Macroeconomic Risk and Hedge Fund Returns

Online Appendix

To save space in the paper, we present some of our findings in the Online Appendix. Section I examines potential data bias issues related to our study as discussed in the hedge fund literature. Section II provides a detailed description of the principal component analysis. Section III presents results from model-independent, nonparametric measures of macroeconomic risk proxied by the degree of disagreement among the expectations of a large number of professional forecasters. Section IV describes the mutual fund database and reports the number of mutual funds, yearly attrition rates, and their summary statistics. Table I describes the hedge fund database, fund characteristics, and their summary statistics. Table II reports descriptive statistics of the risk factors commonly used in the hedge fund literature. Table III shows results from quintile portfolios of hedge funds sorted based on the standard risk factor betas. Table IV provides univariate portfolio analysis for the eight individual measures of uncertainty beta. Table V shows results from univariate portfolios of hedge funds sorted based on uncertainty betas generated from nonparametric measures of macroeconomic risk proxied by dispersion in economic forecasts. Table VI presents summary statistics for the mutual funds database.

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I. Potential Hedge Fund Data Bias Issues

Hedge fund studies can be subject to potential data bias issues. Brown, Goetzmann, Ibbotson, and Ross (1992), Fung and Hsieh (2000), Liang (2000), and Edwards and Caglayan (2001) cover these well-known data bias problems extensively in the hedge fund literature. The first potential data bias in a hedge fund study is the survivorship bias if the database does not include the returns of non-surviving hedge funds. In our study, for the sample period January 1994 – March 2012, we do have monthly return histories of 3,139 funds in the live funds (survivor) database and 7,166 funds in the graveyard (defunct) database. We estimate that if the returns of non-surviving hedge funds (graveyard database) had been excluded from the analyses, there would have been a survivorship bias of 2.41% in average annual hedge fund returns (the difference between the annualized average return of only surviving funds in the sample and the annualized average return of all surviving and non-surviving funds in the sample).[1]

Another important data bias in a hedge fund study is called the back-fill bias. Once a hedge fund is included into a database, that fund's previous returns are automatically added to that database as well (this process is called "back-filling"). This practice in the hedge fund industry is problematic, because it generates an incentive only for successful hedge funds to report their initial returns to the database vendor, and as a result, it may generate an upward bias in returns of newly reporting hedge funds during their early histories. Fung and Hsieh (2000) report that the median backfill period is about 12 months based on the TASS database from 1994 to 1998. They adjust for this bias by dropping the first 12 months of returns of all individual hedge funds in their sample and report a back-fill bias estimate of 1.4% per annum (see also Malkiel and Saha (2005) and Kosowski, Naik, and Teo (2007) for previous literature on back-fill bias and how they adjust their samples to mitigate the impact of back-fill bias on their results). In a recent study Aggarwal and Jorion (2010) propose an alternative method to measure the magnitude of the back-fill bias. They measure the back-fill period as the difference between a fund's inception date and the date the fund is added to the database. They identify a fund as "non-back-filled" if the back-fill period is below 180 days. In other words, they divide the hedge fund sample into two subsamples, and hedge funds whose inception date and database entry date are in proximity are classified as non-back-filled funds, and the rest of funds in the sample (whose back-fill periods are more than 180 days) are classified as back-filled funds. Then, they calculate the average annual return difference between back-filled funds and non-back-filled funds to measure the magnitude of back-fill bias. Following Aggarwal and Jorion's (2010) procedure, we identify 7,340 hedge funds as back-filled funds in our sample, and estimate a back-fill bias of 1.80% for the sample period January 1994 – March 2012.[2]

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

[2] This finding is comparable to earlier studies of hedge funds. Bali, Brown, and Caglayan (2011, 2012), for example, report a back-fill bias estimate of 2.09% and 2.03%, respectively.

In our study, we find that the median back-fill period (i.e, the number of days between the inception date and the date the fund is added to the database) is 575 days (around 18 months) across all hedge funds. In order to check whether the back-fill bias has any significant impact on our main findings, we delete the first 18 months of returns of all individual hedge funds in our sample, and check the predictive power of the broad measure of economic uncertainty index beta on future fund returns for this modified sample. As an alternative to etimating the median back-fill period, we also apply a more straightforward method, and use only the returns after a fund enters the database, and check if the broad measure of economic uncertainty index beta still predicts future hedge fund returns for this second modified sample as well. The results from the univariate Fama-MacBeth cross-sectional regressions for these two modified samples of hedge funds turn out to be very similar to the result reported from our main sample in Table 3 of the main text. Specifically, while the average slope coefficient on the broad economic uncertainty index beta is 0.4201 (with a Newey-West *t*-statistic of 2.81) for our main sample in Panel A of Table 3, it is 0.4141 (with a Newey-West *t*-statistic of 2.60) for the first 18-month-deleted-return modified sample, and it is 0.4428 (with a Newey-West *t*-statistic of 2.75) for the sample that utilizes only the retruns after hedge funds are added to the database. In sum, we can conclude that the positive and significant link between the uncertainty index beta and future hedge fund returns persist even after taking care of the back-fill bias.

