Macroeconomic Uncertainty and Expected Stock Returns

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Abstract

This paper introduces a broad index of macroeconomic uncertainty based on the ex-ante measures of cross-sectional dispersion in economic forecasts by the Survey of Professional Forecasters. We estimate individual stock exposures to a newly proposed measure of economic uncertainty index and find that the resulting uncertainty beta predicts a significant proportion of the cross-sectional dispersion in stock returns. After controlling for a large set of stock characteristics and risk factors, we find the predicted negative relation between uncertainty beta and future stock returns remains economically and statistically significant. The significantly negative uncertainty premium is robust to alternative measures of uncertainty index and distinct from the negative market volatility risk premium identified by earlier studies.

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1. Introduction

Merton's (1973) seminal paper indicates that, in a multi-period economy, investors have incentive to hedge against future stochastic shifts in consumption and investment opportunity sets. This implies that state variables that are correlated with changes in consumption and investment opportunities are priced in capital markets such that an asset's covariance with these state variables is related to its expected returns.

Macroeconomic variables are widely accepted candidates for these systematic risk factors because innovations in economic indicators can generate global impacts on stock fundamentals, such as cash flows, risk-adjusted discount factors, and investment opportunities. There are several channels by which macroeconomic fundamentals such as output growth, inflation, and unemployment have significant impacts on expected returns. To the extent that investors pursue opportunities arising from changing economic circumstances, we would expect that returns from investment in risky assets are influenced by the extent to which investors vary their exposure to leading economic indicators.

According to the intertemporal capital asset pricing model (ICAPM) of Merton (1973), 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. Hence, when choosing a portfolio at time t, ICAPM investors consider how their wealth at time $t+1$ might vary with future state variables. This implies that like CAPM investors, ICAPM investors prefer high expected return and low return variance, but they are also concerned with the covariances of portfolio returns with state variables that affect future investment opportunities. Bloom, Bond, and Reenen (2007), Bloom (2009), Chen (2010), Allen, Bali, and Tang (2012), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), and Stock and Watson (2012) provide theoretical and empirical support for the idea that time variation in the conditional volatility of macroeconomic shocks is linked to real economic activity. Thus, economic uncertainty is a relevant state variable affecting future consumption and investment decisions.

Motivated by the aforementioned studies, we examine the role of macroeconomic uncertainty in the cross-sectional pricing of individual stocks. We argue that disagreement over changes in macroeconomic fundamentals can be considered a source of macroeconomic uncertainty. We quantify this uncertainty with ex-ante measures of cross-sectional dispersion in economic forecasts from the Survey of Professional Forecasters. These uncertainty measures provided by the Federal Reserve Bank of Philadelphia determine the degree of disagreement between the expectations of professional forecasters. In our empirical analysis, we use seven different measures of cross-sectional dispersion in quarterly forecasts for output, inflation, and unemployment as alternative proxies for economic uncertainty.

We quantify an unexpected change in economic predictions of professional forecasters by estimating an autoregressive process for each dispersion measure. The standardized residuals from the autoregressive model remove the predictable component of the dispersion measures and can be viewed as a measure of uncertainty shock. We estimate individual stock exposure to the standardized residuals and find that the resulting uncertainty betas from all seven measures of uncertainty shock predict a significant proportion of the cross-sectional dispersion in stock returns.

In addition to individual measures of disagreement over macroeconomic fundamentals, we introduce two broad indices of economic uncertainty based on the average and the first principal component of the standardized residuals for the seven dispersion measures. These economic uncertainty indices are generated using the past information only, so that there is no look-ahead bias in our empirical analyses. Moreover, these uncertainty indices are formed based on the ex-ante predictions of professional forecasters so that we provide out-of-sample performance of the ex-ante measure of the uncertainty beta in predicting the cross-sectional variation in future stock returns.

First, we estimate time-varying uncertainty betas using 20-quarter (and 60-month) rolling regressions of excess returns on the newly proposed economic uncertainty index for each stock trading at the NYSE, Amex, and Nasdaq. Then, we examine the performance of these quarterly (and monthly) uncertainty betas in predicting the cross-sectional dispersion in future stock returns. Specifically, we sort stocks into decile portfolios by their uncertainty beta during the previous quarter (or month) and examine the monthly returns on the resulting portfolios from October 1973 to December 2012. Stocks in the lowest uncertainty beta decile generate about 8% more annual returns compared to stocks in the highest uncertainty beta decile. After controlling for the well-known market, size, book-to-market, and momentum factors of Fama and French (1993) and Carhart (1997), we find the difference between the returns on the portfolios with the highest and lowest uncertainty beta (4-factor alpha) remains negative and highly significant.

The significantly negative uncertainty premium is consistent with the intertemporal capital asset pricing models of Merton (1973) and Campbell (1993, 1996). An increase in economic uncertainty reduces future investment and consumption opportunities. To hedge against unfavorable shifts in investment opportunity sets, investors prefer to hold stocks that have higher covariance with economic uncertainty (stocks with higher uncertainty beta). This is because an increase in economic uncertainty increases the return on high uncertainty beta stocks due to positive intertemporal correlation. Hence, when economic uncertainty increases, although their optimal consumption and future investment opportunities decline, investors compensate for this loss by obtaining a stronger wealth effect through the increase in the returns of stocks that have a positive correlation with economic uncertainty. Therefore, through the intertemporal hedging demand, investors prefer to hold stocks with higher uncertainty beta, and accept lower compensation from these stocks in the form of lower expected returns.

In addition to the rational asset pricing explanation of the negative uncertainty premium, there exists a behavioral explanation based on differences of opinion and short-sales constraints along the lines of Miller (1977).[1] Suppose that stocks with high uncertainty beta are subject to overpricing because investor opinions differ about their prospects and they are hard to short. When macroeconomic uncertainty increases, the range of investor opinions about their prospects broadens. More extreme optimists end up holding these stocks, and their prices increase. The uncertainty beta can thus be viewed as an indirect way to measure dispersed opinion and overpricing. This view suggests that these stocks should have particularly low returns when economic uncertainty is high. Although exploring Miller's hypothesis itself is beyond the scope of this paper, we show later in the paper that stocks with high uncertainty beta have particularly low returns during economic recessions with larger differences of opinion.

[1]Miller (1977) hypothesizes that stock prices reflect an upward bias as long as divergence of opinion exists among investors about stock value and pessimistic investors do not hold sufficient short positions because of institutional or behavioral reasons. In Miller's model, overvaluation of securities is observed because pessimists are restricted to holding zero shares although they prefer holding a negative quantity, and the prices of securities are mainly determined by the beliefs of the most optimistic investors. Since divergence of opinion is likely to increase with firm-specific uncertainty, Miller predicts a negative relation between firm-specific uncertainty and expected stock returns.

To ensure that it is the uncertainty beta that is driving documented return differences rather than well-known stock characteristics or risk factors, we perform bivariate portfolio sorts and re-examine the raw return and alpha differences. We control for size and book-to-market (Fama and French 1992, 1993), momentum (Jegadeesh and Titman 1993), short-term reversal (Jegadeesh 1990), illiquidity (Amihud 2002), co-skewness (Harvey and Siddique 2000), idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang 2006), analyst earnings forecast dispersion (Diether, Malloy, Scherbina 2002), market volatility beta (Ang et al. 2006 and Campbell et al. 2012), firm age (Shumway 2001), and leverage (Bhandari 1988). After controlling for this large set of stock return predictors, we find the negative relation between uncertainty beta and future returns remains highly significant. We also examine the cross-sectional relation between uncertainty beta and expected returns at the stock-level using the Fama-MacBeth (1973) regressions. After all variables are controlled for simultaneously, the cross-sectional regressions provide strong corroborating evidence for an economically and statistically significant negative relation between the uncertainty beta and future stock returns.

We provide a battery of robustness checks. We investigate whether our results are driven by small, illiquid, and low-priced stocks, or stocks trading at the Amex and Nasdaq exchanges. We find that negative uncertainty premium is highly significant in the cross-section of NYSE stocks, S&P 500 stocks, and the 1,000 and 500 largest and most liquid stocks in the Center for Research in Security Prices (CRSP) universe. We show that the cross-sectional predictability results are robust across different time periods, and for both economic recessions and expansions. However, consistent with theoretical predictions, the uncertainty premium is higher during bad states of the economy. We also examine the long-term predictive power of uncertainty beta and find that the negative relation between the uncertainty beta and future stock returns is not just a one-month affair. The economic uncertainty beta predicts cross-sectional variations in stock returns nine months into the future. Finally, we show that the negative uncertainty premium is significant when we use the alternative measures of the economic uncertainty index developed by Jurado, Ludvigson, and Ng (2013). Moreover, this negative uncertainty premium is distinct from the negative volatility risk premium identified by earlier studies.

The paper is organized as follows. Section 2 describes the data and variables. Section 3 presents a simple extension of Merton's (1973) conditional asset pricing model with economic uncertainty.

Section 4 provides portfolio-level analyses and stock-level cross-sectional regressions that examine a comprehensive list of control variables. Section 5 controls for exposure to stock market volatility. Section 6 investigates whether our main findings remain intact when we use alternative measures of the economic uncertainty index proposed by other studies. Section 7 concludes the paper.

2. Data and variable definitions

This section first describes the data on cross-sectional dispersion in economic forecasts, and then introduces an index of macroeconomic uncertainty. Finally, we provide the definitions of the stock-level predictive variables used in cross-sectional return predictability.

2.1. Cross-sectional dispersion in economic forecasts

The Federal Reserve Bank of Philadelphia releases measures of cross-sectional dispersion in economic forecasts from the Survey of Professional Forecasters, calculating the degree of disagreement between the expectations of different forecasters.[2] In our empirical analyses, we use the cross-sectional dispersion in quarterly forecasts for the U.S. real gross domestic product (GDP) growth, real GDP (RGDP) level, nominal GDP (NGDP) level, NGDP growth, GDP price index level, GDP price index growth (inflation rate forecast), and unemployment rate. These dispersion measures are model-independent, nonparametric measures of economic uncertainty obtained from disagreements among professional forecasters.[3] The cross-sectional dispersion measures are defined as the percent difference between the 75th and 25th percentiles (the interquartile range) of the projections for quarterly growth or levels:

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

$$Dispersion\ Measure(Level) = 100 \times log(75th\ Level/25th\ Level). \tag{2}$$

[2]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.

[3]The Federal Reserve Bank of Philadelphia provides a partial list of the forecasters who participated in the survey. Professional forecasters are generally academics at research institutions and economists at major investment banks, consulting firms, and central banks in the United States and abroad. The number of professional forecasters who participate in the survey changes over time. Figure A1 of the online appendix presents the number of forecasts for the current quarter's real GDP growth over the sample period 1968:Q4−2012:Q4. The number of forecasts for the other six macro variables is almost identical for the period 1968−2012.

Panel A in Table A1 of the online appendix presents the descriptive statistics of the quarterly cross-sectional dispersion measures for the sample period 1968:Q4−2012:Q4. The volatility and max-min differences of the dispersion measures are quite high compared to their means, implying significant time-series variation in the economic uncertainty measures. Panel B of Table A1 shows that the cross-sectional dispersion measures are generally highly correlated with each other (in the range of 0.74−0.95), and reflect common sources of ambiguity about the state of the aggregate economy. On the other hand, some of the correlations reported in Panel B of Table A1 are lower, in the range of 0.34−0.59, implying that each dispersion measure has the potential to capture different aspects of uncertainty and disagreement over financial and macroeconomic fundamentals.

Figure A2 of the online appendix displays the quarterly time-series plots of the cross-sectional dispersion measures for the sample period 1968:Q4−2012:Q4. The visual depiction of the dispersion measures in Figure A2 indicates that these economic uncertainty measures closely follow large falls and rises in financial and economic activity. Specifically, economic uncertainty is higher during economic and financial market downturns. Similarly, uncertainty is higher during periods corresponding to high levels of default and credit risk as well as stock market crashes. Lastly, uncertainty about inflation, uncertainty about output growth, and uncertainty about unemployment are generally higher during bad states of the economy corresponding to periods of high unemployment, low output growth, and low economic activity.[4]

2.2. Economic uncertainty index

In this section, we introduce a broad index of economic uncertainty based on innovations in the cross-sectional dispersion in economic forecasts. As presented in the last column of Table A1, Panel A, the cross-sectional dispersion measures are highly persistent. The first-order autocorrelation coefficients are in the range of 0.28 and 0.73, but they are significantly below one. Therefore, unexpected change (or shock) to economic predictions of professional forecasters is not defined with a simple change in

[4]Specifically, the spikes in Figure A2 closely follow major economic and financial crisis such as the 1973 oil crisis, the 1973−1974 stock market crash, the 1979−1982 high interest rate period, the 1980s Latin American debt crisis, the 1989-1991 savings and loan crisis in the United States, the recession of the early 1990s, the 1997−1998 Asian and Russian financial crises, the recession of the early 2000s, and the recent global financial crisis (2007-2009).

dispersion measures. Instead, we estimate the following autoregressive of order one, AR(1), process for each dispersion measure:

$$Z_t = \omega_0 + \omega_1 Z_{t-1} + \varepsilon_t, \tag{3}$$

where Z_t is one of the seven measures of cross-sectional dispersion in economic forecasts; the real GDP growth and level, the nominal GDP growth and level, the GDP price index growth and level (proxying for the inflation rate), and the unemployment rate.

For each dispersion measure and for each quarter, we estimate equation (3) using the quarterly rolling regressions over a 20-quarter fixed window period. Then, we generate the standardized residuals from the AR(1) model for each dispersion measure. The economic uncertainty index (UNC^{AVG}) is defined as the average of the standardized residuals for the seven dispersion measures, and it can be viewed as a broad measure of the shock to dispersion in the forecasts of output, inflation and unemployment.

The first-order autocorrelation coefficients of the innovations in dispersion measures are in the range of -0.04 and -0.18, much lower than the serial correlations in raw measures of dispersion (in absolute magnitude). This result indicates that the standardized residuals from the AR(1) model successfully remove the predictable component of the dispersion measures so that the economic uncertainty index (UNC^{AVG}) is a measure of uncertainty shock capturing different aspects of disagreement over macroeconomic fundamentals and also reflecting unexpected news or surprise about the state of the aggregate economy.

It is important to note that the economic uncertainty index is generated for each quarter using the past information only, so that there is no look-ahead bias in our empirical analyses. Moreover, the economic uncertainty index is formed based on the ex-ante predictions of professional forecasters so that exposure of stocks to innovations in dispersion measures is an ex-ante measure of the uncertainty beta. Thus, we investigate purely out-of-sample cross-sectional predictive power of economic uncertainty.

One may argue that not all dispersion measures contribute equally to overall uncertainty in the macro economy. To address this potential concern, we introduce an alternative measure of the economic uncertainty index using the principal component analysis (PCA). Specifically, we extract the first principal component of the innovations in seven dispersion measures without imposing equal weights. This alternative economic uncertainty index is defined as the first principal component of the standardized residuals from AR(1) regressions, $Stdres$, for the seven dispersion measures. Our results indicate that the first principal component of the innovations in seven dispersion measures explains about two thirds of the total variation in these measures. Hence, we obtain a broad measure of economic uncertainty using this first component:[5]

$$\begin{aligned} UNC_t^{PCA} = \; & w_{1,t} \times Stdres_t^{RGDP-growth} + w_{2,t} \times Stdres_t^{RGDP-level} + \\ & w_{3,t} \times Stdres_t^{NGDP-growth} + w_{4,t} \times Stdres_t^{NGDP-level} + \\ & w_{5,t} \times Stdres_t^{PGDP-growth} + w_{6,t} \times Stdres_t^{PGDP-level} + \\ & w_{7,t} \times Stdres_t^{UNEMP}. \end{aligned} \tag{4}$$

Although the weights attached to the standardized residuals are not reported, the economic uncertainty index obtained from the first principal component (UNC^{PCA}) loads fairly evenly on the innovations in seven dispersion measures, suggesting a strong correlation with the simpler uncertainty index (UNC^{AVG}) defined as the average of the standardized residuals for the seven dispersion measures.

Figure 1 depicts the two broad indices of economic uncertainty (UNC^{AVG} and UNC^{PCA}) which are almost identical (with a sample correlation of 0.986). Similar to our findings for individual dispersion measures (shown in Figure A2), 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 tracks large fluctuations in business conditions.

[5]Note that we do not have a look-ahead bias when estimating the first principal component of the residuals because we use the expanding window with the first estimation window set to be the first 20 quarters and then updated on a quarterly basis. Hence, the weights ($w_{1,t} \dots w_{7,t}$) attached to the standardized residuals in equation (4) are time dependent.

2.3. Cross-sectional return predictors

Our stock sample includes all common stocks traded on the NYSE, Amex, and Nasdaq exchanges from July 1963 through December 2012. We eliminate stocks with a price per share less than \$5 or more than \$1,000. The daily and monthly return and volume data are from CRSP. We adjust stock returns for delisting to avoid survivorship bias (Shumway 1997).[6] Accounting variables are obtained from the merged CRSP-Computstat database. Analysts' earnings forecasts come from the Institutional Brokers' Estimate System (I/B/E/S) dataset and cover the period from 1983 to 2012. In this section, we provide the definitions of the stock-level variables used in predicting cross-sectional returns.

For each stock and for each quarter in our sample, we estimate the economic uncertainty beta from the time-series rolling regressions of excess stock returns on the economic uncertainty index over a 20-quarter fixed window period:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{AVG} + \varepsilon_{i,t}, \tag{5}$$

where $R_{i,t}$ is the excess return on stock i in quarter t, UNC_t^{AVG} is the economic uncertainty index in quarter t, defined as the average of the standardized residuals in equation (3) for seven dispersion measures, and $\beta_{i,t}^{UNC}$ is the economic uncertainty beta for stock i in quarter t.[7]

Following Fama and French (1992), we estimate the market beta of individual stocks using monthly returns over the prior 60 months if available (or a minimum of 24 months). The size (SIZE) is computed as the natural logarithm of the product of the price per share and the number of shares outstanding (in million dollars). Following Fama and French (1992, 1993, 2000), the natural logarithm of the book-to-market equity ratio at the end of June of year t, denoted BM, is computed as the book value of stockholders' equity, plus deferred taxes and investment tax credit (if available), minus the book value of preferred stock at the end of last fiscal year, $t-1$, scaled by the market value of equity at the end

[6] Specifically, when a stock is delisted, we use the delisting return from CRSP, if available. Otherwise, we assume the delisting return is -100%, unless the reason for delisting is coded as 500 (reason unavailable), 520 (went to over-the-counter), 551–573, 580 (various reasons), 574 (bankruptcy), or 584 (does not meet exchange financial guidelines). For these observations, we assume that the delisting return is -30%.

