Cross-Sectional Dispersion in Economic Forecasts and Expected Stock Returns

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Keywords: Economic uncertainty, dispersion in economic forecasts, cross-section of stock returns, return predictability.

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Abstract

This paper estimates exposures of individual stocks to measures of cross-sectional dispersion in economic forecasts from the Survey of Forecasters that are interpreted as measures of economic uncertainty. We find that the resulting economic uncertainty betas predict a significant proportion of the cross-sectional dispersion in stock returns. Stocks in the lowest uncertainty beta decile generate 6.8% to 8.3% more annual raw and risk-adjusted returns compared to stocks in the highest uncertainty beta decile. After controlling for a large set of firm characteristics and risk factors, the negative relation between uncertainty betas and future stock returns remains economically and statistically significant. Hence, we argue that economic uncertainty is a powerful determinant of the cross-sectional differences in stock returns.

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1. Introduction

In his seminal paper, Merton (1973) indicates that in a multi-period economy, investors have incentive to hedge against future stochastic shifts in the 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 in the sense that an asset's covariance with those state variables affects its expected returns. Ross (1976) further documents that securities affected by such priced risk factors should earn risk premia in a risk-averse economy.

Macroeconomic variables are widely accepted candidates for these systematic risk factors because unexpected changes in macroeconomic variables can generate global impacts on firm fundamentals, such as cash flows, risk-adjusted discount factors, and investment opportunities. There are several channels by which macroeconomic fundamentals such as output growth, inflation, and unemployment have significant impacts on firm values and expected returns. To the extent that investors pursue opportunities arising from changing economic circumstances, we would expect that return from investments in risky assets is 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. In other words, when choosing a portfolio at time t, ICAPM investors consider how their wealth at time $t+1$ might vary with future state variables. This implies that like CAPM investors, ICAPM investors prefer high expected return and low return variance, but they are also concerned with the covariances of portfolio returns with state variables that affect future investment opportunities. Bloom, Bond, and Reenen (2007), Bloom (2009), Chen (2010), Stock and Watson (2012), and Allen, Bali, and Tang (2012) provide theoretical and empirical evidence linking macroeconomic shocks to aggregate output, employment, and investment dynamics. Hence, economic uncertainty is a relevant state variable affecting future consumption and investment decisions.

Motivated by the aforementioned studies, we examine the role of economic uncertainty in the cross-sectional pricing of individual stocks. We argue that disagreement over changes in macroeconomic fundamentals can be considered a source of economic uncertainty. We quantify this uncertainty with 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 among the expectations of professional forecasters.

In our empirical analysis, we use the cross-sectional dispersion in quarterly forecasts for output, inflation, and unemployment as alternative measures of economic uncertainty. First, we estimate time-varying uncertainty betas using 20-quarter (and 60-month) rolling regressions of excess returns on the uncertainty measures for each stock trading at 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 over the period October 1973 to December 2012. Stocks in the lowest uncertainty beta decile generate 6.8% to 8.3% 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), the difference between returns on the portfolios with the highest and lowest uncertainty beta (4-factor alpha) remains negative and highly significant.

To ensure that it is not well-known firm characteristics or risk factors, rather than the uncertainty beta, that are driving the documented return differences, 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), and analysts earnings forecast dispersion (Diether, Malloy, and Scherbina 2002). After controlling for this large set of stock return predictors, 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 firm-level using the Fama-

MacBeth (1973) regressions. After controlling for all variables simultaneously, the cross-sectional regressions provide strong corroborating evidence for an economically and statistically significant negative relation between uncertainty beta and future stock returns.

We provide a battery of robustness checks. We show that our results hold for different forecast horizons of professional forecasters. We present evidence that both the quarterly and monthly measures of uncertainty betas have similar, strong predictive power for the cross-sectional variation in future stock returns. 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 CRSP universe. We show that the cross-sectional predictability results are robust across different time periods. Finally, we investigate long-term predictive power of uncertainty beta, and find that the negative relation between uncertainty beta and future stock returns is not just a one-month affair. Economic uncertainty beta predicts the cross-sectional variation in stock returns nine months into the future.

Campbell (1993, 1996) provides a two-factor ICAPM in which unexpected increase in market volatility represents deterioration in the investment opportunity set or decrease in optimal consumption. In this setting, a positive covariance of returns with volatility shocks (or unexpected changes in market volatility) predicts a lower return on the stock. Ang et al. (2006) test whether exposures of individual stocks to the changes in market volatility predict the cross-sectional variation in stock returns. They find a negative cross-sectional relation between the volatility betas and future stock returns, i.e., stocks with higher (lower) exposure to the changes in option implied market volatility generate lower (higher) return next month. Campbell, Giglio, Polk, and Turley (2012) introduce a theoretical model to allow for stochastic volatility in Campbell's (1993, 1996) ICAPM, and find a significantly negative volatility risk premium in the cross-section of 25 size/book-to-market equity portfolios.

Motivated by Ang et al. (2006) and Campbell et al. (2012), we test whether the predictive power of uncertainty beta remains intact after controlling for exposures of individual stocks to the changes in aggregate stock market volatility. Bivariate portfolio level analyses and multivariate Fama-MacBeth regressions show that the predictive power of uncertainty beta is not driven by implied or realized market volatility betas. We find a significant, negative premium of economic uncertainty in the cross-section of individual stocks, and 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 the portfolio-level analyses and firm-level cross-sectional regressions that examine a comprehensive list of control variables. Section 5 presents a battery of robustness checks. Section 6 controls for exposures to stock market volatility. Section 7 introduces a broad index of economic uncertainty and tests whether stock exposure to the broad index is a powerful determinant of the cross-sectional differences in stock returns. Section 8 concludes the paper.

2. Data and Variable Definitions

This section first describes alternative measures of economic uncertainty and then provides the definitions of firm-level predictive variables used in the 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 among the expectations of different forecasters.[1] In our main analyses, we use the cross-sectional dispersion in quarterly forecasts for the U.S. real Gross Domestic Product (GDP) growth and quarterly forecasts for the U.S. real GDP level. In our robustness check analysis, we also use the quarterly forecasts for the nominal GDP level, the nominal GDP growth, the GDP price index level, the GDP price index growth (inflation rate forecast), and the unemployment rate as alternative measures of economic uncertainty.

[1] 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.

These dispersion measures are model-independent, nonparametric measures of economic uncertainty obtained from disagreements among professional forecasters. The cross-sectional dispersion measures are defined as the percent difference between the 75th percentile and the 25th percentile (the interquartile range) of the projections for the quarterly growth or level:

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

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

Table 1, Panel A 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 1 reports the correlations among the dispersion measures. The correlation between the cross-sectional dispersion in quarterly forecasts of the real GDP growth and the real GDP level is very high, 0.94. As expected, the correlation between the quarterly forecast dispersion of the nominal GDP growth and the nominal GDP level is very high as well, 0.95. Similarly, the correlation between the quarterly forecast dispersion of the GDP price index level and the GDP price index growth is again positive and very high, 0.74. These strong correlations between the growth and level forecasts for the real GDP (RGDP), nominal GDP (NGDP), and the GDP price index (PGDP) are clearly observed in Figure 1 as well.

Panel B of Table 1 also shows that the correlations between the quarterly forecast dispersions of the real GDP growth/level, nominal GDP growth/level, and the GDP price index growth/level are in the range of 0.41 to 0.81. The correlations between the quarterly forecast dispersions of the real GDP growth/level and the unemployment rate are 0.49 and 0.53, respectively. Similarly, the correlations between the quarterly forecast dispersions of the nominal GDP growth/level and the unemployment rate are 0.34 and 0.37. Finally, the correlations between the quarterly forecast dispersions of the GDP price index growth/level and the unemployment rate are 0.39 and 0.46. Overall, these cross-sectional dispersion measures are highly correlated with each other and they reflect common sources of ambiguity about the state of the aggregate economy. On the other hand, each dispersion measure has the potential to capture different aspects of uncertainty and disagreement over financial and macroeconomic fundamentals.

Figure 1 displays the quarterly time-series plots of the cross-sectional dispersion measures for the sample period 1968:Q4−2012:Q4. A visual depiction of the dispersion measures in Figure 1 indicates that these economic uncertainty measures closely follow large falls and rises of financial and economic activity. Specifically, the economic uncertainty is higher during economic and financial market downturns. Similarly, the uncertainty is higher during periods corresponding to high levels of default and credit risk as well as stock market crashes. Lastly, the uncertainty about inflation, the uncertainty about output growth, and the 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.

2.2. Cross-sectional return predictors

Our stock sample includes all common stocks traded on the NYSE, Amex, and Nasdaq exchanges, covering the period from July 1963 through December 2012. We eliminate stocks with price per share less than $5 or more than $1,000. The daily and monthly return and volume data are from the Center for Research in Security Prices (CRSP). We adjust stock returns for delisting in order to avoid survivorship bias (Shumway 1997).[2] 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 firm-level predictive variables used in cross-sectional return predictability.

[2]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 OTC), 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%.

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

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the excess return on stock i in quarter t, UNC_t is the economic uncertainty measure in quarter t, and $\beta_{i,t}^{UNC}$ is the economic uncertainty beta for stock i in quarter t. In addition to the quarterly measures of uncertainty beta, we use the monthly measures that are estimated from the time-series rolling regressions of excess stock returns on the monthly measures of economic uncertainty over a 60-month fixed window period.

Following Fama and French (1992), we estimate market beta of individual stocks using monthly returns over the prior 60 months if available (or a minimum of 24 months). The firm size (LNME) 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, and 2000), the natural logarithm of the book-to-market equity ratio at the end of June of year t, denoted LNBM, 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 for the last fiscal year end in $t-1$, scaled by the market value of equity at end of December of $t-1$. 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:

$$ILLIQ_{i,t} = Avg\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right], \tag{4}$$

where $R_{i,d}$ and $VOLD_{i,d}$ are the daily return and dollar trading volume for stock i on day d, respectively.[3] A firm is required to have at least 15 daily return observations in month t. The Amihud's illiquidity measure is scaled by 10^6.

Following Harvey and Siddique (2000), the firm's monthly co-skewness (COSKEW) is defined as the estimate of γ_i in the regression using the monthly return observations over the prior 60 months (if at least 24 months are available):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \gamma_i (R_{m,t} - R_{f,t})^2 + \varepsilon_{i,t}, \tag{5}$$

where R_i, R_f, and R_m are the monthly returns on stock i, the one-month Treasury bills, and the CRSP value-weighted index, respectively.

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:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i \left(R_{m,d} - R_{f,d}\right) + \gamma_i SMB_d + \varphi_i HML_d + \varepsilon_{i,d}, \tag{6}$$

where $R_{i,d}$, $R_{f,d}$, and $R_{m,d}$ are, respectively, the daily returns on stock i, the one-month Treasury bills, 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.

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

3. A Conditional Asset Pricing Model with Economic Uncertainty

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

$$\mu_i = A \cdot \sigma_{im} + B \cdot \sigma_{ix}, \tag{7}$$

where μ_i denotes the unconditional expected excess return on risky asset i, σ_{im} denotes the unconditional covariance between the excess returns on the risky asset i and the market portfolio m, and σ_{ix} denotes a $(1 \times k)$ row of unconditional covariances between the excess returns on the risky asset i and the k-dimensional state variables x. A is the relative risk aversion of market investors and B measures the market's aggregate reaction to shifts in a k-dimensional state vector that governs the stochastic investment opportunity set. Equation (7) states that in equilibrium, investors are compensated in terms of expected return for bearing market risk and for bearing the risk of unfavorable shifts in the investment opportunity set.

The second term in equation (7) reflects the investors' demand for the asset as a vehicle to hedge against unfavorable shifts in the investment opportunity set. An "unfavorable" shift in the investment opportunity set is defined as a change in x such that future consumption c will fall for a given level of future wealth. That is, an unfavorable shift is an increase in x if $\partial c/\partial x < 0$ and a decrease in x if $\partial c/\partial x > 0$. Merton (1973) shows that all risk-averse utility maximizers will attempt to hedge against such shifts in the sense that if $\partial c/\partial x < 0$ ($\partial c/\partial x > 0$), then, ceteris paribus, they will demand more for an asset, the more positively (negatively) correlated the asset's return is with changes in x. Thus, if the ex post opportunity set is less favorable than is anticipated, investors will expect to be compensated by a higher level of wealth through the positive correlation of the returns.

Merton (1973) uses the example of stochastic interest rate to illustrate the role of intemporal hedging demand. He points out that a positive covariance of asset returns with interest rate shocks (or unexpected changes 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 the changes in interest rate because they will be compensated by a higher level of wealth through positive correlation of the returns. That asset can be viewed as a hedging instruments. 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 expected return on the asset.

