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Is Economic Uncertainty Priced in the Cross-Section of Stock Returns?*

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Abstract

We investigate the role of economic uncertainty in the cross-sectional pricing of individual stocks and equity portfolios. We estimate stock exposure to an economic uncertainty index and show that stocks in the lowest uncertainty beta decile generate 6% more annualized risk-adjusted return compared to stocks in the highest uncertainty beta decile. We find that the uncertainty premium is driven by the outperformance (underperformance) by stocks with negative (positive) uncertainty beta. Our results indicate that uncertainty-averse investors demand extra compensation to hold stocks with negative uncertainty beta and they are willing to pay high prices for stocks with positive uncertainty beta.

JEL Classification: G11; G12; C13; E20; E30

Keywords: Economic uncertainty; Uncertainty aversion; Cross-section of stock returns; ICAPM; Return predictability

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1. Introduction

Merton's (1973) seminal article indicates that, in a multi-period economy, investors have incentive to hedge against future stochastic shifts in consumption and investment opportunity sets. This implies that state variables that are correlated with changes in consumption and investment opportunities are priced in capital markets such that an asset's covariance with these state variables is related to its expected returns. Macroeconomic variables are widely accepted candidates for these systematic risk factors because innovations in economic indicators can generate significant impacts on expected returns through several channels. To the extent that investors pursue opportunities arising from changing economic circumstances, we would expect that returns from investment in risky assets are influenced by the extent to which investors vary their exposure to economic fundamentals.

Gomes, Kogan, and Zhang (2003), Bloom (2009), Allen, Bali, and Tang (2012), Drechsler (2013), and Jurado, Ludvigson, and Ng (2015) provide theoretical and empirical support for the idea that time variation in the conditional volatility of macroeconomic shocks is linked to real economic activity and asset returns. Thus, 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 and equity portfolios. We quantify uncertainty using the economic uncertainty index of Jurado, Ludvigson, and Ng (2015, hereafter JLN), defined as the conditional volatility of the unforecastable component of a large number of economic indicators. We estimate stock exposure to the uncertainty index and provide the out-of-sample performance of exante measures of the uncertainty beta in predicting the cross-sectional variation in future stock returns.

First, we estimate the uncertainty beta using 60-month rolling regressions of excess returns on the economic uncertainty index of JLN (2015) for each stock trading in the New York Stock Exchange (NYSE), American Stock Exchange (Amex), and Nasdaq. Then, we examine the performance of the monthly uncertainty beta in predicting the cross-sectional dispersion in future stock returns. Specifically, we sort individual stocks into decile portfolios by their uncertainty beta during the previous month and examine the monthly returns on the resulting portfolios from July 1977 to December 2014. Stocks in the lowest uncertainty beta decile generate about 6% more annual returns compared to stocks in the highest uncertainty beta decile. After controlling for the well-known market, size, book-to-market, momentum, liquidity, investment, and profitability factors of Fama and French (1993, 2015), Carhart (1997), Pastor and Stambaugh (2003), and Hou, Xue, and Zhang (2015), we find the difference between the returns on the portfolios with the highest and lowest uncertainty beta (seven-factor alpha) remains negative and highly significant.

These results are also consistent with a well-established literature that distinguishes risk and uncertainty, showing that investors care not only about the mean and variance of asset returns but also on the uncertainty of events over which the future return distribution occurs. Since the future return distribution is influenced by the state of the economy, economic uncertainty enters an investor's utility function. In this setting, our results suggest the possibility of a preference-based explanation of the economic uncertainty premium: Due to their negative uncertainty beta, the returns of individual stocks in decile 1 correlate negatively with increases in economic uncertainty, hence uncertainty-averse investors would demand extra compensation in the form of higher expected return to hold these stocks with negative uncertainty beta. On the other hand, with their positive uncertainty beta, the returns of individual stocks in decile 10 correlate positively with increases in economic uncertainty. Since stocks with positive uncertainty beta would be viewed as relatively safer assets at times of increased economic uncertainty, investors are willing to pay higher prices for these stocks and accept lower returns.