[7] As discussed in Section4.5 and Section 5, we use alternative specifications of equation (5) when estimating β^{UNC}. Specifically, we control for market return and market volatility factors and show that alternative measures of uncertainty beta generate very similar results in cross-sectional return predictability. Section 4.5 also shows that our main findings remain intact when we replace UNC^{AVG} with UNC^{PCA} in the estimation of the uncertainty beta.

of December of year $t-1$. Depending on availability, the redemption, liquidation, or par value (in that order) is used to estimate the book value of preferred stock.

Following Jegadeesh and Titman (1993), momentum (MOM) is the cumulative return of a stock over a period of 11 months ending one month prior to the portfolio formation month. Following Jegadeesh (1990), short-term reversal (REV) is defined as the stock return over the prior month.

Following Amihud (2002), we measure the illiquidity of stock i in month t, denoted ILLIQ, as the ratio of daily absolute stock return to daily dollar trading volume averaged within the month:

$$ILLIQ_{i,t} = Avg\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right], \tag{6}$$

where $R_{i,d}$ and $VOLD_{i,d}$ are the daily return and dollar trading volume for stock i on day d, respectively.[8] A stock is required to have at least 15 daily return observations in month t. Amihud's illiquidity measure is scaled by 10^6.

Following Harvey and Siddique (2000), the stock's monthly co-skewness (COSKEW) is defined as:

$$COSKEW_{i,t} = \frac{E\left[\varepsilon_{i,t} R_{m,t}^2\right]}{\sqrt{E\left[\varepsilon_{i,t}^2\right] E\left[R_{m,t}^2\right]}}, \tag{7}$$

where $\varepsilon_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t})$ is the residual from the regression of the excess stock return ($R_{i,t}$) against the contemporaneous excess return on the CRSP value-weighted index ($R_{m,t}$) using the monthly return observations over the prior 60 months (if at least 24 months are available). The risk-free rate is measured by the return on one-month Treasury bills.[9]

[8] Following Gao and Ritter (2010), we adjust for institutional features so that Nasdaq and NYSE/Amex volumes are counted. Specifically, divisors of 2.0, 1.8, 1.6, and 1 are applied to the Nasdaq volume for the periods prior to February 2001, between February 2001 and December 2001, between January 2002 and December 2003, and in January 2004 and later years, respectively.

[9] At an earlier stage of the study, following Mitton and Vorkink (2007), co-skewness is defined as the estimate of $\gamma_{i,t}$ in the regression using the monthly return observations over the prior 60 months with at least 24 monthly return observations available: $R_{i,t} = \alpha_i + \beta_i R_{m,t} + \gamma_{i,t} R_{m,t}^2 + \varepsilon_{i,t}$, where $R_{i,t}$ and $R_{m,t}$ are the monthly excess returns on stock i and the CRSP value-weighted index, respectively. The risk-free rate is measured by the return on one-month Treasury bills. In addition to using monthly returns over the past five years, we use continuously compounded daily returns over the past 12 months when estimating co-skewness of individual stocks. Our main findings from these two alternative measures of the co-skewness turn out to be very similar to those reported in our tables and they are available upon request.

Following Ang, Hodrick, Xing, and Zhang (2006), the monthly idiosyncratic volatility of stock i (IVOL) is computed as the standard deviation of the daily residuals in a month from the regression:

$$R_{i,d} = \alpha_i + \beta_i R_{m,d} + \gamma_i SMB_d + \varphi_i HML_d + \varepsilon_{i,d}, \tag{8}$$

where $R_{i,d}$ and $R_{m,d}$ are, respectively, the excess daily returns on stock i and the CRSP value-weighted index, and SMB_d and HML_d are the daily size and book-to-market factors of Fama and French (1993).

Following Diether, Malloy, and Scherbina (2002), analyst earnings forecast dispersion (DISP) is the standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecast.

Following earlier studies, we also control for firm age, leverage and industry dummy. Firm age (AGE) is defined as the total number of months between the date when a stock first appears on the CRSP database and the portfolio formation month. We use a proxy for leverage (LEV) defined as the ratio of net total asset to the market capitalization of a stock. We control for the industry effect by assigning each stock to one of the 10 industries based on its four-digit SIC code. The industry definitions are obtained from the online data library of Kenneth French.

3. A conditional asset pricing model with economic uncertainty

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

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

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 market portfolio m, and σ_{ix} denotes the $(1 \times k)$th row of unconditional covariances between the excess returns on risky asset i and the k-dimensional state variables x. The variable 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. Equation (9) states that in equilibrium, investors are compensated in terms of expected returns for bearing market risk and the risk of unfavorable shifts in the investment opportunity set.

The second term in equation (9) reflects investors' demand for the asset as a vehicle to hedge against unfavorable shifts in the investment opportunity set. Merton (1973) uses the example of stochastic interest rate to illustrate the role of intertemporal hedging demand. He points out that a positive covariance of asset returns with interest rate shocks (or innovations in interest rate) predicts a lower return on the risky asset. In the context of Merton's ICAPM, an increase in interest rate predicts a decrease in investment demand (since the cost of borrowing is high) and a decrease in optimal consumption, which leads to an unfavorable shift in the investment opportunity set. Risk-averse investors will demand more of an asset, the more positively correlated the asset's return is with changes in the interest rate because they will be compensated by a higher level of wealth through the positive correlation of the returns. That asset can be viewed as a hedging instrument. In other words, an increase in the covariance of returns with interest rate risk leads to an increase in the hedging demand, which in equilibrium reduces the expected return on the asset.[10,11]

There is substantial evidence that economic uncertainty is a relevant state variable affecting future consumption and investment decisions. Bloom (2009), Bloom, Bond, and Reenen (2007), and Bloom et al. (2012) introduce a theoretical model linking macroeconomic shocks to aggregate output, employment and investment dynamics. Chen (2010) proposes a model that shows how business cycle variations in economic uncertainty and risk premiums influence stocks' financing decisions. Chen (2010) also shows that countercyclical fluctuations in risk prices arise through stocks' responses to macroeconomic conditions. Stock and Watson (2012) find that the decline in aggregate output and employment during the recent crisis period is driven by financial and macroeconomic shocks. Allen, Bali,

[10] Assets that covary positively with interest rates may have higher or lower average returns (controlling for their covariance with current wealth) depending on whether the coefficient of relative risk aversion is greater or less than one. Thus, Merton (1973) points out that the relation between changes in interest rates and optimal consumption depends on preferences, but his footnote 34 (Merton 1973, p.885) indicates that the relation holds "for most people."

[11] We should note that the consumption-based interpretation of the role of intertemporal hedging demand is not general because with Epstein-Zin preferences, investors may either choose to increase current consumption, lower it, or keep it unchanged (for a given level of wealth) in response to unfavorable shifts in investment opportunities. Hence, our discussion here depends on investor preferences in the context of a consumption-based asset pricing model too.

and Tang (2012) show that downside risk in the financial sector predicts future economic downturns, linking economic uncertainty to future investment opportunity set.[12]

Hence, our finding that individual stocks that have higher exposure to the innovations in the economic uncertainty index earn commensurately lower returns than other stocks is consistent with the intertemporal hedging demand argument of Merton (1973). Following the aforementioned studies, we argue that an increase in economic uncertainty is an unfavorable shift in the investment opportunity set. Since an increase in economic uncertainty makes investors concerned about their future outcomes, it reduces optimal consumption. Investors cut their consumption and investment demand so that they can save more to hedge against possible future downturns in the economy. To hedge against such an unfavorable shift, investors prefer holding stocks that have higher covariance with economic uncertainty. This is because an increase in economic uncertainty will increase the returns on these stocks due to positive intertemporal correlation.[13] Hence, when economic uncertainty increases, although their optimal consumption and future investment opportunities decline, investors compensate for this loss by obtaining a stronger wealth effect through the increase in the returns on those stocks that have positive correlation with economic uncertainty. Therefore, through the intertemporal hedging demand, investors are willing to hold stocks with higher covariance with economic uncertainty, and they pay higher prices and accept lower returns for stocks with higher uncertainty beta.[14]

Following Bali and Engle (2010), we model time variation in expected returns and covariances by including time-varying parameters in the conditional ICAPM:

$$E[R_{i,t+1}|\Omega_t] = A \cdot cov[R_{i,t+1}, R_{m,t+1}|\Omega_t] + B \cdot cov[R_{i,t+1}, \Delta X_{t+1}|\Omega_t], \quad (10)$$

[12]By defining investors' uncertainty as the dispersion of predictions of mean market returns obtained from the forecasts of aggregate corporate profits. Anderson, Ghysels, and Juergens (2009) find a positive intertemporal relation between the level of uncertainty and excess market returns. In a conditional asset pricing model with time-varying volatility in the consumption growth process, Bali and Zhou (2014) find a positive relation between volatility uncertainty and future stock returns.

[13]We compute the contemporaneous and predictive correlations between the quarterly growth rate of consumption and the economic uncertainty index. For the sample period 1968:Q4−2012:Q4, the intertemporal correlations between consumption growth and the economic uncertainty index are positive, in the range of 0.18 and 0.20, and highly significant.

[14]Campbell's (1993, 1996) two-factor ICAPM model use a similar argument for an increase in stock market volatility being an unfavorable shift in the investment opportunity set. Campbell, Giglio, Polk, and Turley (2012) extend the earlier work of Campbell (1993, 1996) to allow for stochastic volatility.

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

We re-write equation (10) in terms of conditional betas, instead of conditional covariances:

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

where $\tilde{A} = A \cdot var[R_{m,t+1}|\Omega_t]$, $\tilde{B} = B \cdot var[X_{t+1}|\Omega_t]$, 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 innovation in the state variable X, defined as the ratio of the conditional covariance between $R_{i,t+1}$ and ΔX_{t+1} to the conditional variance of ΔX_{t+1}:[15]

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

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

Other studies (e.g., Bloom, Bond, and Van Reenen 2007; Bloom 2009; Bloom et al. 2012; Bekaert, Engstrom, and Xing 2009; Ludvigson and Ng 2009; Chen 2010; Stock and Watson 2012; Allen, Bali, and Tang 2012; and Bali, Brown, and Caglayan 2014) provide theoretical and empirical evidence that economic uncertainty is a relevant state variable proxying for consumption and investment opportunities in the conditional ICAPM framework. Hence, the economic uncertainty index used in this paper can be viewed as a proxy for the state variable X in equation (13). The beta in equation (12) is referred to as the "market beta", while the beta in equation (13) is referred to as the "uncertainty beta".

[15] Note that $\tilde{A}$ and $\tilde{B}$ are time-varying parameters that are estimated for each month using the cross-section of stock returns, the market beta, and the uncertainty beta in multivariate Fama-MacBeth regressions.

4. Empirical results

In this section, we conduct parametric and nonparametric tests to assess the predictive power of economic uncertainty betas over future stock returns. First, we start with univariate portfolio-level analyses. Second, we discuss average portfolio characteristics to obtain a clear picture of the composition of uncertainty beta portfolios. Third, we conduct bivariate portfolio-level analyses to examine the predictive power of uncertainty betas after controlling for well-known stock characteristics and risk factors. Fourth, we present the univariate and multivariate cross-sectional regression results. Finally, we provide the results from a battery of robustness checks.

4.1. Univariate portfolio-level analysis

Exposures of individual stocks to macroeconomic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty index using a 20-quarter fixed window estimation. The first set of uncertainty betas (β^{UNC}) are obtained using the sample from 1968:Q4 to 1973:Q3. Then, these quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months (October 1973, November 1973, and December 1973). This quarterly rolling regression approach is used until the sample is exhausted in December 2012. The cross-sectional return predictability results are reported from October 1973 to December 2012.

Table 1 presents the univariate portfolio results. For each month, we form decile portfolios by sorting individual stocks based on their uncertainty betas (β^{UNC}), where decile 1 contains stocks with the lowest β^{UNC} during the past quarter, and decile 10 contains stocks with the highest β^{UNC} during the previous quarter. The first column in Table 1 reports the average uncertainty betas for the decile portfolios formed on β^{UNC} using the CRSP breakpoints with equal numbers of stocks in the decile portfolios. The last four columns in Table 1 present the average excess returns and the 4-factor alphas on the value-weighted and equal-weighted portfolios.

The first column of Table 1 shows that when moving from decile 1 to decile 10, there is significant cross-sectional variation in the average values of β^{UNC}; the average uncertainty beta increases from -22.70 to 26.06. Another notable point in Table 1 is that for the value-weighted portfolio, the next-month average excess return decreases almost monotonically from 0.98% to 0.32% per month, when moving from the lowest β^{UNC} to the highest β^{UNC} decile. The average return difference between decile 10 (high-β^{UNC}) and decile 1 (low-β^{UNC}) is -0.66% per month with a Newey-West (1987) t-statistic of -2.75. This result indicates that stocks in the lowest β^{UNC} decile generate about 7.92% higher annual returns compared to stocks in the highest β^{UNC} decile.

In addition to the average raw returns, Table 1 presents the magnitude and statistical significance of the difference in intercepts (Fama-French-Carhart, or FFC, four factor alphas) from the regression of the high-minus-low portfolio returns on a constant, excess market returns (MKT), a size factor (SMB), a book-to-market factor (HML), and a momentum factor (MOM), following Fama and French (1993) and Carhart (1997).[16] As shown in the third column of Table 1, for the value-weighted portfolio, the 4-factor (FFC) alpha decreases almost monotonically from 0.44% to -0.33% per month, when moving from the lowest β^{UNC} to the highest β^{UNC} decile. The difference in alphas between the high-β^{UNC} and low-β^{UNC} portfolios is -0.77% per month with a Newey-West t-statistic of -2.99. This indicates that after controlling for the well-known size, book-to-market, and momentum factors, the return difference between the high-β^{UNC} and low-β^{UNC} stocks remains negative and statistically significant.

The last two columns of Table 1 show that similar results are obtained from the equal-weighted portfolios of β^{UNC}. The average excess returns and the FFC alphas on the uncertainty beta portfolios decrease almost monotonically. The average return and alpha differences between the high-β^{UNC} and low-β^{UNC} portfolios are about the same, -0.58% per month, and highly significant with Newey-West t-statistics larger than 3 in absolute magnitude.

Next, we investigate the source of risk-adjusted return differences between the high-β^{UNC} and low-β^{UNC} portfolios: Is it due to outperformance by low-β^{UNC} stocks, or underperformance by high-β^{UNC} stocks, or both? For this, we focus on the economic and statistical significance of the risk-adjusted returns of decile 1 vs. decile 10. As reported in Table 1, for both value-weighted and equal-weighted portfolios, the FFC alphas of stocks in decile 1 (low-β^{UNC} stocks) are significantly positive, whereas the FFC alphas of stocks in decile 10 (high-β^{UNC} stocks) are significantly negative. Hence, we conclude

[16]SMB (small minus big), HML (high minus low), and MOM (winner minus loser) are described in and obtained from Kenneth French's data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

that the significantly negative alpha spreads between high-β^{UNC} and low-β^{UNC} stocks is due to both the outperformance by low-β^{UNC} stocks and the underperformance by high-β^{UNC} stocks.[17]

Of course, the economic uncertainty betas documented in Table 1 are for the portfolio formation month, not for the subsequent month over which we measure average returns. Investors may pay high prices for stocks that have exhibited high uncertainty beta in the past in the expectation that this behavior will be repeated in the future, but a natural question is whether these expectations are rational. Table A2 of the online appendix investigates this issue by presenting the average quarter-to-quarter portfolio transition matrix. Specifically, Panel A of Table A2 presents the average probability that a stock in decile i (defined by the rows) in one quarter will be in decile j (defined by the columns) in the subsequent quarter. If the uncertainty betas were completely random, then all the probabilities should be approximately 10%, since a high or low uncertainty beta in one quarter should say nothing about the uncertainty beta in the following quarter. Instead, all the diagonal elements of the transition matrix exceed 10%, illustrating that the uncertainty beta is highly persistent. Of greater importance, this persistence is especially strong for the extreme portfolios. Panel A shows that for the one-quarter ahead persistence of β^{UNC}, stocks in decile 1 (decile 10) have a 73.95% (73.53%) chance of appearing in the same decile next quarter. Similarly, Panel D of Table A2 shows that for the four-quarter ahead persistence of β^{UNC}, stocks in decile 1 (decile 10) have a 54.03% (54.68%) chance of appearing in the same decile next four quarters.[18]

These results indicate that the estimated historical uncertainty betas successfully predict future uncertainty betas and hence they are good proxies for the true conditional betas, which is important for interpretations of the results in terms of an equilibrium model such as the ICAPM. These results also show that the uncertainty betas are not simply characteristics of firms that result in differences in expected returns, but they are proxies for a source of macroeconomic uncertainty.

[17] As shown in Table A3 of the online appendix, very similar results are obtained when decile portfolios are formed based on the NYSE breakpoints, which are used to alleviate the concerns that the CRSP decile breakpoints are distorted by the large number of small Nasdaq and Amex stocks (Fama and French, 1992).

[18] Note that stocks in decile 1 have about 74% probability of being in deciles 1-2, all of which exhibit low uncertainty beta in the portfolio formation month and high returns in the subsequent month. Similarly, stocks in decile 10 have about 72% probability of being in deciles $9-10$, all of which exhibit high uncertainty beta in the portfolio formation month and low returns in the subsequent month.