There is substantial evidence that economic uncertainty is a relevant state variable affecting future consumption and investment decisions. Bloom (2009) and Bloom, Bond, and Reenen (2007) introduce a theoretical model linking macroeconomic shocks to aggregate output, employment and investment dynamics. Chen (2010) proposes a model that shows how business cycle variation in economic uncertainty and risk premia influences firms' financing decisions. The Chen model also shows that countercyclical fluctuations in risk prices arise through firms' responses to macroeconomic conditions. Stock and Watson (2012) find that the decline in aggregate output and employment during the recent crisis period are driven by financial and macroeconomic shocks. Allen, Bali, and Tang (2012) show that downside risk in the financial sector predicts future economic downturns, linking economic uncertainty to future investment opportunity set. Bali, Brown, and Caglayan (2014) provide evidence that macroeconomic risk is priced in the cross-section of individual hedge funds investing on equity portfolios.

Hence, our finding that individual stocks have higher exposure to economic uncertainty 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 increase in economic uncertainty is an unfavorable shift in the investment opportunity set. Since increase in economic uncertainty creates fear on investors, it reduces optimal consumption as well. Investors cut their consumption and investment demand, and instead they prefer to save more to hedge against possible future downturns in the economy. To hedge against this unfavorable shift, investors would like to hold stocks that have higher covariance with economic uncertainty. This is because an increase in economic uncertainty will increase the return on these stocks due to positive intertemporal correlation.[4] Hence, when economic uncertainty increases, although their optimal consumption and future investment opportunities decline, investors compensate this loss by getting higher wealth effect through the increase in the return on these stocks that have positive correlation with economic uncertainty. Therefore, through the intertemporal hedging demand, investors will be willing to hold stocks with higher correlation with economic uncertainty, and they accept lower compensation from these stocks in the form of lower expected return.[5]

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

$$E[R_{i,t+1}|\Omega_t] = A \cdot cov[R_{i,t+1}, R_{m,t+1}|\Omega_t] + B \cdot cov[R_{i,t+1}, X_{t+1}|\Omega_t], \tag{8}$$

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

We re-write equation (8) in terms of conditional betas, instead of conditional covariances:

$$E[R_{i,t+1}|\Omega_t] = \tilde{A} \cdot E[\beta_{im,t+1}|\Omega_t] + \tilde{B} \cdot E[\beta_{ix,t+1}|\Omega_t], \tag{9}$$

[4]Table A1 of the online appendix presents the correlations between the CRSP index return and the cross-sectional dispersion in real GDP growth and real GDP level forecasts. The results are reported for the quarterly and monthly data frequency and for the cross-sectional dispersion of current GDP forecasts (RGDP0) as well as for 1-quarter to 4-quarter ahead forecasts (RGDP1-RGDP4). For the sample period 1968:Q4−2012:Q4, the intertemporal correlations between the market returns and the economic uncertainty measures are positive without exception.

[5]In his two-factor ICAPM model, Campbell (1993, 1996) uses similar argument for 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 $\tilde{A} = A \cdot var[R_{m,t+1}|\Omega_t]$, $\tilde{B} = B \cdot var[X_{t+1}|\Omega_t]$, 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 state variable X, defined as the ratio of the conditional covariance between $R_{i,t+1}$ and X_{t+1} to the conditional variance of X_{t+1}:

$$E[\beta_{im,t+1}|\Omega_t] = \frac{cov[R_{i,t+1}, R_{m,t+1}|\Omega_t]}{var[R_{m,t+1}|\Omega_t]}, \quad (10)$$

$$E[\beta_{ix,t+1}|\Omega_t] = \frac{cov[R_{i,t+1}, X_{t+1}|\Omega_t]}{var[X_{t+1}|\Omega_t]}, \quad (11)$$

Other studies (e.g., Bloom, Bond, and Van Reenen 2007; Bloom 2009; Bekaert, Engstrom, and Xing 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 measures used in this paper can be viewed as a proxy for the state variable X in equation (11). The beta in equation (10) is referred to as "market beta", while the beta in equation (11) is referred to as "uncertainty beta".

As described in Section 2.2, the quarterly measures of uncertainty betas are estimated from the time-series regressions of excess stock returns on the quarterly measures of economic uncertainty over a 20-quarter rolling window period. As will be discussed later in the paper, the monthly measures of uncertainty betas are estimated from the time-series regressions of excess stock returns on the monthly measures of economic uncertainty over a 60-month rolling window period.

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 the univariate portfolio level analyses. Second, we discuss average portfolio characteristics to get a clear picture of the composition of uncertainty beta portfolios. Third, we provide the bivariate portfolio level analyses to examine the predictive power of uncertainty betas after controlling for the well-known firm characteristics and risk factors. Finally, we present the univariate and multivariate cross-sectional regression results.

4.1. Univariate portfolio level analysis

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Exposures of individual stocks to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measure using a 20-quarter fixed window estimation. The first set of uncertainty betas (β^{UNC}_{growth}) 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 for the sample period October 1973 to December 2012.

Table 2 presents the univariate portfolio results. For each month, we form decile portfolios by sorting individual stocks based on their uncertainty betas (β^{UNC}_{growth}), where decile 1 contains stocks with the lowest β^{UNC}_{growth} during the past quarter, and decile 10 contains stocks with the highest β^{UNC}_{growth} during the previous quarter. Table 2 reports the average monthly returns (in percentage), average uncertainty beta, and average market share for the decile portfolios formed on β^{UNC}_{growth} using the CRSP breakpoints (the left panel) and the NYSE breakpoints (the right panel).

We first discuss the portfolio results from the CRSP breakpoints with equal number of stocks in decile portfolios. Table 2 shows that when moving from decile 1 to 10, there is significant cross-sectional variation in the average values of β^{UNC}_{growth}; the average uncertainty beta increases from -7.73 to 9.39. Another notable point in Table 2 is that the next-month average returns on the uncertainty beta portfolios decrease almost monotonically from 1.46% to 0.89% per month, when moving from the lowest β^{UNC}_{growth} to the highest β^{UNC}_{growth} decile. The average raw return difference between decile 10 (High β^{UNC}_{growth}) and decile 1 (Low β^{UNC}_{growth}) is -0.57% per month with a Newey-West (1987) t-statistic of

-3.59. This result indicates that stocks in the lowest β^{UNC}_{growth} decile generate about 6.8% more annual returns compared to stocks in the highest β^{UNC}_{growth} decile.

In addition to the average raw returns, Table 2 also presents the magnitude and statistical significance of the difference in intercepts (Fama-French-Carhart four factor alphas) from the regression of the High−Low portfolio returns on a constant, the excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), and a momentum factor (MOM), following Fama and French (1993) and Carhart (1997).[6] As shown in the last row of Table 2, the difference in alphas between the High β^{UNC}_{growth} and Low β^{UNC}_{growth} portfolios is -0.69% per month with a Newey-West t-statistic of -3.96. This indicates that after controlling for the well-known size, book-to-market, and momentum factors, the return difference between the High β^{UNC}_{growth} and Low β^{UNC}_{growth} stocks remains negative and statistically significant.

As shown in the right panel of Table 2, very similar results are obtained when decile portfolios are formed based on the NYSE breakpoints, which are used to alleviate the concern that the CRSP decile breakpoints are distorted by the large number of small Nasdaq and Amex stocks (see Fama and French 1992). Similar to our earlier findings, there is significant cross-sectional variation in the average values of β^{UNC}_{growth}; the average uncertainty beta increases from -7.73 to 9.39 when moving from decile 1 to 10. The next-month average returns on the uncertainty beta portfolios decrease almost monotonically from 1.48% to 0.91% per month, yielding the same average return difference of -0.57% per month with a somewhat higher t-statistic of -3.84. The corresponding difference in 4-factor Fama-French-Carhart (FFC) alphas is also identical, -0.69% per month, with a higher t-statistic of -4.19.

Table 2 also reports the average market shares of the decile portfolios sorted by the uncertainty beta. As shown in the third column of the left panel (CRSP breakpoints), stocks in the extreme deciles (Decile 1 and 10) are relatively smaller compared to stocks in Deciles 2 to 9. More specifically, stocks in Decile 1 (with the lowest β^{UNC}_{growth}) have an average market share of 6.5%, whereas stocks in Decile 10 (with the highest β^{UNC}_{growth}) have an average market share of 3.7%. When stocks are sorted into portfolios based on the NYSE breakpoints, the average market shares of deciles 1 and 10 are somewhat higher

[6]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/.

compared to the portfolios from the CRSP breakpoints. However, as shown in the last column of Table 2 (right panel, NYSE breakpoints), stocks in the extreme deciles (Decile 1 and 10) are still relatively smaller compared to stocks in Deciles 2 to 9; stocks in Decile 1 have an average market share of 9.5%, whereas stocks in Decile 10 have an average market share of 5.3%. Overall, these results indicate that stocks in the extreme deciles are relatively smaller, but the economic uncertainty betas do not have a monotonic relation with firm size.[7]

4.2. Average portfolio characteristics

To get a clearer picture of the composition of the uncertainty beta portfolios, Table 3 presents summary statistics for the stocks in the deciles. Specifically, the table reports the cross-sectional average of various characteristics for the stocks in each decile averaged across the months. We report average values for the economic uncertainty beta (β^{UNC}_{growth}), 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), the co-skewness (COSKEW), the idiosyncratic volatility (IVOL), the analyst dispersion (DISP), and the price in dollars (PRC). Definitions of these variables are given in Section 2.2.

The portfolios exhibit some interesting patterns. Average market betas are identical for the Low β^{UNC}_{growth} and High β^{UNC}_{growth} portfolios. Stocks in the extreme deciles (Decile 1 and 10) are relatively smaller compared those in Deciles 2 to 9. As expected, the last column of Table 3 shows that stocks in the Low β^{UNC}_{growth} and High β^{UNC}_{growth} portfolios have somewhat lower share price compared those in Deciles 2 to 9, but there is no monotonically increasing or decreasing pattern in the average price of the stocks in the uncertainty beta portfolios. Average book-to-market ratios are similar across the portfolios, although if anything high uncertainty beta portfolios do have a slight value tilt. As discussed earlier, average return on the high uncertainty beta portfolio is lower, implying that low returns to high uncertainty beta

[7] We replicate our analysis in Table 2 by measuring economic uncertainty with the cross-sectional dispersion in the current quarter forecasts of real GDP level (output level). Table A2 of the online appendix shows that the results are very similar to those reported in Table 2. As will be discussed later, we replicate our main analysis reported in follow-up tables using the quarterly forecasts of real GDP level and the results from the forecasts of output growth and output level turn out to be very similar.

stocks cannot be explained by the size and book-to-market effects since small and value stocks in the High β^{UNC}_{growth} portfolio are expected to generate higher returns.

A notable point in Table 3 is that stocks in the extreme deciles (Decile 1 and 10) have relatively higher past one year return, i.e., stocks in the Low β^{UNC}_{growth} and High β^{UNC}_{growth} 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 a potential explanation for the predictive power of the uncertainty betas either.

Interestingly, stocks in the extreme deciles (Decile 1 and 10) have relatively higher past one month return as well, i.e., stocks in the Low β^{UNC}_{growth} and High β^{UNC}_{growth} 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 to low (high) uncertainty beta stocks.

There are no significant differences in liquidity, idiosyncratic volatility, and analyst dispersion of average stocks in the Low β^{UNC}_{growth} and High β^{UNC}_{growth} portfolios, but consistent with earlier studies, small and relatively low-priced stocks in the High β^{UNC}_{growth} portfolio are slightly less liquid, they are somewhat more volatile, and they have little higher analyst dispersion compared to those in the Low β^{UNC}_{growth} portfolio. However, the differences are so trivial that similar to our findings from size, price, and value effects, liquidity, volatility, and dispersion cannot explain the return predictability of the uncertainty betas.

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}_{growth} and High β^{UNC}_{growth} portfolios, average co-skewness increases almost monotonically from -1.79 to -0.85. Harvey and Siddique (2000) find that stocks with high co-skewness generate low returns. Hence, co-skewness may potentially explain the high (low) returns to 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, firm size, book-to-market, momentum, short-term reversal, liquidity, co-skewness, idiosyncratic volatility, and analysts dispersion. Specifically, we test whether the negative relation between 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 uncertaity betas and future stock returns after controlling for the well-known cross-sectional return predictors. We perform bivariate portfolio sorts on economic uncertainty beta (β^{UNC}_{growth}) in combination with the 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), and analyst dispersion (DISP). Table 4 reports the 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 economic uncertainty beta (β^{UNC}_{growth}) so that decile 1 (decile 10) contains stocks with the lowest (highest) β^{UNC}_{growth}. The first column of Table 4 averages portfolio returns across the 10 BETA deciles to produce decile portfolios with dispersion in β^{UNC}_{growth}, but which contain all market betas of firms. This procedure creates a set of β^{UNC}_{growth} portfolios with very similar levels of market beta, and hence these β^{UNC}_{growth} portfolios control for differences in market beta. The row (High$-$Low) in the first column of Table 4 shows that after controlling for the market beta, the average return difference between the High β^{UNC}_{growth} and Low β^{UNC}_{growth} portfolios is about -0.45% per month with a Newey-West t-statistic of -3.48. The $10-1$ difference in the 4-factor alphas is -0.47% per month with a t-statistic of -3.36. Thus, the market beta does not explain the high (low) returns to low (high) uncertainty beta stocks.