This significantly negative uncertainty premium is also consistent with the intertemporal capital asset pricing model (ICAPM) of Merton (1973) and Campbell (1993, 1996). An increase in economic uncertainty reduces future investment and consumption opportunities. To hedge against such an unfavorable shift, investors prefer to hold stocks whose returns increase in times of economic uncertainty. When economic uncertainty rises, investors suffer through a reduction in optimal consumption and future investment opportunities. They are able to compensate for this loss by holding stocks that positively correlate with this economic uncertainty. This intertemporal hedging demand argument implies that investors are willing to hold stocks with higher covariance with economic uncertainty, and they pay higher prices and accept lower returns for stocks with higher uncertainty beta.

To ensure that it is the uncertainty beta that is driving documented return differences rather than well-known stock characteristics or risk factors, we perform bivariate portfolio sorts and re-examine the raw return and alpha differences. We control for size and book-to-market (Fama and French, 1992, 1993), momentum (Jegadeesh and Titman, 1993), short-term reversal (Jegadeesh, 1990), illiquidity (Amihud, 2002), co-skewness (Harvey and Siddique, 2000), idiosyncratic volatility (Ang et al., 2006), analyst earnings forecast dispersion (Diether, Malloy, and Scherbina, 2002), the market volatility beta (Ang et al., 2006; and Campbell et al., 2017), demand for lottery-like stocks (Bali, Cakici, and Whitelaw, 2011), investment and profitability (Fama and French, 2015; and Hou, Xue, and Zhang, 2015). After controlling for this large set of stock return predictors, we find the negative relation between the uncertainty beta and future returns remains economically significant. We also examine the cross-sectional relation at the stock-level using the Fama-MacBeth (1973) regressions. After all variables are controlled for simultaneously, the cross-sectional regressions provide strong corroborating evidence for an economically and statistically significant negative relation between the uncertainty beta and future stock returns.

We also replicate our main analyses using the cross-section of equity portfolios as test assets. Specifically, we utilize a large number of portfolios that include stocks sorted by the industry, size, book-to-market, investment, and profitability characteristics. Similar to our findings from individual stocks, the results show that economic uncertainty is negatively priced in the cross-section of equity portfolios.

We investigate the robustness of our findings. First, we test if our results are driven by small, illiquid, and low-priced stocks. We find that the uncertainty premium is highly significant in the cross-section of the Standard & Poor's (S&P) 500 stocks, and the 1,000 largest and most liquid stocks in the Center for Research in Security Prices (CRSP) universe. Second, we provide evidence of significant nonlinearity and time-series variation in uncertainty premium. Consistent with theoretical predictions, the uncertainty premium is estimated to be much higher during recessions and periods of high economic uncertainty, compared to expansionary and relatively tranquil periods. Third, we estimate the uncertainty beta from alternative factor models and economic uncertainty indices, and show that alternative measures of the uncertainty beta remain a significant predictor of future stock returns. Fourth, we investigate the long-term predictive power of the uncertainty beta and find that the predictability is not just a one-month affair. The uncertainty beta predicts cross-sectional variation in stock returns 11 months into the future. Finally, we examine the significance of uncertainty premium for stocks in each of the ten industries determined based on the four-digit Standard Industrial Classification (SIC) code, and the uncertainty premium turns out to be significant in eight out of ten industries.

The paper is organized as follows. Section 2 provides theoretical evidence that justifies the cross-sectional relation between the uncertainty beta and expected returns. Section 3 describes the data and variables. Section 4 presents the empirical results. Section 5 concludes the paper.

