and other actual funds, and not to use any duplicated funds (and hence returns) in our analyses, we first omit all non-USD-based hedge funds from our sample. That is, we keep in our database only the hedge funds reporting their returns in USD. Next, if a hedge fund has both an off-shore fund and an on-shore fund with multiple share classes, we keep the fund with the longest return history in our database and remove all the other share classes of that particular fund from our sample. This way, we make sure that each hedge fund is represented only once in our database. After removing all non-USD-based hedge funds and multiple share classes, we observe that our actual sample size of hedge funds is 10,305. That is, our database, during our sample period January 1994–March 2012, contains information on a total of 10,305 distinct, non-duplicated hedge funds, of which 7,166 are defunct funds and the remaining 3,139 are live funds.

The TASS database, in addition to reporting monthly returns (net of fees) and monthly assets under management, also provides information on certain fund characteristics, including management fees, incentive fees, redemption periods, minimum investment amounts, and lockup and leverage provisions.

Table I of the online appendix provides summary statistics on hedge fund numbers, returns, assets under management (AUM), and fee structures for the sample of 10,305 hedge funds.[5] For each year, Panel A of Table I reports number of funds entering the database, number of funds dissolved, total AUM at the end of each year (in $ billion), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted hedge fund portfolio. One important characteristic about TASS is that it includes no defunct funds from 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 AUM since the end of 2007, the starting point of the recent worldwide financial crisis. The AUM in our database increased exponentially from a small $55 billion in 1994 to $928 billion in 2007, and the number of operating hedge funds increased almost seven times to 5,179 in December 2007 from 786 in January 1994. However, both these figures reversed course beginning in 2008 with the start of the financial crisis; the number of operating hedge funds fell by more than one-third, to below 3,300, while total AUM dropped by almost half, to $509 billion by the end of December 2011. In addition, the yearly attrition rates in Panel A of Table I (ratio of the number of dissolved funds to the total number of funds at the beginning of the year) paints a similar picture: from 1994 to 2007, on average, the annual attrition rate in the database was only 8.2%; between 2008 and 2011, however, this annual figure increased by almost 2.5 times to 19.6%. These statistics simply reflect the severity of the financial crisis of the past few years. In 2008 and 2011 alone, for example, hedge funds on average lost 1.56% and 0.51% (return) per month, respectively.

Panel B of Table I in the online appendix reports the cross-sectional mean, median, standard deviation, minimum, and maximum values for certain hedge fund characteristics for the sample period January 1994–March 2012. One interesting point evident in Panel B is the short lifespan of hedge funds. The median age (number of months in existence since inception) is only 56 months, a little over four-and-a-half years. This short lifespan is mostly due to the fact that hedge fund managers must first cover all losses from previous years before getting paid in

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

the current year. This forces hedge fund managers to dissolve quickly and form new hedge funds after a bad year, instead of trying to cover losses in subsequent years. Another remarkable observation that can be detected from this panel is the large size disparity seen among hedge funds. When we measure fund size as average monthly AUM over the life of the fund, we see that the mean hedge fund size is $89 million, while the median hedge fund size is only $40 million. This suggests that there are a few hedge funds with very large AUM in our database, which reflects true hedge fund industry conditions.

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

3.2. Standard risk factors

In our empirical analysis, we first utilize the standard risk factors commonly used in the hedge fund literature: (1) *MKT*: excess return on the value-weighted NYSE/Amex/Nasdaq Center for Research in Security Prices (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) $\Delta 10Y$: Fung and Hsieh (2004) long-term interest rate factor, defined as the monthly change in ten-year, constant-maturity Treasury yields; (6) $\Delta CrdSpr$: Fung and Hsieh (2004) credit risk factor, defined as the monthly change in the difference between BAA-rated corporate bond yields and ten-year constant-maturity Treasury yields; (7) *BDTF*: Fung-Hsieh (2001) bond trend-following factor measured as the return of Primitive Trend-Following Strategy (PTFS) 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.[6]

Panel A of Table II in the online appendix reports the time-series mean, median, standard deviation, minimum, and maximum monthly percentage returns of the 11 risk factors (identified from the hedge fund literature) for the full sample period, January 1994–March 2012. Panel B of Table II presents the correlation matrix of the same 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 ten factors, only *SMB* and $\Delta 10Y$ are positively correlated with *MKT*; they are 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. Macroeconomic risk factors

In this section, we first generate a list of state variables that potentially affect investor consumption and investment opportunities. The state variables utilized in this study are the financial and economic indicators widely used in the literature: (1) *DEF*: default spread measured as the difference between yields on BAA-rated and AAA-rated corporate bonds; (2) *DIV*: aggregate dividend yield on the Standard & Poor's (S&P) 500 Index; (3) *GDP*: U.S. monthly growth rate of real GDP per capita; (4) *INF*: monthly inflation rate based on the U.S. consumer price index; (5) *MKT*: excess return on the value-weighted NYSE/Amex/Nasdaq (CRSP) equity market index; (6) *RREL*: relative T-bill rate, defined as the difference between the three-month T-bill rate and its 12-month backward moving average; (7) *TERM*: term spread measured as the difference between yields on ten-year and three-month Treasury securities; and (8) *UNEMP*: the U.S. monthly unemployment rate defined as the number of unemployed as a percentage of the labor force.[7]

We propose alternative measures of macroeconomic risk by estimating the time-varying conditional volatility of the aforementioned state variables based on the following Multivariate Asymmetric GARCH model with a Vector Autoregressive process:

$$\begin{bmatrix} Z_{i,t+1} \\ Z_{j,t+1} \end{bmatrix} = \begin{bmatrix} b_0^i \\ b_0^j \end{bmatrix} + \begin{bmatrix} b_1^i & b_2^i \\ b_1^j & b_2^j \end{bmatrix} \begin{bmatrix} Z_{i,t} \\ Z_{j,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t+1} \\ \varepsilon_{j,t+1} \end{bmatrix} \tag{1}$$

$$E[\varepsilon_{i,t+1}^2 | \Omega_t] \equiv \sigma_{i,t+1}^2 = \gamma_0^i + \gamma_1^i \varepsilon_{i,t}^2 + \gamma_2^i \sigma_{i,t}^2 + \gamma_3^i \varepsilon_{i,t}^2 D_{i,t} \tag{2}$$

$$E[\varepsilon_{j,t+1}^2 | \Omega_t] \equiv \sigma_{j,t+1}^2 = \gamma_0^j + \gamma_1^j \varepsilon_{j,t}^2 + \gamma_2^j \sigma_{j,t}^2 + \gamma_3^j \varepsilon_{j,t}^2 D_{j,t} \tag{3}$$

$$E_t[\varepsilon_{i,t+1}\varepsilon_{j,t+1} | \Omega_t] \equiv \sigma_{ij,t+1} = \gamma_0^{ij} + \gamma_1^{ij} \varepsilon_{i,t}\varepsilon_{j,t} + \gamma_2^{ij} \sigma_{ij,t} + \gamma_3^{ij} \varepsilon_{i,t}\varepsilon_{j,t} D_{i,t} D_{j,t} \tag{4}$$

[6] 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*, and *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.

[7] BAA- and AAA-rated rated corporate bond yields, three-month T-bill rates, and ten-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. One-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. Monthly aggregate dividend yields on the S&P 500 Index and the monthly inflation rate are obtained from Robert Shiller's online data library: http://www.econ.yale.edu/~shiller/data.htm. Monthly unemployment rates are obtained from the Bureau of Labor Statistics: http://www.bls.gov/cps/lfcharacteristics.htm#unemp. Real GDP per capita is obtained from the Federal Reserve Bank of St. Louis: http://research.stlouisfed.org/fred2/.

$D_{i,t}=1$ for $\varepsilon_{i,t}<0$ and $D_{i,t}=0$ otherwise

$D_{j,t}=1$ for $\varepsilon_{j,t}<0$ and $D_{j,t}=0$ otherwise,

where $Z_{i,t+1}$ ($Z_{j,t+1}$) is one of the eight state variables in month $t+1$; $Z=[DEF, DIV, GDP, INF, MKT, RREL, TERM, UNEMP]$.

Eq. (1) is a Vector Autoregressive of order one, VAR(1), process to account for serial correlation (persistence) in state variables and their cross-correlations simultaneously. Ω_t in Eqs. (2)–(4) denotes the information set at time t that investors use to form expectations about the state variables. In Eq. (2), $\sigma^2_{i,t+1}$ is the time-t expected conditional variance of $Z_{i,t+1}$, estimated using the Threshold GARCH (TGARCH) model of Glosten, Jagannathan, and Runkle (1993), which allows positive and negative economic shocks to have different impacts on conditional variance. Dummy variable $D_{i,t}$ equals one when $\varepsilon_{i,t}$ is negative and zero otherwise. If γ^i_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.