We control for the market capitalization (SIZE) in a similar way, with the results reported in the second column in Table 4. Again the effect of uncertainty beta is preserved after controlling for firm size, with an average raw return difference between the High β^{UNC}_{growth} and Low β^{UNC}_{growth} deciles of -0.60%

per month and a corresponding t-statistic of -3.84. The $10-1$ difference in the 4-factor FFC alphas is also negative, -0.68% per month, and highly significant.

Table 4 shows that after controlling for the other cross-sectional return predictors (book-to-market, momentum, short-term reversal, illiquidity, co-skewness, volatility, and analyst dispersion), the average return differences between the High β^{UNC}_{growth} and Low β^{UNC}_{growth} portfolios are in the range of -0.33% to -0.66% 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 -0.40% to-0.72%, which are also highly significant. These results indicate that the well-known cross-sectional effects (including co-skewness) cannot explain the low returns to stocks with high uncertainty beta.

4.4. Firm level cross-sectional regressions

So far we have tested the significance of 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 uncertainty beta and expected returns at the firm 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}_{growth}) with and without the 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:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta^{UNC}_{i,t} + \lambda_{2,t} \cdot X_{i,t} + \varepsilon_{i,t+1}, \tag{12}$$

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 month 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, and analyst dispersion). The cross-sectional regressions are run at the monthly frequency from October 1973 to December 2012. To compute standard errors we take into account potential autocorrelation and heteroscedasticity in the cross-sectional coefficients and compute Newey-West (1987) t-statistics on the time series of slope coefficients. The Newey-West standard errors are computed with six lags.

Table 5 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 betas 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 -0.043 with a t-statistic of -4.14.

To delineate the economic significance of this average slope coefficient, we use the average values of the uncertainty betas in the decile portfolios. Table 2 shows that the difference in $\beta_{i,t}^{UNC}$ values between average stocks in the first and tenth decile is $17.12[= 9.39-(-7.73)]$. If a stock were to move from the first decile to the tenth decile of $\beta_{i,t}^{UNC}$ what would be the change in that stock's expected return? The average slope coefficient of -0.043 on $\beta_{i,t}^{UNC}$ in Table 5 represents an economically significant decrease of $-0.043 \times 17.12 = -0.74\%$ per month in the average stock's expected return for moving from the first to the tenth decile of $\beta_{i,t}^{UNC}$.[8]

The second column in Table 5 controls for the market beta (BETA), market capitalization (SIZE), and book-to-market ratio (BM), a cross-sectional regression specification corresponding to the 3-factor model of Fama and French (1993). The third column in Table 5 controls for the market beta (BETA), market capitalization (SIZE), book-to-market ratio (BM), and momentum (MOM), a cross-sectional

[8]The implied return difference of 74 basis points per month is larger than the return spread of 0.57% per month that we obtained from the univariate decile portfolios in Table 2. However, the uncertainty betas have strong time-series variation, and the outlier observations of uncertainty betas influence the monthly slope coefficients from the Fama-MacBeth regressions. Hence, in some cases the average slopes on the uncertainty betas translate into larger monthly return differences, as compared to the decile portfolios.

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; -0.034 and -0.023 with the Newey-West t-statistics of -4.24 and -3.54, respectively.

The last column in Table 5 controls for all variables simultaneously, including the the market beta, size, book-to-market, momentum, short-term reversal, illiquidity, co-skewness, idiosyncratic volatility, and analyst dispersion. In this more general specification, the average slope on $\beta_{i,t}^{UNC}$ remains negative, -0.024, and highly significant with the Newey-West t-statistic of -3.86. The average slope coefficient of -0.024 on $\beta_{i,t}^{UNC}$ 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) will generate a return in the following month by about 0.41%, controlling for everything else.

In general, the coefficients on 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 on idiosyncratic volatility and analyst dispersion are negative and significant. The average slope on 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 on co-skewness is positive but statistically insignificant, which contradicts the implications of the three-moment asset pricing models but is consistent with some prior empirical evidence. The average slope on illiquidity is negative and significant, contradicting with the positive illiquidity premium of Amihud (2002).

The clear conclusion is that the cross-sectional regressions provide strong corroborating evidence for an economically and statistically significant negative relation between economic uncertainty betas and future stock returns, consistent with the two-factor intertemporal asset pricing model of Campbell (1993, 1996), and Campbell et al. (2012).

5. Robustness Check

This section provides a battery of robustness checks. First, we test whether our main findings remain intact when economic uncertainty is proxied by the cross-sectional dispersion in 1-quarter to 4-quarter ahead forecasts (instead of the current quarter forecast). Second, we examine whether the monthly measures of uncertainty betas predict future stock returns. Third, we investigate whether our results are sensitive to different stock samples. Fourth, we test whether our findings are robust across subsample periods. Finally, we investigate long-term predictive power of the uncertainty betas.

5.1. Real GDP forecasts for one to four quarters ahead

Economic uncertainty has so far been measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. In this section, we test whether our results are robust across different forecast horizons of professional forecasters. Specifically, economic uncertainty is proxied by the cross-sectional dispersion in 1-quarter to 4-quarter ahead forecasts of real GDP growth, denoted by QTR1 to QTR4. First, exposures of individual stocks to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the uncertainty measures using a 20-quarter fixed window estimation. Then, these quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months. Table 6 reports the average monthly returns for the decile portfolios formed on the uncertainty betas using the CRSP breakpoints. As presented in the last two rows, the average raw return and risk-adjusted return differences between Decile 1 (Low β^{UNC}_{growth}) and Decile 10 (High β^{UNC}_{growth}) are negative and highly significant without exception. The average return differences are -0.48%, -0.62%, -0.35%, and -0.39% per month for the uncertainty betas corresponding to the cross-sectional dispersion in 1-quarter to 4-quarter ahead forecasts of real GDP growth, respectively. The 4-factor FFC alpha differences between Deciles 1 and 10 are in the range of -0.44% to -0.54% per month. Table 6 provides evidence that our main findings hold for different forecast horizons of professional forecasters.

5.2. Results from monthly measures of uncertainty beta

The original data on the cross-sectional dispersion in forecasts of real GDP growth provided by the Federal Reserve Bank of Philadelphia are in quarterly frequency. Hence, we have so far used the quarterly measures of economic uncertainty beta in predicting the cross-sectional variation in future stock returns. In this section, we use monthly measures of uncertainty betas to test whether the data frequency of economic uncertainty measures affects our main findings.

First, we use a linear interpolation to convert the quarterly data on the dispersion measures to monthly frequency. Once we generate the monthly measures of economic uncertainty, for each firm and for each month in our sample, exposures of individual stocks to economic uncertainty are obtained from the monthly rolling regressions of excess stock returns on the economic uncertainty measures using a 60-month fixed window estimation. Then, these monthly uncertainty betas are used to predict the cross-section of one-month ahead stock returns.

Table 7 reports the average monthly returns, average uncertainty beta, and average market share for the decile portfolios formed on β^{UNC}_{growth} using the CRSP breakpoints (the left panel) and the NYSE breakpoints (the right panel). Overall, the results are very similar to those reported in Table 2. As shown in the left panel of Table 7, the next-month average returns on the monthly uncertainty beta portfolios decrease almost monotonically from 1.43% to 0.99% per month, yielding an average return difference of -0.44% per month with a t-statistic of -2.43. The corresponding difference in 4-factor FFC alphas is almost identical to our earlier finding in Table 2, -0.61% per month, with a t-statistic of -3.07. As presented in the right panel of Table 7, very similar findings are obtained when decile portfolios are formed based on the NYSE breakpoints. Table 7 shows that the monthly measures of economic uncertainty betas have similar, strong predictive power for the cross-sectional variation in monthly stock returns.

5.3. Different stock samples

As discussed in Section 2.2, our original sample includes all common stocks traded on the NYSE, Amex, and Nasdaq exchanges. In this section, we investigate whether our results are driven by small, low-priced, and illiquid stocks, or stocks trading at the Amex and Nasdaq exchanges. 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 the market capitalization in the CRSP universe; (v) Largest 1,000 stocks based on the 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.

We replicate our main findings for these seven different stock samples and Table 8 reports the average monthly returns for the decile portfolios formed on β^{UNC}_{growth}. As shown in the first column, for the NYSE stocks, the one-month ahead average returns on the uncertainty beta portfolios decrease almost monotonically from 1.45% to 0.88% per month, yielding an average return difference of -0.57% per month with a t-statistic of -3.21. The corresponding difference in 4-factor FFC alphas is -0.71% per month with a t-statistic of -3.38. The second column presents almost identical results for the 'Large' stocks with market capitalizations greater than the 50th NYSE size percentile. The average raw return and risk-adjusted return differences between the High β^{UNC}_{growth} and Low β^{UNC}_{growth} portfolios are -0.57% and -0.75% per month, respectively, with the corresponding t-statistics of -3.08 and -3.77.

The third column of Table 8 shows that, for the S&P 500 stocks, the one-month ahead average returns on the uncertainty beta portfolios decrease almost monotonically from 1.42% to 0.92% per month, yielding a similar average return difference of -0.50% per month with a t-statistic of -2.34. The corresponding difference in 4-factor FFC alphas is again similar, -0.68% per month, with a t-statistic of -2.89.

When we look at the uncertainty beta portfolios of the 500 largest, 1,000 largest, 500 most liquid, and 1,000 most liquid stocks, we see almost identical results. The average return differences are in the range of −0.49% to −0.62% per month, and the 4-factor FFC alpha differences range from −0.58% to −0.81% per month. These raw and risk-adjusted return differences are highly statistically significant as well. Table 8 clearly shows that our main findings hold for the NYSE stocks, S&P 500 stocks, and the large and liquid stocks as well.

5.4. Different time periods

Since the original data on the cross-sectional dispersion in forecasts of real GDP growth provided by the Federal Reserve Bank of Philadelphia cover the period from 1968:Q4 to 2012:Q4, the cross-sectional return predictability results are based on the sample period October 1973−December 2012. In this section, we investigate whether our results are robust across different time periods.

Table 9 reports the average monthly returns for the decile portfolios formed on β_{growth}^{UNC} for two subsample periods: October 1973−May 1993 and June 1993−December 2012. Overall, the results are very similar to those reported for the full sample in Table 2. As shown in the left panel of Table 9, for the first subperiod (October 1973−May 1993), the one-month ahead average returns on the uncertainty beta portfolios decrease almost monotonically from 1.66% to 1.04% per month, yielding an average return difference of −0.62% per month with a t-statistic of −3.33. The corresponding difference in 4-factor FFC alphas is −0.55% per month with a t-statistic of −2.68. As presented in the right panel of Table 9, very similar findings are obtained for the second subperiod (June 1993−December 2012) as well; the average raw and risk-adjusted return differences between the High β_{growth}^{UNC} and Low β_{growth}^{UNC} portfolios are −0.52% and −0.68% per month and highly significant. Table 9 provides evidence that the cross-sectional return predictability results are robust across the two subsample periods.

5.5. Long-term predictability

Our analyses have so far focused on the one-month ahead return predictability. However, from a practical standpoint it would make sense to investigate the predictive power of uncertainty betas for longer-term investment horizons, as some investors and portfolio managers may prefer longer portfolio holding periods or investment horizons beyond one month.

In this section, we examine the long-term predictive power of the economic uncertainty betas 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 measure using a 20-quarter fixed window estimation. The first set of quarterly uncertainty betas (β^{UNC}_{growth}) are 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:Q4−2012:Q4.

Table 10 reports the average 1-quarter, 2-quarter, 3-quarter, and 4-quarter ahead returns for the univariate decile portfolios formed on β^{UNC}_{growth} using the CRSP breakpoints. As presented in the last two rows, the average raw return and risk-adjusted return differences between the High β^{UNC}_{growth} and Low β^{UNC}_{growth} portfolios are negative and statistically significant for 1-quarter to 3-quarter ahead predictability. The average return differences are, respectively, −1.59%, −1.52%, and −1.20% per quarter with the t-statistics of −2.50, −2.49, and −2.13 for 1-quarter to 3-quarter ahead return predictions. The corresponding 4-factor FFC alpha differences are −2.33%, −2.24%, and −1.52% per quarter with the t-statistics of −3.05, −2.99, and −2.68. The cross-sectional relation between the uncertainty betas and 4-quarter ahead returns is negative, but it is not economically and statistically significant.