The last possible data bias in a hedge fund study is called the multi-period sampling bias. Investors generally ask for a minimum of 36 months of return history before making a decision whether to invest in a hedge fund or not. Therefore, in a hedge fund study, inclusion of hedge funds with shorter return histories than 36 months would be misleading to those investors who seek past performance data to make investment decisions. Also, a minimum 36-month return history requirement makes sense from a statistical perspective to be able to run regressions and get sensible estimates of alphas and betas for individual hedge funds in the sample. Therefore, we require that all hedge funds in the sample have at least 36 months of return history in our study. This 36-month minimum return history requirement, however, decreases our sample size from 10,305 to 7,190 (i.e., 3,115 funds in the sample have return histories less than 36 months). There is a slight chance that we might introduce a new survivorship bias into the system due to deletion of these 3,115 hedge funds from the sample (funds that had return histories less than 36 months most probably dissolved due to bad performance). In an effort to find the impact of these deleted 3,115 hedge funds on total hedge fund performance, we compare the performance of hedge funds *before* and *after* the 36-month return history requirement and find that the annual average return of hedge funds that pass the 36-month requirement (7,190 funds) is only 0.51% higher than the annual average return of all hedge funds (10,305 funds) in the sample, a small insignificant percentage difference between the two samples in terms of survivorship bias considerations.[3]

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

II. Principal Component Analysis

Principal Component Analysis (PCA) is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.[4] Consider a data matrix, X, with zero mean (the sample mean of the distribution has been subtracted from the data set) and standard deviation of one, where each of the *n* rows represents a different repetition of the experiment, and each of the *p* columns gives a particular kind of data.

Mathematically, the transformation is defined by a set of *p*-dimensional vectors of weights or *loadings* $w_{(k)} = (w_1,..., w_p)_{(k)}$ that map each row vector $x_{(i)}$ of X to a new vector of principal component scores $\theta_{(i)} = (\theta_1,..., \theta_p)_{(i)}$ is given by $\theta_{k(i)} = x_{(i)} \cdot w_{(k)}$ in such a way that the individual variables of θ considered over the data set successively inherit the maximum possible variance from x, with each loading vector w constrained to be a unit vector.

The first loading vector $w_{(1)}$ thus has to satisfy

$$w_{(1)} = \arg\max_{\|w\|=1} \left\{ \sum_i (\theta_1)_{(i)}^2 \right\} = \arg\max_{\|w\|=1} \left\{ \sum_i \left(x_{(i)} \cdot w\right)^2 \right\} \tag{1}$$

Equivalently, writing this in matrix form gives

$$w_{(1)} = \arg\max_{\|w\|=1} \left\{ \sum_i \|\mathrm{Xw}\|^2 \right\} = \arg\max_{\|w\|=1} \left\{ \mathrm{w}^{\mathrm{T}} \mathrm{X}^T \mathrm{Xw} \right\} \tag{2}$$

Since $w_{(1)}$ has been defined to be a unit vector, it equivalently also satisfies

$$w_{(1)} = \arg\max_{\|w\|=1} \left\{ \frac{\mathrm{w}^{\mathrm{T}} \mathrm{X}^T \mathrm{Xw}}{\mathrm{w}^{\mathrm{T}} \mathrm{w}} \right\} \tag{3}$$

The quantity to be maximized can be recognized as a Rayleigh quotient. A standard result for a symmetric matrix such as $\mathrm{X}^T \mathrm{X}$ is that the quotient's maximum possible value is the largest eigenvalue of the matrix, which occurs when w is the corresponding eigenvector. With $w_{(1)}$ found, the first component of a data vector $x_{(i)}$ can then be given as a score $\theta_{1(i)} = x_{(i)} \cdot w_{(k)}$ in the transformed co-ordinates, or as the corresponding vector in the original variables, $\left\{x_{(i)} \cdot w_{(1)}\right\} w_{(1)}$.

[4] PCA was originally introduced by Pearson (1901) as an analogue of the principal axes theorem in mechanics, and later it was independently developed and named by Hotelling (1936).