In Eq. (4), $\sigma_{ij,t+1}$ is the time-t expected conditional covariance between $Z_{i,t+1}$ and $Z_{j,t+1}$. This time-varying conditional covariance specification in a Multivariate GARCH model is originally introduced by Engle and Kroner (1995) and then used by Bollerslev, Engle, and Wooldridge (1988) and Bali (2008) to investigate the empirical validity of conditional asset pricing models. It is important to note that Eqs. (1)–(4) introduce a more generalized version of the Multivariate GARCH model used by earlier studies. For example, when modeling the conditional variance–covariance matrix, Engle and Kroner (1995), Bollerslev, Engle, and Wooldridge (1988), and Bali (2008) use the Symmetric GARCH model of Bollerslev (1986), whereas we use the Asymmetric GARCH (TGARCH) model of Glosten, Jagannathan, and Runkle (1993) to allow negative and positive shocks to have different impacts on the conditional variance–covariance matrix. Moreover, earlier studies use either a constant conditional mean or GARCH-in-mean process without taking into account autocorrelation in state variables.

We estimate Eqs. (1)–(4) simultaneously using the maximum likelihood methodology. As shown in Eqs. (5) and (6), we denote the residual vector by U_t and the conditional variance–covariance matrix by V_t:

$$U_t=\begin{bmatrix}\varepsilon_{i,t}\\ \varepsilon_{j,t}\end{bmatrix}=\begin{bmatrix}Z_{i,t}-b^i_0-b^i_1 Z_{i,t-1}-b^i_2 Z_{j,t-1}\\ Z_{j,t}-b^j_0-b^j_1 Z_{i,t-1}-b^j_2 Z_{j,t-1}\end{bmatrix}, \tag{5}$$

$$V_t=\begin{bmatrix}\sigma^2_{i,t} & \sigma_{ij,t}\\ \sigma_{ij,t} & \sigma^2_{j,t}\end{bmatrix}, \tag{6}$$

then under the assumption of conditional multivariate normality, the log-likelihood function is written as:

$$\log L(\Theta)=-\frac{1}{2}\sum_{t=1}^{N}[\,\ln(2\pi)+\ln|V_t|+U_t^{\mathrm{T}}V_t^{-1}U_t], \tag{7}$$

where Θ denotes the vector of parameters in Eqs. (1)–(4), and N denotes the number of monthly observations for each series.

Macroeconomic risk is measured by the conditional standard deviation (or volatility) of the aforementioned economic indicators. The monthly data for *DEF*, *DIV*, *GDP*, *INF*, *MKT*, *RREL*, *TERM*, and *UNEMP* cover the period January 1960–March 2012. When estimating Eqs. (1)–(4), we use the sample from January 1960 to December 1993, and begin making one-month-ahead 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 a monthly expanding sample until the sample is exhausted in March 2012. This recursive volatility forecasting procedure generates macroeconomic risk factors for the full sample period January 1994–March 2012.

Fig. 1 displays monthly time-series plots of the eight measures of macroeconomic risk. A notable point in Fig. 1 is that the uncertainty measures closely follow large falls and rises in financial and macroeconomic activity. Specifically, uncertainty about default risk (*DEF_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, uncertainty about 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. Uncertainty about aggregate dividend yield (*DIV_U*) and uncertainty about the equity market (*MKT_U*) are significantly higher during stock market crashes as well. Lastly, uncertainty about inflation (*INF_U*), uncertainty about output growth (*GDP_U*), and uncertainty about unemployment (*UNEMP_U*) are generally higher during bad economic states, 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 macroeconomic risk measures for the sample period January 1994–March 2012. Panel B of Table 1 displays the correlation matrix for the eight macroeconomic risk factors. A notable point in Panel B is that the correlations among the macroeconomic risk factors are all positive and very high. In fact, average cross-correlation among the macroeconomic risk factors is approximately 0.50.

Panel C of Table 1 presents correlations between the standard risk and economic uncertainty (macroeconomic risk) factors for the sample period, January 1994–March 2012. Interestingly, the correlations are generally low and exhibit no clear pattern. Focusing on the negative correlations in Panel C, the average correlation between the risk and uncertainty factors is -0.10, with a minimum of -0.28 and a maximum of -0.002. Among the positive correlations, the average correlation between the risk and uncertainty factors is 0.06, with a minimum of 0.0005 and a maximum of 0.16. These results suggest that the risk and uncertainty factors potentially capture different aspects of hedge fund returns.

3.4. Economic uncertainty index

Since macroeconomic risk factors introduced in the paper are measures of conditional volatility, they are

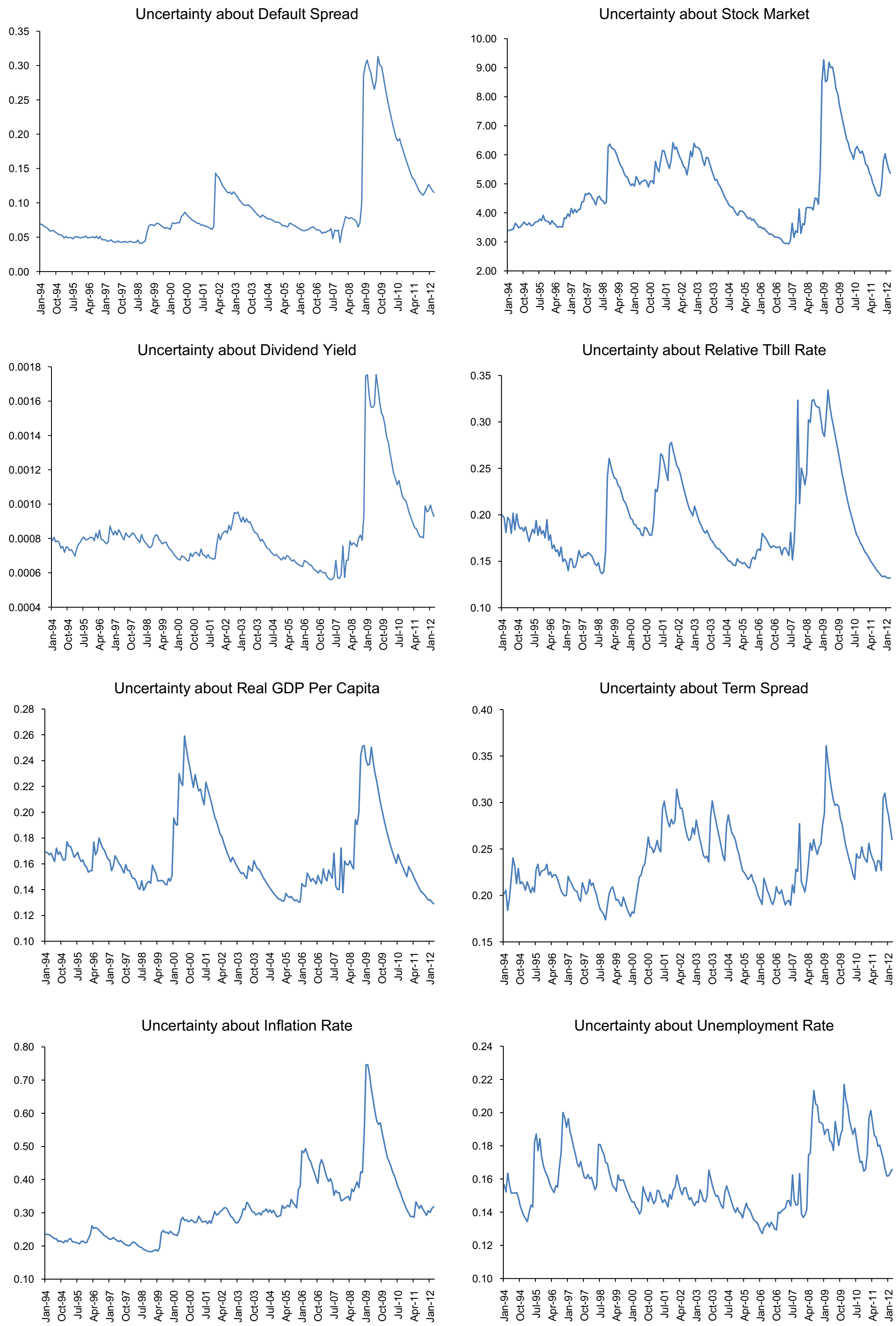

Fig. 1. Alternative measures of macroeconomic risk. This figure presents alternative measures of macroeconomic risk for the sample period January 1994–March 2012. Macroeconomic risk measures are defined as the time-varying conditional volatility of the state variables; *DEF*, *DIV*, *GDP*, *INF*, *MKT*, *RREL*, *TERM*, and *UNEMP*. As presented in Eqs. (1)–(4), they are estimated using the Multivariate TGARCH model with a Vector Autoregressive process.

Table 1

Summary statistics for alternative measures of macroeconomic risk.