Table 10 clearly shows that the negative relation between economic uncertainty betas and future stock returns is not just a one-month affair. The quarterly measures of uncertainty betas predict the cross-sectional variation in stock returns nine months into the future.

6. Controlling for Exposures to Stock Market Volatility

Campbell (1993, 1996) provides a two-factor ICAPM in which unexpected increase in market volatility represents deterioration in the investment opportunity set or decrease in optimal consumption. In this setting, a positive covariance of returns with volatility shocks (or unexpected changes 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 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.[9]

Ang et al. (2006) test whether exposures of individual stocks to the changes in market volatility predict the cross-sectional variation in future stock returns. They first estimate exposures of individual stocks to the changes in VXO (the S&P 100 index option implied volatility). 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, i.e., stocks with higher (lower) exposure to the changes in VXO generate lower (higher) return next month. Bali and Engle (2010) investigate the significance of negative market volatility risk premium in the conditional ICAPM framework and find that equity portfolios with higher conditional covariance with the changes in expected future market volatility yield lower expected returns. Coval and Shumway (2001) and Bakshi and Kapadia (1993) 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 they show that prices of both components are significantly negative.

In this section, motivated by the aforementioned studies, we test whether the predictive power of economic uncertainty beta remains intact after controlling for exposures of individual stocks to the changes in aggregate stock market volatility. Following Ang et al. (2006), we use the S&P 100 index option implied volatility (VXO) as a proxy for market volatility. Following Campbell et al. (2012), stock market volatility is also proxied by the quarterly realized market variance calculated as the sum of squared daily market returns in a quarter.

[9]Campbell et al. (2012) extend the earlier work of Campbell (1993, 1996) to allow for stochastic volatility. They show that growth stocks underperform value stocks because they hedge two types of deterioration in investment opportunities: declining expected stock returns and increasing volatility.

Similar to our quarterly measures of uncertainty betas, we estimate the volatility betas ($\beta_{i,t}^{RVOL}$, $\beta_{i,t}^{VXO}$) from the univariate time-series regressions of excess stock returns on the changes in aggregate variance measures:

$$
\begin{aligned}
R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t + \varepsilon_{i,t}, \quad &(13)\\
R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{RVOL} \cdot \Delta VAR_t^{Realized} + \varepsilon_{i,t}, \quad &(14)\\
R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{VXO} \cdot \Delta VAR_t^{VXO} + \varepsilon_{i,t}, \quad &(15)
\end{aligned}
$$

where $R_{i,t}$ is the excess return on stock i at time t, UNC_t is the economic uncertainty measure, ΔVAR_t^{VXO} is the change in the S&P 100 index option implied variance, and $\Delta VAR_t^{Realized}$ is the change in the realized market variance. $\beta_{i,t}^{UNC}$, $\beta_{i,t}^{RVOL}$, and $\beta_{i,t}^{VXO}$ are the measures of economic uncertainty beta, implied market volatility beta, and realized market volatility beta, respectively.[10]

As described in Section 2.2, the quarterly measures of uncertainty beta in equation (13) are estimated from the time-series rolling regressions of excess stock returns on the quarterly measures of economic uncertainty over a 20-quarter fixed window period. To be consistent with the quarterly measures of uncertainty betas, we estimate the volatility betas ($\beta_{i,t}^{RVOL}$, $\beta_{i,t}^{VXO}$) from the time-series rolling regressions of excess stock returns on the changes in aggregate variance measures over a 20-quarter fixed window period. Then, we test whether the predictive power of $\beta_{i,t}^{UNC}$ remains intact after controlling for $\beta_{i,t}^{RVOL}$ and $\beta_{i,t}^{VXO}$.

Table 11 presents results from the conditional bivariate sorts on economic uncertainty beta after controlling for $\beta_{i,t}^{RVOL}$ and $\beta_{i,t}^{VXO}$. As shown in the first column of Table 11, after controlling for the realized market volatility beta ($\beta_{i,t}^{RVOL}$), the significantly negative link between the uncertainty betas and future stock returns remains intact. The one-month ahead average returns on the uncertainty beta portfolios decrease almost monotonically from 1.43% to 0.95% per month, yielding an average return difference of -0.48% per month with a t-statistic of -3.15. The corresponding difference in 4-factor FFC alphas is -0.46% per month with a t-statistic of -2.70. As presented in the second column of

[10]We should note that the daily data on the S&P 100 index option implied volatility (VXO) are available from January 2, 1986. Thus, our cross-sectional return predictability results from the VXO data are based on the sample period January 1986−December 2012.

Table 11, similar findings are obtained when we control for the implied volatility beta ($\beta_{i,t}^{VXO}$). The next-month average returns on the uncertainty beta portfolios decrease almost monotonically from 1.28% to 0.76% per month, yielding the same average return difference of -0.48% per month with a similar t-statistic of -3.18. The corresponding difference in 4-factor FFC alphas is also very similar, -0.55% per month, with a t-statistic of -2.67. These results clearly show that exposures of individual stocks to the changes in market volatility do not diminish the predictive power of the uncertainty betas.

We further investigate the potential interaction between the uncertainty betas and the volatility betas by controlling for the excess market return and the realized market volatility in the estimation of the uncertainty betas. Specifically, we generate the economic uncertainty betas using the following time-series regression specifications:

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

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t + \beta_{i,t}^{RVOL} \cdot \Delta VAR_t^{Realized} + \varepsilon_{i,t}, \tag{17}$$

$$R_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{RVOL} \cdot \Delta VAR_t^{Realized} + \varepsilon_{i,t}, \tag{18}$$

where $R_{i,t}$ is the excess return on stock i in quarter t, MKT_t is the excess market return in quarter t, and $\Delta VAR_t^{Realized}$ is the change in the quarterly realized market variance. In equations (16)$-$(18), the economic uncertainty beta ($\beta_{i,t}^{UNC}$), the market beta ($\beta_{i,t}^{MKT}$), and the realized market volatility beta ($\beta_{i,t}^{RVOL}$) are estimated simultaneously using the time-series rolling regressions of excess stock returns on UNC_t, MKT_t, and $\Delta VAR_t^{Realized}$ over a 20-quarter fixed window period.

To examine the predictive power of β_{growth}^{UNC} estimated from equations (16)$-$(18), we first form univariate decile portfolios by sorting individual stocks based on their uncertainty betas (β_{growth}^{UNC}). Panel A of Table 12 shows that similar to our original findings in Table 2, the next-month average returns on the uncertainty beta portfolios decrease almost monotonically when moving from the lowest β_{growth}^{UNC} to the highest β_{growth}^{UNC} portfolios. The average return differences between the High β_{growth}^{UNC} and Low β_{growth}^{UNC} portfolios are in the range of -0.44% to -0.59% per month with the t-statistics ranging from -3.61 to -3.66. The corresponding differences in 4-factor FFC alphas are in the range of -0.47% to -0.63% per month with the t-statistics ranging from -3.32 to -3.87.

Panel B of Table 12 presents results from the conditional bivariate sorts on economic uncertainty beta after controlling for the realized volatility betas estimated from equations (16)−(18). Controlling for $\beta_{i,t}^{RVOL}$ does not affect the significance of β_{growth}^{UNC} in bivariate portfolios. The one-month ahead average returns on the uncertainty beta portfolios decrease almost monotonically. The average return differences between the High β_{growth}^{UNC} and Low β_{growth}^{UNC} portfolios are in the range of −0.47% to −0.57% per month and highly significant with the t-statistics ranging from −3.62 to −3.70. The corresponding differences in 4-factor FFC alphas are also negative and highly significant.

Finally, we investigate the predictive power of uncertainty betas after controlling for the realized volatility betas in multivariate Fama-MacBeth regressions. In Panel C of Table 12, we re-run the earlier cross-sectional regressions (reported in Table 5) after adding the realized volatility beta ($\beta_{i,t}^{RVOL}$) estimated from equations (16)−(18). The results indicate that after accounting for the realized volatility beta, the market beta, and all other control variables, the average slope on the economic uncertainty beta (β_{growth}^{UNC}) remains negative and statistically significant.

As shown in the last two columns of Table 12, Panel C, the average slopes on the realized volatility beta ($\beta_{i,t}^{RVOL}$) are negative and significant at the 5.5% level in the second column (t-statistic$= -1.92$) and 7.5% level (t-statistic$= -1.78$) in the third column. These cross-sectional regression results are consistent with the theoretical and empirical findings of Campbell (1993, 1996), Ang et al. (2006), and Campbell et al. (2012) that stocks with higher (lower) exposure to the changes in market volatility generate lower (higher) return next month.

Ang et al. (2006) estimate the implied market volatility beta from the bivariate time-series regressions of excess stock returns on the excess market returns and the changes in implied volatility:

$$R_{i,d} = \alpha_{i,t} + \beta_{i,t}^{MKT} \cdot MKT_d + \beta_{i,t}^{VXO} \cdot \Delta VAR_d^{VXO} + \varepsilon_{i,d}, \qquad (19)$$

where $R_{i,d}$ is the excess return of stock i on day d, MKT_d is the excess market return on day d, and ΔVAR_d^{VXO} is the change in the S&P 100 index option implied variance (VXO) on day d. Ang et al.

(2006) use daily data in a month and estimate equation (19) to generate the implied market volatility beta of stock i in month t ($\beta_{i,t}^{VXO}$).

Panel A of Table 13 presents results from the conditional bivariate sorts on economic uncertainty beta after controlling for the implied market volatility beta. When the economic uncertainty beta is estimated with equation (13) (which is the original measure of β_{growth}^{UNC} used in Tables 2−5), the first column of Panel A, Table 13, shows that the significantly negative link between the uncertainty betas and future stock returns remains intact after controlling for the implied volatility beta ($\beta_{i,t}^{VXO}$). The one-month ahead average return difference between the High β_{growth}^{UNC} and Low β_{growth}^{UNC} portfolios is −0.50% per month with a t-statistic of −2.48. The corresponding difference in 4-factor FFC alphas is −0.63% per month with a t-statistic of −3.09. As presented in the second column in Table 13, Panel A, similar findings are obtained when the economic uncertainty beta is estimated with equation (16). In this case, after controlling for the implied volatility beta ($\beta_{i,t}^{VXO}$), the one-month ahead average return difference between the High β_{growth}^{UNC} and Low β_{growth}^{UNC} portfolios is −0.35% per month with a t-statistic of −2.35. The corresponding difference in 4-factor FFC alphas is −0.42% per month with a t-statistic of −3.06. These results provide evidence that exposures of individual stocks to the changes in implied market volatility do not wipe out the predictive power of economic uncertainty betas.

We also examine the predictive power of uncertainty betas after controlling for the implied volatility betas in multivariate Fama-MacBeth regressions. In Panel B of Table 13, we re-run the earlier cross-sectional regressions (reported in Table 5) after adding the implied volatility beta ($\beta_{i,t}^{VXO}$) estimated from equation (19). The results indicate that after accounting for the implied volatility beta and all other control variables, the average slope on the economic uncertainty beta (β_{growth}^{UNC}) remains negative and statistically significant. As shown in the last row of Table 13, Panel B, the average slopes on the implied volatility beta ($\beta_{i,t}^{VXO}$) are negative but marginally significant (in some cases) with the t-statistics ranging from −1.68 to −1.97.

These results provide clear evidence that the predictive power of uncertainty betas is not driven by exposures of individual stocks to the changes in market volatility. We identify a significant negative premium of economic uncertainty in the cross-section of individual stocks, and this negative uncertainty premium is distinct from the negative volatility risk premium identified by earlier studies.

7. A Broad Index of Economic Uncertainty

We have so far used the cross-sectional dispersion in quarterly forecasts for the real GDP growth as a proxy for economic uncertainty. In the online appendix, we replicated our main findings using the quarterly forecasts for the real GDP level. Tables A2 to A4 of the online appendix clearly show that the results from the forecasts of output growth and output level are very similar. In addition to the quarterly forecasts for the real GDP growth and real GDP level, we use the cross-sectional dispersion in quarterly forecasts for the nominal GDP level, the nominal GDP growth, the GDP price index level, the GDP price index growth, and the unemployment rate as alternative measures of economic uncertainty.