III. Cross-Sectional Dispersion in Economic Forecasts

In this section, we check whether hedge funds' exposures to alternative measures of macroeconomic risk generate similar results obtained from the VAR–GARCH based parametric 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, calculating the the degree of disagreement among the expectations of different forecasters.[5] Specifically, in this section, we use the cross-sectional dispersion in quarterly forecasts for the U.S. gross domestic product (GDP), industrial production (IP), and inflation rate (INF) as alternative measures of macroeconomic risk. Different from the VAR–GARCH based parametric measures of macroeconomic risk, these dispersion measures are model-independent, nonparametric measures obtained from disagreements among professional forecasters. The cross-sectional dispersion measures are defined as the percent difference between the 75th percentile and the 25th percentile (the interquartile range) of the projections for the quarterly level:

$$\text{Dispersion Measure} = 100 \times \log(\text{75th Level}/\text{25th Level}) \tag{4}$$

The original data provided by the Federal Reserve Bank of Philadelphia are quarterly. We use a linear interpolation to convert the quarterly data to monthly frequency. Figure I of the online appendix presents monthly time-series plots of the cross-sectional dispersion measures for the sample period January 1994 – March 2012. A visual depiction of the cross-sectional dispersion measures in Figure I of the online appendix and the Economic Uncertainty Index in Figure 2 of the main text suggests that the model-independent, nonparametric measures of macroeconomic risk are closely related to the GARCH-based parametric measure of macroeconomic risk. The correlations between the Economic Uncertainty Index obtained from the principal component analysis and the cross-sectional dispersion in economic forecast measures for the GDP, IP, and INF are 0.72, 0.80, and 0.59, respectively. These positive and high correlations suggest that hedge funds' exposures to the nonparametric measures of macroeconomic risk may potentially capture the cross-sectional differences in hedge fund returns.

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

[5] The Survey of Professional Forecasters is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990.

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

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

IV. Mutual Fund Database

This study uses monthly returns of individual mutual funds from CRSP Mutual Fund database. Originally in our database there are 48,218 funds that report monthly returns at some point during our sample period from January 1994 to March 2012. Most of the mutual funds in the CRSP database, however, 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. However, the CRSP Mutual Fund database assigns a separate fund id number to each share class of the same fund, treating these share classes as if they are separate funds. In order to distinguish between share classes and funds, and not to use any duplicated funds (and hence returns) in our analyses, we first remove the multiple share classes of mutual funds from our study. We do this by keeping only the share class with the smallest fund id number (within a mutual fund family) in the database, and by removing the rest of the share classes of that particular mutual fund family from our analyses. This way, we make sure that each mutual fund family is represented with a single share class in our database. After removing multiple share classes, our sample size of mutual funds drops from 48,218 funds to 16,881 funds. That is, 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 this online appendix provides summary statistics both on numbers and returns of these single-share class, non-duplicated mutual funds. For each year, Table VI reports the number of funds entered into database, number of funds dissolved, attrition rate (the ratio of number of dissolved funds to the total number of funds at the beginning of the year), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted mutual fund portfolio.

The most notable point in Table VI is a sharp increase in the yearly attrition rates of mutual funds after year 2007, the starting point of the big worldwide financial crisis. From 1994 to 2007, on average, the annual attrition rate in the database was only 5.02%; however, this annual figure jumped to 10.67% in 2008 and to 9.63% in 2009 (the two highest figures detected in our sample period), giving an indication on how harsh the financial crisis is felt in the mutual fund industry in the last couple of years. In line with this jump in attrition rates, just during 2008, for example, mutual funds on average lost 2.67% (return) per month, generating the largest losses ever for their investors since the start of our analysis in 1994.

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Table I. Descriptive Statistics of Hedge Funds

There are total of 10,305 hedge funds that reported monthly returns to TASS for the years between 1994 and 2011 in this database, of which 7,166 are defunct funds and 3,139 are live funds. For each year from 1994 to 2011, Panel A reports the number of hedge funds, total assets under management (AUM) at the end of each year by all hedge funds (in billion \$s), and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted hedge fund portfolio. Panel B reports for the sample period January 1994 – March 2012 the cross-sectional mean, median, standard deviation, minimum, and maximum statistics for hedge fund characteristics including returns, size, age, management fee, incentive fee, redemption period, and minimum investment amount.