Panel A presents the time-series mean, median, standard deviation, minimum, and maximum values for alternative measures of macroeconomic risk for the sample period January 1994–March 2012. Macroeconomic risk measures are defined as the time-varying conditional volatility of the state variables; *DEF*, *DIV*, *GDP*, *INF*, *MKT*, *RREL*, *TERM*, and *UNEMP*. As presented in Eqs. (1)–(4), alternative measures of macroeconomic risk are estimated using the Multivariate TGARCH model with a Vector Autoregressive process. The definitions of these alternative measures of macroeconomic risk are provided in detail in Section 3.3 of the main text. Panel B reports correlation coefficients between alternative macroeconomic risk factors and Panel C represents correlation coefficients between standard risk factors and macroeconomic risk factors.

Panel A: Macroeconomic risk factors

	N	Mean	Median	Std. dev.	Minimum	Maximum
DEF_U: Uncertainty about default premium	219	0.09	0.07	0.06	0.04	0.31
DIV_U: Uncertainty about aggregate dividend yield	219	0.00	0.00	0.00	0.00	0.00
GDP_U: Uncertainty about real GDP per capita	219	0.17	0.16	0.03	0.13	0.26
INF_U: Uncertainty about the inflation rate	219	0.31	0.29	0.11	0.18	0.75
MKT_U: Uncertainty about the equity market	219	4.86	4.62	1.35	2.93	9.27
RREL_U: Uncertainty about short-term interest changes	219	0.19	0.18	0.05	0.13	0.33
TERM_U: Uncertainty about term spread	219	0.23	0.23	0.04	0.17	0.36
UNEMP_U: Uncertainty about the unemployment rate	219	0.16	0.15	0.02	0.13	0.22

Panel B: Correlation matrix of the macroeconomic risk factors

	DEF_U	*DIV_U*	*GDP_U*	*INF_U*	*MKT_U*	*RREL_U*	*TERM_U*	*UNEMP_U*
DEF_U	1.000							
DIV_U	0.911	1.000						
GDP_U	0.401	0.422	1.000					
INF_U	0.741	0.599	0.330	1.000				
MKT_U	0.802	0.816	0.510	0.437	1.000			
RREL_U	0.451	0.463	0.633	0.438	0.548	1.000		
TERM_U	0.612	0.552	0.424	0.454	0.641	0.455	1.000	
UNEMP_U	0.489	0.617	0.247	0.195	0.423	0.299	0.227	1.000

Panel C: Correlations between the standard risk and macroeconomic risk factors

	DEF_U	*DIV_U*	*GDP_U*	*INF_U*	*MKT_U*	*RREL_U*	*TERM_U*	*UNEMP_U*
MKT	0.065	0.107	−0.167	−0.023	0.086	−0.157	−0.033	−0.008
SMB	0.089	0.069	0.034	0.074	0.130	0.114	0.080	0.002
HML	−0.016	−0.052	0.161	−0.010	−0.039	−0.003	0.147	−0.061
MOM	−0.222	−0.239	−0.149	−0.225	−0.214	−0.082	−0.166	−0.037
Δ10Y	−0.002	0.001	−0.060	0.041	0.009	0.040	−0.017	−0.067
ΔCRDSPR	−0.240	−0.284	0.043	−0.155	−0.254	0.003	−0.156	0.041
BDTF	−0.114	−0.060	0.030	−0.158	−0.029	0.051	−0.138	0.059
FXTF	−0.091	−0.089	0.029	−0.022	−0.071	0.062	−0.061	0.040
CMTF	−0.127	−0.114	−0.099	−0.067	−0.115	−0.028	−0.134	0.028
IRTF	−0.117	−0.112	0.150	0.032	−0.130	0.151	−0.087	0.006
SKTF	−0.100	−0.074	0.003	0.010	−0.163	−0.012	−0.095	0.075

highly persistent and correlated with each other. To sufficiently capture the common variation among the correlated factors of economic uncertainty, we develop a broad index of macroeconomic risk by using Principal Component Analysis (PCA). In addition to investigating the predictive power of each uncertainty beta separately, we test whether funds' exposures to the broad index of economic uncertainty explain a significant proportion of the cross-sectional variation in hedge fund returns.

The first principal component from PCA has the interpretation of being the single linear combination of the uncertainty factors that explains most of the time-series variation we see in these factors.[8] We use the PCA to extract the common component of the eight macroeconomic risk factors that capture different dimensions of the aggregate economy: *DEF_U*, *DIV_U*, *GDP_U*, *INF_U*, *MKT_U*, *RREL_U*, *TERM_U*, and *UNEMP_U*. The eigenvalues of the eight components are 4.64, 1.02, 0.85, 0.60, 0.39, 0.34, 0.10, and 0.06, respectively, indicating that the first principal component explains about 62% of the corresponding sample variance. Hence, we conclude that the first principal component sufficiently captures the common variation among the eight uncertainty factors. As shown in Eq. (8), the principal component analysis yields a set of factor loadings in the range of 0.26 to 0.42, and in turn generates a broad measure of economic uncertainty index (*UNC*):

$$\begin{aligned} UNC_t = {} & 0.42\, DEF\_U_t + 0.34\, DIV\_U_t + 0.33\, GDP\_U_t \\ & + 0.42\, INF\_U_t + 0.41\, MKT\_U_t + 0.29\, RREL\_U_t \\ & + 0.26\, TERM\_U_t + 0.32\, UNEMP\_U_t \end{aligned} \tag{8}$$

Eq. (8) indicates that the economic uncertainty index UNC_t has somewhat higher loadings on the conditional volatility of the default spread, inflation rate, and the aggregate stock market (in the range of 0.41 and 0.42), whereas relatively smaller

[8] Section II of the online appendix provides a detailed description of the principal component analysis.

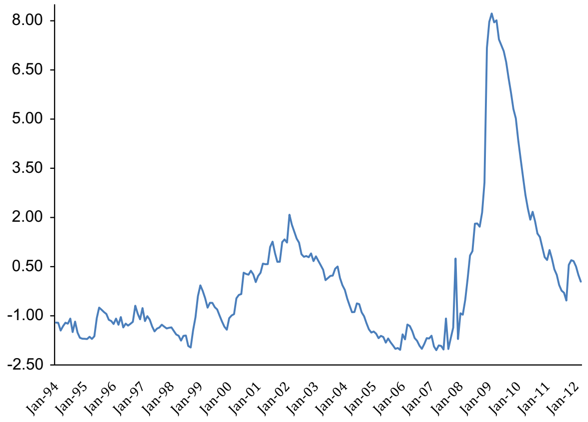

Fig. 2. Economic uncertainty index. Principal Component Analysis (PCA) is used to extract the common component of the eight macroeconomic risk factors (*DEF_U*, *DIV_U*, *GDP_U*, *INF_U*, *MKT_U*, *RREL_U*, *TERM_U*, and *UNEMP_U*) presented in Fig. 1. This figure plots the economic uncertainty index obtained from the first principal component for the sample period January 1994–March 2012.

weights are given to the conditional volatility of the relative T-bill rate and term spread (in the range of 0.26 to 0.29). The index loads fairly evenly on the conditional volatility of the aggregate dividend yield, per capita real GDP growth, and unemployment (in the range of 0.32 to 0.34).

Fig. 2 presents time-series plots of the economic uncertainty index (UNC_t) obtained from the first principal component of the eight factors. Similar to our findings from individual macroeconomic risk factors presented in Fig. 1, the broad index of economic uncertainty is generally higher during bad states of the economy corresponding to periods of high unemployment, low output growth, and low economic activity. The economic uncertainty index also closely follows large fluctuations in business conditions and the recent financial crisis period.

4. A conditional asset pricing model with macroeconomic risk

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

$$\mu_i = A\sigma_{im} + B\sigma_{ix}, \tag{9}$$

where μ_i denotes the unconditional expected excess return on risky asset i, σ_{im} denotes the unconditional covariance between the excess returns on 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. (9) shows 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; Bali and Engle, 2010):

$$E[R_{i,t+1}|\Omega_t] = A\mathrm{cov}[R_{i,t+1}, R_{m,t+1}|\Omega_t] + B\mathrm{cov}[R_{i,t+1}, X_{t+1}|\Omega_t], \tag{10}$$

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, $E[R_{i,t+1}|\Omega_t]$ is the expected excess return on the risky asset i at time $t+1$ conditional on the information set at time t, $\mathrm{cov}[R_{i,t+1}, R_{m,t+1}|\Omega_t]$ measures the time-t expected conditional covariance between the excess returns on risky asset i and the market portfolio m, and $\mathrm{cov}[R_{i,t+1}, X_{t+1}|\Omega_t]$ measures the time-t expected conditional covariance between the excess returns on risky asset i and the state variable X, which affects future investment opportunities.