Table A5 of the online appendix presents results from the univariate decile portfolios of stocks sorted on exposures to the cross-sectional dispersion in forecasts of the (i) nominal GDP level; (ii) nominal GDP growth; (iii) GDP price index level; (iv) GDP price index growth; and (v) unemployment rate. As presented in Table A5, the average return differences between Decile 1 and Decile 10 are negative and statistically significant, expect for the unemployment rate. The average return differences are -0.48%, -0.45%, -0.51%, and -0.52% per month and highly significant for the uncertainty betas corresponding to the forecasts of the nominal GDP level, the nominal GDP growth, the GDP price index level, and the GDP price index growth, respectively. As reported in the last column of Table A5, the average return difference is negative, but statistically insignificant for the unemployment rate. The corresponding 4-factor FFC alpha differences between Deciles 1 and 10 are negative and statistically significant without exception. The alpha differences are in the range of -0.34% to -0.61% per month for the forecasts of the nominal GDP level, the nominal GDP growth, the GDP price index level, and the GDP price index growth. For the unemployment rate, the corresponding alpha difference is -0.28% per month with the t-statistic of -2.13. Table A5 provides evidence that our main findings hold for alternative measures of economic uncertainty.

In this section, we introduce a broad index of economic uncertainty. We use the principal component analysis (PCA) to extract the common component of the seven economic uncertainty variables that capture different dimensions of the aggregate economy: 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 Eigen values of the seven components are 4.59, 1.03, 0.68, 0.33, 0.26, 0.07, and 0.03, respectively, indicating that the first principal component explains about 66 percent of the corresponding sample variance. We, therefore, conclude that the first principal component sufficiently capture the common variation among the seven economic uncertainty measures. This leads us to measure the broad economic uncertainty index ($INDEX^{UNC}$) in quarter t as:

$$\begin{aligned} INDEX_t^{UNC} &= 0.43 \times RGDP_t^{growth} + 0.34 \times RGDP_t^{level} + \\ &\quad 0.40 \times NGDP_t^{growth} + 0.41 \times NGDP_t^{level} + \\ &\quad 0.28 \times PGDP_t^{growth} + 0.43 \times PGDP_t^{level} + \\ &\quad 0.33 \times UNEMP_t. \end{aligned} \tag{20}$$

Equation (20) indicates that the $INDEX^{UNC}$ loads fairly evenly on the seven economic uncertainty variables. The Pearson correlation coefficients between $INDEX^{UNC}$ and RGDP growth and level, NGDP growth and level, PGDP growth and level, and UNEMP are 0.91, 0.73, 0.85, 0.88, 0.60, 0.93, and 0.72, respectively. Although the seven uncertainty measures are significantly correlated with each other, they are not as highly correlated as with $INDEX^{UNC}$, suggesting that the first principal component sufficiently summarizes the common variation among the seven economic uncertainty measures, while reducing the potential measurement errors associated with the individual uncertainty measures.

Figure 2 depicts the quarterly broad index of economic uncertainty. Similar to our findings from individual uncertainty variables, the broad index of economic uncertainty is generally higher during bad states of the economy corresponding to periods of high unemployment, low output growth, and low economic activity. The Economic Uncertainty Index also closely follows large fluctuations in business conditions.

We now perform portfolio-level and cross-sectional regression analyses to assess the predictive power of the Economic Uncertainty Index over future stock returns. We first start with the univariate portfolio level analyses. Exposures of individual stocks to the Economic Uncertainty Index are obtained from time-series rolling regressions of excess stock returns on the broad uncertainty index using a 20-quarter fixed window estimation.

Table 14 presents the univariate portfolio results. Panel A reports the average monthly returns, average uncertainty beta, and average market share for the decile portfolios formed on β^{UNC}_{index} using the CRSP breakpoints (the left panel) and the NYSE breakpoints (the right panel). The cross-sectional return predictability results are reported for the sample period October 1973 to December 2012. The results in the left panel show that the one-month ahead average returns on the uncertainty beta portfolios decrease almost monotonically from 1.49% to 0.89% per month, yielding an average return difference of -0.60% per month with a t-statistic of -3.96. The corresponding difference in FFC alphas between the High β^{UNC}_{index} and Low β^{UNC}_{index} portfolios is -0.69% per month with a t-statistic of -4.14. As shown in the right panel, very similar results are obtained when decile portfolios are formed based on the NYSE breakpoints.

We also examine the predictive power of the uncertainty betas from the broad Economic Uncertainty Index in univariate and multivariate Fama-MacBeth regressions after controlling for a large set of stock return predictors. Panel B of Table 14 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 economic uncertainty beta and the cross-section of future stock returns. The average slope from the monthly regressions of realized returns on β^{UNC}_{index} alone is -0.039 with a t-statistic of -4.03. To delineate the economic significance of this average slope coefficient, we use the average values of β^{UNC}_{index} in the decile portfolios. Panel A of Table 14 shows that the difference in β^{UNC}_{index} values between average stocks in the first and tenth decile is 17.54, which implies an economically significant decrease of $-0.039 \times 17.54 = -0.68\%$ per month in the average stock's expected return for moving from the first to the tenth decile of β^{UNC}_{index}. Columns (2) to (6) of Panel B show that the predictive power of β^{UNC}_{index} remains intact after simultaneously controlling for a large set of return predictors, including the market beta, size, book-to-market, momentum, short-term reversal, illiquidity, co-skewness, idiosyncratic volatility, analyst dispersion, and exposures to stock market volatility measured by β^{RVOL} estimated from equation (14) and β^{VXO} estimated from equation (19).

These results show that the broad index of economic uncertainty is a powerful determinant of the cross-sectional differences in stock returns.

8. Conclusion

This paper investigates the role of economic uncertainty in the cross-sectional pricing of individual stocks. Economic uncertainty is quantified with 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, nominal GDP growth/level, the GDP price index growth/level, and unemployment rate. First, we estimate time-varying uncertainty betas using quarterly and monthly rolling regressions of excess returns on the uncertainty measures for each stock trading at NYSE, Amex, and Nasdaq. Then, we examine the performance of these quarterly and monthly uncertainty betas 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 6.8% to 8.3% per annum. Bivariate portfolio-level analyses and firm-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, and dispersion in analysts' earnings estimates generate similar results. After controlling for each of these variables one-by-one and controlling for all variables simultaneously, the results provide evidence for a significantly negative link between uncertainty beta and future stock returns. Our main findings also hold for different time periods and for different stock samples including the NYSE stocks, the S&P 500 stocks, and the large and liquid stocks as well. The results also indicate significant long-term forecasting performance of uncertainty beta, predicting the cross-section of expected returns nine months into the future.

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

Finally, we introduce a broad index of economic uncertainty. We use the principal component analysis to extract the common component of the seven economic uncertainty variables that capture different dimensions of the aggregate economy. We test the performance of newly proposed uncertainty index in predicting cross-sectional dispersion in stock returns. After controlling for a large set of firm characteristics and risk factors, portfolio-level and cross-sectional regression analyses indicate a negative and significant link between the uncertainty index beta and future stock returns.

References

Adrian, T., and J. Rosenberg, 2008, "Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk," *Journal of Finance*, 63, 2997–3030.

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

Amihud, Y., 2002, "Illiquidity and stock returns: Cross-section and time-series effects," *Journal of Financial Markets*, 5, 31–56.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006, "The cross-section of volatility and expected returns," *Journal of Finance*, 61, 259–299.

Bakshi, G., and N. Kapadia, 1993, "Delta Hedged Gains and the Negative Market Volatility Risk Premium," *Review of Financial Studies*, 16, 527–566.

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

Bali, T. G., S. J. Brown, and M. O. Caglayan, 2014, "Macroeconomic Risk and Hedge Fund Returns," *Journal of Financial Economics*, forthcoming.

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

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

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

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

Campbell, J. Y., 1993, "Intertemporal Asset Pricing Without Consumption Data," *American Economic Review*, 83, 487–512.

——— , 1996, "Understanding Risk and Return," *Journal of Political Economy*, 104, 298–345.

Campbell, J. Y., S. Giglio, C. Polk, and R. Turley, 2012, "An Intertemporal CAPM with Stochastic Volatility," Working paper, Harvard University.

Carhart, M. M., 1997, "On persistence in mutual fund performance," *Journal of Finance*, 52(1), 57–82.

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

Coval, J., and T. Shumway, 2001, "Expected Option Returns," *Journal of Finance*, 56, 983–1009.

Diether, K., C. Malloy, and A. Scherbina, 2002, "Differences of opinion and the cross-section of stock returns," *Journal of Finance*, 57, 2113–2141.

Fama, E. F., and K. R. French, 1992, "The cross-section of expected stock returns," *Journal of Finance*, 46, 427–466.

——— , 1993, "Common risk factors in the returns of stocks and bonds," *Journal of Financial Economics*, 33, 3–56.

——— , 2000, “Characteristics, covariances, and average returns: 1929-1997,” *Journal of Finance*, 55, 389–406.

Fama, E. F., and J. MacBeth, 1973, “Risk, return and equilibrium: Empirical tests,” *Journal of Political Economy*, 51, 55–84.

Gao, X., and J. R. Ritter, 2010, “The Marketing of Seasoned Equity Offerings,” *Journal of Financial Economics*, 97, 33–52.

Harvey, C. R., and A. Siddique, 2000, “Conditional skewness in asset pricing tests,” *Journal of Finance*, 55, 1263–1295.

Jegadeesh, N., 1990, “Evidence of predictable behavior of security returns,” *Journal of Finance*, 45, 881–898.

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

Merton, R. C., 1973, “An intertemporal capital asset pricing model,” *Econometrica*, 41(5), 867–887.

Newey, W. K., and K. D. West, 1987, “A simple, positive-definite, heteroscedasticity and autocorrelation consistent covariance matrix,” *Econometrica*, 55, 703–708.

Ross, S. A., 1976, “The arbitrage theory of capital asset pricing,” *Journal of Economic Theory*, 13, 341–360.

Shumway, T., 1997, “The delisting bias in CRSP data,” *Journal of Finance*, 52, 327–340.

Stock, J. H., and M. W. Watson, 2012, “Disentangling the channels of the 2007-2009 recession,” *Brookings Papers on Economic Activity*, Forthcoming.

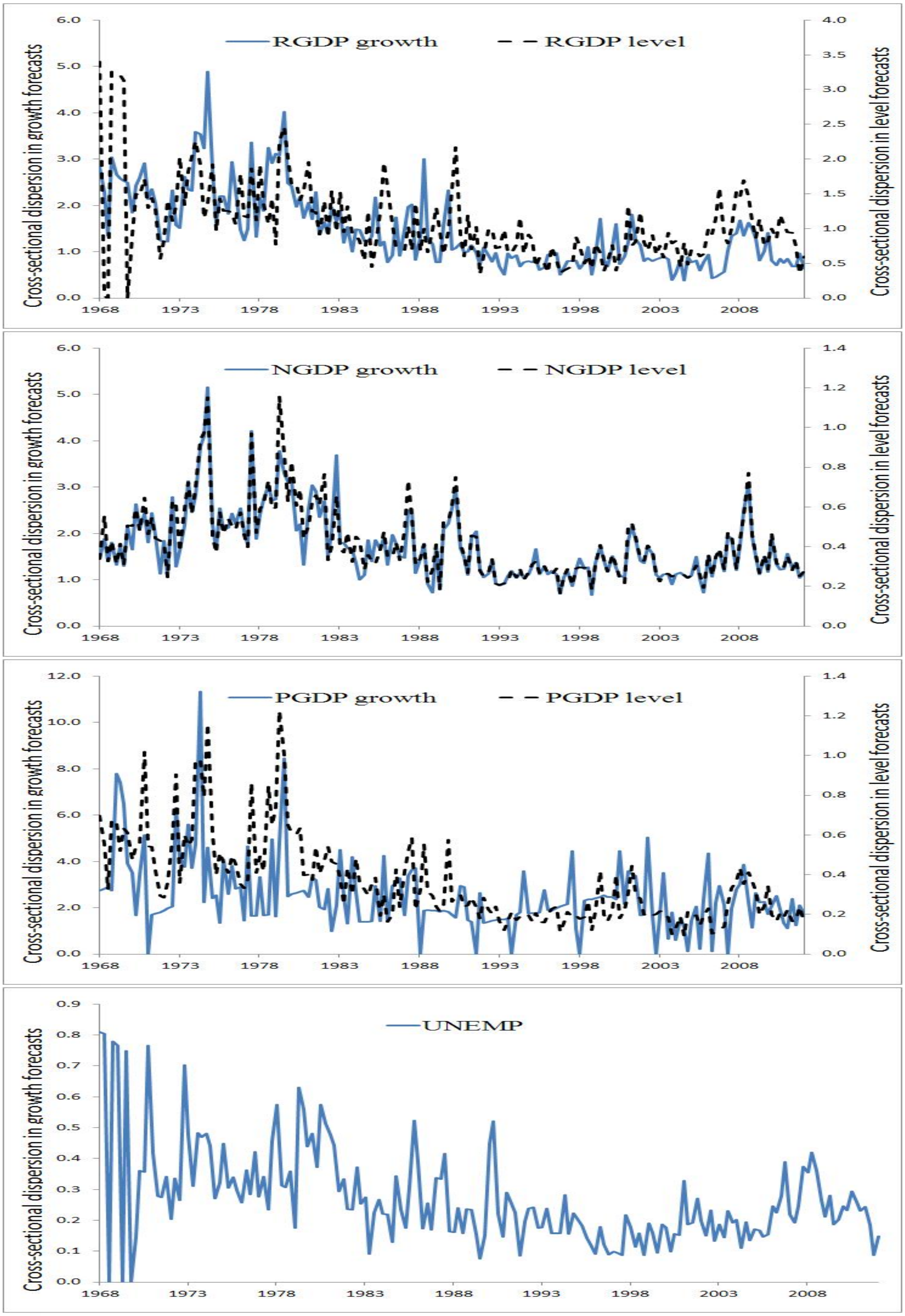

Figure 1. Cross-Sectional Dispersion in Economic Forecasts. The four panels (moving from the top to the bottom) depict the cross-sectional dispersion in the current quarter forecasts of real GDP (RGDP) growth and level, nominal GDP (NGDP) growth and level, GDP price index (PGDP) growth and level, and unemployment rate (UNEMP). The sample period is 1968:Q4−2012:Q4.