4.2. Average portfolio characteristics

To obtain a clearer picture of the composition of the uncertainty beta portfolios, Table 2 presents summary statistics for the stocks in the deciles. Specifically, Table 2 reports the cross-sectional averages of various characteristics for the stocks in each decile averaged across the months. We report average values for the uncertainty beta (β^{UNC}), the market share (Mkt. shr.), the market beta (BETA), the log market capitalization (SIZE), the log book-to-market ratio (BM), the return over the 11 months prior to portfolio formation (MOM), the return in the portfolio formation month (REV), a measure of illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), firm age (AGE), leverage (LEV), and the price in dollars (PRC). The definitions of these variables are given in Section 2.3.

The portfolios exhibit interesting patterns. Average market betas are higher for the low-β^{UNC} and high-β^{UNC} portfolios, compared to deciles 2 to 9. Not surprisingly, stocks in the high-β^{UNC} portfolio have somewhat higher market betas than those in the low-β^{UNC} portfolio. Stocks in the extreme deciles (deciles 1 and 10) are relatively smaller compared to those in deciles 2 to 9. As expected, the last column of Table 2 shows that stocks in the low-β^{UNC} and high-β^{UNC} portfolios have somewhat lower share prices compared to those in deciles 2 to 9, but there is no monotonically increasing or decreasing pattern in the average prices of the stocks in the uncertainty beta portfolios. Average book-to-market and leverage ratios are lower for the low-β^{UNC} and high-β^{UNC} portfolios, compared to deciles 2 to 9. Since there is no significant difference between the size, value, and leverage characteristics of stocks in the low-β^{UNC} and high-β^{UNC} portfolios, the predictive power of the uncertainty beta cannot be explained by size, book-to-market, and distress risk.

A notable point in Table 1 is that stocks in the extreme deciles (deciles 1 and 10) have higher past one year returns, that is, stocks in the low-β^{UNC} and high-β^{UNC} portfolios are momentum winners compared to those in deciles 2 to 9. Since there is no monotonically increasing or decreasing pattern in the past one year return of uncertainty portfolios, momentum cannot be an explanation for the predictive power of the uncertainty beta either.

Interestingly, stocks in the extreme deciles (deciles 1 and 10) have higher past one month returns as well, that is, stocks in the low-β^{UNC} and high-β^{UNC} portfolios are short-term winners compared to those in deciles 2 to 9. But again there is no monotonically increasing or decreasing pattern in the past one month return of the uncertainty beta portfolios. Hence, short-term reversal cannot explain the high (low) returns on low (high) uncertainty beta stocks.

There are no significant differences in the liquidity, idiosyncratic volatility, analyst dispersion, and firm age of average stocks in the low-β^{UNC} and high-β^{UNC} portfolios, but consistent with earlier studies, small and lower-priced stocks in the low-β^{UNC} and high-β^{UNC} portfolios are somewhat more volatile, illiquid, younger, and have a higher analyst dispersion compared to those in deciles 2 to 9. However, the differences in the liquidity, volatility, dispersion, and age of stocks in deciles 1 and 10 are so trivial that similar to our findings for size, price, value, leverage, momentum, and reversal effects, the liquidity, volatility, dispersion, and age cannot explain the return predictability of the uncertainty beta.

The only variable that seems to have a strong correlation with the uncertainty beta (at the portfolio level) is co-skewness. When moving from the low-β^{UNC} to the high-β^{UNC} portfolios, average co-skewness increases monotonically from -0.09 to -0.02. Harvey and Siddique (2000) find that stocks with high co-skewness generate low returns. Hence, co-skewness may potentially explain the high (low) returns on low (high) uncertainty beta stocks.

We address this potential concern in the following two sections. Although there are no striking patterns in average portfolio characteristics (with the exception of co-skewness), in the following sections, we provide different ways of dealing with the potential interaction of the uncertainty beta with the market beta, size, book-to-market, momentum, short-term reversal, liquidity, co-skewness, idiosyncratic volatility, analyst dispersion, firm age, and leverage. Specifically, we test whether the negative relation between the economic uncertainty beta and the cross-section of expected returns still holds once we control for the usual suspects using bivariate portfolio sorts and Fama-MacBeth (1973) regressions.

4.3. Bivariate portfolio-level analysis

This section examines the relation between the uncertainty beta and future stock returns after controlling for well-known cross-sectional return predictors. We perform bivariate portfolio sorts on the economic uncertainty beta (β^{UNC}) in combination with the market beta (BETA), the log market capitalization (SIZE), the log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), firm age (AGE), and leverage (LEV). Table 3 reports the value-weighted portfolio results of these conditional bivariate sorts.

We control for the market beta (BETA) by first forming decile portfolios ranked based on BETA. Then, within each BETA decile, we sort stocks into decile portfolios ranked based on the economic uncertainty beta (β^{UNC}) so that decile 1 (decile 10) contains stocks with the lowest (highest) β^{UNC}. The first column of Table 3 averages value-weighted portfolio returns across the 10 BETA deciles to produce decile portfolios with dispersion in β^{UNC} but that contain all the stocks' market betas. This procedure creates a set of β^{UNC} portfolios with very similar levels of market beta, and hence these β^{UNC} portfolios control for differences in market beta. The row (High$-$Low) in the first column of Table 3 shows that after controlling for the market beta, the average return difference between the high-β^{UNC} and low-β^{UNC} value-weighted portfolios is about -0.55% per month with a Newey-West t-statistic of -3.46. The $10-1$ difference in the 4-factor alphas is -0.48% per month with a t-statistic of -2.91. Thus, the market beta does not explain the high (low) returns on low (high) uncertainty beta stocks.

We control for market capitalization (SIZE) similarly, with the results reported in the second column in Table 3. Again the effect of uncertainty beta is preserved after controlling for size, with an average raw return difference between the high-β^{UNC} and low-β^{UNC} deciles of -0.52% per month and a corresponding t-statistic of -2.49. The $10-1$ difference in the FFC alphas is also negative, -0.45% per month, and highly significant.

Table 3 shows that after controlling for the other cross-sectional return predictors (book-to-market, momentum, short-term reversal, illiquidity, co-skewness, volatility, analyst dispersion, age, and leverage), the average return differences between the high-β^{UNC} and low-β^{UNC} portfolios are in the range of -0.41% to -0.68% per month. These average raw return differences are both economically and statistically significant. The corresponding risk-adjusted return differences are averaged in the range of -0.55% to-0.73%, and are also highly significant. These results indicate that well-known cross-sectional effects (including co-skewness) cannot explain the low returns to stocks with high uncertainty beta.

4.4. Stock level cross-sectional regressions

So far we have tested the significance of the economic uncertainty beta as a determinant of the cross-section of future 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 uncertainty betas 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 factors simultaneously. Consequently, we now examine the cross-sectional relation between the uncertainty beta and expected returns at the stock level using the Fama and MacBeth (1973) regressions.

We present the time-series averages of the slope coefficients from the regressions of one-month ahead stock returns on the economic uncertainty beta (β^{UNC}) with and without control variables. The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables on average have non-zero premiums. Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{UNC} + \lambda_{2,t} \cdot X_{i,t} + \varepsilon_{i,t+1}, \tag{14}$$

where $R_{i,t+1}$ is the realized return on stock i in month $t+1$, $\beta_{i,t}^{UNC}$ is the quarterly economic uncertainty beta of stock i in months t, $t-1$, and $t-2$, and $X_{i,t}$ is a collection of stock-specific control variables observable at time t for stock i (market beta, size, book-to-market, momentum, short-term reversal, illiquidity, co-skewness, idiosyncratic volatility, analyst dispersion, age, and leverage). The cross-sectional regressions are run at a monthly frequency from October 1973 to December 2012. When calculating the standard errors of the average slope coefficients, we take into account autocorrelation and heteroscedasticity in the time-series slope coefficients from cross-sectional regressions. The Newey-West (1987) adjusted standard errors are computed with six lags.

Panel A of Table 4 reports the time series averages of the slope coefficients and the Newey-West t-statistics in parentheses. The univariate regression results reported in the first column indicate a negative and statistically significant relation between the economic uncertainty beta and the cross-section of future stock returns. The average slope from the monthly regressions of realized returns on $\beta_{i,t}^{UNC}$ alone is -0.016 with a t-statistic of -3.37.

To delineate the economic significance of this average slope coefficient, we use the average values of the uncertainty betas in the decile portfolios. Table 1 shows that the difference in $\beta_{i,t}^{UNC}$ values between average stocks in the first and 10th deciles is $48.76[= 26.06-(-22.70)]$. If a stock were to move from the first to the 10th decile of $\beta_{i,t}^{UNC}$, what would be the change in that stock's expected return? The average slope coefficient of -0.016 on $\beta_{i,t}^{UNC}$ in Panel A of Table 4 represents an economically significant decrease of $-0.016 \times 48.76 = -0.78\%$ per month in the average stock's expected return for moving from the first to the 10th decile of $\beta_{i,t}^{UNC}$.

The second column in Panel A of Table 4 controls for the market beta (BETA), market capitalization (SIZE), and the book-to-market (BM), a cross-sectional regression specification corresponding to the 3-factor model of Fama and French (1993). The third column controls for the market beta (BETA), market capitalization (SIZE), the book-to-market (BM), and momentum (MOM), a cross-sectional regression specification corresponding to the 4-factor model of Fama and French (1993) and Carhart (1997). In both specifications, the average slopes from the monthly regressions of realized returns on $\beta_{i,t}^{UNC}$ are negative and highly significant; -0.014 and -0.012 with Newey-West t-statistics of -3.80 and -3.64, respectively.

Column (4) controls for all variables (except for age and leverage) simultaneously, including the market beta, size, the book-to-market, momentum, short-term reversal, illiquidity, co-skewness, idiosyncratic volatility, analyst dispersion, age, and leverage. In this more general specification, the average slope of $\beta_{i,t}^{UNC}$ remains negative, -0.011, and highly significant with a Newey-West t-statistic of -4.50. The average slope coefficient of -0.011 for $\beta_{i,t}^{UNC}$ implies that a portfolio short-selling stocks with the highest uncertainty beta (stocks in decile 10) and buying stocks with the lowest uncertainty beta (stocks in decile 1) generates a return in the following month of about 0.54%, controlling for everything else. The last column includes firm age and leverage to a large set of controls, and the main findings remain intact.

In general, the coefficients of the individual control variables are also as expected; the size effect is negative and significant, the value effect is positive and significant, stocks exhibit intermediate-term momentum and short-term reversals, and the average slopes of idiosyncratic volatility and analyst dispersion are negative and significant. The average slope of the market beta (BETA) is positive but statistically insignificant, which contradicts the implications of the CAPM but is consistent with prior empirical evidence. The average slope of co-skewness is negative but statistically insignificant. The average slope of illiquidity is negative and significant, contradicting the positive illiquidity premium identified by earlier studies. The average slope coefficients on firm age and leverage are statistically insignificant because they are correlated with some of the control variables such as firm size and book-to-market.[19]

In Panel B of Table 4, we control for the industry effect. For each month, we assign each stock to one of the 10 industries based on the four-digit SIC code and replicate our firm-level cross-sectional regressions with and without the large set of firm characteristics and risk factors.

The univariate regression results reported in the first column of Table 4, Panel B indicate a negative and statistically significant relation between the uncertainty beta and future stock returns after controlling for the industry effect; the average slope coefficient is -0.014 with a Newey-West t-statistic of -3.64. As expected, the average slope on β^{UNC} is somewhat smaller in absolute magnitude (-0.014 in Panel B vs. -0.016 in Panel A) after controlling for the industry effect. However, the average slope of -0.014 still represents an economically significant decrease of -0.68% per month in the average stock's expected return for moving from the first to the 10th decile of β^{UNC}.

The last four columns in Panel B of Table 4 examines the significance of uncertainty beta after controlling for the industry effect and a sequential set of other cross-sectional predictors. Columns

[19]In the online appendix, we replicate multivariate Fama-MacBeth regressions with standardized residuals for each dispersion measure separately. Table A4 shows that the average slope coefficients on each component of UNC^{AVG} are negative and statistically significant, indicating that our main findings hold for individual measures of economic uncertainty. These results also imply that all seven measures of dispersion in economic forecasts (i.e., output, inflation, and unemployment) contribute significantly to the predictability of stock returns.

(2) and (3) show that when controlling for the industry as well as the size, book-to-market and momentum effects, the average slopes from the monthly regressions of returns on β^{UNC} are negative and highly significant; -0.013 and -0.011 with t-statistics of -3.77 and -3.76, respectively. The last two columns present results from the more general specifications including all other control variables along with the industry effect. As shown in Columns (4) and (5), the average slope of β^{UNC} remains negative at -0.009 and highly significant. The average slope coefficient of -0.009 for β^{UNC} implies that a portfolio short-selling stocks with the highest uncertainty beta and buying stocks with the lowest uncertainty beta generates a return in the following month of about 0.44%, controlling for the industry effect and everything else.[20]

Finally, we test whether the economic uncertainty beta remains significant in multivariate Fama-MacBeth regressions after controlling for the betas with respect to the Fama-French-Carhart factors. For each month from October 1968 to December 2012, we estimate the Fama-French-Carhart model using a 60-month rolling window with a minimum of 24 observations and updated monthly:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \cdot R_{m,t} + \beta_{i,t}^{SMB} \cdot SMB_t + \beta_{i,t}^{HML} \cdot HML_t + \beta_{i,t}^{MOM} \cdot MOM_t + \varepsilon_{i,t}, \tag{15}$$

and then control for β_i^{MKT}, β_i^{SMB}, β_i^{HML}, and β_i^{MOM} simultaneously.

Panel C of Table 4 shows that the average slopes on β^{UNC} remains negative, in the range of -0.013 and -0.009, and highly significant after controlling for the betas with respect to the Fama-French-Carhart factors along with the other firm characteristics (short-term reversal, illiquidity, co-skewness, idiosyncratic volatility, dispersion, age, and leverage). In general, the coefficients of the individual control variables in Panel C are similar to those reported in Panel A and B of Table 4. The only exceptions are firm age and leverage. The last column of Panel C shows that the average slope on AGE is negative and significant, indicating higher average return on younger firms. The average slope

[20] At an earlier stage of the study, we replicate our main finding using the value-weighted 38 and 48 industry portfolios of Fama and French (1997). We first estimate exposures of the industry portfolios to the economic uncertainty index (β^{UNC}) and then form univariate value-weighted portfolios based on β_{ind}^{UNC}. Table A5 of the online appendix shows that the average return and alpha differences between the high-β_{ind}^{UNC} and low-β_{ind}^{UNC} portfolios are negative and significant, indicating that the negative uncertainty premium is prevalent in the cross-section of industry portfolios as well.

on LEV is positive and marginally significant, indicating higher average return on firms with higher leverage.

4.5. Robustness check

In this section, we summarize empirical findings from a battery of robustness checks. The results are reported in Tables A6−A11 of the online appendix.

4.5.1. Subsample analysis

First, we investigate whether our results are sensitive to different stock samples. As discussed in Section 2.3, our original sample includes all common stocks traded on the NYSE, Amex, and Nasdaq exchanges. We further investigate whether our results are driven by small, low-priced, and illiquid stocks, or stocks trading at the Amex and Nasdaq exchanges. The sensitivity of our main findings is tested for seven different stock samples: (i) NYSE stocks only; (ii) Large stocks, defined as those with market capitalization greater than the 50th NYSE size percentile at the beginning of each month; (iii) S&P 500 stocks; (iv) The largest 500 stocks in the CRSP universe, based on the market capitalization; (v) The largest 1,000 stocks in the CRSP universe, based on the market capitalization; (vi) The most liquid 500 stocks in the CRSP universe, based on Amihud's (2002) illiquidity measure; and (vii) The most liquid 1,000 stocks in the CRSP universe, based on Amihud's (2002) illiquidity measure. We replicate our main findings for these seven different stock samples based on the value-weighted portfolios. As shown in Table A6 of the online appendix, our main findings hold for all stock samples considered in the paper; the FFC alpha spread between the high-β^{UNC} and low-β^{UNC} portfolios is in the range of −0.47% and −0.62% per month and statistically significant for the NYSE stocks, and S&P 500 stocks, and large and liquid stocks.

4.5.2. Subperiod analysis

We now test whether our findings are robust across different time periods. Since the original data on the cross-sectional dispersion in economic forecasts provided by the Federal Reserve Bank of Philadelphia cover the period 1968:Q4 to 2012:Q4, the cross-sectional return predictability results are based on the sample period from October 1973 to December 2012. The first two columns of Table A7 in the online appendix shows that the cross-sectional return predictability results are robust across the two subsample periods. Although the FFC alpha spreads between the high-β^{UNC} and low-β^{UNC} portfolios are negative and significant for both subperiods, the FFC alpha spread is larger for the second subperiod with more severe economic and market downturns, compared to the first subperiod; -0.97% per month for June 1993$-$December 2012 vs. -0.58% per month for October 1973$-$May 1993.

4.5.3. Recessions vs. expansions

In this section, we examine whether the macroeconomic uncertainty premium is higher during recessions in which economic activity (including investment and consumption) is low and the marginal utility of wealth is high. We determine states of the economy based on the Chicago FED National Activity Index (CFNAI)[21] and the National Bureau of Economic Research (NBER) recession dummy taking the value of one if the U.S. economy is in recession in a month as determined by the NBER. Table A8 of the online appendix shows that the uncertainty premium is much higher when the CFNAI index is below -0.7 and during the NBER recession months. These results are consistent with the intertemporal capital asset pricing models of Merton (1973) and Campbell (1993, 1996). During economic downturns, ICAPM investors are more concerned about potential declines in their consumption and investment opportunities. Because of elevated fear and uncertainty during downturns of the economy, investors cut their investment and consumption demand. To compensate for this loss, they prefer to hold stocks that have high covariance with economic uncertainty (stocks with high uncertainty beta) because when uncertainty increases, the returns of high uncertainty beta stocks increase and generate an additional wealth effect that compensates for the loss in consumption. Thus, investors increase their intertemporal hedging demand even further when economic uncertainty is high during recessions and they are willing to accept lower expected returns for hedging purposes. The empirical results in Table A8 are consistent

[21] The CFNAI is a monthly index designed to assess overall economic activity and related inflationary pressure. It is the weighted average of 85 existing monthly indicators of national economic activity. It is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward the trend growth rate over time, a positive index reading corresponds to growth above the trend and a negative index reading corresponds to growth below the trend. A CFNAI index value below -0.7 following a period of economic expansion indicates an increasing likelihood that a recession has begun.

with the theoretical prediction that the uncertainty premium is higher during bad states of the economy. The FFC alpha spread between the high-β^{UNC} and low-β^{UNC} portfolios is -1.80% per month (t-statistic $=-3.44$) during NBER recessions and -1.86% per month (t-statistic$=-2.98$) during the CFNAI-based recessionary periods. Whereas, the FFC alpha spreads are much smaller in absolute magnitude during expansionary periods; -0.62% per month (t-statistic $=-2.26$) during NBER expansions and -0.57% per month (t-statistic $=-2.08$) during the CFNAI-based expansionary periods.