To be consistent with earlier studies in the hedge fund literature (e.g., Bali, Brown, and Caglayan, 2011, 2012), we re-write Eq. (10) in terms of conditional betas, instead of conditional covariances:

$$E[R_{i,t+1}|\Omega_t] = \tilde{A}\, E[\beta_{im,t+1}|\Omega_t] + \tilde{B}\, E[\beta_{ix,t+1}|\Omega_t], \tag{11}$$

where $\tilde{A} = A\mathrm{var}[R_{m,t+1}|\Omega_t]$, $\tilde{B} = B \cdot \mathrm{var}[X_{t+1}|\Omega_t]$, and $E[\beta_{im,t+1}|\Omega_t]$ 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 $E[\beta_{ix,t+1}|\Omega_t]$ 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}:

$$E\left[\beta_{im,t+1}|\Omega_t\right] = \frac{\mathrm{cov}[R_{i,t+1}, R_{m,t+1}|\Omega_t]}{\mathrm{var}[R_{m,t+1}|\Omega_t]}, \tag{12}$$

$$E\left[\beta_{ix,t+1}|\Omega_t\right] = \frac{\mathrm{cov}[R_{i,t+1}, X_{t+1}|\Omega_t]}{\mathrm{var}[X_{t+1}|\Omega_t]}. \tag{13}$$

Other studies (e.g., Bloom, Bond, and Van Reenen, 2007; Bloom, 2009; Chen, 2010; Stock and Watson, 2012; Allen, Bali, and Tang, 2012; Bali and Zhou, 2013) provide theoretical and empirical evidence that macroeconomic uncertainty is a relevant state variable proxying for consumption and investment opportunities in the conditional ICAPM framework. Hence, the broad index of economic uncertainty generated in this paper can be viewed as a proxy for the state variable X in Eqs. (10) and (11). The beta in Eq. (12) is referred to as "risk factor beta," while the beta in Eq. (13) is referred to as "uncertainty index beta."

5. Empirical results

In this section, we conduct parametric and nonparametric tests to assess the predictive power of standard risk factor betas and uncertainty betas over future hedge fund returns. First, we conduct univariate portfolio-level analysis. Second, we present results from univariate and multivariate cross-sectional regressions controlling for fund characteristics, risk, and liquidity attributes. Finally, we investigate whether the predictive power of uncertainty betas for future fund returns remains intact during subsample periods when significant structural breaks are observed.

5.1. Univariate portfolio analysis of the standard risk factor betas

In this section, we estimate the standard risk factor betas for each fund in our sample using the first three years of monthly returns, from January 1994 to December 1996, and then follow a monthly rolling regression approach with a fixed estimation window of 36 months:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{F} F_t + \varepsilon_{i,t}, \tag{14}$$

where $R_{i,t}$ is the excess return of fund i in month t, F_t is the standard risk factor in month t, and $\beta_{i,t}^{F}$ is the risk factor beta for fund i in month t. Note that risk factor F in Eq. (14) represents one of the 11 risk factors tested in this study; *MKT*, *SMB*, *HML*, *MOM*, *△10Y*, *△CrdSpr*, *BDTF*, *FXTF*, *CMTF*, *IRTF*, and *SKTF*.

Once we generate the standard risk factor betas ($\beta_{i,t}^{F}$), for each month from January 1997 to March 2012, we form quintile portfolios by sorting hedge funds based on their $\beta_{i,t}^{F}$, 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 average values of the risk factor betas and the next-month average returns for each quintile. The last two rows in Table III display the average raw and risk-adjusted return differences between quintiles 5 and 1.

Univariate quintile portfolios in Table III provide no evidence for a significant link between standard risk factor betas and future returns. Hedge fund exposure to the 11 commonly used risk factors do not predict 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 portfolio analysis of the uncertainty betas

In this section, we examine whether hedge fund exposures to the macroeconomic risk factors (*DEF_U*, *DIV_U*, *GDP_U*, *INF_U*, *MKT_U*, *RREL_U*, *TERM_U*, and *UNEMP_U*) can predict the cross-sectional variation in hedge fund returns. We estimate the monthly uncertainty betas for each fund from the time-series regressions of hedge fund returns on the macroeconomic risk factors over a 36-month rolling-window period:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{U} U_t + \varepsilon_{i,t}, \tag{15}$$

where $R_{i,t}$ is excess return of fund i in month t, U_t is macroeconomic risk (uncertainty) factor in month t, and $\beta_{i,t}^{U}$ is the uncertainty beta for fund i in month t. Note that the macroeconomic risk factor U in Eq. (15) represents one of the eight uncertainty measures proposed in this study.

Table IV of the online appendix provides univariate portfolio results for the eight alternative measures of uncertainty betas. 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 IV, 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 default risk ($\beta_{i,t}^{DEF\_U}$) increases from −95.25 to 113.41. Similar large cross-sectional spreads are observed for the other uncertainty beta measures as well.

Another notable point from Table IV is that when 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 unemployment ($\beta_{i,t}^{UNEMP\_U}$) and the uncertainty beta portfolio for 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 return increases from 0.076% to 0.734% per month. This indicates a monthly average return difference of 0.658% between quintiles 5 and 1, with a Newey-West (1987) t-statistic of 2.47, 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 7.9% higher 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 the Fama-French-Carhart 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 IV, the nine-factor alpha difference between quintiles 5 and 1 is 0.595% with a t-statistic of 2.04. 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 $\beta_{i,t}^{RREL\_U}$ and $\beta_{i,t}^{UNEMP\_U}$. Specifically, when hedge funds are sorted into univariate quintile portfolios based on their exposures to uncertainty with respect to default risk ($\beta_{i,t}^{DEF\_U}$), aggregate dividend yield ($\beta_{i,t}^{DIV\_U}$), real GDP growth per capita $\beta_{i,t}^{GDP\_U}$, the inflation rate ($\beta_{i,t}^{INF\_U}$), the equity market ($\beta_{i,t}^{MKT\_U}$), and term spread ($\beta_{i,t}^{TERM\_U}$), the average return differences between the highest and lowest uncertainty beta quintiles range from 0.53% to 0.75% per month, corresponding to annualized return differences of 6.4% to 9.0%. The Newey-West t-statistics of these return spreads range from 2.07 to 2.63.

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 (nine-factor alpha) remains strong and highly significant for all uncertainty betas, again except for $\beta_{i,t}^{RREL\_U}$ and $\beta_{i,t}^{UNEMP\_U}$ (see the last row of Table IV).

In addition to time-varying volatility of economic indicators generated from the Multivariate VAR–GARCH model as proxies for macroeconomic risk, we use cross-sectional dispersion in quarterly forecasts on macroeconomic variables as alternative measures of macroeconomic risk. The Federal Reserve Bank of Philadelphia releases measures of cross-sectional dispersion in economic forecasts from the Survey of Professional Forecasters (SPF), calculating the degree of disagreement among the expectations of different forecasters. Specifically, we use cross-sectional dispersion in quarterly forecasts for U.S. gross domestic product, industrial production, and inflation rate as alternative measures of macroeconomic risk. As discussed in the online appendix (Section III and Table V), our main findings from these model-independent, nonparametric measures of macroeconomic risk turn out to be similar to those reported in Table V of the online appendix. Hence, our results are robust to different measures of macroeconomic risk obtained from parametric (GARCH) and nonparametric (SPF) measures.

5.3. *Univariate portfolio analysis of the uncertainty index beta*

In this section, we test whether exposures of hedge funds to the broad index of economic uncertainty (*UNC*) can predict the cross-sectional differences in hedge fund returns. We estimate funds' exposures to *UNC* from the time-series regressions over a 36-month rolling-window period:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC}\, UNC_t + \varepsilon_{i,t}, \tag{16}$$

where $R_{i,t}$ is excess return of fund *i* in month *t*, UNC_t is the broad index of economic uncertainty in month *t*, and $\beta_{i,t}^{UNC}$ is the uncertainty index beta for fund *i* in month *t*. Note that the economic uncertainty index (*UNC*) in Eq. (8) obtained from the first principal component sufficiently captures the common variation among the eight factors of macroeconomic risk.

We conduct portfolio-level analysis to investigate the cross-sectional predictive power of $\beta_{i,t}^{UNC}$. For each month, from January 1997 to March 2012, hedge funds are sorted into quintile portfolios based on their $\beta_{i,t}^{UNC}$, where quintile 1 contains hedge funds with the lowest $\beta_{i,t}^{UNC}$ and quintile 5 contains hedge funds with the highest $\beta_{i,t}^{UNC}$. Table 2 reports the average $\beta_{i,t}^{UNC}$, average next-month return, and the nine-factor alpha for each of the five uncertainty index beta sorted quintiles. The second column of Table 2 shows that moving from quintile 1 to 5, we observe that average returns on the $\beta_{i,t}^{UNC}$ portfolios increase monotonically from −0.043% to 0.852% per month, showing that the average return difference between quintiles 5 and 1 (High $\beta_{i,t}^{UNC}$–Low $\beta_{i,t}^{UNC}$) is about 0.90% per month with a Newey-West *t*-statistic of 3.30. This result indicates that hedge funds in the highest $\beta_{i,t}^{UNC}$ quintile generate 10% more annual return compared to hedge funds in the lowest $\beta_{i,t}^{UNC}$ quintile.