2. Theoretical evidence

Earlier studies (e.g., Liu and Zhang, 2008; Ludvigson and Ng, 2009; Chen, 2010; Stock and Watson, 2012; Allen, Bali, and Tang, 2012; Drechsler, 2013; Jurado, Ludvigson, and Ng, 2015; Bekaert, Engstrom, and Ermolov, 2015; and Bekaert and Engstrom, 2017) provide theoretical and empirical evidence suggesting that economic uncertainty is a relevant state variable proxying for consumption and investment opportunities in the conditional ICAPM framework.

Following Merton (1973) and Campbell (1993, 1996), we argue that an increase in economic uncertainty is an unfavorable shift in the investment opportunity set. Since an increase in economic uncertainty makes investors concerned about future outcomes, it reduces optimal consumption. Investors cut their consumption and investment demand so that they can save more to hedge against possible future downturns in the economy. To hedge against such an unfavorable shift, investors prefer holding stocks that have higher covariance with economic uncertainty. This is because an increase in economic uncertainty will increase the returns on these stocks due to positive intertemporal correlation. Hence, when economic uncertainty increases, although their optimal consumption and future investment opportunities decline, investors compensate for this loss by obtaining a stronger wealth effect through an increase in the returns on those stocks that have positive correlation with economic uncertainty. Therefore, through intertemporal hedging demand, investors are willing to hold stocks with higher covariance with economic uncertainty, and they pay higher prices and accept lower returns for stocks with higher uncertainty beta.[1]

In addition to the conditional ICAPM framework (e.g., Bali, 2008; and Bali and Engle, 2010), the negative uncertainty premium can be motivated theoretically from the long-standing literature on uncertainty aversion and two-stage expected utility theory. The concepts of risk and risk aversion are the basis of a wide variety of models in economics and finance. Although less attention is paid in formal models to the phenomenon of uncertainty, there is now a well-established literature on uncertainty aversion and second-order beliefs.[2] Studies that link uncertainty to second-order risk aversion indicate that investors care not only about the mean and variance of asset returns, but also on the uncertainty of events over which the future return distribution occurs. In addition, Ellsberg's (1961) experimental evidence demonstrates that the distinction between risk and uncertainty is meaningful empirically because people prefer to act on known rather than unknown or ambiguous probabilities. Hence, studies that investigate the impact of uncertainty in asset pricing show that when investors are unsure of the correct probability law governing the market return, they demand a higher premium in order to hold the market portfolio.[3] Since the future return distribution is influenced by the state of the economy, economic uncertainty enters an investor's utility function. In this setting, our results suggest the possibility of a preference-based explanation of the uncertainty premium.

Another potential explanation is that if investors' preferences or expectations about economic uncertainty are sufficiently dispersed and economic uncertainty is sufficiently high, investors with relatively high

[1] By defining investor uncertainty as the dispersion of predictions of mean market returns obtained from the forecasts of aggregate corporate profits, Anderson, Ghysels, and Juergens (2009) find that the price of investor uncertainty is significantly positive. Using measures of uncertainty estimated from a regime-switching model of market return and of output, Ozoguz (2009) finds a negative relation between investor uncertainty and asset returns. Bekaert, Engstrom, and Xing (2009) focus on economic uncertainty proxied by the conditional volatility of dividend growth and find that both the conditional volatility of cash flow growth and time-varying risk aversion are important determinants of equity returns. In a conditional asset pricing model with time-varying volatility in the consumption growth process, Bali and Zhou (2016) find a positive relation between volatility uncertainty and future stock returns.

[2] A partial list includes Schmeidler (1989), Segal (1987, 1990), Epstein (1999), Klibanoff, Marinacci, and Mukerji (2005), Nau (2006), Ergin and Gul (2009), Seo (2009), Neilson (2010), and Conte and Hey (2013).