4.5.4. Long-term predictability

In this section, we investigate the long-term predictive power of the uncertainty beta. Our analyses have so far focused on one-month ahead return predictability. However, from a practical standpoint it would make sense to investigate the predictive power of the uncertainty beta for longer investment horizons, since some investors and portfolio managers may prefer longer portfolio holding periods or investment horizons beyond one month. We examine the long-term predictive power of the economic uncertainty beta using quarterly stock returns and quarterly uncertainty betas. Exposures of individual stocks to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty index using a 20-quarter fixed window estimation. The first set of quarterly uncertainty betas (β^{UNC}) is obtained using the sample from 1968:Q4 to 1973:Q3. This quarterly rolling regression approach is used until the sample is exhausted in 2012:Q4. Then, these quarterly uncertainty betas are used to predict the cross-section of 1-quarter to 4-quarter ahead stock returns for the sample period 1974:Q1-2012:Q4. Table A9 of the online appendix clearly shows that the negative relation between the economic uncertainty beta and future stock returns is not just a one-month affair. Based on the FFC alpha spreads on the value-weighted portfolios of β^{UNC}, the quarterly measures of uncertainty beta predict cross-sectional variation in stock returns 9 months into the future.

4.5.5. An alternative measure of the economic uncertainty beta

In this section, we test whether an alternative measure of the economic uncertainty beta predicts future stock returns. As shown in equation (5), the uncertainty beta is obtained from a univariate time-series regression of excess stock returns on the economic uncertainty index. We now estimate the uncertainty beta controlling for the market factor. Specifically, for each stock and for each quarter, we estimate the uncertainty beta from the quarterly rolling regressions of excess stock returns on the economic uncertainty index and the excess market return over a 20-quarter fixed window period:

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

where $R_{i,t}$ is the excess return on stock i, $R_{m,t}$ is the excess market return, and UNC_t^{AVG} is the economic uncertainty index defined as the average of the standardized residuals from the AR(1) model for the seven dispersion measures.

Table A10 of the online appendix presents the time-series averages of the slope coefficients from the cross-sectional regressions of one-month ahead stock returns on the economic uncertainty beta ($\beta_{i,t}^{UNC}$) and the market beta ($\beta_{i,t}^{MKT}$) obtained from equation (16) plus the control variables. Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{UNC} + \lambda_{2,t} \cdot \beta_{i,t}^{MKT} + \lambda_{3,t} \cdot X_{i,t} + \varepsilon_{i,t}, \tag{17}$$

Similar to our findings in Panel A of Table 4, the average slope coefficients on β_i^{UNC} are negative, in the range of -0.012 and -0.016, and significant with Newey-West t-statistics ranging from -3.14 to -4.77. In general, the coefficients of the individual control variables are very similar to those presented in Table 4, Panel A. The only exception is the market beta. The last two columns of Table A10 show that the average slope on β_i^{MKT} is positive and marginally significant in some of the specifications controlling for β_i^{UNC} and firm characteristics.

4.5.6. An alternative measure of the economic uncertainty index

As discussed in Section 2.2, we introduce an alternative measure of the economic uncertainty index based on the first principal component of the standardized residuals from AR(1) regressions for the seven dispersion measures. In this section, we test if this alternative measure of the uncertainty index affects our main findings. Specifically, for each stock and for each quarter, we estimate the uncertainty beta from the quarterly rolling regressions of excess stock returns on the PCA-based economic uncertainty index (UNC_t^{PCA}) over a 20-quarter fixed window period:

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{PCA} + \varepsilon_{i,t}. \tag{18}$$

Table A11 of the online appendix presents the time-series averages of the slope coefficients from the Fama-MacBeth cross-sectional regressions of one-month ahead stock returns on the alternative measure of the uncertainty beta (β_i^{UNC}) obtained from equation (18) plus the control variables. Similar to our findings in Panel A of Table 4, the average slope coefficients on β_i^{UNC} are negative, in the range of -0.041 and -0.032, and significant with Newey-West t-statistics ranging from 3.21 to 4.45. In general, the coefficients of the individual control variables are very similar to those presented in Table 4, Panel A. Overall, these results indicate that the cross-sectional predictive power of economic uncertainty remains intact when we replace UNC_t^{AVG} with UNC_t^{PCA} in the estimation of the uncertainty beta.

5. Controlling for Exposure to Stock Market Volatility

Campbell (1993, 1996) provides a two-factor ICAPM in which an unexpected increase in market volatility represents deterioration in the investment opportunity set or a decrease in optimal consumption. In this setting, a positive covariance of returns with volatility shocks (or innovations in market volatility) predicts a lower return on the stock. In the context of Campbell's ICAPM, an increase in market volatility predicts a decrease in optimal consumption and hence an unfavorable shift in the investment opportunity set. Risk-averse investors will demand more of a stock, the more positively correlated the stock's return is with changes in market volatility because they will be compensated by a higher level of wealth through the positive correlation of the returns. That stock can be viewed as a hedging instrument. In other words, an increase in the covariance of returns with volatility risk leads to an increase in the hedging demand, which in equilibrium reduces expected return on the stock.[22]

[22]Campbell et al. (2012), extending the earlier work of Campbell (1993, 1996), estimate market variance innovations based on a vector autoregression approach, and find a negative market variance risk premium in the cross-section of equity portfolios.

Ang et al. (2006) test whether the exposure of individual stocks to changes in market volatility predict cross-sectional variation in future stock returns. They first estimate the exposure of individual stocks to changes in the S&P 100 index option implied volatility (VXO). Then, they sort stocks into quintile portfolios based on these implied volatility betas. They find a negative cross-sectional relation between the volatility betas and future stock returns, that is, stocks with higher (lower) exposure to changes in the VXO generate lower (higher) returns in the next month. Bali and Engle (2010) investigate the significance of a negative market volatility risk premium in the conditional ICAPM framework and find that equity portfolios with higher conditional covariance with changes in expected future market volatility yield lower expected returns. Coval and Shumway (2001) and Bakshi and Kapadia (2003) find the volatility risk premium to be negative in equity option markets. Adrian and Rosenberg (2008) decompose equity market volatility into short- and long-term components and show that the prices of both components are significantly negative. Bansal, Kiku, Shaliastovich, and Yaron (2014) show that equities have negative volatility betas and hence equities carry positive volatility risk premia.

In this section, motivated by the aforementioned studies, we test whether the predictive power of economic uncertainty beta remains intact after controlling for the exposure of individual stocks to changes in aggregate stock market volatility. Following Ang et al. (2006), we use the VXO as a proxy for market volatility.

In addition to option implied volatility, we use expected realized market variance to generate an alternative measure of volatility innovation. Specifically, market variance innovation ($\Delta VAR_t^{Realized}$) is defined as the residual from the time-series regression of the realized market variance in quarter t against a vector of lagged quarterly state variables over the period 1968:Q4−2012:Q4. Following Campbell, Giglio, Polk, and Turley (2012), the state variables include (i) the log real return on the market (R_m), defined as the difference between the log return on the CRSP value-weighted stock index and the log return on the Consumer Price Index (CPI); (ii) the market variance itself (VAR), defined as the sum of the squared daily returns on the CRSP value-weighted stock index in a quarter; (iii) the log price-earnings ratio (P/E) of Shiller (2000), constructed as the price of the S&P 500 index divided by a one-quarter lagged 10-year trailing moving average of aggregate earnings of companies in the S&P500 index; (iv) the term yield spread (TERM), computed as the difference between the log yield on the 10-year US Constant Maturity Bond and the log yield on the 3-month US Treasury Bill; (v) the small-stock value spread (VS), constructed following Campbell and Vuolteenaho (2004); and (vi) the default spread (DEF), calculated as the difference between the log yields on Moody's BAA and AAA bonds. Daily and monthly stock market returns are obtained from the CRSP database; the CPI, Treasury yields, and yields on Moody's BAA and AAA are downloaded from the Federal Reserve Bank of St. Louis; data used to calculate P/E are obtained from Robert Shiller's website; and data used to measure VS are obtained from Kenneth French's website.

First, we investigate the potential interaction between the economic uncertainty beta and the market volatility beta by controlling for the realized and implied market volatility innovations in the estimation of the uncertainty beta. Specifically, for each stock and for each quarter, we estimate the uncertainty beta from the quarterly rolling regressions of excess stock returns on the economic uncertainty index and the change in market volatility over a 20-quarter fixed window period:

$$\text{Model 1}: \; R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{AVG} + \beta_{i,t}^{RVOL} \cdot \Delta VAR_t^{Realized} + \varepsilon_{i,t}, \tag{19}$$

$$\text{Model 2}: \; R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{AVG} + \beta_{i,t}^{VXO} \cdot \Delta VAR_t^{VXO} + \varepsilon_{i,t}, \tag{20}$$

where $R_{i,t}$ is the excess return on stock i, UNC_t^{AVG} is the economic uncertainty index defined as the average of the standardized residuals from the AR(1) model for the seven dispersion measures, $\Delta VAR_t^{Realized}$ is the change in the expected realized market variance, ΔVAR_t^{VXO} is the change in the S&P 100 index option implied variance, and β_i^{UNC}, β_i^{RVOL}, and β_i^{VXO} are the measures of the economic uncertainty beta, the expected realized market volatility beta, and the implied market volatility beta, respectively.[23]

We use two more specifications to control for the market volatility factor and the excess market return simultaneously in the estimation of the uncertainty beta:

$$\text{Model 3}: \; R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{AVG} + \beta_{i,t}^{RVOL} \cdot \Delta VAR_t^{Realized} + \beta_{i,t}^{MKT} \cdot R_{m,t} + \varepsilon_{i,t}, \tag{21}$$

$$\text{Model 4}: \; R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{AVG} + \beta_{i,t}^{VXO} \cdot \Delta VAR_t^{VXO} + \beta_{i,t}^{MKT} \cdot R_{m,t} + \varepsilon_{i,t}, \tag{22}$$

[23] We should note that the daily data on the VXO are available from January 2, 1986. Thus, our cross-sectional return predictability results from the VXO data are based on the sample period from January 1986 to December 2012.

Once we estimate the economic uncertainty beta from Model 1, 2, 3, and 4, we form the value-weighted decile portfolios by sorting individual stocks based on β_i^{UNC}. Panel A of Table 5 shows that the FFC alpha differences between the high-β_i^{UNC} and low-β_i^{UNC} portfolios are negative, in the range -0.53% and -0.89% per month, and highly significant with Newey-West t-statistics ranging from -2.19 to -2.91. These results indicate that the predictive power of the uncertainty beta remains highly significant after accounting for the interaction between the uncertainty beta and the market volatility beta.

Next, we test whether the predictive power of β_i^{UNC} remains intact when controlling for β_i^{RVOL} and β_i^{VXO} in conditional bivariate sorts. Panel B of Table 5 shows that after controlling for the expected realized market volatility beta (β_i^{RVOL}), the significantly negative link between the uncertainty beta and future stock returns remains intact. The FFC alpha difference between the high-β_i^{UNC} and low-β_i^{UNC} portfolios is -0.71% per month with a t-statistic of -3.67 when β_i^{UNC} and β_i^{RVOL} are estimated with Model 1, and -0.70% per month with a t-statistic of -3.46 when β_i^{UNC} and β_i^{RVOL} are estimated with Model 3. The last two columns of Table 5, Panel B shows that similar findings are obtained when we control for the implied volatility beta (β_i^{VXO}). The FFC alpha difference between the high-β_i^{UNC} and low-β_i^{UNC} portfolios is -0.85% per month with a t-statistic of -3.11 when β_i^{UNC} and β_i^{VXO} are estimated with Model 2, and -0.73% per month with a t-statistic of -2.83 when β_i^{UNC} and β_i^{VXO} are estimated with Model 4. These results clearly show that exposure of individual stocks to changes in market volatility does not diminish the predictive power of the uncertainty beta.

Finally, we examine the predictive power of the uncertainty beta after controlling for the market volatility beta and firm characteristics in multivariate Fama-MacBeth regressions. In Panel C of Table 5, we re-run the earlier cross-sectional regressions (reported in Table 4, Panel A) with β_i^{UNC}, β_i^{MKT}, β_i^{RVOL} and β_i^{VXO} estimated from Models 1, 2, 3, and 4. The results indicate that after accounting for the expected realized volatility beta, the implied volatility beta, market beta, and all other control variables, the average slope of the economic uncertainty beta remains negative and highly significant. In general, the coefficients of the individual control variables are very similar to those presented in Table 4. A notable point in Table 5, Panel C is that the average slope on β_i^{RVOL} and β_i^{VXO} are statistically insignificant, indicating that the negative volatility risk premium is subsumed by the highly significant negative premium of economic uncertainty.

Portfolio level analyses and cross-sectional regressions provide clear evidence that the predictive power of the uncertainty beta is not driven by the exposure of individual stocks to changes in market volatility. We identify a significant negative premium of economic uncertainty in the cross-section of individual stocks, and that is distinct from the volatility risk premium identified by earlier studies.

6. Alternative Measures of the Economic Uncertainty Index

In this section, we test whether our main findings are robust to alternative measures of the economic uncertainty index proposed by other studies.

Jurado, Ludvigson, and Ng (2013) use a large number of financial and macroeconomic variables to provide a new measure of macroeconomic uncertainty, defined as the common variation in the unforecastable component of a large number of economic indicators.[24] Their empirical analysis forms forecasts and common uncertainty from this large dataset covering the period January 1959−December 2011. The correlation between the quarterly measure of the economic uncertainty index proposed in this paper and the quarterly macroeconomic uncertainty measure of Jurado et al. (2013) is 0.37 for the common sample period from 1968:Q4 to 2011:Q4.

Bali, Brown, and Caglayan (2014) propose alternative measures of macroeconomic risk by estimating the time-varying conditional volatility of eight macroeconomic variables based on the multivariate asymmetric GARCH model with a vector autoregressive process.[25] Since macroeconomic risk factors introduced by Bali et al. (2014) are measures of conditional volatility, they are highly persistent and correlated with each other. To sufficiently capture the common variation among correlated factors of economic uncertainty, they develop a broad index of macroeconomic risk using principal component

[24]Jurado, Ludvigson, and Ng (2013) combine the macro and financial monthly datasets used by Ludvigson and Ng (2007, 2010). Specifically, the first dataset used by Jurado et al. (2013) is an updated version of the 132 macroeconomic series used by Ludvigson and Ng (2010). The second dataset is an updated monthly version of the 147 financial time series used by Ludvigson and Ng (2007). Jurado et al. (2013) combine the macro and financial datasets together into one large macroeconomic dataset to estimate forecasting factors in these 279 ($= 132 + 147$) series.

[25]The macroeconomic variables used by Bali, Brown, and Caglayan (2014) are the default spread, the term spread, the de-trended short-term interest rate, the aggregate dividend yield, the aggregate stock market index, the growth rate of real GDP per capita, the inflation rate, and the unemployment rate.

analysis. The correlation between the quarterly measure of the economic uncertainty index proposed in this paper and the quarterly macroeconomic risk index of Bali et al. (2014) is 0.42 for the common sample period, 1994:Q1−2012:Q1.

Figure 2 plots the quarterly measures of the economic uncertainty index proposed in this paper, the macroeconomic uncertainty measure of Jurado, Ludvigson, and Ng (2013), denoted JLN, and the macroeconomic risk index of Bali, Brown, and Caglayan (2014), denoted BBC. Figure 2 clearly shows that all three measures of the economic uncertainty index are highly correlated and they closely follow large fluctuations in business conditions including major economic and financial crises. However, the economic uncertainty index proposed in this paper UNC^{AVG} has stronger time-series variation.

Since the economic uncertainty indices of Jurado, Ludvigson, and Ng (2013) and Bali, Brown, and Caglayan (2014) are available at the monthly frequency with large number of observations (compared to quarterly data), we perform portfolio-level analyses to assess the cross-sectional predictive power of JLN and BBC using monthly data. Exposures of individual stocks to economic uncertainty are obtained from monthly rolling regressions of excess stock returns on monthly measures of the economic uncertainty index using a 60-month fixed window estimation. Monthly economic uncertainty is proxied by 1-month to 12-month macroeconomic uncertainty measures of Jurado, Ludvigson, and Ng (2013) (denoted JLN_1 to JLN_{12}) and the macroeconomic risk index of Bali, Brown, and Caglayan (2014) (denoted BBC). Then, these monthly uncertainty betas are used to predict cross-sectional variation in one-month-ahead returns.

Table 6 reports average monthly returns for the decile portfolios formed on economic uncertainty betas using the CRSP breakpoints. As presented in the last row of Table 6, for the uncertainty measures of Jurado, Ludvigson, and Ng (2013), the Fama-French-Carhart 4-factor alpha differences between decile 1 and decile 10 are in the range of −0.52% to −0.56% per annum with t-statistics ranging from −2.66 to −3.07. As shown in the last column of Table 6, for the macroeconomic risk index of Bali, Brown, and Caglayan (2014), the FFC 4-factor alpha difference between decile 1 and decile 10 is economically large, −0.90% per annum, and significant with a t-statistic of −1.80.[26]

[26]Note that the monthly index of macroeconomic risk proposed by Bali, Brown, and Caglayan (2014) is available for the much shorter sample period from January 1994 to March 2012. Besides, we use the first 60 observations to estimate the

Overall, these results show that the negative relation between the uncertainty beta and future stock returns is economically and statistically significant, and robust across different measures of the economic uncertainty index.