Table 2 also presents the nine-factor alpha of each $\beta_{i,t}^{UNC}$ quintile. The last column of Table 2 shows that moving from quintile 1 to 5, the nine-factor alpha on the $\beta_{i,t}^{UNC}$ portfolios increases monotonically from −0.120% to 0.757% per month, leading to a nine-factor alpha difference of 0.88% with a *t*-statistic of 2.93. This suggests that after controlling for the market, size, book-to-market, momentum, and five trend-following factors, the return difference between the High $\beta_{i,t}^{UNC}$ and Low $\beta_{i,t}^{UNC}$ funds remains positive and significant, implying that the nine factors commonly used in the hedge fund literature do not explain the positive relation between the uncertainty index beta and the cross-section of hedge fund returns.

Table 2
Univariate portfolios of hedge funds sorted by β^{UNC}.

Quintile portfolios are formed every month from January 1997 to March 2012 by sorting hedge funds based on their uncertainty index betas (β^{UNC}). Quintile 1 is the portfolio of hedge funds with the lowest uncertainty index betas, and quintile 5 is the portfolio of hedge funds with the highest uncertainty index betas. The table reports average β^{UNC} in each quintile, the next-month average returns, and the nine-factor alphas for each quintile. The last row shows the average monthly raw return difference and the nine-factor alpha difference between High β^{UNC} and Low β^{UNC} quintiles. 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 of the return and alpha spreads.

Quintiles	Average β^{UNC} in each quintile	Next-month average returns	Next-month 9-factor alphas
Low β^{UNC}	−1.597	−0.043	−0.120
		(−0.16)	(−0.78)
Q2	−0.295	0.238	0.131
		(1.47)	(1.52)
Q3	0.161	0.321	0.227
		(2.14)	(2.30)
Q4	0.630	0.475	0.407
		(3.15)	(3.45)
High β^{UNC}	2.122	0.852	0.757
		(3.68)	(3.24)
High β^{UNC}–Low β^{UNC}		**0.895**	**0.877**
t-Statistic		**(3.30)**	**(2.93)**

Lastly, we investigate the source of this significant return difference between the High $\beta_{i,t}^{UNC}$ and Low $\beta_{i,t}^{UNC}$ funds: is it due to outperformance by the High $\beta_{i,t}^{UNC}$ funds, or underperformance by the Low $\beta_{i,t}^{UNC}$ funds, or both? For this, we compare the economic and statistical significance of the average returns and nine-factor alphas of Quintile 1 vs. Quintile 5. Table 2 shows that the average return and the nine-factor alpha of Quintile 1 are −0.04% and −0.12% per month with the *t*-statistics of −0.16 and −0.78, respectively, indicating that the average raw and risk-adjusted returns of the Low $\beta_{i,t}^{UNC}$ funds are economically and statistically insignificant. On the other hand, the average return and the nine-factor alpha of Quintile 5 are 0.85% and 0.76% per month with the *t*-statistics of 3.68 and 3.24, respectively, implying economically large and statistically significant positive returns for the High $\beta_{i,t}^{UNC}$ funds. These results provide evidence that the positive and significant return difference between the High $\beta_{i,t}^{UNC}$ and Low $\beta_{i,t}^{UNC}$ funds is due to outperformance by the High $\beta_{i,t}^{UNC}$ funds.

5.4. *Uncertainty index beta in cross-sectional regressions with control variables*

So far we have tested the significance of the uncertainty index beta as a determinant of the cross-section of hedge fund returns at the portfolio level. This portfolio-level analysis has the advantage of being nonparametric in the sense that we do not impose a functional form on the relation between the uncertainty index beta and future returns. The portfolio-level analysis also has two potentially significant disadvantages. First, it throws away a large amount of information in the cross-section via aggregation. Second, it is a difficult setting in which to control for multiple effects or fund characteristics simultaneously. Consequently, we now examine the cross-sectional relation between the uncertainty index beta and future returns at the individual fund level using Fama and MacBeth (1973) regressions.

We present the time-series averages of the slope coefficients from the regressions of one-month-ahead hedge fund excess returns on the uncertainty index beta and a large set of control variables. The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables, on average, have nonzero premiums. Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$\begin{aligned} R_{i,t+1} = {} & \lambda_{0,t} + \lambda_{1,t}\beta_{i,t}^{UNC} + \lambda_{2,t}R_{i,t} + \lambda_{3,t}\, SIZE_{i,t} + \lambda_{4,t}\, AGE_{i,t} \\ & + \lambda_{5,t}\, MGMTFEE_i + \lambda_{6,t}\, INCENTIVEFEE_i \\ & + \lambda_{7,t}\, REDEMPTION_i + \lambda_{8,t}\, MININVEST_i \\ & + \lambda_{9,t}\, D\_LOCKUP_i + \lambda_{10,t}\, D\_LEVERAGE_i + \varepsilon_{i,t+1} \end{aligned} \tag{17}$$

where $R_{i,t+1}$ is the excess return of fund i in month $t+1$, and $\beta_{i,t}^{UNC}$ is the uncertainty index beta for fund i in month t. *SIZE*, *AGE*, *MGMTFEE*, *INCENTIVEFEE*, *REDEMPTION*, *MININVEST*, *D_LOCKUP*, and *D_LEVERAGE* are fund characteristics: *SIZE* is measured as monthly assets under management in billions of dollars; *AGE* is measured as the number of months in existence since inception; *MGMTFEE* is a fixed percentage fee of assets under management, typically ranging from 1% to 2%; *INCENTIVEFEE* 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 the investor can redeem the invested amount from the fund; *MININVEST* is the minimum initial investment amount (measured in millions of 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 (one if the fund requires investors not to withdraw initial investments for a pre-specified term, usually 12 months, zero otherwise); *D_LEVERAGE* is the dummy variable for leverage (one if the fund uses leverage, zero otherwise). We also include 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.

Table 3, Panel A presents average intercept and slope coefficients from the Fama-MacBeth cross-sectional regressions for the full sample period January 1997–March 2012. The Newey-West adjusted *t*-statistics are given in parentheses. We first investigate the cross-sectional relation between $\beta_{i,t}^{UNC}$ and future hedge fund returns without taking into account fund characteristics, risk, and liquidity factors. Consistent with our earlier findings from the univariate portfolio analysis, Regression (1) in Panel A of Table 3 provides evidence for a positive and highly significant relation between $\beta_{i,t}^{UNC}$ and hedge fund returns. The average slope from the monthly univariate regressions of one-month-ahead returns on $\beta_{i,t}^{UNC}$ alone is 0.4201 with a Newey-West *t*-statistic of 2.81.

After confirming a significantly positive link between $\beta_{i,t}^{UNC}$ and future returns in univariate Fama-MacBeth regressions, we now control for all fund characteristics and risk factors simultaneously and test whether hedge fund exposure to the broad index of economic uncertainty remains a strong predictor of future returns. Regression (2) in Panel A of Table 3 shows that the average slope on $\beta_{i,t}^{UNC}$ is 0.3757 with a Newey-West *t*-statistic of 2.89, implying that after controlling for a large set of fund characteristics and risk factors considered in earlier work, the positive relation between the uncertainty index beta and future hedge fund returns remains economically and statistically significant.

A notable point in Table 3 is that the average slope coefficients on the control variables are consistent with earlier studies. Regression (2) in Panel A of Table 3 shows that the average slope on the lagged fund returns ($R_{i,t}$) is positive and statistically significant.[9] Another interesting observation that emerges from Table 3, Panel A is that the incentive fee variable has a positive and significant coefficient in monthly Fama-MacBeth regressions, even when other fund characteristics are added to the regression equation. 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 other studies (see Brown, Goetzmann, and Ibbotson, 1999; Liang, 1999; and Edwards and Caglayan, 2001). As in the lagged return result, however, the significance of incentive fee does not change the predictive power of the uncertainty index beta on future hedge fund returns. One last noteworthy point from Table 3, Panel A is that the redemption period, the minimum investment amount, and the dummy for lockup variables, which are used by Aragon (2007) to measure illiquidity of hedge fund portfolios, also have positive and significant average slope coefficients. This suggests that funds that use lockup and other share restrictions that enable funds to invest in illiquid assets earn higher returns in succeeding months, an outcome that coincides with the findings in Aragon (2007). However, even the significance of these liquidity variables does not alter or reduce the predictive power of the uncertainty index beta over hedge fund returns.

[9] A similar result, that there is serial dependence in hedge fund returns, is also found by Agarwal and Naik (2000), Getmansky, Lo, and Makarov (2004), Jagannathan, Malakhov, and Novikov (2010), and Bali, Brown, and Caglayan (2011, 2012). Jegadeesh and Titman (1993, 2001) find momentum in stock returns for three-, six-, nine-, and 12-month horizons, although Jegadeesh (1990) and Lehmann (1990) provide strong evidence for the short-term reversal effect in individual stock returns for the one-week to one-month horizon. In addition to accounting for lagged returns in Fama-MacBeth regressions, we control for this phenomenon using the Carhart (1997) momentum factor in portfolio-level analyses.