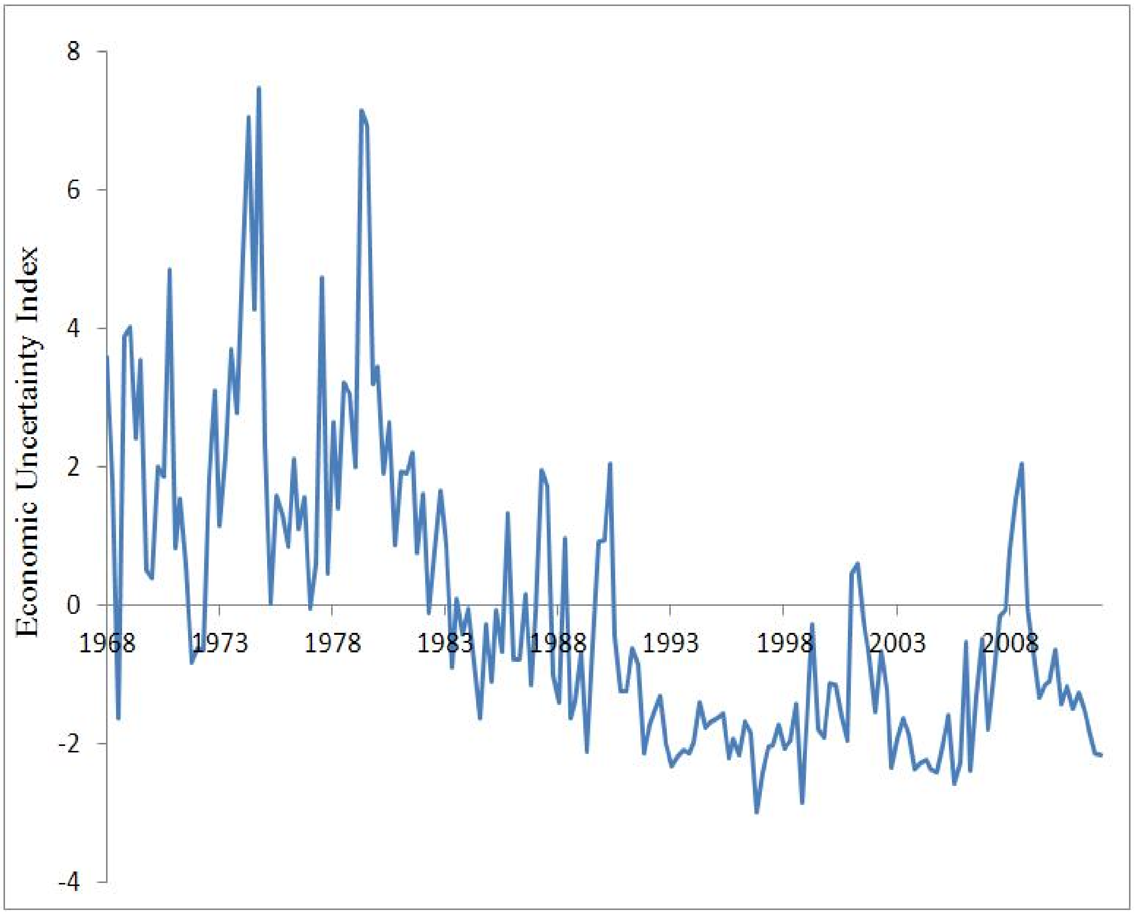

Figure 2. Economic Uncertainty Index. This figure depicts the quarterly broad index of economic uncertainty, defined as the first principal component of seven uncertainty variables that capture different dimensions of the aggregate economy: The cross-sectional dispersion in the current quarter forecasts 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 to 2012:Q4.

Table 1

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	25th percentile	Median	75th percentile	Maximum
RGDP growth	1.45	0.82	0.38	0.82	1.21	1.96	4.89
RGDP level	0.36	0.22	0.09	0.20	0.30	0.46	1.23
NGDP growth	1.74	0.75	0.68	1.17	1.52	2.08	5.16
NGDP level	0.42	0.18	0.17	0.28	0.36	0.50	1.16
PGDP growth	1.08	0.59	0.00	0.70	0.95	1.34	3.40
PGDP level	0.27	0.16	0.00	0.17	0.23	0.34	0.81
UNEMP	2.49	1.55	0.00	1.65	2.13	2.94	11.33

Panel B. Correlation coefficients

	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 2
Univariate Portfolios of Stocks Sorted by Economic Uncertainty Betas

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures using a 20-quarter fixed window estimation. The first set of uncertainty betas (β^{UNC}_{growth}) 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 monthly returns (in percentage), average uncertainty beta, and average market share for the decile portfolios formed on β^{UNC}_{growth} using the CRSP breakpoints (the left panel) and the NYSE breakpoints (the right panel). 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.

	CRSP breakpoints			NYSE breakpoints		
Decile	Return	β^{UNC}_{growth}	Mkt shr	Return	β^{UNC}_{growth}	Mkt shr
1 (Low)	1.46	-7.73	6.5%	1.48	-6.88	9.5%
2	1.47	-3.81	11.9%	1.42	-3.20	12.3%
3	1.38	-2.26	12.9%	1.38	-1.95	12.0%
4	1.33	-1.19	13.4%	1.32	-1.04	12.1%
5	1.34	-0.28	12.7%	1.35	-0.25	11.4%
6	1.28	0.60	11.3%	1.27	0.52	10.1%
7	1.25	1.56	10.8%	1.29	1.35	9.9%
8	1.12	2.75	9.2%	1.19	2.37	9.0%
9	1.02	4.54	7.6%	1.07	3.89	8.3%
10 (High)	0.89	9.39	3.7%	0.91	8.51	5.3%
High - Low	-0.57			-0.57		
	(-3.59)			(-3.84)		
FFC alpha	-0.69			-0.69		
	(-3.96)			(-4.19)		

Table 3
Portfolio Characteristics

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures using a 20-quarter fixed window estimation. This table presents the time-series averages of the average values of various characteristics for the stocks within each decile and each portfolio formation month. Average values are reported for (β^{UNC}_{growth}), market beta (BETA), market capitalization (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), and price per share (PRC). The sample period is October 1973−December 2012.

Quintile	β^{UNC}_{growth}	BETA	SIZE	BM	MOM	REV	ILLIQ	COSKEW	IVOL	DISP	PRC
β^{UNC}_{growth} (Low)	-7.73	1.54	1,469	0.83	37.29	2.77	1.00	-1.79	2.52	0.15	20.79
2	-3.81	1.22	2,878	0.90	22.49	2.04	0.93	-1.48	2.05	0.11	25.19
3	-2.26	1.11	3,185	0.92	19.11	1.82	0.85	-1.21	1.89	0.10	26.67
4	-1.19	1.05	3,151	0.94	17.62	1.71	0.83	-0.99	1.81	0.10	27.56
5	-0.28	1.01	2,941	0.95	16.64	1.70	0.77	-0.91	1.77	0.09	27.50
6	0.60	1.02	2,493	0.95	16.13	1.64	0.78	-0.93	1.80	0.10	26.95
7	1.56	1.06	2,257	0.95	15.54	1.65	0.84	-0.89	1.86	0.11	25.80
8	2.75	1.13	1,891	0.94	15.61	1.66	0.91	-0.82	1.96	0.13	24.28
9	4.54	1.25	1,516	0.93	17.66	1.75	0.95	-0.92	2.14	0.14	21.88
β^{UNC}_{growth} (High)	9.39	1.54	708	0.93	30.64	2.36	1.09	-0.85	2.57	0.18	17.62

Table 4
Bivariate Portfolio Sorts

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures 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. 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}_{growth}). 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), and analyst dispersion (DISP). The control variables are defined in Section 2.2. 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.

Quintile	BETA	SIZE	BM	MOM	REV	ILLIQ	COSKEW	IVOL	DISP
β^{UNC}_{growth} (Low)	1.42	1.45	1.51	1.36	1.47	1.49	1.42	1.50	1.38
2	1.37	1.49	1.43	1.39	1.43	1.47	1.46	1.42	1.29
3	1.34	1.39	1.35	1.29	1.40	1.40	1.34	1.37	1.32
4	1.34	1.35	1.28	1.31	1.33	1.39	1.37	1.30	1.25
5	1.32	1.34	1.33	1.34	1.29	1.31	1.30	1.34	1.18
6	1.27	1.27	1.21	1.28	1.28	1.32	1.30	1.26	1.21
7	1.21	1.26	1.23	1.25	1.20	1.25	1.25	1.15	1.13
8	1.19	1.13	1.13	1.18	1.13	1.09	1.15	1.14	1.00
9	1.10	1.00	1.04	1.11	1.02	0.99	1.03	1.04	0.98
β^{UNC}_{growth} (High)	0.97	0.84	0.98	1.02	0.96	0.83	0.92	1.02	0.80
High Low	-0.45	-0.60	-0.53	-0.33	-0.51	-0.66	-0.50	-0.48	-0.58
	(-3.48)	(-3.84)	(-3.61)	(-2.99)	(-3.44)	(-4.13)	(-3.22)	(-3.40)	(-3.53)
FFC alpha	-0.47	-0.68	-0.59	-0.40	-0.61	-0.72	-0.60	-0.58	-0.71
	(-3.36)	(-3.87)	(-3.38)	(-3.34)	(-3.53)	(-4.11)	(-3.41)	(-3.77)	(-4.04)

Table 5
Fama-MacBeth Cross-Sectional Regressions

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures using a 20-quarter fixed window estimation. These quarterly uncertainty betas (β^{UNC}_{growth}) 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 defined in Section 2.2. 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. Newey-West adjusted t-statistics are reported in parentheses. The sample period is October 1973−December 2012.

	(1)	(2)	(3)	(4)
Intercept	0.811	0.991	0.928	1.824
	(3.28)	(3.92)	(3.74)	(6.94)
β^{UNC}_{growth}	-0.043	-0.034	-0.023	-0.024
	(-4.14)	(-4.24)	(-3.54)	(-3.86)
BETA		0.094	0.075	0.168
		(0.78)	(0.65)	(1.44)
SIZE		-0.047	-0.053	-0.133
		(-1.73)	(-1.95)	(-4.56)
BM		0.207	0.209	0.161
		(2.94)	(3.11)	(2.43)
MOM			0.007	0.006
			(5.48)	(4.57)
REV				-0.030
				(-7.60)
ILLIQ				-0.027
				(-2.27)
COSKEW				0.005
				(0.81)
IVOL				-0.217
				(-6.78)
DISP				-0.169
				(-2.06)

Table 6
Cross-Sectional Dispersion in Real GDP Forecasts for One to Four Quarters Ahead

Economic uncertainty is measured by the cross-sectional dispersion in 1-quarter to 4-quarter forecasts of real GDP growth. Forecasts of real GDP growth for one to four quarters ahead are denoted by QTR1 to QTR4. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures 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 the uncertainty betas 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	QTR1	QTR2	QTR3	QTR4
1 (Low)	1.45	1.52	1.41	1.31
2	1.38	1.41	1.35	1.36
3	1.32	1.36	1.31	1.41
4	1.35	1.33	1.26	1.32
5	1.27	1.34	1.26	1.35
6	1.24	1.26	1.30	1.29
7	1.21	1.17	1.23	1.30
8	1.23	1.14	1.22	1.19
9	1.12	1.12	1.14	1.08
10 (High)	0.97	0.89	1.06	0.92
High - Low	-0.48	-0.62	-0.35	-0.39
	(-2.39)	(-2.49)	(-2.24)	(-2.08)
FFC alpha	-0.44	-0.54	-0.47	-0.52
	(-1.95)	(-2.21)	(-2.79)	(-2.57)

Table 7
Univariate Portfolios of Stocks Sorted by Monthly Economic Uncertainty Betas

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Monthly measures of economic uncertainty are obtained from the linear interpolation of the quarterly measures of GDP forecast dispersion. Monthly exposures of individual stocks to economic uncertainty are obtained from monthly rolling regressions of excess stock returns on the economic uncertainty measures using a 60-month fixed window estimation. Then, these monthly uncertainty betas are used to predict the cross-section of one-month ahead stock returns. This table reports the average monthly returns (in percentage), average uncertainty beta, and average market share for the decile portfolios formed on β^{UNC}_{growth} using the CRSP breakpoints (the left panel) and the NYSE breakpoints (the right panel). 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.