7. Conclusion

This paper investigates the role of economic uncertainty in the cross-sectional pricing of individual stocks. Economic uncertainty is quantified with ex-ante measures of cross-sectional dispersion in economic forecasts from the Survey of Professional Forecasters, determining the degree of disagreement among professional forecasters over changes in macroeconomic fundamentals. Seven different measures of economic uncertainty are used in our empirical analyses: the cross-sectional dispersion in quarterly forecasts for the real GDP growth/level, the nominal GDP growth/level, the GDP price index growth/level, and the unemployment rate.

We introduce a broad index of economic uncertainty based on the innovations in the cross-sectional dispersion of economic forecasts so that the index is a measure of uncertainty shock capturing different aspects of disagreement over macroeconomic fundamentals and also reflecting unexpected news or surprise about the state of the aggregate economy. After building the broad index of economic uncertainty, we test its out-of-sample performance in predicting the cross-sectional variation in future stock returns.

Univariate portfolio-level analyses indicate that decile portfolios that are long in stocks with the lowest uncertainty beta and short in stocks with the highest uncertainty beta yield average raw and risk-adjusted returns of 7.9% to 9.2% per annum. Bivariate portfolio-level analyses and stock-level cross-sectional regressions that control for well-known pricing effects, including size, book-to-market, momentum, short-term reversal, liquidity, co-skewness, idiosyncratic volatility, dispersion in analysts' earnings estimates, firm age, and leverage generate similar results. After controlling for each of these variables one-by-one and then controlling for all variables simultaneously, the results provide evidence of a significantly negative link between the uncertainty beta and future stock returns. Our main findings also hold for different time periods including recessions and expansions, and for different stock samples

uncertainty beta. Hence, the long-short portfolio analysis for the macroeconomic risk index of Bali et al. (2014) covers the period from January 1999 through March 2012. Due to the relatively small number of observations ($n = 159$), the t-statistic of the FFC 4-factor alpha difference (t-statistic=-1.80) is smaller than those reported for the economic uncertainty index proposed in this paper and by Jurado, Ludvigson, and Ng (2013).

including the NYSE stocks, the S&P 500 stocks, and large and liquid stocks. The results also indicate the significant long-term forecasting performance of the uncertainty beta, predicting the cross-section of expected returns nine months into the future.

We also test whether the predictive power of the uncertainty beta remains intact after controlling for the exposure of individual stocks to changes in aggregate stock market volatility. The results show that the predictive power of the uncertainty beta is not driven by the market volatility beta, implying a significantly negative premium of economic uncertainty in the cross-section of individual stocks that is distinct from the negative volatility risk premium identified by earlier studies.

Finally, we test whether the negative relation between the uncertainty beta and future stock returns is robust to alternative measures of the economic uncertainty index generated by large macroeconomic datasets or by sophisticated econometric methodologies. The results indicate that the broad index of economic uncertainty proposed by other studies also provides accurate predictions of future returns. Hence, macroeconomic uncertainty is a powerful determinant of cross-sectional differences in stock returns.

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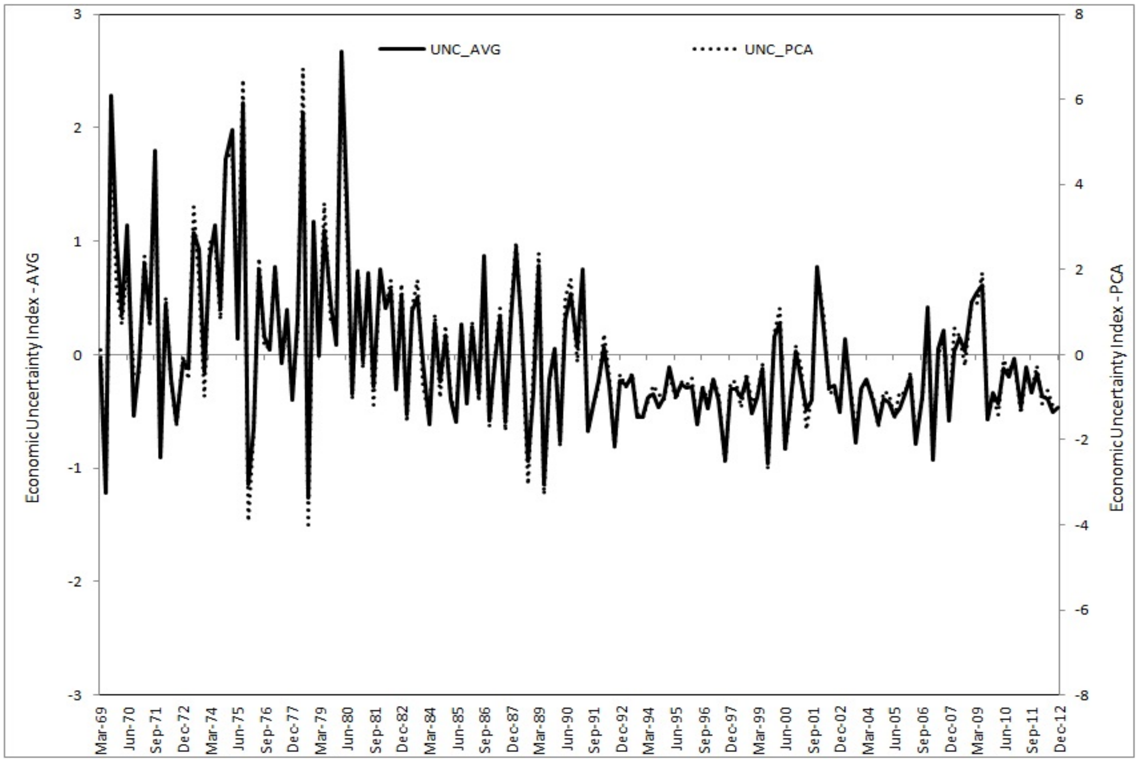

Figure 1. Economic uncertainty index. In the figure, the solid line depicts the quarterly economic uncertainty index, defined as the average of the standardized residuals from the AR(1) model for the seven dispersion measures; the dashed line depicts the quarterly economic uncertainty index, defined as the first principal component of the standardized residuals from the AR(1) model for the seven dispersion measures. The seven dispersion measures are the cross-sectional dispersion in the current quarter forecasts of real GDP (RGDP) growth and level, nominal GDP (NGDP) growth and level, GDP price index (PGDP) growth and level, and unemployment rate (UNEMP). The sample period is from 1968:Q4 to 2012:Q4.

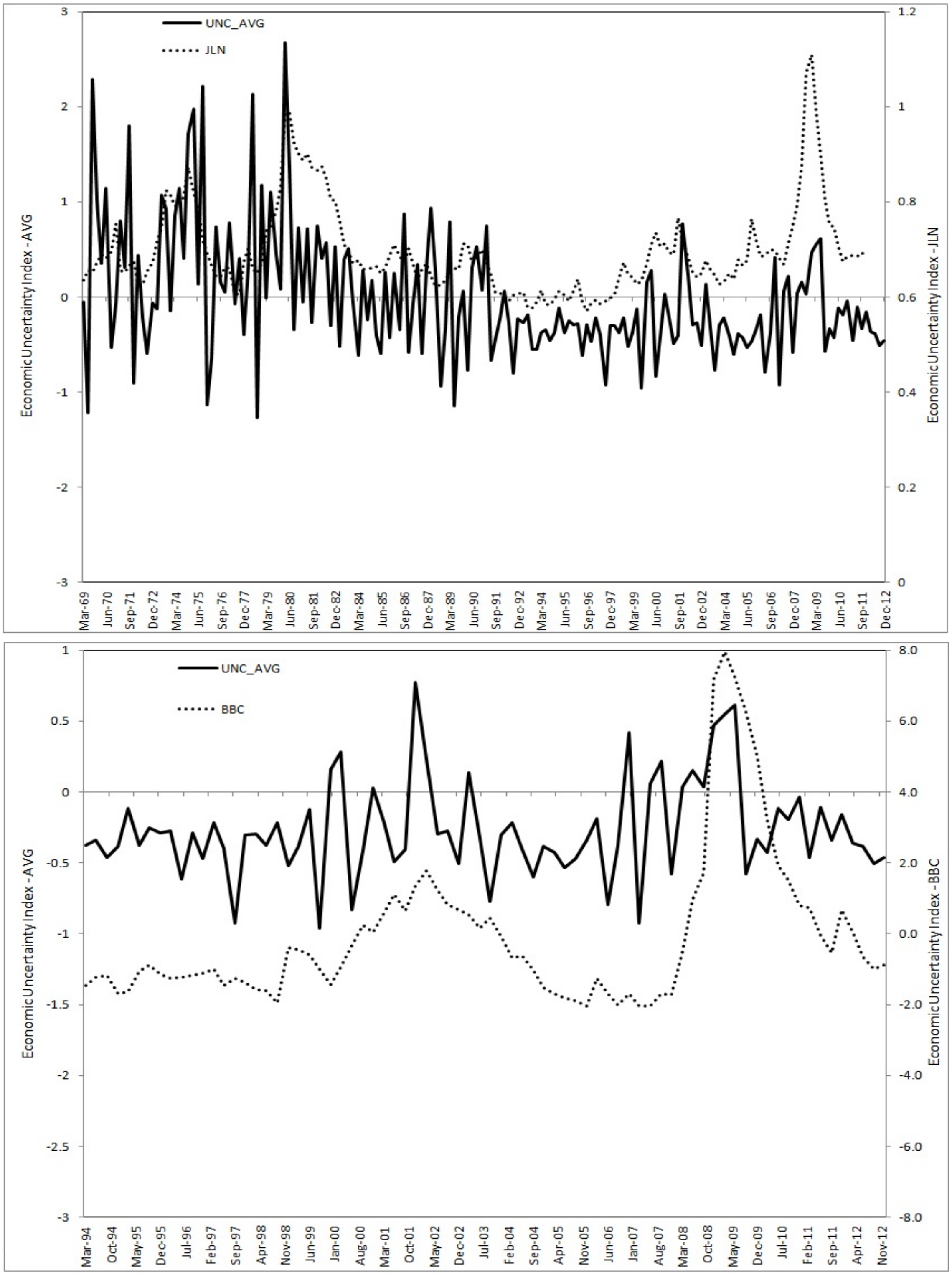

Figure 2. Alternative Measures of Economic Uncertainty Index. This figure plots the quarterly alternative measures of the macroeconomic uncertainty index. In the upper panel, the solid line and the dashed line, respectively, represent the economic uncertainty index proposed in this paper and by Jurado, Ludvigson, and Ng (2013), denoted JLN, for the common period 1968:Q4−2012:Q4. In the lower panel, the solid line and the dashed line, respectively, represent the economic uncertainty index proposed in this paper and by Bali, Brown, and Caglayan (2014), denoted BBC, for the common period 1994:Q1−2012:Q4..

Table 1
Univariate Portfolios of Stocks Sorted by Economic Uncertainty Beta

Economic uncertainty index is measured by the average of the standardized residuals from the AR(1) model for the seven dispersion measures using the expanding window with the first estimation window set to be the first 20 quarters and then updated on a quarterly basis. The seven dispersion measures are the cross-sectional dispersion in the current quarter forecasts of real GDP (RGDP) growth and level, nominal GDP (NGDP) growth and level, GDP price index (PGDP) growth and level, and unemployment rate (UNEMP). Individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index using a 20-quarter fixed window estimation. The first set of uncertainty betas (β^{UNC}) are obtained using the sample from 1968:Q4 to 1973:Q3. Then, these quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months (October 1973, November 1973, and December 1973). The first column in the table reports the average uncertainty beta of individual stocks in each β^{UNC} decile; the next four columns present and the average value- and equal-weighted excess return (RET−RF) and the corresponding Fama-French-Carhart 4-factor alpha (FFC alpha) for each β^{UNC} decile. The last row presents the average return differences and the FFC alpha differences between Decile 1 (Low) and Decile 10 (High). Newey-West adjusted *t*-statistics are given in parentheses. The sample period is October 1973−December 2012.

		Value-weighted		Equal-weighted	
Decile	β^{UNC}	RET−RF	FFC alpha	RET−RF	FFC alpha
1 (Low)	−22.70	0.98	0.44	1.10	0.29
		(3.12)	(2.39)	(3.63)	(2.44)
2	−11.78	0.80	0.28	1.02	0.27
		(3.13)	(2.28)	(3.98)	(3.13)
3	−7.53	0.70	0.18	0.98	0.25
		(2.97)	(1.75)	(4.05)	(3.49)
4	−4.52	0.68	0.16	0.95	0.22
		(3.03)	(2.03)	(4.10)	(3.38)
5	−1.91	0.63	0.08	0.94	0.23
		(2.92)	(0.91)	(4.12)	(4.21)
6	0.63	0.45	−0.06	0.83	0.10
		(2.01)	(−0.81)	(3.59)	(1.49)
7	3.39	0.59	0.08	0.84	0.11
		(2.63)	(1.01)	(3.59)	(1.78)
8	6.76	0.46	−0.09	0.80	0.04
		(2.00)	(−1.19)	(3.28)	(0.74)
9	11.76	0.41	−0.14	0.72	−0.06
		(1.51)	(−1.25)	(2.74)	(−0.92)
10 (High)	26.06	0.32	−0.33	0.52	−0.29
		(0.99)	(−2.50)	(1.64)	(−3.31)
High−Low		−0.66	−0.77	−0.58	−0.58
		(−2.75)	(−2.99)	(−3.75)	(−3.39)

Table 2
Portfolio Characteristics

This table reports averages of the average values of various characteristics of individual stocks in each β^{UNC} decile, including the uncertainty beta (β^{UNC}), market share (Mkt. shr.), stock price per share (PRC), market beta (BETA), market capitalization measured in million dollars (SIZE), book-to-market equity ratio (BM), momentum (MOM), reversal (REV), illiquidity ratio (ILLIQ), co-skewness measure (COSKEW), idiosyncratic volatility (IVOL), analyst forecast dispersion (DISP), firm age (AGE), and leverage (LEV). The sample period is October 1973−December 2012.

Variables	1 (Low)	2	3	4	5	6	7	8	9	10 (High)
β^{UNC}	−22.7	−11.78	−7.53	−4.52	−1.91	0.63	3.39	6.76	11.76	26.06
Mkt. shr.	6.29%	9.63%	10.88%	11.98%	12.52%	12.84%	12.06%	10.25%	8.7%	4.85%
PRC	20.29	24.52	26.35	26.76	27.26	27.44	26.46	24.96	22.68	17.94
BETA	1.40	1.14	1.07	1.03	1.02	1.04	1.08	1.15	1.29	1.67
SIZE	1,125	1,955	2,456	2,827	2,905	3,139	2,938	2,431	1,913	980
BM	0.88	0.92	0.93	0.94	0.94	0.94	0.94	0.93	0.92	0.89
MOM	33.72	21.39	18.68	17.70	17.03	16.61	16.71	17.17	18.98	32.20
REV	2.69	2.00	1.77	1.69	1.68	1.63	1.71	1.72	1.87	2.53
ILLIQ	1.02	0.94	0.82	0.81	0.78	0.80	0.83	0.85	0.92	1.12
COSKEW	−0.09	−0.08	−0.07	−0.06	−0.05	−0.04	−0.04	−0.03	−0.03	−0.02
IVOL	2.45	2.04	1.88	1.80	1.79	1.80	1.86	1.95	2.14	2.60
DISP	0.15	0.12	0.10	0.10	0.10	0.10	0.12	0.13	0.14	0.18
AGE	201	236	249	259	266	265	260	249	227	187
LEV	3.44	3.82	4.05	4.16	4.00	3.85	3.59	3.40	3.34	2.93

Table 3
Bivariate Portfolio Sorts

In this table, stocks are first sorted into deciles based on one control variable, and then stocks within each control variable decile are further sorted into deciles based on uncertainty beta (β^{UNC}). The bivariate portfolios are formed based on the CRSP breakpoints. This table reports the average monthly returns (in percentage) for each uncertainty beta decile, averaged across the ten control groups within the same uncertainty beta decile. The control variables are market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), firm age (AGE), and leverage (LEV). The control variables are defined in Section 2.3. The last two rows present the average return differences and the Fama-French-Carhart 4-factor alpha (FFC alpha) differences between Decile 1 (Low) and Decile 10 (High). Newey-West adjusted t-statistics are given in parentheses. The sample period is October 1973−December 2012.

Decile	BETA	SIZE	BM	MOM	REV	ILLIQ	COSKEW	IVOL	DISP	AGE	LEV
Low-β^{UNC}	0.99	1.01	0.95	0.78	1.02	0.98	0.99	0.97	0.97	0.97	0.92
2	0.84	1.09	0.86	0.71	0.77	0.93	0.81	0.78	0.86	0.76	0.82
3	0.70	0.99	0.76	0.72	0.64	0.92	0.80	0.72	0.76	0.81	0.68
4	0.77	0.96	0.76	0.75	0.82	0.87	0.75	0.83	0.79	0.67	0.86
5	0.66	0.90	0.78	0.53	0.70	0.83	0.75	0.58	0.67	0.75	0.67
6	0.60	0.83	0.56	0.62	0.57	0.73	0.62	0.58	0.60	0.63	0.63
7	0.58	0.84	0.67	0.65	0.55	0.72	0.60	0.53	0.64	0.58	0.56
8	0.59	0.80	0.68	0.46	0.50	0.72	0.62	0.48	0.51	0.51	0.62
9	0.46	0.69	0.62	0.45	0.55	0.56	0.54	0.36	0.43	0.43	0.57
High-β^{UNC}	0.44	0.50	0.52	0.36	0.43	0.41	0.33	0.29	0.36	0.36	0.51
High−Low	−0.55	−0.52	−0.42	−0.42	−0.59	−0.57	−0.66	−0.68	−0.61	−0.61	−0.41
	(−3.46)	(−2.49)	(−3.54)	(−4.02)	(−3.12)	(−2.98)	(−3.34)	(−3.60)	(−2.86)	(−3.67)	(−2.28)
FFC alpha	−0.48	−0.45	−0.55	−0.72	−0.65	−0.68	−0.66	−0.63	−0.70	−0.71	−0.73
	(−2.91)	(−2.66)	(−3.16)	(−4.08)	(−3.29)	(−3.74)	(−3.44)	(−3.66)	(−3.50)	(−3.67)	(−2.83)

Table 4
Fama-MacBeth Cross-Sectional Regressions

This table reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on a set of lagged predictive variables using the Fama-MacBeth methodology. In Panel A, the control variables are market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), firm age (AGE), and leverage (LEV). Panel B presents the same set of regression results controlling for the industry effects. Panel C replaces BETA, SIZE, BM, and MOM in Panel A with their stock-level exposure measures: β^{MKT}, β^{SMB}, β^{HML}, and β^{MOM}, estimated from time-series regressions using month data over the past 60 months. β^{UNC} is winsorized at the 1% and 99% levels to reduce the influence of outliers. Newey-West adjusted t-statistics are reported in parentheses. The sample period is October 1973−December 2012.