Table 3
Fama-MacBeth regressions of hedge fund returns on the uncertainty index beta and 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 index beta with and without control variables. 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 full sample period (in Panel A) as well as for four subsample periods separately (in Panels B through E). Newey-West *t*-statistics are reported in parentheses to determine the statistical significance of the average intercept and slope coefficients. Numbers in bold denote statistical significance of the average slope coefficients.

	Intercept	β^{UNC}	*LagRet*	*Size*	*Age*	*MgmtFee*	*IncentFee*	*Redemption*	*MinInvest*	*D_Lockup*	*D_Lever*
Panel A: 1997:01–2012:03											
(1)	0.3938	**0.4201**									
	(3.17)	**(2.81)**									
(2)	0.0365	**0.3757**	**0.0858**	−0.0174	0.0002	0.0562	**0.0094**	**0.0014**	**0.0088**	**0.1188**	0.0030
	(0.26)	**(2.89)**	**(4.78)**	(−0.41)	(0.37)	(1.43)	**(4.37)**	**(1.83)**	**(2.86)**	**(3.04)**	(0.16)
Panel B: 1997:01–1998:08											
(1)	0.1603	**0.1240**									
	(0.31)	**(2.21)**									
(2)	−0.4988	**0.1101**	0.0406	**0.3134**	**0.0042**	0.0911	0.0064	0.0032	**0.0264**	**0.4027**	0.0255
	(−0.58)	**(2.12)**	(0.85)	**(3.02)**	**(2.00)**	(0.49)	(0.57)	(0.82)	**(2.10)**	**(2.99)**	(0.30)
Panel C: 1998:09–2000:02											
(1)	0.9339	**0.3011**									
	(2.87)	**(1.95)**									
(2)	0.9370	**0.2404**	**0.1206**	−0.1170	−0.0014	**−0.2421**	0.0097	**0.0043**	0.0148	−0.0610	0.0148
	(3.25)	**(2.11)**	**(2.08)**	(−0.55)	(−0.98)	**(−2.32)**	(1.34)	**(2.33)**	(1.06)	(−0.41)	(0.12)
Panel D: 2000:03–2008:09											
(1)	0.3250	**0.2204**									
	(2.19)	**(2.70)**									
(2)	0.0078	**0.2263**	**0.0894**	−0.0623	−0.0004	**0.1037**	**0.0084**	0.0009	**0.0075**	**0.0909**	−0.0193
	(0.06)	**(2.72)**	**(4.00)**	(−1.39)	(−0.98)	**(1.92)**	**(4.02)**	(1.01)	**(1.93)**	**(2.00)**	(−1.08)
Panel E: 2008:10–2012:03											
(1)	0.4424	**1.1018**									
	(1.74)	**(2.09)**									
(2)	−0.0241	**0.9267**	**0.0836**	−0.0220	0.0002	0.0511	**0.0130**	0.0005	**0.0011**	**0.1289**	**0.0418**
	(−0.14)	**(1.99)**	**(1.86)**	(−0.31)	(0.44)	(1.49)	**(4.00)**	(0.46)	**(2.09)**	**(1.88)**	**(1.72)**

5.5. Structural breaks and subsample analysis

We now investigate whether the predictive power of the uncertainty index beta 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 Long Term Capital Management (LTCM) in September 1998 and the peak of the technology bubble in March 2000. The cross-sectional relation between hedge fund exposure to macroeconomic risk and their future returns may be time-varying as well, since hedge funds have the capacity to change their trading strategies depending on market conditions during the analyzed sample period. Following Fung, Hsieh, Naik, and Ramadorai (2008), we use a version of the Chow (1960) test, in which we replace the standard error covariance matrix with the 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 (collapse of LTCM), March 2000 (peak of the technology bubble), and September 2008 (collapse of Lehman Brothers). We then investigate the significance of the cross-sectional link between expected returns and the uncertainty index beta 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, Panels B through E of Table 3 provide evidence of a positive and significant relation between the uncertainty index beta and hedge fund returns for all subsample periods without an exception. In four subsample periods, the average slope coefficient on the uncertainty index beta ranges from 0.1101 to 1.1018, with statistically significant *t*-statistics ranging in between 1.95 and 2.72, The results clearly show that with and without controlling for a large set of variables, hedge fund exposure to the broad index of economic uncertainty is an important determinant of the cross-sectional dispersion in hedge fund returns for all states of the economy (contraction or expansion).

Another interesting point from Table 3 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 a few variables turn out to be robust predictors of future fund returns. Average slopes on lagged return are positive and significant in almost all subsample periods, with the exception of the first subsample period, January 1997–August 1998. Similarly, average slopes on the minimum initial investment amount and the dummy variable for lockup are also positive and significant in almost all subsample periods with the exception of the second subsample period, September 1998–February 2000.

Analyzing other fund characteristics during the subsample periods, we find that 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). Lastly, average slopes on redemption, size, age, and the dummy variable for leverage (one if the fund uses leverage, zero otherwise) are positive and significant only in one of the four subsample periods analyzed.

6. Macro-timing ability of hedge funds and mutual funds

In this section, we first classify hedge funds into three groups (directional, semi-directional, and non-directional) and test whether the predictive power of the uncertainty index beta changes among different hedge fund strategies. Second, we test whether hedge funds have the ability to time fluctuations in macroeconomic variables. Finally, we investigate whether mutual fund exposure to the economic uncertainty index predicts future returns, and also analyze their ability to time changes in macroeconomic conditions.

6.1. Predictive power of uncertainty betas by hedge fund investment style

We now 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 market risk altogether (non-directional strategies, such as equity market neutral, fixed income arbitrage, and convertible arbitrage funds), and some try to diversify 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 exposure to a specific macroeconomic risk factor by different investment strategy groups. Even within the same investment style group, one can observe varying degrees of exposure to the same macroeconomic risk factor over time, as hedge fund managers adjust their exposures dynamically in response to changing market conditions.

To understand the variation in uncertainty index betas among different investment strategies clearly, Table 4 presents, for each of the three investment styles separately, the cross-sectional average of individual hedge funds' time-series standard deviation of uncertainty betas. Moreover, in the last row of Table 4, we also report the cross-sectional average of individual funds' maximum minus minimum (max–min) uncertainty beta differences. We expect greater variation in uncertainty index betas for a given strategy (i.e., larger standard deviation of uncertainty betas, and larger max–min uncertainty beta spreads) to improve the explanatory power of the uncertainty index betas over future fund returns for that strategy. For comparison purposes, the cross-sectional averages of these two statistics across all hedge funds (irrespective of hedge fund strategy) are also reported in the last column of Table 4.[10]

Table 4 clearly demonstrates that the standard deviation and max–min differences of the uncertainty index betas increase monotonically as we move from the non-directional to the directional strategy group. In other words, directional funds, which include managed futures, emerging market, and global macro hedge funds, have very high standard deviations and max–min differences of uncertainty index betas when compared to non-directional and semi-directional funds. Also, non-directional funds' standard deviations and max–min differences of uncertainty index betas are relatively smaller compared

Table 4
Dynamics of hedge funds' uncertainty index betas by three broad hedge fund style categories.

The first row of this table presents the number of funds existing in each of the three broad hedge fund investment style categories. The second row reports the percentage of hedge funds in the total sample for each of the three hedge fund investment styles. The last two rows report the cross-sectional average of individual funds' time-series standard deviations (Std. dev.) of the uncertainty index betas, and the cross-sectional average of individual funds' max minus min time-series differences (max–min) of uncertainty index 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 the last column. As can be noticed by reading 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 index 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 index betas are considerably smaller compared to the All hedge fund group, while Directional strategies' standard deviations and max–min differences of the uncertainty index 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 index betas that are very similar to the all hedge fund group.

	Non-directional category	Semi-directional category	Directional category	All hedge funds
Number of funds	654	4,923	1,352	6,929
% Of funds in total sample	9.44	71.05	19.51	100.00
Std. dev. of β^{UNC}	0.57	0.76	1.17	0.82
Max–min of β^{UNC}	2.50	3.35	5.21	3.63

[10] In our sample, there are 261 hedge funds that do not report their investment styles to the TASS database. For this reason, we exclude these 261 hedge funds from this specific analysis on the variation of uncertainty betas among different hedge fund investment styles, and thus base our analyses on a total of 6,929 funds, instead of 7,190 funds.

Table 5
Univariate portfolios of uncertainty index beta 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 index betas. Quintile 1 (5) is the portfolio of hedge funds with the lowest (highest) uncertainty index betas in each hedge fund category. The table reports the differences in next-month returns and nine-factor alphas between quintiles 5 and 1. Newey-West t-statistics are given in parantheses. Numbers in bold denote statistical significance.

	Q5–Q1 Average return difference	Q5–Q1 9-Factor alpha difference
Non-directional	**0.445**	0.392
	(2.01)	(1.62)
Semi-directional	**0.826**	**0.769**
	(3.53)	**(3.01)**
Directional	**1.030**	**0.923**
	(2.40)	**(2.25)**

to both directional and semi-directional funds. Finally, semi-directional funds have standard deviations and max–min differences of uncertainty index betas very similar to the overall hedge fund group.