[3] See, e.g., Epstein and Wang (1994), Epstein and Zhang (2001), Chen and Epstein (2002), Maccheroni, Marinacci, and Rustichini (2006), Epstein and Schneider (2008, 2010), Guidolin and Francesca (2013), and Bianchi, Ilut, and Schneider (2017).

aversion against economic uncertainty and/or pessimistic ambiguity expectations may cease or reduce their participation in a stock. As a result of this limited participation, stocks with high uncertainty beta are held only by investors with a sufficiently optimistic view on economic uncertainty or low aversion against economic uncertainty. Hence, stocks with high uncertainty beta require low uncertainty premium.[4]

3. Data and variable definitions

This section describes the data on economic uncertainty and the stock-level predictive variables used in cross-sectional return predictability.

3.1. Economic uncertainty index

Jurado, Ludvigson, and Ng (2015) develop a factor-based estimate of economic uncertainty. They select a rich set of time-series that represent broad categories of macroeconomic activities: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, bond and stock market indexes, and foreign exchange measures. They estimate the conditional volatility of the unpredictable component of the future value of each series, and then aggregate individual conditional volatilities into a macro uncertainty index. We obtain the one-month, three-month, and 12-month-ahead economic uncertainty indices (UNC^m, UNC^q, and UNC^y) from Sydney Ludvigson's website.

Fig. 1 shows that the three economic uncertainty indices are highly correlated,[5] and are generally higher during bad states of the economy, corresponding to periods of high unemployment, low output growth, and low economic activity. The economic uncertainty indices also track large fluctuations in business conditions.

[4]Earlier studies provide evidence that limited participation in a stock can lead to a lower equity premium. See, e.g., Uppal and Wang (2003), Cao, Wang, and Zhang (2005), Chapman and Polkovnichenko (2009), and Bossaerts et al. (2010).

[5]The correlations between the one-, three- and 12-month-ahead uncertainty indices are, respectively, 99.63% for UNC^m and UNC^q, 95.68% for UNC^m and UNC^y, and 97.71% for UNC^q and UNC^y.

[**fig.** 1 about here.]

3.2. Cross-sectional return predictors

Our stock sample includes all common stocks traded on the NYSE, Amex, and Nasdaq exchanges from July 1972 through December 2014.[6] We eliminate stocks with a price per share less than \$5 or more than \$1,000. The daily and monthly return and volume data are from the CRSP. We adjust stock returns for delisting to avoid survivorship bias (Shumway, 1997).[7] Accounting variables are obtained from the merged CRSP-Compustat database. Analysts' earnings forecasts come from the Institutional Brokers' Estimate System (I/B/E/S) data set and cover the period from 1983 to 2014. In this section, we provide the definitions of the stock-level variables used in predicting cross-sectional returns. We require at least 24 monthly observations and 15 daily observations be available for variables estimated using monthly data over the past 60 months and daily data over the past one month, respectively.

For each stock and for each month in our sample, we estimate the uncertainty beta from the monthly rolling regressions of excess stock returns (R) on the economic uncertainty index (UNC) over a 60-month fixed window after controlling for the market (MKT), size (SMB), book-to-market (HML), momentum (UMD), liquidity (LIQ), investment ($R_{I/A}$), and profitability (R_{ROE}) factors of Fama and French (1993), Carhart (1997), Pastor and Stambaugh (2003), and Hou, Xue, and Zhang (2015):

$$\begin{aligned} R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{SMB} \cdot SMB_t + \beta_{i,t}^{HML} \cdot HML_t + \\ & \quad \beta_{i,t}^{UMD} \cdot UMD_t + \beta_{i,t}^{LIQ} \cdot LIQ_t + \beta_{i,t}^{R_{I/A}} \cdot R_{I/A,t} + \beta_{i,t}^{R_{ROE}} \cdot R_{ROE,t} + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

[6] Our sample starts from July 1972 because the quarterly earnings announcement date (quarterly Compustat item "RDQ") is not largely available before 1972. As a result, the investment and profitability factors of Hou, Xue, and Zhang (2015), that we use in estimating stock exposure to economic uncertainty, start from July 1972.