Panel A. Monthly Fama-MacBeth regressions

Variable	(1)	(2)	(3)	(4)	(5)
Intercept	0.844	1.007	0.940	1.798	1.959
	(3.47)	(3.91)	(3.73)	(6.74)	(6.34)
β^{UNC}	−0.016	−0.014	−0.012	−0.011	−0.011
	(−3.37)	(−3.80)	(−3.64)	(−4.50)	(−4.50)
BETA		0.116	0.088	0.163	0.140
		(0.96)	(0.79)	(1.43)	(1.28)
SIZE		−0.052	−0.057	−0.132	−0.126
		(−1.91)	(−2.14)	(−4.50)	(−4.40)
BM		0.188	0.191	0.158	0.163
		(2.72)	(2.85)	(2.39)	(2.69)
MOM			0.007	0.006	0.006
			(4.88)	(4.56)	(4.27)
REV				−0.03	−0.032
				(−7.52)	(−7.98)
ILLIQ				−0.026	−0.026
				(−2.15)	(−2.23)
COSKEW				−0.093	−0.096
				(−0.81)	(−0.93)
IVOL				−0.219	−0.216
				(−6.80)	(−6.92)
DISP				−0.167	−0.169
				(−2.01)	(−2.05)
AGE					−0.032
					(−0.90)
LEV					−0.013
					(−0.19)

Table 4 – continued

Panel B. Controlling for the industry effects

Variable	(1)	(2)	(3)	(4)	(5)
Intercept	0.793	0.962	0.898	1.845	1.949
	(3.10)	(3.51)	(3.33)	(6.07)	(6.23)
β^{UNC}	−0.014	−0.013	−0.011	−0.009	−0.009
	(−3.64)	(−3.77)	(−3.76)	(−4.37)	(−4.29)
BETA		0.100	0.074	0.127	0.114
		(0.95)	(0.75)	(1.30)	(1.21)
SIZE		−0.051	−0.055	−0.130	−0.123
		(−1.94)	(−2.09)	(−4.50)	(−4.29)
BM		0.219	0.219	0.217	0.184
		(3.67)	(3.73)	(3.66)	(3.36)
MOM			0.006	0.005	0.005
			(4.67)	(4.29)	(4.10)
REV				−0.035	−0.036
				(−9.06)	(−9.35)
ILLIQ				−0.026	−0.026
				(−2.21)	(−2.25)
COSKEW				−0.017	−0.027
				(−0.19)	(−0.29)
IVOL				−0.221	−0.219
				(−7.47)	(−7.54)
DISP				−0.185	−0.187
				(−2.20)	(−2.23)
AGE					−0.038
					(−1.18)
LEV					0.035
					(0.63)

Table 4 – continued

Panel C. Using exposures to the Market, SMB, HML, and MOM factors

Variable	(1)	(2)	(3)	(4)	(5)
Intercept	0.844	0.726	0.686	0.930	1.503
	(3.47)	(4.09)	(3.93)	(5.59)	(5.27)
β^{UNC}	−0.016	−0.013	−0.013	−0.011	−0.009
	(−3.37)	(−3.50)	(−3.35)	(−4.12)	(−3.75)
β^{MKT}		0.051	0.063	0.160	0.158
		(0.42)	(0.48)	(1.11)	(1.13)
β^{SMB}		0.073	0.097	0.137	0.104
		(0.91)	(1.15)	(1.66)	(1.32)
β^{HML}		0.131	0.141	0.130	0.076
		(1.53)	(1.62)	(1.49)	(1.05)
β^{MOM}			−0.181	−0.16	−0.121
			(−1.91)	(−1.66)	(−1.28)
REV				−0.033	−0.036
				(−8.17)	(−8.78)
ILLIQ				0.001	−0.004
				(0.06)	(−0.37)
COSKEW				−0.2	−0.173
				(−1.63)	(−1.47)
IVOL				−0.157	−0.156
				(−4.51)	(−4.80)
DISP				−0.264	−0.247
				(−2.36)	(−2.33)
AGE					−0.116
					(−2.81)
LEV					0.090
					(1.68)

Table 5
Alternative Measures of Uncertainty Betas Estimated after Controlling for Market Returns and Market Variance

In this table, individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index after controlling innovations in expected realized volatility ($\Delta RVOL$) in Model 1, $\Delta RVOL$ and excess market returns (R_m) in Model 2, innovations in option implied variance (ΔVXO) in Model 3, and ΔVXO and R_m in Model 4 using a 20-quarter fixed window estimation:

$$
\begin{aligned}
\text{Model 1}: R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{AVG} + \beta_{i,t}^{RVOL} \cdot \Delta VAR_t^{Realized} + \varepsilon_{i,t}, \\
\text{Model 2}: R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{AVG} + \beta_{i,t}^{VXO} \cdot \Delta VAR_t^{VXO} + \varepsilon_{i,t}, \\
\text{Model 3}: R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{AVG} + \beta_{i,t}^{RVOL} \cdot \Delta VAR_t^{Realized} + \beta_{i,t}^{MKT} \cdot R_{m,t} + \varepsilon_{i,t}, \\
\text{Model 4}: R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t^{AVG} + \beta_{i,t}^{VXO} \cdot \Delta VAR_t^{VXO} + \beta_{i,t}^{MKT} \cdot R_{m,t} + \varepsilon_{i,t}.
\end{aligned}
$$

These quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months based on (i)univariate portfolio analysis, (ii) conditional bivariate analysis after controlling for stock's exposures to innovations in expected market variance (β^{RVOL} estimated from Models 1 and 2 and exposures to innovations in option implied variance (β^{VXO}) estimated from Models 3 and 4, and (iii) monthly cross-sectional Fama-MacBeth regressions. Panel A reports the average β^{UNC} of individual stocks within each decile sorted on β^{UNC} and the Fama-French-Carhart 4-factor alpha (FFC alpha) for each β^{UNC} decile and the difference between Decile 1 (Low) and Decile 10 (High). Panel B reports the 4-factor alpha for each β^{UNC} decile after controlling for exposures to innovations in market variance. Panel C reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on a set of lagged predictive variables using the Fama-MacBeth methodology, including market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), firm age (AGE), leverage (LEV), exposures to innovations in market variance. β^{UNC} is winsorized at the 1% and 99% levels to reduce the influence of outliers. Newey-West adjusted t-statistics are reported in parentheses. The sample period is October 1973−December 2012.

Table 5 – continued

Panel A. Univariate portfolios sorted by β^{UNC}

Decile	Model (1)		Model (2)		Model (3)		Model (4)	
	β^{UNC}	FFC alpha	β^{UNC}	FFC alpha	β^{UNC}	FFC alpha	β^{UNC}	FFC alpha
1 (Low)	−22.96	0.40	−22.66	0.22	−29.57	0.51	−30.55	0.37
		(2.43)		(1.45)		(1.91)		(1.32)
2	−11.84	0.22	−11.21	0.27	−14.46	0.33	−14.7	0.41
		(2.20)		(2.37)		(1.94)		(2.14)
3	−7.52	0.22	−6.83	0.23	−8.79	0.17	−8.81	0.14
		(2.22)		(3.07)		(1.15)		(1.03)
4	−4.47	0.18	−3.74	0.10	−4.82	0.19	−4.71	0.15
		(1.67)		(1.02)		(1.55)		(1.19)
5	−1.8	0.01	−1.1	0.09	−1.39	0.15	−1.29	0.05
		(0.13)		(1.16)		(1.15)		(0.40)
6	0.84	−0.03	1.49	−0.08	1.96	0.10	2.00	0.19
		(−0.51)		(−1.15)		(0.93)		(2.21)
7	3.68	0.10	4.31	0.09	5.66	0.13	5.62	0.02
		(1.18)		(1.18)		(1.36)		(0.17)
8	7.17	−0.17	7.72	−0.14	10.23	−0.11	10.05	−0.1
		(−2.35)		(−1.77)		(−1.07)		(−0.92)
9	12.34	−0.18	12.90	−0.13	17.19	−0.15	16.85	−0.2
		(−1.50)		(−1.31)		(−0.93)		(−1.49)
10 (High)	27.21	−0.28	27.88	−0.31	38.06	−0.38	37.58	−0.41
		(−2.06)		(−2.37)		(−2.01)		(−2.07)
High−Low		−0.68		−0.53		−0.89		−0.78
		(−2.91)		(−2.46)		(−2.45)		(−2.19)

Table 5 – continued

Panel B. Bivariate portfolio sorts

Decile	Control for β^{RVOL} in Model 1	Control for β^{RVOL} in Model 2	Control for β^{VXO} in Model 3	Control for β^{VXO} in Model 4
1 (Low)	0.96	0.91	1.10	0.96
2	0.77	0.75	0.80	0.82
3	0.74	0.64	0.75	0.70
4	0.75	0.76	0.67	0.67
5	0.68	0.58	0.86	0.74
6	0.64	0.57	0.56	0.68
7	0.64	0.63	0.62	0.68
8	0.55	0.50	0.53	0.70
9	0.55	0.67	0.47	0.45
10 (High)	0.30	0.33	0.37	0.39
High−Low	−0.66	−0.58	−0.73	−0.57
	(−3.67)	(−3.15)	(−2.80)	(−2.28)
FFC alpha	−0.71	−0.70	−0.85	−0.73
	(−3.67)	(−3.46)	(−3.11)	(−2.83)

Table 5 – continued

Panel C. Fama-MacBeth regressions

Variable	Model 1		Model 2		Model 3		Model 4	
Intercept	0.949	1.963	0.923	1.932	0.715	1.680	0.746	1.683
	(3.78)	(6.39)	(3.52)	(6.00)	(2.04)	(4.41)	(2.13)	(4.30)
β^{UNC}	−0.012	−0.011	−0.013	−0.012	−0.007	−0.006	−0.009	−0.007
	(−3.64)	(−4.61)	(−3.77)	(−4.82)	(−3.24)	(−2.60)	(−3.59)	(−3.24)
BETA	0.103	0.152	0.129	0.136	0.188	0.173	0.134	0.115
	(0.88)	(1.35)	(1.39)	(1.70)	(1.35)	(1.33)	(1.19)	(1.22)
SIZE	−0.059	−0.126	−0.058	−0.124	−0.022	−0.087	−0.022	−0.087
	(−2.21)	(−4.43)	(−2.11)	(−4.30)	(−0.70)	(−2.75)	(−0.67)	(−2.72)
BM	0.188	0.149	0.208	0.164	0.130	0.102	0.134	0.103
	(2.81)	(2.28)	(3.09)	(2.50)	(1.48)	(1.15)	(1.51)	(1.16)
MOM	0.006	0.006	0.006	0.006	0.005	0.004	0.004	0.003
	(4.64)	(4.06)	(4.29)	(3.71)	(2.61)	(2.11)	(2.34)	(1.68)
REV		−0.032		−0.031		−0.021		−0.021
		(−8.06)		(−7.76)		(−4.65)		(−4.61)
ILLIQ		−0.027		−0.026		−0.033		−0.032
		(−2.27)		(−2.11)		(−2.06)		(−1.95)
COSKEW		−0.106		−0.135		−0.075		−0.078
		(−1.01)		(−1.23)		(−0.54)		(−0.52)
IVOL		−0.214		−0.212		−0.13		−0.126
		(−6.92)		(−6.33)		(−3.27)		(−2.99)
DISP		−0.169		−0.166		−0.06		−0.058
		(−2.06)		(−2.01)		(−1.40)		(−1.35)
AGE		−0.032		−0.03		−0.039		−0.036
		(−0.92)		(−0.83)		(−0.97)		(−0.88)
LEV		−0.013		−0.014		−0.001		−0.002
		(−0.19)		(−0.22)		(−0.01)		(−0.02)
β^{RVOL}	0.071	0.065	−0.13	−0.187				
	(0.39)	(0.34)	(−0.59)	(−0.87)				
β^{VXO}					1.038	0.457	−7.798	−7.088
					(0.36)	(0.18)	(−1.56)	(−1.54)

Table 6

Univariate Portfolios of Stocks Sorted by Exposures to Alternative Measures of the Economic Uncertainty Index

Individual stocks' exposures to economic uncertainty are obtained from monthly rolling regressions of excess stock returns on monthly economic uncertainty measures using a 60-month fixed window estimation. Monthly economic uncertainty is proxied, respectively, by 1-month to 12-month macroeconomic uncertainty measures of Jurado, Ludvigson, and Ng (2013) (denoted JLN_1 to JLN_{12}) and the macroeconomic risk index of Bali, Brown, and Caglayan (2014) (denoted BBC). Then, these monthly uncertainty betas are used to predict the cross-sectional variation in one-month ahead returns. This table reports the average monthly returns (in percentage) for the decile portfolios formed on economic uncertainty betas using the CRSP breakpoints. The last row presents the Fama-French-Carhart 4-factor alpha (FFC alpha) differences between Decile 1 (Low) and Decile 10 (High). Newey-West adjusted t-statistics are given in parentheses.

Decile	β_1^{JLN}	β_2^{JLN}	β_3^{JLN}	β_4^{JLN}	β_5^{JLN}	β_6^{JLN}	β_7^{JLN}	β_8^{JLN}	β_9^{JLN}	β_{10}^{JLN}	β_{11}^{JLN}	β_{12}^{JLN}	β^{BBC}
1 (Low)	1.33	1.33	1.33	1.35	1.35	1.35	1.34	1.35	1.35	1.35	1.36	1.35	1.18
2	1.32	1.35	1.36	1.34	1.36	1.36	1.35	1.35	1.35	1.34	1.33	1.34	1.06
3	1.24	1.27	1.26	1.26	1.25	1.24	1.26	1.26	1.26	1.27	1.27	1.26	1.00
4	1.21	1.20	1.22	1.22	1.21	1.20	1.19	1.20	1.20	1.20	1.20	1.18	0.93
5	1.18	1.16	1.13	1.11	1.13	1.14	1.16	1.15	1.13	1.14	1.13	1.15	0.88
6	1.12	1.12	1.12	1.11	1.11	1.10	1.10	1.10	1.12	1.12	1.12	1.13	0.89
7	1.15	1.17	1.17	1.19	1.18	1.17	1.16	1.13	1.13	1.13	1.14	1.14	0.88
8	1.09	1.06	1.09	1.08	1.09	1.11	1.11	1.12	1.13	1.13	1.13	1.11	0.77
9	1.11	1.09	1.10	1.11	1.11	1.10	1.11	1.11	1.11	1.11	1.10	1.11	0.90
10 (High)	0.97	0.98	0.96	0.96	0.96	0.96	0.96	0.96	0.95	0.95	0.96	0.96	0.86
FFC alpha	-0.56	-0.54	-0.55	-0.55	-0.55	-0.54	-0.54	-0.54	-0.53	-0.53	-0.53	-0.52	-0.90
	(-3.07)	(-2.94)	(-2.97)	(-2.94)	(-2.90)	(-2.84)	(-2.79)	(-2.82)	(-2.77)	(-2.75)	(-2.72)	(-2.66)	(-1.80)

Macroeconomic Uncertainty and Expected Stock Returns

Online Appendix

Table A1 presents the summary statistics for the cross-sectional dispersion in economic forecasts. Table A2 presents the quarter-to-quarter portfolio transition matrix. Table A3 presents the results from the univariate portfolios of stocks sorted by economic uncertainty bets using the NYSE breakpoints. Table A4 reports the results of Fama-MacBeth regressions of excess stock returns on exposure to innovations in individual macroeconomic dispersion measures. Table A5 presents the results of univariate sorts using returns on the 38 and 48 value-weighted industry portfolios as the test assets. Table A6 presents the results from the univariate portfolios of stocks sorted by uncertainty betas for seven different stock samples: (i) NYSE stocks only; (ii) Large stocks, defined as those with market capitalization greater than the 50th NYSE size percentile at the beginning of each month; (iii) the S&P 500 stocks; (iv) Largest 500 stocks based on market capitalization in the CRSP universe; (v) Largest $1,000$ stocks based on market capitalization in the CRSP universe; (vi) 500 most liquid stocks in the CRSP universe based on the Amihud's (2002) illiquidity measure; and (vii) $1,000$ most liquid stocks in the CRSP universe based on the Amihud's (2002) illiquidity measure. Table A7 presents the results from the univariate portfolios of stocks sorted by uncertainty betas for two subsample periods: October 1973$-$May 1993 and June 1993$-$December 2012. Table A8 presents the results of univariate portfolio sorts on economic uncertainty beta for economic recessions and expansions. Table A9 reports the average quarterly returns for the univariate portfolios formed based on uncertainty betas in the following five quarters. Table A11 reports the results of Fama-MacBeth regressions after controlling for market returns in estimating individual stocks' uncertainty beta. Figure A1 depicts the number of forecasts for the current quarter real GDP growth over the sample period 1968:Q4$-$2012:Q4. Figure A2 depicts the cross-sectional dispersion in the current quarter forecasts of real GDP (RGDP) growth and level, nominal GDP (NGDP) growth and level, GDP price index (PGDP) growth and level, and unemployment rate (UNEMP) over the sample period 1968:Q4$-$2012:Q4.