Based on this new set of results on the time-series variation of the uncertainty index betas among hedge fund investment strategies, we expect our main finding—a positive and significant link between uncertainty index beta and future hedge fund returns, obtained for the overall hedge fund category, 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 the uncertainty index beta over future hedge fund returns for the three aforementioned investment strategies separately, and check whether indeed a larger variation in betas through time is associated with stronger predictive power of the uncertainty beta. We perform this test by forming univariate quintile portfolios of uncertainty index beta for each investment style separately and by analyzing the next-month return and alpha differences between the high- and low-uncertainty beta quintiles.

Table 5 reports next-month average return spreads as well as the nine-factor alpha differences between the high- and low-uncertainty index beta quintiles. The statistically significant average return and alpha spreads in Table 5, particularly for the semi-directional and directional strategies, confirm our conjecture. As shown in Table 5, the return and nine-factor alpha spreads between high-uncertainty index beta (quintile 5) and low-uncertainty index beta (quintile 1) funds increase monotonically as we move from non-directional to directional funds. Specifically, while the return spread between high-uncertainty index beta funds and low-uncertainty index beta funds is 0.45% per month for the non-directional funds, it is 0.83% per month for the semi-directional funds, and 1.03% per month for the directional funds. The nine-factor alpha spreads follow a similar pattern among the three investment strategies; 0.39% per month for the non-directional strategies, 0.77% per month for the semi-directional strategies, and 0.92% per month for the directional strategies. More importantly, the statistical significance of these return and alpha spreads between high- and low-uncertainty beta funds is quite high for the semi-directional and directional funds (Newey West t-statistics ranging in between 2.25 and 3.53). On the other hand, the statistical significance of the return and alpha spreads between quintiles 5 and 1 is weaker for the non-directional funds, in fact insignificant for the nine-factor alpha with a t-statistic of 1.62.

Combining these new sets of results with the results obtained earlier on the time-series variation of uncertainty index betas across different investment styles, we observe an economically and statistically stronger relation between uncertainty index beta and future returns for funds with sizeable and greater variation in uncertainty betas.[11] One possible explanation for this could be the macro-timing ability of hedge fund managers. In the next section, we provide a formal test of the macro-timing ability of directional, semi-directional, and non-directional hedge funds.

6.2. Macro-timing ability of hedge funds

Our results thus far suggest that some hedge funds (particularly, directional and semi-directional funds) correctly adjust their exposures to changes in financial and macroeconomic conditions, hence, 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 funds following non-directional strategies, because the time-series variation in betas for these strategies is quite low in comparison to directional and semi-directional strategies.

While the results from the above analysis suggest the existence of a possible macro-timing ability by fund managers in directional and semi-directional hedge funds, the analysis conducted thus far is not a direct test for macro-timing. In this section, we modify the market-timing test of Henriksson and Merton (1981) in our context of macroeconomic risk. Then, we implement a similar methodology for each of the three broad categories of hedge fund styles separately to determine whether funds' ability to time macroeconomic changes is specific to a group of hedge funds. We investigate macro-timing ability of hedge funds using pooled panel regressions based on the Henriksson and Merton model[12]:

$$R_{i,t} = \alpha + \beta_1\, UNC_t + \beta_2\, UNC_t^{high} + \varepsilon_{i,t}, \tag{18}$$

[11] In Table 4, in addition to reporting the time-series variation of uncertainty index 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 the total sample. A notable point in the first two rows of Table 4 is that the total number of funds in the non-directional category is only 654 (out of 6,929 funds), corresponding to 9.44% of the hedge fund sample. On the other hand, the total number of funds following semi-directional and directional strategies is 6,275, corresponding to 90.56% of the hedge fund universe. These results indicate that the significantly positive link between uncertainty index betas and future returns holds for more than 90% of the overall hedge fund sample.

[12] Similar methodology is also used in a different context by Jagannathan and Korajczyk (1986), Chen and Liang (2007), Cao, Chen, Liang, and Lo (2013), and Caglayan and Ulutas (2014).

where $R_{i,t}$ is excess return of fund i in month t, UNC_t is the broad index of economic uncertainty in month t, and UNC_t^{high} is the economic uncertainty index implying macro-timing ability:

$$UNC_t^{high} = \left\{ \begin{matrix} UNC_t & \text{if } UNC_t \text{ is higher than its time}-\text{series median} \\ 0 & \text{otherwise} \end{matrix} \right\}.$$

In Eq. (18), regression parameters α, β_1, and β_2 are the intercept, the uncertainty beta, and the parameter for macro-timing ability, respectively. In this regression specification, a positive and significant estimate of β_2 implies superior macro-timing ability of individual hedge funds.

Table 6 presents the estimated values of β_2 and the corresponding t-statistics from the pooled panel regression specification in Eq. (18), where individual hedge fund excess returns are regressed on the economic uncertainty index as well as on the index implying macro-timing ability for the sample period January 1994–March 2012. Eq. (18) is estimated separately for each of the three hedge fund categories (directional, semi-directional, and non-directional). The t-statistics reported in parentheses are estimated using clustered robust standard errors, accounting for two dimensions of cluster correlation (fund and year). This approach allows for correlations among different funds in the same year as well as correlations among different years in the same fund [see Petersen (2009) for estimation of clustered robust standard errors].

As reported in Table 6, β_2 is estimated to be positive, 0.741, and highly significant with a t-statistic of 2.47 for the directional hedge funds. β_2 is also positive, 0.395, and statistically significant with a t-statistic of 2.08 for the semi-directional hedge funds. However, the statistical and economic significance of β_2 is higher for the directional funds compared to the semi-directional funds. This indicates that directional hedge fund managers have higher capability to time fluctuations in macroeconomic changes. Consistent with our expectation, Table 6 shows that β_2 is economically and statistically insignificant for the non-directional funds, providing no evidence of macro-timing ability for the non-directional hedge fund managers.

Overall, these results make sense in the real world setting of hedge funds, as directional funds willingly take direct exposure to macroeconomic risk factors, relying on their market-timing and volatility-timing ability to generate superior returns. Since these are funds with vigorous investment strategies that are highly exposed to macroeconomic risk, timing the switch in economic trends is essential to their success. Besides, from a hedge fund manager's perspective, risk and especially uncertainty are equally to be feared. However, while risk-averse hedge fund managers avoid risk, they actually seek out uncertainty, as they perceive that dealing with uncertainty is part of what they are compensated for. In sum, our previous results, which show a stronger link between uncertainty index beta and future returns for directional and semi-directional funds, can be attributed to evidence of superior macro-timing ability found only among directional and semi-directional hedge fund managers.

Table 6
Macro-timing tests of directional, semi-directional, and non-directional hedge funds and mutual funds. This table investigates the macro-timing ability of directional, semi-directional, and non-directional hedge funds, and mutual funds. In the first three columns, individual hedge fund excess returns are regressed on the economic uncertainty index as well as on the index implying macro-timing ability using pooled panel regressions for the sample period January 1997–March 2012. Macro-timing ability of hedge funds is tested using a model similar to Henriksson and Merton (1981):

$$R_{i,t} = \alpha + \beta_1 \, UNC_t + \beta_2 \, UNC_t^{high} + \varepsilon_{i,t},$$

where $R_{i,t}$ is excess return of fund i in month t, UNC_t is the broad index of economic uncertainty in month t, and UNC_t^{high} is the economic uncertainty index implying macro-timing ability:

$$UNC_t^{high} = \left\{ \begin{matrix} UNC_t & \text{if } UNC_t \text{ is higher than its time}-\text{series median} \\ 0 & \text{otherwise} \end{matrix} \right\}.$$

In this regression specification, a positive and significant value of β_2 implies superior macro-timing ability of individual hedge funds. For the t-statistics reported in parentheses, clustered robust standard errors are estimated to account for two dimensions of cluster correlation (fund and year). This approach allows for correlations among different funds in the same year as well as correlations among different years in the same fund. In the last column, the same exact analysis is conducted for mutual funds. Numbers in bold denote statistical significance.

	Non-directional hedge funds	Semi-directional hedge funds	Directional hedge funds	Mutual funds
β_2	−0.028	**0.395**	**0.741**	0.621
	(−0.17)	**(2.08)**	**(2.47)**	(1.53)

6.3. Evidence from mutual funds

We think that an alternative way to explain superior performance of directional and semi-directional hedge funds is to compare and contrast hedge funds with mutual funds. Therefore, in this section, we provide evidence from mutual funds by replicating our main analyses for the mutual fund industry for the same sample period, January 1994–March 2012.[13] We first investigate whether mutual funds' exposure to the broad macroeconomic risk factor predicts their future returns. We then analyze whether mutual funds have the ability to time macroeconomic changes.