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

The excess market returns (MKT) and the factors high-minus-low (HML) and winner-minus-losers (UMD) are from Kenneth French's data library. The liquidity factor (LIQ) is from Lubos Pastor's data library. When estimating β^{UNC} in Eq. (1), we use the size (SMB), investment ($R_{I/A}$), and profitability (R_{ROE}) factors of Hou, Xue, and Zhang (2015).[8, 9] In Section 4.7, we present results from alternative measures of β^{UNC} estimated with different combinations of these factors and the results turn out to be very similar to those reported in our main tables.

When estimating the alpha of β^{UNC}-sorted portfolios, we use four different factor models: (i) the five-factor model relative to excess market return, size factor, a book-to-market factor, a momentum factor, and a liquidity factor; (ii) the five-factor model relative to the market, size, book-to-market, investment, and profitability factors; (iii) the four-factor model relative to the market, size, investment, and profitability factors; (iv) the seven-factor model relative to the market, size, book-to-market, momentum, liquidity, investment, and profitability factors. As will be discussed in Section 4, our main findings from alternative factor models are very similar.

Following Fama and French (1992), we estimate the market beta of individual stocks using monthly returns over the prior 60 months if available. The size (SIZE) is computed as the natural logarithm of the product of the price per share and the number of shares outstanding (in millions of dollars). Following Fama and French (1992, 1993, 2000), the natural logarithm of the book-to-market equity ratio at the end of June of year t, denoted BM, is computed as the book value of stockholder equity plus deferred taxes and investment tax credit (if available) minus the book value of preferred stock at the end of the last fiscal, $t-1$, scaled by

[8]Following Hou, Xue, and Zhang (2015), the size, investment, and profitability factors are calculated from triple sorts. Specifically, at the end of June of year t, CRSP stocks are independently sorted into two size groups using the median NYSE size breakpoint, and three I/A groups using the NYSE 30th and 70th percentile values of I/A for the fiscal year ending in calendar year $t-1$. Next, for each portfolio formation month, stocks are independently sorted into three groups by the NYSE breakpoints for the 30th and 70th percentiles of quarterly ROE. Earnings data on the Compustat quarterly database are used in the months immediately following the most recent public quarterly earnings announcement dates (Compustat quarterly item RDQ).

[9]The intersections of the two size, three investment, and three profitability groups result in 18 portfolios. Monthly value-weighted portfolio returns are calculated. The monthly size factor is the difference between the simple average of the monthly value-weighted returns on the nine small size portfolios and the simple average of the value-weighted monthly returns on the nine big size portfolios. The monthly investment factor is the difference between the simple average of the value-weighted monthly returns on the six low investment portfolios and the simple average of the value-weighted monthly returns on the six high investment portfolios. Finally, the monthly profitability factor is the difference between the simple average of the value-weighted monthly returns on the six high profitability portfolios and the simple average of the value-weighted monthly returns on the six low profitability portfolios.

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

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

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

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

where $\varepsilon_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t})$ is the residual from the regression of the excess stock return ($R_{i,t}$) against the contemporaneous excess return on the CRSP value-weighted index ($R_{m,t}$) using the monthly return observations over the prior 60 months. The risk-free rate is measured by the return on one-month Treasury bills.[10]

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

$$ILLIQ_{i,t} = Avg\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right], \tag{3}$$

where $R_{i,d}$ and $VOLD_{i,d}$ are the daily return and dollar trading volume for stock i on day d, respectively.[11] A stock is required to have at least 15 daily return observations in month t. Amihud's illiquidity measure is

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

[11] Following Gao and Ritter (2010), we adjust for institutional features so that the Nasdaq and NYSE/Amex volumes are counted. Specifically, divisors of 2.0, 1.8, 1.6, and 1.0 are applied to the Nasdaq volume for the periods prior to February 2001, between February 2001 and December 2001, between January 2002 and December 2003, and in January 2004 and later years, respectively.

scaled by 10^6.