Table A1

Summary Statistics for the Cross-Sectional Dispersion in Economic Forecasts

Panel A reports the descriptive statistics for the cross-sectional dispersion in the current quarter forecasts of real GDP (RGDP) growth and level, nominal GDP (NGDP) growth and level, GDP price index (PGDP) growth and level, and unemployment rate (UNEMP). Panel B reports the correlation coefficients between these dispersion measures. The sample period is October 1973−December 2012.

Panel A. Descriptive statistics

	Mean	Std. dev.	Minimum	Median	Maximum	AR(1)
RGDP growth	1.45	0.82	0.38	1.21	4.89	0.73
RGDP level	0.36	0.22	0.09	0.3	1.23	0.72
NGDP growth	1.74	0.75	0.68	1.52	5.16	0.62
NGDP level	0.42	0.18	0.17	0.36	1.16	0.63
PGDP growth	1.08	0.59	0	0.95	3.4	0.46
PGDP level	0.27	0.16	0	0.23	0.81	0.34
UNEMP	2.49	1.55	0	2.13	11.33	0.28

Panel B. Correlation coefficients for level variables

	RGDP level	NGDP growth	NGDP level	PGDP growth	PGDP level	UNEMP
RGDP growth	0.94	0.77	0.77	0.56	0.52	0.49
RGDP level		0.75	0.81	0.55	0.59	0.53
NGDP growth			0.95	0.44	0.41	0.34
NGDP level				0.45	0.48	0.37
PGDP growth					0.74	0.46
PGDP level						0.39

Table A2
Transition matrix

This table reports the average quarter-to-quarter portfolio transition matrix in one to four quarters ahead. The sample period is October 1973−December 2012.

Panel A. One-quarter ahead

Decile	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Total
1 (Low)	73.95%	13.45%	3.25%	2.09%	1.33%	1.32%	1.09%	1.12%	1.17%	1.23%	100.00%
2	12.99%	53.55%	17.57%	5.41%	2.81%	2.10%	1.72%	1.38%	1.12%	1.35%	100.00%
3	2.95%	17.12%	45.76%	18.45%	6.37%	3.17%	2.06%	1.45%	1.65%	1.01%	100.00%
4	1.89%	5.36%	17.47%	41.79%	18.55%	6.66%	3.27%	1.88%	1.72%	1.39%	100.00%
5	1.49%	2.59%	6.40%	17.69%	40.11%	18.54%	6.50%	3.29%	1.85%	1.55%	100.00%
6	1.14%	1.99%	3.35%	6.41%	17.97%	40.29%	17.86%	6.40%	2.78%	1.80%	100.00%
7	1.21%	1.51%	2.08%	3.40%	6.31%	17.55%	43.09%	17.72%	5.12%	2.02%	100.00%
8	1.59%	1.32%	1.57%	2.00%	3.37%	6.01%	17.24%	47.03%	16.55%	3.33%	100.00%
9	1.37%	1.55%	1.64%	1.57%	1.93%	2.71%	5.05%	16.15%	55.63%	12.41%	100.00%
10 (High)	1.75%	1.81%	1.38%	1.36%	1.49%	1.34%	1.87%	3.27%	12.21%	73.53%	100.00%

Panel B. Two-quarter ahead

Decile	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Total
1 (Low)	65.89%	17.38%	4.99%	2.86%	1.68%	1.64%	1.37%	1.34%	1.34%	1.50%	100.00%
2	16.43%	41.70%	20.70%	8.02%	4.19%	2.65%	2.00%	1.67%	1.41%	1.22%	100.00%
3	4.66%	19.55%	33.17%	19.89%	9.47%	4.98%	2.96%	2.22%	1.77%	1.34%	100.00%
4	2.66%	7.78%	19.23%	29.96%	19.22%	9.60%	4.96%	2.88%	2.10%	1.61%	100.00%
5	1.78%	4.01%	8.74%	19.14%	28.70%	19.35%	9.17%	4.74%	2.64%	1.72%	100.00%
6	1.43%	2.70%	4.83%	8.86%	18.96%	28.91%	19.23%	8.76%	4.17%	2.15%	100.00%
7	1.45%	2.14%	2.91%	4.81%	9.02%	19.01%	31.06%	19.49%	7.33%	2.78%	100.00%
8	1.49%	1.78%	2.17%	2.89%	4.49%	8.39%	19.24%	35.26%	19.76%	4.53%	100.00%
9	1.77%	1.77%	1.84%	2.37%	2.75%	3.60%	7.19%	19.07%	44.01%	15.64%	100.00%
10 (High)	1.97%	1.97%	1.79%	1.74%	1.64%	2.09%	2.87%	4.62%	15.45%	65.85%	100.00%

Table A2 – continued

Panel C. Three-quarter ahead

Decile	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Total
1 (Low)	59.60%	18.96%	6.68%	3.69%	2.42%	2.01%	1.64%	1.65%	1.58%	1.75%	100.00%
2	17.39%	34.74%	20.60%	9.89%	5.58%	3.63%	2.65%	2.18%	1.86%	1.48%	100.00%
3	6.12%	19.26%	27.52%	19.20%	11.05%	6.23%	3.75%	2.98%	2.10%	1.79%	100.00%
4	3.30%	9.65%	18.53%	24.51%	18.32%	11.00%	6.36%	3.84%	2.53%	1.96%	100.00%
5	2.21%	5.21%	10.15%	18.24%	23.49%	18.16%	10.78%	6.06%	3.54%	2.17%	100.00%
6	1.79%	3.35%	6.14%	10.50%	17.96%	23.98%	18.36%	10.08%	5.38%	2.46%	100.00%
7	1.64%	2.59%	3.82%	6.20%	10.33%	18.21%	25.71%	19.02%	9.05%	3.43%	100.00%
8	1.66%	2.16%	2.91%	3.74%	5.95%	9.84%	18.99%	29.10%	20.00%	5.65%	100.00%
9	2.08%	1.99%	2.21%	2.76%	3.50%	4.92%	8.79%	19.74%	37.19%	16.84%	100.00%
10 (High)	2.24%	2.56%	2.02%	2.10%	2.18%	2.75%	3.79%	5.90%	16.90%	59.55%	100.00%

Panel D. Four-quarter ahead

Decile	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	Total
1 (Low)	54.03%	19.66%	8.21%	4.65%	3.15%	2.42%	2.00%	1.92%	1.88%	2.08%	100.00%
2	17.53%	29.72%	19.81%	11.23%	6.76%	4.40%	3.53%	2.72%	2.36%	1.96%	100.00%
3	7.36%	18.44%	23.52%	18.32%	11.88%	7.26%	4.71%	3.66%	2.74%	2.10%	100.00%
4	3.96%	10.49%	17.60%	21.24%	17.25%	11.69%	7.48%	4.85%	3.25%	2.20%	100.00%
5	2.72%	6.59%	11.06%	16.58%	20.12%	17.40%	11.41%	7.02%	4.34%	2.76%	100.00%
6	2.12%	4.22%	7.18%	11.45%	16.90%	20.55%	17.58%	10.95%	6.09%	2.98%	100.00%
7	2.09%	3.11%	4.94%	7.30%	11.07%	16.91%	22.08%	18.19%	10.08%	4.23%	100.00%
8	1.93%	2.84%	3.48%	4.47%	7.07%	11.20%	17.94%	25.13%	19.31%	6.63%	100.00%
9	2.42%	2.27%	2.62%	3.50%	4.17%	6.13%	10.05%	19.25%	32.39%	17.21%	100.00%
10 (High)	2.71%	2.59%	2.51%	2.44%	2.68%	3.26%	4.32%	7.05%	17.76%	54.68%	100.00%

Table A3

Univariate Portfolios of Stocks Sorted by Economic Uncertainty Betas using the NYSE Breakpoints

In this table, individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index using a 20-quarter fixed window estimation. The first set of uncertainty betas (β^{UNC}) are obtained using the sample from 1968:Q4 to 1973:Q3. Then, these quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months (October 1973, November 1973, and December 1973). This table reports the value-weighted and equal-weighted monthly returns (in percentage) and the Fama-French-Carhart 4-factor alpha for the decile portfolios formed on β^{UNC} using the NYSE breakpoints. The last two rows present the average return differences and the Fama-French-Carhart 4-factor alpha (FFC alpha) differences between Decile 1 (Low) and Decile 10 (High). Newey-West adjusted t-statistics are given in parentheses. The sample period is October 1973−December 2012.

	Value-weighted		Equal-weighted	
Decile	RET−RF	FFC4 alpha	RET−RF	FFC4 alpha
1 (Low)	0.91	0.39	1.10	0.30
	(3.00)	(2.25)	(3.73)	(2.62)
2	0.81	0.27	0.98	0.23
	(3.43)	(2.67)	(3.88)	(2.61)
3	0.67	0.10	0.99	0.26
	(2.85)	(1.16)	(4.10)	(3.64)
4	0.71	0.22	0.95	0.24
	(3.19)	(2.44)	(4.15)	(3.71)
5	0.56	0.00	0.90	0.19
	(2.60)	(−0.04)	(3.96)	(3.33)
6	0.43	−0.06	0.83	0.12
	(1.96)	(−0.80)	(3.63)	(1.67)
7	0.61	0.13	0.89	0.16
	(2.79)	(1.61)	(3.80)	(2.68)
8	0.46	−0.07	0.80	0.05
	(1.96)	(−0.90)	(3.29)	(0.75)
9	0.49	−0.07	0.78	0.01
	(2.00)	(−0.67)	(3.07)	(0.17)
10 (High)	0.37	−0.26	0.59	−0.21
	(1.22)	(−2.32)	(1.96)	(−2.91)
High−Low	−0.54	−0.65	−0.51	−0.51
	(−2.40)	(−2.76)	(−3.81)	(−3.37)

Table A4
Fama-MacBeth Cross-Sectional Regressions

Economic uncertainty index is measured by the standardized residuals from the AR(1) model for a dispersion measure using the expanding window with the first estimation window set to be the first 20 quarters and then updated on a quarterly basis. The seven dispersion measures are the cross-sectional dispersion in the current quarter forecasts of real GDP (RGDP) growth and level, nominal GDP (NGDP) growth and level, GDP price index (PGDP) growth and level, and unemployment rate (UNEMP). The Individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index using a 20-quarter fixed window estimation. These quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months after controlling for a large set of stock return predictors after controlling for a large set of stock return predictors, including market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), firm age (AGE), and leverage (LEV). This table reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on a set of lagged predictive variables using the Fama-MacBeth methodology. β^{UNC} is winsorized at the 1% and 99% levels to reduce the influence of outliers. Newey-West adjusted t-statistics are reported in parentheses. The sample period is October 1973−December 2012.

	RGDP		NGDP		PGDP		UNEMP
Variable	Growth	Level	Growth	Level	Growth	Level	
Intercept	1.953	1.938	1.959	1.947	1.975	1.975	1.992
	(6.32)	(6.28)	(6.29)	(6.25)	(6.29)	(6.27)	(6.38)
β^{UNC}	-0.011	-0.003	-0.008	-0.002	-0.002	-0.001	-0.013
	(-3.55)	(-3.28)	(-3.38)	(-2.60)	(-1.94)	(-1.85)	(-1.90)
BETA	0.125	0.126	0.148	0.145	0.126	0.126	0.141
	(1.15)	(1.16)	(1.32)	(1.31)	(1.17)	(1.15)	(1.28)
LNME	-0.124	-0.124	-0.124	-0.124	-0.120	-0.122	-0.127
	(-4.28)	(-4.30)	(-4.27)	(-4.30)	(-4.15)	(-4.22)	(-4.36)
LNBM	0.159	0.171	0.161	0.159	0.160	0.162	0.166
	(2.62)	(2.82)	(2.68)	(2.63)	(2.67)	(2.68)	(2.74)
MOM	0.006	0.006	0.006	0.006	0.006	0.006	0.006
	(4.49)	(4.45)	(4.41)	(4.39)	(4.03)	(3.97)	(4.13)
REV	-0.032	-0.032	-0.031	-0.032	-0.032	-0.032	-0.032
	(-7.92)	(-7.89)	(-7.98)	(-7.98)	(-8.02)	(-8.09)	(-7.98)
ILLIQ	-0.027	-0.027	-0.026	-0.027	-0.027	-0.027	-0.028
	(-2.29)	(-2.25)	(-2.23)	(-2.24)	(-2.30)	(-2.32)	(-2.34)
COSKEW	-0.127	-0.091	-0.113	-0.107	-0.121	-0.104	-0.151
	(-1.24)	(-0.87)	(-1.06)	(-1.00)	(-1.21)	(-1.02)	(-1.42)
IVOL	-0.215	-0.216	-0.217	-0.217	-0.218	-0.218	-0.216
	(-6.93)	(-6.93)	(-6.96)	(-6.96)	(-7.04)	(-7.04)	(-6.98)
DISP	-0.171	-0.167	-0.171	-0.171	-0.170	-0.168	-0.168
	(-2.06)	(-2.03)	(-2.08)	(-2.09)	(-2.05)	(-2.09)	(-2.07)
LNAGE	-0.031	-0.030	-0.033	-0.031	-0.036	-0.035	-0.034
	(-0.89)	(-0.86)	(-0.93)	(-0.89)	(-1.01)	(-0.97)	(-0.96)
LNAM	-0.004	-0.008	-0.009	-0.007	-0.012	-0.011	-0.009
	(-0.07)	(-0.12)	(-0.13)	(-0.10)	(-0.18)	(-0.16)	(-0.14)

Table A5
Univariate Portfolios Using Industry Portfolios as Test Assets

In this table, individual industries' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess returns for the 38 and 48 Fama-French value-weighted industry portfolios on the quarterly economic uncertainty index using a 20-quarter fixed window estimation. The first set of uncertainty betas (β^{UNC}) are obtained using the sample from 1968:Q4 to 1973:Q3. Then, these quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months (October 1973, November 1973, and December 1973). This table reports the average uncertainty beta (β^{UNC}), average monthly returns (in percentage), and the Fama-French-Carhart 4-factor alpha for the decile portfolios formed on β^{UNC}. The last two rows present the average return differences and the Fama-French-Carhart 4-factor alpha (FFC alpha) differences between Decile 1 (Low) and Decile 10 (High). Newey-West adjusted t-statistics are given in parentheses. The sample period is October 1973−December 2012.

	38 industries			48 industries		
Decile	β^{UNC}	RET−RF	FFC alpha	β^{UNC}	RET−RF	FFC alpha
1 (Low)	−8.25	1.06	0.44	−8.89	1.10	0.41
		(3.83)	(2.35)		(4.28)	(2.47)
2	−4.73	0.69	0.09	−4.73	0.67	0.04
		(2.70)	(0.65)		(2.76)	(0.30)
3	−3.22	0.66	0.01	−3.08	0.71	0.01
		(2.55)	(0.05)		(2.73)	(0.10)
4	−2.12	0.76	0.12	−1.76	0.63	0.04
		(3.25)	(1.00)		(2.55)	(0.41)
5	−0.95	0.62	0.04	−0.65	0.68	0.01
		(2.35)	(0.39)		(2.51)	(0.09)
6	0.12	0.56	−0.06	0.39	0.65	0.03
		(2.02)	(−0.61)		(2.63)	(0.37)
7	1.13	0.58	0.01	1.69	0.60	0.00
		(2.34)	(0.04)		(2.33)	(−0.01)
8	2.37	0.60	0.02	3.14	0.56	−0.05
		(2.68)	(0.15)		(2.31)	(−0.47)
9	3.90	0.53	−0.06	4.85	0.52	−0.13
		(2.13)	(−0.52)		(1.96)	(−1.06)
10 (High)	7.35	0.52	−0.22	8.77	0.46	−0.29
		(1.76)	(−1.36)		(1.60)	(−1.96)
High−Low		−0.54	−0.67		−0.63	−0.70
		(−1.99)	(−2.31)		(−2.90)	(−2.92)

Table A6
Different Stock Samples

In this table, individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index using a 20-quarter fixed window estimation. These quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months. Sensitivity of our main findings is tested for seven different stock samples: (i) NYSE stocks only; (ii) Large stocks, defined as those with market capitalization greater than the 50th NYSE size percentile at the beginning of each month; (iii) the S&P 500 stocks; (iv) Largest 500 stocks based on market capitalization in the CRSP universe; (v) Largest 1,000 stocks based on market capitalization in the CRSP universe; (vi) 500 most liquid stocks in the CRSP universe based on the Amihud's (2002) illiquidity measure; and (vii) 1,000 most liquid stocks in the CRSP universe based on the Amihud's (2002) illiquidity measure. This table reports the average monthly returns (in percentage) for the decile portfolios formed on β^{UNC} using the CRSP breakpoints. The last two rows present the average return differences and the Fama-French-Carhart 4-factor alpha (FFC alpha) differences between Decile 1 (Low) and Decile 10 (High). Newey-West adjusted t-statistics are given in parentheses. The sample period is October 1973−December 2012.