The primary differences between hedge funds and mutual funds are:

- Hedge funds employ a range of investment tools, including options, leverage, and short-selling, whereas

[13] We use monthly returns of individual mutual funds from the CRSP Mutual Fund database. However, most of the mutual funds in the CRSP database have multiple share classes designed for different client types. That is, a mutual fund may have a retail share class, an institutional share class, or a retirement share class. All of these share classes in essence constitute the same strategy, therefore their returns are highly correlated. As discussed in Section IV of the online appendix, we make sure that each mutual fund is represented with a single share class in our database. After removing multiple share classes, our database contains information on a total of 16,881 distinct, non-duplicated mutual funds, of which 6,303 are defunct funds and the remaining 10,578 are live funds. Table VI of the online appendix provides summary statistics both on numbers and returns of these single-share class, non-duplicated mutual funds.

mutual funds tend to invest primarily on the long side without extensively using other tools. The majority of mutual funds are long only, while hedge funds utilize much more aggressive dynamic trading strategies.

- Because hedge funds rely on hedging instruments and shorting techniques, they are more likely to outperform mutual funds in a bear (down) market.
- Mutual funds seek *relative returns*, or those compared to a benchmark or index. A mutual fund's sole goal is to beat the benchmark. Therefore, if the index is down 10% but the mutual fund is down only 8%, it is considered a success. On the flip side, hedge funds seek *absolute returns*, not related to index or benchmark performance.
- Hedge fund managers receive a performance fee at the end of the year paid from investor gains. Mutual funds typically do not charge performance fees. The most common hedge fund fee structure is the 2/20—a 2% flat management fee skimmed off the top, and a 20% fee on all profits. Most mutual funds charge less than 2% in total fees.
- The founder of a hedge fund is the General Partner and an investor in the fund. The manager of a mutual fund is seldom the owner and may not be a significant fund investor.
- Hedge funds have lockup periods typically of at least one year. That is, each investment must remain in the hedge fund for at least one year (the lockup period). Withdrawals are permitted only with advance notice following the lockup period. Therefore, in difficult market periods or economic conditions, some hedge funds put up gates that restrict redemptions. On the other hand, investments in mutual funds are essentially liquid and are not impacted by lock-ups or gates.[14]

The primary similarity between hedge funds and mutual funds is that both are managed portfolios. In other words, a manager or group of managers selects investments and adds them to a single portfolio. However, hedge funds are managed in a more aggressive manner than mutual funds. From the ability to short-sell stocks to taking positions in options, hedge fund managers are more aggressive, as they attempt to generate the best gains possible for clients. With such an aggressive stance, hedge funds are in a better position to earn money even when the market is falling.

From an investment style perspective, mutual funds can be viewed as highly regulated hedge funds with a larger number of investors and larger AUM. Since mutual funds do not use dynamic trading strategies, we do not expect mutual fund exposure to macroeconomic risk to explain cross-sectional differences in mutual fund returns. Along the same lines, we do not expect mutual funds to have significant macro-timing ability either.

To test these conjectures, we first estimate monthly uncertainty betas for each mutual fund from the time-series regressions of mutual fund excess returns on the broad index of economic uncertainty over a 36-month rolling-window period. Once we generate the uncertainty index betas for mutual funds, for each month from January 1997 to March 2012, we form quintile portfolios by sorting mutual funds based on their uncertainty index betas.

Table 7
Univariate portfolios of mutual funds sorted by β^{UNC}.

Quintile portfolios are formed every month from January 1997 to March 2012 by sorting mutual funds based on their uncertainty index betas (β^{UNC}). Quintile 1 is the portfolio of mutual funds with the lowest uncertainty index betas, and quintile 5 is the portfolio of mutual funds with the highest uncertainty index betas. The table reports average β^{UNC} in each quintile, the next-month average returns, and the nine-factor alphas for each quintile. The last row shows the average monthly raw return difference and the nine-factor alpha difference between High β^{UNC} and Low β^{UNC} quintiles. 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 of the return and alpha spreads.

Quintiles	Average β^{UNC} in each quintile	Next-month average returns	Next-month 9-factor alphas
Low β^{UNC}	−1.259	0.005	−0.142
		(0.01)	(−0.58)
Q2	−0.509	0.123	−0.166
		(0.38)	(−0.86)
Q3	−0.084	0.243	−0.046
		(0.90)	(−0.26)
Q4	0.372	0.375	0.170
		(1.87)	(0.88)
High β^{UNC}	1.050	0.474	0.078
		(1.64)	(0.35)
High β^{UNC}–Low β^{UNC}		0.469	0.220
t-Statistic		(1.44)	(0.53)

Table 7 presents the average $\beta_{i,t}^{UNC}$, average next-month return, and the nine-factor alpha for each of the five uncertainty index beta sorted quintiles. The second column of Table 7 shows the average return difference between quintiles 5 and 1 (High $\beta_{i,t}^{UNC}$–Low $\beta_{i,t}^{UNC}$) is about 0.47% per month with a Newey-West *t*-statistic of 1.44. As shown in the last column of Table 7, even weaker return spread is obtained from the risk-adjusted returns. The nine-factor alpha difference between quintiles 5 and 1 is about 0.22% per month with a Newey-West *t*-statistic of 0.53. This result indicates that mutual funds in the highest $\beta_{i,t}^{UNC}$ quintile do not generate economically or statistically higher risk-adjusted return than mutual funds in the lowest $\beta_{i,t}^{UNC}$ quintile. Overall, the univariate quintile portfolios in Table 7 provide no evidence for a significant link between uncertainty betas of mutual funds and their future returns. Mutual fund exposure to the broad index of economic uncertainty does not predict the cross-sectional variation in mutual fund returns.

To test our second conjecture, we investigate the macro-timing ability of mutual funds with the same Henriksson and Merton (1981) model that we utilize in our earlier analysis for hedge funds. The last column of Table 6 presents the estimated value of β_2 and the corresponding *t*-statistic for mutual funds. Essentially, Eq. (18) is estimated with a pooled panel regression for the sample period January 1994–March 2012, this time using mutual fund excess returns as the dependent

[14] There are other major differences between hedge funds and mutual funds that are not listed here, such as differences in their regulations, asset allocation, and performance disclosure policies.

variable. The t-statistic reported in parentheses is again estimated using clustered robust standard errors, accounting for two dimensions of cluster correlation (fund and year). Table 6 shows that for the broad index of economic uncertainty, β_2 is statistically insignificant (a coefficient of 0.621 with a t-statistic of 1.53) for mutual funds, providing no evidence of macro-timing ability for mutual fund managers.

In sum, the results show that directional and semi-directional hedge fund managers have the ability to actively vary their exposure to macroeconomic risk up or down in a timely fashion according to the macroeconomic conditions and state of the financial markets. As a result, they can generate superior returns, and there exists a positive and stronger link between their uncertainty betas and future returns. On the other hand, mutual funds and non-directional hedge funds seem to have no macro-timing ability. In line with this finding, there is no evidence of a significant cross-sectional link between uncertainty betas and future returns for mutual funds and non-directional hedge funds.

7. Conclusion

Earlier studies pay no attention to the distinction between financial risk and macroeconomic uncertainty in the cross-sectional pricing of individual hedge funds. This paper contributes to the literature by examining the relative performance of hedge fund exposure to risk and uncertainty factors in terms of these factors' ability to explain cross-sectional differences in hedge fund returns. We first introduce alternative measures of macroeconomic risk based on 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 excess 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 macroeconomic risk (uncertainty) factors. 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 macroeconomic risk, hedge funds in the highest uncertainty beta quintile generate 6% to 9% higher average annual returns compared to funds in the lowest uncertainty beta quintile. After controlling for the Fama-French (1993) and Carhart (1997) four factors and the Fung-Hsieh (2001) five trend-following factors, the positive relation between uncertainty beta and risk-adjusted returns (nine-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 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 beta and hedge fund returns in all of the subsample periods examined.

We also test the performance of hedge fund exposure to various standard risk factors in predicting their future returns. The results provide no evidence for a significant link between these risk factor betas and future fund returns. On the other hand, we find for the first time that macroeconomic risk 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 standard measures of risk, macroeconomic risk is a stronger determinant of the cross-sectional dispersion in hedge fund returns.

In addition, we investigate whether the predictive power of uncertainty beta for future fund returns changes across specific hedge fund categories. Empirical analysis indicates that the economic and statistical significance of the uncertainty betas gradually improves as we move from the least directional to the most directional strategies, implying a stronger relation between uncertainty beta and future returns for funds with sizeable time-series variation in uncertainty betas. We also show that directional and semi-directional hedge fund managers have the ability to time macroeconomic changes by increasing (decreasing) portfolio exposure to macroeconomic risk factors when macroeconomic risk is high (low). However, non-directional hedge funds and mutual funds do not have significant macro-timing ability. Our results indicate that the predictive power of uncertainty beta emanates from hedge funds' competence in detecting fluctuations in financial markets and their ability to timely adjust their positions to changes in financial and macroeconomic conditions.

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