	CRSP breakpoints			NYSE breakpoints		
Decile	Return	β^{UNC}_{growth}	Mkt shr	Return	β^{UNC}_{growth}	Mkt shr
1 (Low)	1.43	-2.39	6.8%	1.45	-2.10	10.0%
2	1.44	-1.12	11.6%	1.48	-0.90	12.1%
3	1.45	-0.62	12.3%	1.47	-0.49	12.1%
4	1.43	-0.27	12.8%	1.40	-0.19	11.4%
5	1.37	0.03	12.4%	1.40	0.08	11.3%
6	1.30	0.32	11.7%	1.28	0.34	10.7%
7	1.27	0.63	11.4%	1.30	0.62	10.4%
8	1.15	1.01	9.6%	1.18	0.95	9.4%
9	1.12	1.56	7.5%	1.14	1.44	7.7%
10 (High)	0.99	2.92	3.9%	1.02	2.76	4.9%
High - Low	-0.44			-0.43		
	(-2.43)			(-2.49)		
FFC alpha	-0.61			-0.59		
	(-3.07)			(-3.07)		

Table 8
Different Stock Samples

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures 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}_{growth} 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&P 500	500 largest	1,000 largest	500 most liquid	1,000 most liquid
1 (Low)	1.45	1.34	1.42	1.23	1.38	1.33	1.45
2	1.40	1.31	1.29	1.25	1.37	1.28	1.38
3	1.36	1.16	1.20	1.10	1.23	1.19	1.30
4	1.29	1.20	1.19	1.14	1.25	1.17	1.28
5	1.31	1.14	1.25	1.12	1.21	1.12	1.21
6	1.20	1.14	1.16	1.06	1.16	1.13	1.21
7	1.19	1.08	1.24	1.01	1.17	1.07	1.21
8	1.15	1.02	1.05	0.95	0.98	0.92	1.03
9	1.03	0.93	0.91	0.88	0.97	0.92	1.00
10 (High)	0.88	0.77	0.92	0.74	0.82	0.84	0.83
High Low	-0.57	-0.57	-0.50	-0.49	-0.56	-0.49	-0.62
	(-3.21)	(-3.08)	(-2.34)	(-2.49)	(-3.03)	(-2.54)	(-3.13)
FFC alpha	-0.71	-0.75	-0.68	-0.58	-0.76	-0.64	-0.81
	(-3.38)	(-3.77)	(-2.89)	(-2.79)	(-3.74)	(-3.07)	(-3.88)

Table 9
Subsample Analysis

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures 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}_{growth} 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	October 1973−May 1993	June 1993−December 2012
β^{UNC}_{growth} (Low)	1.66	1.25
2	1.67	1.27
3	1.63	1.13
4	1.55	1.11
5	1.62	1.05
6	1.51	1.06
7	1.49	1.02
8	1.34	0.91
9	1.18	0.85
β^{UNC}_{growth} (High)	1.04	0.73
High - Low	-0.62	-0.52
	(-3.33)	(-2.06)
FFC alpha	-0.55	-0.68
	(-2.68)	(-2.87)

Table 10
Long-term Predictive Power of Economic Uncertainty Betas

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures using a 20-quarter fixed window estimation. Then, these quarterly uncertainty betas are used to predict the quarterly cross-sectional stock returns in the following 12 months (i.e., quarters $1-4$). This table reports the average quarterly returns (in percentage) 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 1973:Q4$-$2012:Q4..

Decile	Quarter 1	Quarter 2	Quarter 3	Quarter 4
1 (Low)	6.11	4.45	4.11	4.09
2	5.26	4.65	4.40	4.35
3	4.77	4.34	4.37	4.40
4	4.64	4.13	4.19	4.38
5	4.52	4.16	4.11	4.10
6	4.43	4.14	4.04	4.09
7	4.41	4.02	3.90	4.18
8	4.21	3.85	3.95	4.07
9	4.03	3.43	3.72	3.89
10 (High)	4.52	2.93	2.91	3.44
High - Low	-1.59	-1.52	-1.20	-0.66
	(-2.50)	(-2.49)	(-2.13)	(-1.46)
FFC alpha	-2.33	-2.24	-1.52	-0.89
	(-3.05)	(-2.99)	(-2.68)	(-1.97)

Table 11
Bivariate Portfolios of Stocks Sorted by Economic Uncertainty Betas after Controlling for Market Volatility Betas Estimated from Univariate Regressions

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Individual stocks' exposures to economic uncertainty and stock market volatility (proxied by realized volatility and option implied volatility) are obtained from equations (13)−(15) using a 20-quarter fixed window estimation. Stocks are first sorted into deciles based on stock market volatility beta ($\beta_{i,t}^{RVOL}$ or $\beta_{i,t}^{VXO}$), and then stocks within each control variable decile are further sorted into deciles based on uncertainty beta (β_{growth}^{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 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 when the market volatility beta is measured by $\beta_{i,t}^{RVOL}$ and is January 1991−December 2012 when the market volatility beta is measured by $\beta_{i,t}^{VXO}$.

Decile	β^{RVOL}	β^{VXO}
β_{growth}^{UNC} (Low)	1.42	1.28
2	1.44	1.24
3	1.39	1.16
4	1.32	1.12
5	1.31	1.19
6	1.29	1.12
7	1.19	1.02
8	1.16	1.04
9	1.06	0.99
β_{growth}^{UNC} (High)	0.95	0.76
High - Low	-0.48	-0.48
	(-3.15)	(-3.18)
FFC alpha	-0.46	-0.45
	(-2.70)	(-2.67)

Table 12
Alternative Measures of Uncertainty Betas Estimated after Controlling for Market Returns and Market Variance

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Individual stocks' exposures to economic uncertainty are obtained from regressing the quarterly excess stock returns on the quarterly cross-sectional dispersion measures after controlling for the quarterly excess market return and/or the quarterly market variance. In Columns 1−3, uncertainty betas are estimated from equations (16)−(18), respectively. The market index is measured by the CRSP value-weighted index returns. These new measures of quarterly uncertainty betas are used to predict the monthly cross-sectional stock returns in the following three months. Panel A reports the average monthly returns (in percentage) for the decile portfolios formed on β^{UNC}_{growth} 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). In Panel B, β^{UNC}_{growth} β^{RVOL} are estimated from equations (16)−(18) simultaneously. Stocks are first sorted into deciles based on β^{RVOL}, and then stocks within each β^{RVOL} decile are further sorted into deciles based on β^{UNC}_{growth}. Panel B reports the average monthly returns (in percentage) for each uncertainty beta decile, averaged across the ten β^{RVOL} deciles within the same uncertainty beta decile. Panel C reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on β^{UNC}_{growth} and a set of lagged predictive variables using the Fama-MacBeth methodology. The control variables (defined in Section 2.2) are the market beta (BETA), log market capitalization (SIZE), log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), coskewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), and exposure to the change in realized market variance (β^{RVOL}). Newey-West adjusted t-statistics are given in parentheses. The sample period is October 1973−December 2012.

Table 12 – continued

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

Decile	(1)	(2)	(3)
β^{UNC}_{growth} (Low)	1.41	1.46	1.37
2	1.43	1.42	1.41
3	1.36	1.39	1.33
4	1.29	1.33	1.33
5	1.35	1.35	1.29
6	1.27	1.28	1.31
7	1.23	1.20	1.20
8	1.18	1.14	1.19
9	1.08	1.10	1.16
β^{UNC}_{growth} (High)	0.93	0.87	0.94
High - Low	-0.48	-0.59	-0.44
	(-3.61)	(-3.66)	(-3.61)
FFC alpha	-0.50	-0.63	-0.47
	(-3.77)	(-3.32)	(-3.87)

Panel B. Bivariate portfolios sorted by β^{UNC}_{growth} after controlling for β^{RVOL}

Decile	(1)	(2)	(3)
β^{UNC}_{growth} (Low)	1.46	1.46	1.46
2	1.45	1.46	1.36
3	1.36	1.39	1.34
4	1.33	1.30	1.32
5	1.30	1.33	1.33
6	1.29	1.29	1.24
7	1.22	1.18	1.22
8	1.13	1.15	1.18
9	1.06	1.07	1.08
β^{UNC}_{growth} (High)	0.93	0.89	0.99
High - Low	-0.53	-0.57	-0.47
	(-3.62)	(-3.70)	(-3.63)
FFC alpha	-0.55	-0.62	-0.48
	(-3.42)	(-3.62)	(-3.73)

Table 12 – continued

Panel C. Fama-MacBeth regressions with β^{UNC}_{growth} controlling for β^{RVOL} and other variables

	(1)	(2)	(3)
Intercept	1.797	1.873	1.800
	(6.76)	(6.47)	(6.78)
β^{UNC}_{growth}	-0.029	-0.030	-0.026
	(-4.58)	(-4.42)	(-4.18)
β^{MKT}	0.143		0.140
	(1.71)		(1.67)
SIZE	-0.129	-0.131	-0.130
	(-4.38)	(-4.33)	(-4.40)
BM	0.176	0.168	0.172
	(2.64)	(2.35)	(2.60)
MOM	0.006	0.006	0.006
	(3.98)	(3.81)	(3.94)
REV	-0.029	-0.029	-0.029
	(-7.27)	(-7.11)	(-7.31)
ILLIQ	-0.026	-0.028	-0.026
	(-2.13)	(-2.15)	(-2.13)
COSKEW	0.005	0.009	0.004
	(0.67)	(1.39)	(0.61)
IVOL	-0.215	-0.207	-0.213
	(-6.24)	(-5.55)	(-6.24)
DISP	-0.166	-0.159	-0.160
	(-2.00)	(-1.95)	(-1.98)
β^{RVOL}		-1.850	-1.463
		(-1.92)	(-1.78)

Table 13
Controlling for Exposures to Option Implied Variance

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP growth. Following Ang et al. (2006), exposures to option implied variance are estimated from equation (19). In Panel A, stocks are first sorted into deciles based on β^{VXO}, and then stocks within each β^{VXO} decile are further sorted into deciles based on uncertainty beta. Panel A reports the average monthly returns (in percentage) for each uncertainty beta decile, averaged across the ten β^{VXO} deciles within the same uncertainty beta decile. Panel B 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. The control variables (defined in Section 2.2) are the 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), and β^{VXO}. β^{UNC}_{growth} under label "Model 1" of Panels A and B is estimated from equation (3); β^{UNC}_{growth} under label "Model 2" is estimated from equation (16). Newey-West adjusted t-statistics are given in parentheses. The sample period is February 1986−December 2012.