Panel A. Summary Statistics Year by Year

						Equal-Weighted Hedge Fund Portfolio Monthly Returns (%)				
Year	**Year Start**	**Entries**	**Dissolved**	**Year End**	**Total AUM (billion $s)**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
1994	786	231	18	999	54.6	-0.02	0.15	0.98	–1.61	1.13
1995	999	302	54	1,247	66.6	1.33	1.47	1.13	–0.94	3.13
1996	1,247	353	113	1,487	89.6	1.45	1.54	1.54	–1.66	3.99
1997	1,487	388	100	1,775	137.2	1.47	1.68	2.01	–1.53	4.83
1998	1,775	396	146	2,025	144.3	0.36	0.36	2.22	–5.14	3.04
1999	2,025	461	167	2,319	178.3	2.04	1.25	2.15	–0.34	6.49
2000	2,319	485	211	2,593	199.8	0.84	0.47	2.24	–2.04	5.47
2001	2,593	593	221	2,965	252.5	0.57	0.69	1.22	–1.64	2.68
2002	2,965	654	252	3,367	293.6	0.28	0.57	0.89	–1.45	1.49
2003	3,367	758	242	3,883	419.9	1.39	1.19	0.95	–0.18	3.42
2004	3,883	867	286	4,464	586.4	0.69	0.78	1.22	–1.33	2.89
2005	4,464	882	428	4,918	659.1	0.76	1.30	1.35	–1.51	1.99
2006	4,918	769	488	5,199	798.5	1.04	1.35	1.42	–1.63	3.41
2007	5,199	716	736	5,179	928.2	1.00	0.97	1.48	–1.74	3.11
2008	5,179	588	1,158	4,609	685.5	-1.56	-1.92	2.57	–6.02	1.83
2009	4,609	517	858	4,268	606.7	1.38	1.27	1.51	–0.88	4.64
2010	4,268	327	710	3,885	557.8	0.75	0.90	1.72	–2.92	3.09
2011	3,885	208	806	3,287	508.8	-0.51	-0.30	1.67	–3.57	1.94

Table I (continued)

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

	N	Mean	Median	Std. Dev.	Minimum	Maximum
Average Monthly Return over the life of the Fund (%)	10,305	0.52	0.51	1.21	–25.14	24.64
Average Monthly AUM over the life of the Fund (million $)	10,305	89.1	40.0	246.6	0.5	8,613.2
Age of the Fund (# of months in existence)	10,305	68.4	56.0	49.2	1.0	219.0
Management Fee (%)	10,202	1.46	1.50	0.66	0.00	10.00
Incentive Fee (%)	10,166	15.44	20.00	7.75	0.00	50.00
Redemption Period (# of days)	10,305	37.1	30.0	32.9	0.0	365.0
Minimum Investment Amount (million $)	10,220	1.29	0.25	15.76	0.00	1,000.0

Table II. Descriptive Statistics of the Standard Risk Factors

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

Panel A. Standard Risk Factors: January 1994 – March 2012

	N	Mean	Median	Std. Dev.	Minimum	Maximum
MKT: Excess return on the value-weighted market index	219	0.53	1.24	4.70	–18.55	11.53
SMB: Fama-French size factor	219	0.21	–0.15	3.58	–16.62	22.06
HML: Fama-French book-to-market factor	219	0.22	0.21	3.40	–12.87	13.88
MOM: Carhart momentum factor	219	0.45	0.66	5.50	–34.75	18.40
Δ10Y: Fung-Hsieh long-term interest rate factor	219	–0.02	–0.04	0.24	–1.11	0.65
ΔCrdSpr: Fung-Hsieh credit spread factor	219	0.01	–0.01	0.20	–0.99	1.45
BDTF: Fung-Hsieh bond trend-following factor	219	–1.42	–5.04	15.07	–25.36	68.86
FXTF: Fung-Hsieh currency trend-following factor	219	–0.40	–4.64	19.19	–30.13	90.27
CMTF: Fung-Hsieh commodity trend-following factor	219	–0.51	–3.01	13.85	–23.04	64.75
IRTF: Fung-Hsieh short-term interest rate trend-following factor	219	1.72	–4.48	27.80	–34.64	221.92
SKTF: Fung-Hsieh stock index trend-following factor	219	–5.07	–6.51	12.93	–30.19	46.15

Table II (continued)