Decile	NYSE	Large	S&P500	500 largest	1,000 largest	500 most liquid	1,000 most liquid
1 (Low)	0.29	0.37	0.45	0.34	0.36	0.40	0.41
	(1.66)	(2.32)	(2.62)	(2.19)	(2.31)	(2.52)	(2.41)
2	0.16	0.18	0.18	0.27	0.22	0.29	0.25
	(1.43)	(1.79)	(1.86)	(2.44)	(2.28)	(2.53)	(2.39)
3	0.10	0.23	0.27	0.19	0.22	0.24	0.23
	(0.99)	(2.46)	(2.65)	(1.98)	(2.45)	(2.58)	(2.40)
4	0.14	0.16	0.11	0.12	0.18	0.09	0.20
	(1.58)	(1.76)	(1.06)	(1.21)	(1.94)	(0.96)	(2.19)
5	0.00	−0.01	0.00	0.02	0.00	−0.02	−0.01
	(−0.02)	(−0.21)	(0.01)	(0.30)	(−0.01)	(−0.29)	(−0.11)
6	−0.11	−0.05	−0.02	−0.06	0.01	−0.04	0.01
	(−1.51)	(−0.61)	(−0.23)	(−0.68)	(0.19)	(−0.42)	(0.07)
7	0.09	0.05	−0.03	0.01	−0.06	0.00	−0.04
	(1.02)	(0.77)	(−0.37)	(0.18)	(−0.73)	(−0.01)	(−0.55)
8	−0.05	−0.09	−0.06	−0.12	−0.02	−0.14	−0.05
	(−0.62)	(−0.95)	(−0.52)	(−1.32)	(−0.26)	(−1.45)	(−0.59)
9	−0.16	−0.15	−0.01	−0.14	−0.13	−0.1	−0.11
	(−1.66)	(−1.37)	(−0.07)	(−1.29)	(−1.17)	(−0.90)	(−0.98)
10 (High)	−0.22	−0.15	−0.14	−0.13	−0.23	−0.17	−0.21
	(−1.81)	(−1.27)	(−1.07)	(−1.03)	(−1.97)	(−1.38)	(−1.78)
High−Low	−0.51	−0.52	−0.59	−0.47	−0.59	−0.56	−0.62
	(−2.35)	(−2.30)	(−2.26)	(−2.04)	(−2.69)	(−2.53)	(−2.73)

Table A7
Subsample Analysis

In this table, individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index using a 20-quarter fixed window estimation. These quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months. This table reports the average monthly returns (in percentage) for the decile portfolios formed on β^{UNC} for two subsample periods: October 1973−May 1993 and June 1993−December 2012. The last two rows present the average return differences and the Fama-French-Carhart 4-factor alpha (FFC alpha) differences between Decile 1 (Low) and Decile 10 (High). Newey-West adjusted t-statistics are given in parentheses.

Decile	Oct 1973−May 1993	June 1993−Dec 2012
1 (Low)	0.19	0.57
	(1.40)	(1.86)
2	0.29	0.25
	(2.87)	(1.25)
3	0.21	0.18
	(2.16)	(1.10)
4	0.14	0.22
	(1.69)	(1.80)
5	−0.03	0.23
	(−0.25)	(1.76)
6	−0.12	0.02
	(−1.46)	(0.19)
7	0.03	0.14
	(0.24)	(1.40)
8	−0.05	−0.11
	(−0.55)	(−1.12)
9	−0.2	−0.16
	(−1.48)	(−0.93)
10 (High)	−0.38	−0.41
	(−2.41)	(−1.98)
High−Low	−0.58	−0.97
	(−2.45)	(−2.34)

Table A8
Univariate portfolio analysis for economic recessions and expansions

In this table, individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index using a 20-quarter fixed window estimation. These quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months. This table reports the Fama-French-Carhart 4-factor alpha (in percentage) for the decile portfolios formed on β^{UNC} and the 4-factor alpha (FFC alpha) differences between Decile 1 (Low) and Decile 10 (High) for economic recessions and expansions. Monthly observations over the period October 1973−December 2012 are divided into the normal (bad) state in which the three-month moving average of the Chicago Fed National Activity Index (CFNAIMA3) is above (below) −0.7 or the U.S. economy in expansion (recession) as marked by the National Bureau of Economic Research (NBER). Newey-West adjusted t-statistics are given in parentheses.

Decile	Recession−NBER	Expansion−NBER	Recession−CFNAI	Recession−CFNAI
1 (Low)	0.85	0.34	0.93	0.35
	(1.95)	(1.86)	(1.77)	(2.01)
2	0.63	0.24	0.46	0.26
	(2.95)	(1.76)	(1.60)	(1.92)
3	0.80	0.04	0.87	0.06
	(3.52)	(0.41)	(3.31)	(0.59)
4	0.36	0.15	0.28	0.10
	(2.11)	(1.62)	(1.67)	(1.14)
5	−0.01	0.08	0.08	0.07
	(−0.05)	(0.86)	(0.45)	(0.79)
6	−0.21	−0.03	−0.13	−0.04
	(−0.87)	(−0.42)	(−0.67)	(−0.55)
7	−0.11	0.12	0.07	0.11
	(−0.47)	(1.64)	(0.34)	(1.55)
8	−0.2	−0.08	−0.09	−0.07
	(−1.00)	(−1.14)	(−0.47)	(−0.94)
9	−0.64	−0.09	−0.87	−0.02
	(−1.85)	(−0.77)	(−3.45)	(−0.20)
10 (High)	−0.95	−0.28	−0.93	−0.22
	(−3.51)	(−1.86)	(−3.13)	(−1.46)
High−Low	−1.8	−0.62	−1.86	−0.57
	(−3.44)	(−2.26)	(−2.98)	(−2.08)

Table A9
Long-term Predictive Power of Economic Uncertainty Betas

In this table, individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index using a 20-quarter fixed window estimation. These quarterly uncertainty betas are used to predict the quarterly cross-sectional stock returns in the following one to five quarters ahead (i.e., quarters 1−5). This table reports the Fama-French-Carhart 4-factor alpha (in percentage) of the quarterly returns for the decile portfolios formed on β^{UNC} as well as the 4-factor alpha (FFC alpha) differences in quarterly returns between Decile 1 (Low) and Decile 10 (High). Newey-West adjusted t-statistics are given in parentheses. The sample period is 1973:Q4−2012:Q4.

Decile	QTR1	QTR2	QTR3	QTR4
1 (Low)	1.60	0.73	0.67	0.60
	(2.38)	(1.59)	(1.71)	(1.68)
2	0.63	1.32	0.82	0.75
	(1.59)	(2.27)	(2.43)	(2.45)
3	0.43	0.38	−0.08	0.71
	(1.18)	(1.55)	(−0.39)	(2.61)
4	0.47	0.25	0.56	0.51
	(2.01)	(0.92)	(1.97)	(2.15)
5	0.45	0.39	0.08	0.13
	(1.49)	(1.41)	(0.42)	(0.49)
6	−0.34	−0.07	−0.11	0.06
	(−1.34)	(−0.28)	(−0.58)	(0.29)
7	0.12	−0.26	0.09	0.33
	(0.60)	(−1.11)	(0.39)	(1.02)
8	−0.31	−0.09	0.12	0.13
	(−1.57)	(−0.31)	(0.58)	(0.41)
9	−0.68	−0.71	−0.25	−0.19
	(−1.88)	(−2.06)	(−0.78)	(−0.55)
10 (High)	−0.48	−0.97	−0.6	−0.31
	(−1.21)	(−2.07)	(−1.51)	(−0.85)
High−Low	−2.08	−1.70	−1.27	−0.92
	(−2.40)	(−2.33)	(−1.99)	(−1.64)

Table A10
Fama-MacBeth Cross-Sectional Regressions after Controlling for Market Return

In this table, individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index after controlling for excess quarterly market returns using a 20-quarter fixed window estimation. These quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months after controlling for a large set of stock return predictors after controlling for a large set of stock return predictors, including market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), firm age (AGE), and leverage (LEV). This table reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on a set of lagged predictive variables using the Fama-MacBeth methodology. β^{UNC} is winsorized at the 1% and 99% levels to reduce the influence of outliers. Newey-West adjusted t-statistics are reported in parentheses. The sample period is October 1973−December 2012.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.880	0.744	0.994	0.908	1.774	1.917
	(3.60)	(3.94)	(3.72)	(3.44)	(6.56)	(5.93)
β^{UNC}	−0.012	−0.017	−0.016	−0.014	−0.013	−0.012
	(−3.14)	(−3.89)	(−4.07)	(−3.76)	(−4.77)	(−4.76)
BETA		0.125	0.155	0.129	0.162	0.144
		(1.18)	(1.60)	(1.43)	(1.95)	(1.84)
SIZE			−0.052	−0.056	−0.129	−0.123
			(−1.83)	(−2.02)	(−4.31)	(−4.26)
BM			0.209	0.209	0.174	0.180
			(2.93)	(3.06)	(2.60)	(2.89)
MOM				0.006	0.006	0.006
				(4.43)	(4.21)	(3.83)
REV					−0.029	−0.030
					(−7.15)	(−7.64)
ILLIQ					−0.025	−0.025
					(−1.98)	(−2.06)
COSKEW					−0.122	−0.122
					(−1.02)	(−1.11)
IVOL					−0.218	−0.214
					(−6.24)	(−6.33)
DISP					−0.164	−0.166
					(−1.95)	(−1.99)
AGE						−0.028
						(−0.78)
LEV						−0.014
						(−0.21)

Table A11
Fama-MacBeth Cross-Sectional Regressions with beta on UNC^{PCA}

Economic uncertainty index is measured by the first principal component of the standardized residuals from the AR(1) model for the seven dispersion measures using the expanding window with the first estimation window set to be the first 20 quarters and then updated on a quarterly basis. The Individual stocks' exposures to economic uncertainty (denoted β^{UNC}) are obtained from quarterly rolling regressions of excess stock returns on the quarterly economic uncertainty index after controlling for excess quarterly market returns using a 20-quarter fixed window estimation. These quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months after controlling for a large set of stock return predictors after controlling for a large set of stock return predictors, including market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), firm age (AGE), and leverage (LEV). This table reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on a set of lagged predictive variables using the Fama-MacBeth methodology. β^{UNC} is winsorized at the 1% and 99% levels to reduce the influence of outliers. Newey-West adjusted t-statistics are reported in parentheses. The sample period is October 1973−December 2012.

Variable	(1)	(2)	(3)	(4)	(5)
Intercept	0.849	1.001	0.936	1.796	1.955
	(3.48)	(3.87)	(3.70)	(6.71)	(6.33)
β^{UNC}	−0.041	−0.037	−0.033	−0.032	−0.032
	(−3.21)	(−3.60)	(−3.55)	(−4.45)	(−4.45)
BETA		0.122	0.093	0.164	0.142
		(1.01)	(0.82)	(1.45)	(1.29)
LNME		−0.052	−0.057	−0.132	−0.126
		(−1.89)	(−2.11)	(−4.49)	(−4.38)
LNBM		0.192	0.193	0.159	0.163
		(2.77)	(2.88)	(2.39)	(2.68)
MOM			0.007	0.006	0.006
			(4.90)	(4.63)	(4.35)
REV				−0.030	−0.032
				(−7.50)	(−7.96)
ILLIQ				−0.026	−0.026
				(−2.15)	(−2.23)
COSKEW				−0.090	−0.094
				(−0.77)	(−0.90)
IVOL				−0.219	−0.215
				(−6.80)	(−6.91)
DISP				−0.168	−0.170
				(−2.02)	(−2.05)
AGE					−0.031
					(−0.89)
LEV					−0.011
					(−0.17)

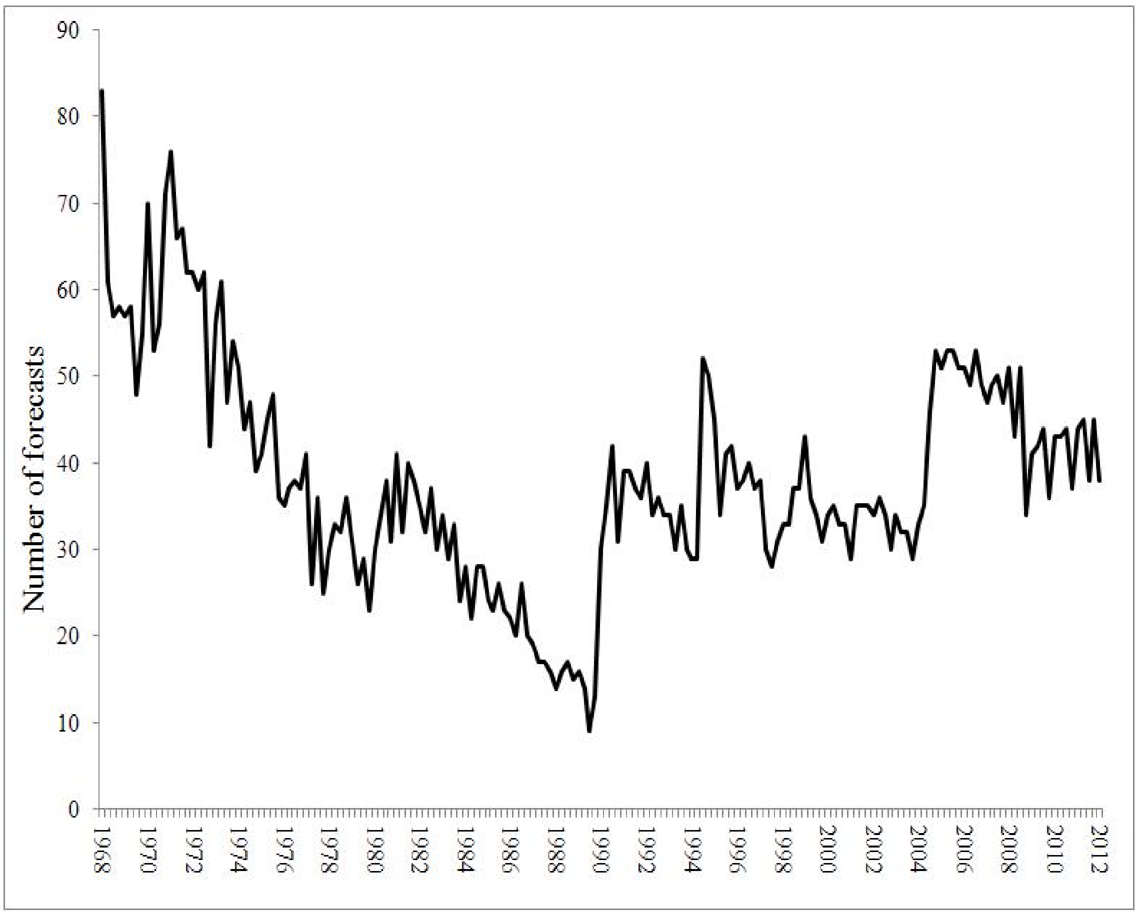

Figure A1. Number of Forecasts This figure depicts the number of forecasts for the current quarter real GDP growth over the sample period 1968:Q4−2012:Q4.

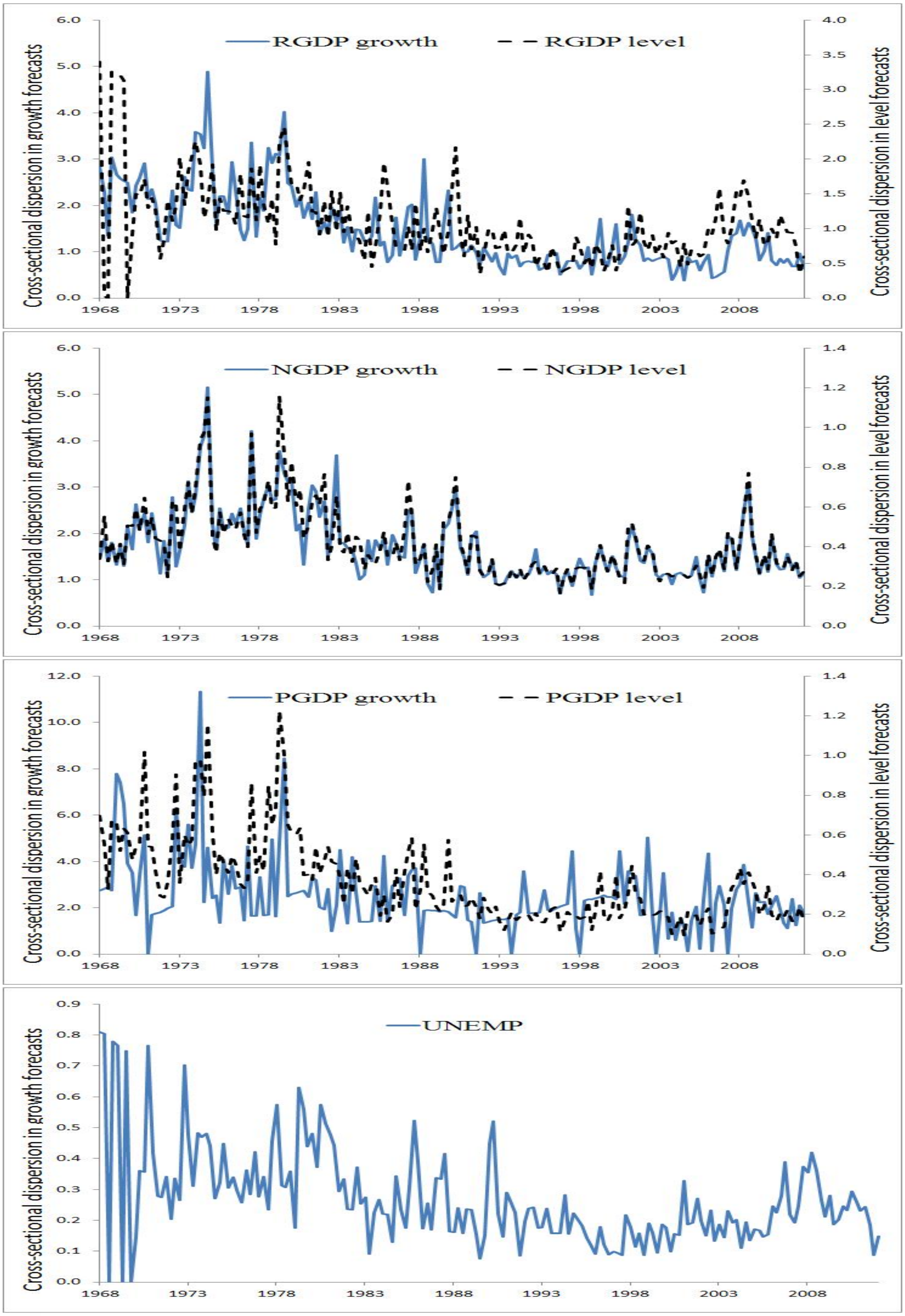

Figure A2. Cross-Sectional Dispersion in Economic Forecasts. The four panels (moving from top to bottom) depict the cross-sectional dispersion in the current quarter forecasts of real GDP (RGDP) growth and level, nominal GDP (NGDP) growth and level, GDP price index (PGDP) growth and level, and unemployment rate (UNEMP). The sample period is 1968:Q4−2012:Q4.