Panel A. Bivariate portfolios sorted by β^{UNC}_{growth} controlling for β^{VXO}

Quintile	Model 1	Model 2
β^{UNC}_{growth} (Low)	1.26	1.21
2	1.20	1.18
3	1.23	1.07
4	1.07	1.08
5	1.11	1.12
6	1.08	1.08
7	1.07	1.07
8	0.96	1.00
9	0.88	0.96
β^{UNC}_{growth} (High)	0.76	0.86
High - Low	-0.50	-0.35
	(-2.48)	(-2.35)
FFC alpha	-0.63	-0.42
	(-3.09)	(-3.06)

Table 13 – continued

Panel B. Fama-MacBeth regressions with β^{UNC}_{growth} controlling for β^{VXO} and other variables

	Model 1				Model 2			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	0.729	0.614	0.576	1.419	0.780	0.620	0.576	1.417
	(2.60)	(2.02)	(1.92)	(4.66)	(2.75)	(2.04)	(1.92)	(4.65)
β^{UNC}_{growth}	-0.035	-0.026	-0.017	-0.014	-0.023	-0.021	-0.014	-0.012
	(-2.84)	(-2.97)	(-2.47)	(-2.06)	(-2.62)	(-2.77)	(-2.10)	(-1.91)
BETA		0.161	0.133	0.192		0.185	0.132	0.187
		(1.09)	(0.95)	(1.40)		(1.20)	(0.94)	(1.38)
SIZE		0.007	-0.001	-0.078		0.006	-0.001	-0.078
		(0.24)	(-0.02)	(-2.60)		(0.22)	(-0.03)	(-2.59)
BM		0.151	0.145	0.128		0.149	0.144	0.129
		(1.92)	(1.92)	(1.68)		(1.88)	(1.89)	(1.68)
MOM			0.006	0.005			0.006	0.005
			(3.87)	(3.26)			(3.58)	(3.29)
ILLIQ				-0.023				-0.023
				(-1.68)				(-1.68)
REV				-0.021				-0.022
				(-5.11)				(-5.13)
COSKEW				0.008				0.008
				(0.97)				(0.93)
IVOL				-0.175				-0.175
				(-4.59)				(-4.60)
DISP				-0.063				-0.063
				(-1.83)				(-1.83)
β^{VXO}	-0.052	-0.077	-0.075	-0.054	-0.054	-0.077	-0.076	-0.054
	(-1.63)	(-1.96)	(-1.95)	(-1.68)	(-1.73)	(-1.97)	(-1.97)	(-1.69)

Table 14
Cross-Sectional Return Predictability of Exposures to the Economic Uncertainty Index

Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the quarterly Uncertainty Index using a 20-quarter fixed window estimation. The Economic Uncertainty Index is defined as the first principal component of seven uncertainty variables that capture different dimensions of the aggregate economy: 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 A reports the average monthly returns (in percentage), average uncertainty beta, and average market share for the decile portfolios formed on β^{UNC}_{index} using the CRSP breakpoints (the left panel) and the NYSE breakpoints (the right panel). 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). Panel B reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on β^{UNC}_{index} and a set of lagged predictive variables using the Fama-MacBeth methodology. The control variables (defined in Section 2.2) are the 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), β^{RVOL} (estimated from equation (14)), and β^{VXO} (estimated from equation (19)). Newey-West adjusted t-statistics are given in parentheses. The sample period for the results reported in Panel A and columns (1) – (5) of Panel B is October 1973−December 2012; the sample period for the results reported in the last column of Panel B is February 1986−December 2012.

Panel A. Univariate portfolios sorted by exposures to economic uncertainty index

	CRSP breakpoints			NYSE breakpoints		
Decile	Return	β^{UNC}_{index}	Mkt shr	Return	β^{UNC}_{index}	Mkt shr
1 (Low)	1.49	-7.38	7.1%	1.47	-6.62	9.5%
2	1.41	-3.72	10.9%	1.42	-3.14	11.9%
3	1.39	-2.24	11.9%	1.39	-1.89	11.4%
4	1.31	-1.19	11.9%	1.29	-0.99	10.9%
5	1.29	-0.27	12.3%	1.28	-0.19	10.9%
6	1.30	0.63	12.0%	1.28	0.59	10.6%
7	1.23	1.62	11.3%	1.25	1.43	10.4%
8	1.18	2.85	10.0%	1.23	2.48	9.4%
9	1.05	4.73	8.3%	1.09	4.03	8.7%
10 (High)	0.89	10.16	4.2%	0.94	9.06	6.3%
High - Low	-0.60			-0.53		
	(-3.96)			(-3.70)		
FFC alpha	-0.69			-0.63		
	(-4.14)			(-4.08)		

Table 14 – continued

Panel B. Fama-MacBeth regressions with β^{UNC}_{index} and control variables

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.782	0.967	0.913	1.814	1.800	1.419
	(3.12)	(3.81)	(3.68)	(6.91)	(6.93)	(4.67)
β^{UNC}_{index}	-0.039	-0.034	-0.026	-0.024	-0.022	-0.017
	(-4.03)	(-4.55)	(-4.04)	(-4.23)	(-3.65)	(-2.75)
BETA		0.090	0.068	0.175	0.189	0.195
		(0.73)	(0.59)	(1.50)	(1.59)	(1.42)
SIZE		-0.047	-0.054	-0.134	-0.133	-0.079
		(-1.73)	(-2.00)	(-4.62)	(-4.62)	(-2.67)
BM		0.198	0.204	0.161	0.159	0.123
		(2.81)	(3.02)	(2.41)	(2.40)	(1.61)
MOM			0.007	0.006	0.006	0.005
			(5.52)	(4.57)	(4.63)	(3.28)
REV				-0.030	-0.030	-0.022
				(-7.61)	(-7.39)	(-5.16)
ILLIQ				-0.027	-0.026	-0.023
				(-2.25)	(-2.22)	(-1.68)
COSKEW				0.006	0.006	0.008
				(0.96)	(0.96)	(1.00)
IVOL				-0.217	-0.216	-0.175
				(-6.77)	(-6.73)	(-4.57)
DISP				-0.166	-0.164	-0.064
				(-2.03)	(-1.99)	(-1.85)
β^{RVOL}					-0.184	
					(-0.29)	
β^{VXO}						-0.054
						(-1.64)

Cross-Sectional Dispersion in Economic Forecasts and Expected Stock Returns

Online Appendix

Table A1 presents the correlations between market returns and economic uncertainty measures. Table A2 provides results from the univariate decile portfolios of stocks sorted by stock exposures to the cross-sectional dispersion in quarterly forecasts of real GDP level (β^{UNC}_{level}). Table A3 shows results from the conditional bivariate portfolios of β^{UNC}_{level} after controlling for a large set of firm characteristics and risk factors. Table A4 reports the average slope coefficients from the Fama-MacBeth cross-sectional regressions of monthly stocks returns on β^{UNC}_{level} and a set of lagged predictive variables. Table A5 presents results from the univariate portfolios of stocks sorted by alternative measures of economic uncertainty betas.

Table A1
Correlations between Market Returns and Economic Uncertainty

This table presents the correlations between the CRSP index return and the cross-sectional dispersion in real GDP level and real GDP growth forecasts. The results are reported for the quarterly and monthly data frequency and for the cross-sectional dispersion of current GDP forecasts (RGDP0) as well as for 1-quarter to 4-quarter ahead forecasts of professional forecasters (RGDP1−RGDP4). The sample period is 1968:Q4−2012:Q4.

Variable	RGDP0	RGDP1	RGDP2	RGDP3	RGDP4
Quarterly Disp. RGDP Level	0.075	0.039	0.041	0.029	0.073
Quarterly Disp. RGDP Growth	0.049	0.084	0.023	0.024	0.090
Monthly Disp. RGDP Level	0.026	0.022	0.001	0.001	0.063
Monthly Disp. RGDP Growth	0.018	0.069	0.016	0.030	0.084

Table A2
Univariate Portfolios of Stocks Sorted by Economic Uncertainty Betas

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP level. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures using a 20-quarter fixed window estimation. The first set of uncertainty betas (β^{UNC}_{level}) 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 monthly returns (in percentage), average uncertainty beta, and average market share for the decile portfolios formed on β^{UNC}_{level} using the CRSP breakpoints (the left panel) and the NYSE breakpoints (the right panel). 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.

	CRSP breakpoints			NYSE breakpoints		
Decile	Return	β^{UNC}_{level}	Mkt shr	Return	β^{UNC}_{level}	Mkt shr
1 (Low)	1.44	-7.14	8.3%	1.43	-6.41	11.1%
2	1.43	-3.52	12.2%	1.44	-2.98	12.7%
3	1.40	-2.03	12.5%	1.37	-1.76	11.5%
4	1.33	-0.97	13.2%	1.35	-0.84	11.9%
5	1.37	-0.04	11.8%	1.38	-0.03	10.5%
6	1.28	0.88	10.7%	1.30	0.78	10.1%
7	1.26	1.88	10.4%	1.26	1.66	9.5%
8	1.12	3.12	9.2%	1.16	2.73	9.1%
9	1.03	5.00	7.5%	1.11	4.32	7.7%
10 (High)	0.88	10.06	4.2%	0.91	9.09	5.9%
High - Low	-0.56			-0.51		
	(-3.30)			(-3.20)		
FFC alpha	-0.67			-0.64		
	(-3.51)			(-3.63)		

Table A3
Bivariate Portfolio Sorts

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP level. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures 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. 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}_{level}). 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 deciles 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), and analyst dispersion (DISP). The control variables are defined in Section 2.2 of the paper. 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.

Quintile	BETA	SIZE	BM	MOM	REV	ILLIQ	COSKEW	IVOL	DISP
β^{UNC}_{level} (Low)	1.37	1.44	1.51	1.34	1.44	1.46	1.40	1.49	1.33
2	1.39	1.45	1.43	1.38	1.40	1.43	1.41	1.40	1.31
3	1.38	1.40	1.35	1.31	1.43	1.46	1.37	1.38	1.33
4	1.31	1.34	1.38	1.32	1.36	1.38	1.35	1.30	1.25
5	1.39	1.38	1.32	1.31	1.31	1.38	1.35	1.37	1.19
6	1.30	1.27	1.30	1.30	1.29	1.32	1.28	1.24	1.16
7	1.21	1.22	1.20	1.27	1.18	1.20	1.22	1.15	1.09
8	1.14	1.14	1.13	1.18	1.13	1.13	1.15	1.14	1.06
9	1.07	1.03	1.05	1.15	1.06	1.01	1.08	1.06	1.00
β^{UNC}_{level} (High)	0.97	0.85	1.00	0.99	0.93	0.87	0.92	1.01	0.84
High Low	-0.40	-0.58	-0.51	-0.35	-0.51	-0.60	-0.49	-0.48	-0.49
	(-3.08)	(-3.57)	(-3.31)	(-2.85)	(-3.18)	(-3.75)	(-3.00)	(-3.33)	(-2.72)
FFC alpha	-0.43	-0.65	-0.58	-0.43	-0.62	-0.67	-0.58	-0.59	-0.61
	(-3.18)	(-3.59)	(-3.17)	(-3.41)	(-3.34)	(-3.84)	(-3.26)	(-3.66)	(-3.11)

Table A4
Fama-MacBeth Cross-Sectional Regressions

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of real GDP level. Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures using a 20-quarter fixed window estimation. These quarterly uncertainty betas (β^{UNC}_{level}) 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 defined in Section 2.2 of the paper. This table reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on β^{UNC}_{level} and a set of lagged predictive variables using the Fama-MacBeth methodology. Newey-West adjusted t-statistics are reported in parentheses. The sample period is October 1973−December 2012.

	(1)	(2)	(3)	(4)
Intercept	0.803	0.981	0.914	1.810
	(3.29)	(3.89)	(3.70)	(6.92)
β^{UNC}_{level}	-0.040	-0.033	-0.024	-0.023
	(-3.75)	(-4.18)	(-3.50)	(-3.47)
BETA		0.096	0.069	0.165
		(0.80)	(0.60)	(1.42)
SIZE		-0.047	-0.052	-0.132
		(-1.71)	(-1.92)	(-4.55)
BM		0.209	0.213	0.170
		(2.97)	(3.17)	(2.56)
MOM			0.007	0.006
			(5.39)	(4.47)
REV				-0.030
				(-7.55)
ILLIQ				-0.027
				(-2.25)
COSKEW				0.006
				(0.95)
IVOL				-0.217
				(-6.78)
DISP				-0.164
				(-2.00)

Table A5
Univariate Portfolios of Stocks Sorted by Alternative Measures of Economic Uncertainty Betas

Economic uncertainty is measured by the cross-sectional dispersion in the current quarter forecasts of either nominal GDP (NGDP) level/growth, GDP price index (PGDP) level/growth, or unemployment rate (UNEMP). Individual stocks' exposures to economic uncertainty are obtained from quarterly rolling regressions of excess stock returns on the economic uncertainty measures using a 20-quarter fixed window estimation. This table reports the average monthly returns (in percentage), average uncertainty beta, and average market share 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	NGDP-level	NGDP-growth	PGDP-level	PGDP-growth	UNEMP
β^{UNC} (Low)	1.38	1.39	1.42	1.42	1.33
2	1.35	1.44	1.46	1.47	1.29
3	1.31	1.36	1.35	1.36	1.25
4	1.30	1.29	1.30	1.35	1.33
5	1.33	1.31	1.27	1.35	1.26
6	1.31	1.25	1.25	1.28	1.26
7	1.28	1.25	1.23	1.20	1.25
8	1.22	1.22	1.22	1.16	1.20
9	1.13	1.08	1.12	1.05	1.22
β^{UNC} (High)	0.91	0.94	0.91	0.90	1.14
High - Low	-0.48	-0.45	-0.51	-0.52	-0.19
	(-3.34)	(-3.25)	(-2.98)	(-2.96)	(-1.63)
FFC alpha	-0.61	-0.53	-0.37	-0.34	-0.28
	(-4.37)	(-3.87)	(-1.99)	(-1.74)	(-2.13)