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

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

Table III. Univariate Portfolios of Standard Risk Factor Betas

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

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

Table IV. Univariate Portfolios of Uncertainty Betas for Hedge Funds

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

	Average Size of β^{DEF_U}	Average Size of β^{DIV_U}	Average Size of β^{GDP_U}	Average Size of β^{INF_U}	Average Size of β^{MKT_U}	Average Size of β^{RREL_U}	Average Size of β^{TERM_U}	Average Size of β^{UNEMP_U}
Q1	–95.248	–143.223	–68.852	–35.312	–1.830	–39.692	–58.237	–112.735
Q2	–23.535	–22.157	–19.077	–7.579	–0.324	–11.602	–12.791	–34.286
Q3	1.148	17.484	–1.671	1.454	0.154	–2.027	2.067	–11.180
Q4	26.705	61.524	15.677	10.929	0.708	7.502	15.914	14.172
Q5	113.413	204.848	71.672	42.148	2.445	37.087	59.028	91.277
	Next-month returns of β^{DEF_U} Quintiles	Next-month returns of β^{DIV_U} Quintiles	Next-month returns of β^{GDP_U} Quintiles	Next-month returns of β^{INF_U} Quintiles	Next-month returns of β^{MKT_U} Quintiles	Next-month returns of β^{RREL_U} Quintiles	Next-month returns of β^{TERM_U} Quintiles	Next-month returns of β^{UNEMP_U} Quintiles
Q1	0.076	0.111	0.141	0.180	0.094	0.277	0.072	0.433
Q2	0.289	0.225	0.292	0.273	0.190	0.304	0.255	0.299
Q3	0.303	0.301	0.327	0.309	0.267	0.292	0.316	0.301
Q4	0.440	0.430	0.407	0.372	0.448	0.366	0.434	0.332
Q5	0.734	0.774	0.675	0.709	0.843	0.603	0.766	0.477
Q5 – Q1 Return Diff.	**0.658** **(2.47)**	**0.662** **(2.63)**	**0.534** **(2.07)**	**0.529** **(2.30)**	**0.750** **(2.32)**	0.326 (0.98)	**0.694** **(2.45)**	0.044 (0.15)
Q5 – Q1 9-factor Alpha Diff.	**0.595** **(2.04)**	**0.665** **(2.10)**	**0.599** **(2.97)**	**0.523** **(2.00)**	**0.543** **(2.02)**	0.366 (1.36)	**0.503** **(2.16)**	0.150 (0.53)

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

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

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

Table VI. Descriptive Statistics of Mutual Funds

There are total of 16,881 mutual funds that reported monthly returns to CRSP Mutual Fund Database for the years between 1994 and 2011 in this database, of which 6,303 are defunct funds and 10,578 are live funds. For each year from 1994 to 2011, this table reports the number of mutual funds, yearly attrition rates, and the mean, median, standard deviation, minimum, and maximum monthly percentage returns on the equal-weighted mutual fund portfolio.

						Equal-Weighted Mutual Fund Portfolio Monthly Returns (%)				
Year	**Year Start**	**Entries**	**Dissolved**	**Year End**	**Attrition Rate (%)**	**Mean**	**Median**	**Std. Dev.**	**Minimum**	**Maximum**
1994	3,108	625	132	3,601	4.25	-0.17	0.18	1.64	-3.08	2.01
1995	3,601	545	78	4,068	2.17	1.37	1.44	0.82	-0.33	2.41
1996	4,068	660	125	4,603	3.07	0.84	0.89	1.37	-2.15	2.98
1997	4,603	782	164	5,221	3.56	0.98	1.01	2.23	-2.31	4.01
1998	5,221	794	171	5,844	3.28	0.78	1.51	3.36	-8.29	3.67
1999	5,844	812	118	6,538	2.02	1.26	1.70	2.25	-2.34	5.16
2000	6,538	851	436	6,953	6.67	0.06	-1.26	3.16	-4.96	4.37
2001	6,953	655	524	7,084	7.54	-0.38	-0.17	3.60	-6.38	4.72
2002	7,084	494	520	7,058	7.34	-0.86	-1.00	3.00	-5.24	3.60
2003	7,058	490	483	7,065	6.84	1.62	1.14	1.98	-1.28	4.85
2004	7,065	469	381	7,153	5.39	0.74	1.25	1.69	-2.49	3.10
2005	7,153	636	485	7,304	6.78	0.52	0.94	1.62	-1.64	2.54
2006	7,304	765	405	7,664	5.54	0.88	1.06	1.52	-2.51	3.27
2007	7,664	946	445	8,165	5.81	0.53	0.65	1.81	-3.03	3.03
2008	8,165	1,977	871	9,271	10.67	-2.67	-1.31	5.05	-14.10	3.41
2009	9,271	1,232	893	9,610	9.63	2.01	2.84	4.46	-6.26	8.42
2010	9,610	925	519	10,016	5.40	1.07	1.69	3.66	-5.34	6.56
2011	10,016	1,064	564	10,516	5.63	-0.13	-0.55	3.51	-6.43	7.56

Figure I. The Cross-Sectional Dispersion in Economic Forecasts

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