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

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

$$R_{i,d} = \alpha_i + \beta_i R_{m,d} + \gamma_i SMB_d + \varphi_i HML_d + \varepsilon_{i,d}, \tag{4}$$

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

We further control for the exposure of individual stocks to changes in aggregate stock market volatility. Following Ang, Hodrick, Xing, and Zhang (2006), we use the VXO as a proxy for market volatility, and 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 using daily data in a month:

$$R_{i,d} \;=\; \alpha_{i,daily} + \beta^{MKT}_{i,daily} \cdot R_{m,d} + \beta^{VXO}_{i,daily} \cdot \Delta VAR^{VXO}_d + \varepsilon_{i,d}, \tag{5}$$

where $R_{i,d}$ is the excess return of stock i on day d, $R_{m,d}$ is the excess market return on day d, ΔVAR^{VXO}_d is the change in the S&P 100 index option implied variance (VXO) on day d, and $\beta^{VXO}_{i,daily}$ is the implied market volatility beta of stock i in month t. The daily data on the VXO for the period January 1986−December 2014 is from the Chicago Board Options Exchange.[12]

Following Bali et al. (2011, 2016), we measure demand for lottery-like stocks using MAX, calculated

[12]One of the most popular proxies for uncertainty is closely related to financial market volatility as measured by the VIX, which has a large component that appears driven by factors associated with time-varying risk-aversion rather than economic uncertainty (Bekaert, Hoerova, and Duca, 2013).

as the average of the five highest daily returns of the stock during the given month t. We require a minimum of 15 daily return observations within the given month to calculate MAX.

Following Hou, Xue, and Zhang (2015), the annual growth rate of total assets, denoted I/A, is measured by the change in book assets (Compustat item AT) divided by lagged AT. The quarterly operating profitability, denoted ROE, is measured by income before extraordinary items (item IBQ) divided by one-quarter-lagged book equity.[13]

Finally, we control for the industry effect by assigning each stock to one of the ten industries based on its four-digit Standard Industrial Classification (SIC) code. The industry definitions are obtained from the online data library of Kenneth French.

4. Empirical results

In this section, we conduct parametric and nonparametric tests to assess the predictive power of the uncertainty beta over future stock returns. First, we start with univariate portfolio-level analyses. Second, we discuss average stock characteristics to obtain a clear picture of the composition of the uncertainty beta portfolios. Third, we conduct bivariate portfolio-level analyses to examine the predictive power of the uncertainty beta after controlling for well-known stock characteristics and risk factors. Fourth, we present the univariate and multivariate cross-sectional regression results. Fifth, we investigate the significance of nonlinearity and time-series variation in uncertainty premium. Sixth, we replicate our main findings using the cross-section of equity portfolios as test assets. Finally, we provide evidence from robustness checks.

[13]Following Davis, Fama, and French (2008), quarterly book equity is shareholders' equity, plus balance-sheet deferred taxes, and investment tax credit (item TXDITCQ) if available, minus book value of preferred stock. Depending on availability, shareholders' equity is measured by stockholder's equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ) in that order. The book value of preferred stock is measured by redemption value (item PSTKRQ) if available or carrying value (item PSTKQ).

4.1. Univariate portfolio-level analysis

Exposures of individual stocks to economic uncertainty are obtained from monthly rolling regressions of excess stock returns on the one-month-ahead uncertainty index using a 60-month fixed window estimation. The first set of uncertainty betas (β^{UNC}) are obtained using the sample from July 1972 to June 1977. Then, these monthly uncertainty betas are used to predict the cross-sectional stock returns in the following month (July 1977). This monthly rolling regression approach is used until the sample is exhausted in December 2014. The cross-sectional return predictability results are reported from July 1977 to December 2014.

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

[Table 1 about here.]

The first column of Table 1 shows that moving from decile 1 to decile 10, there is significant cross-sectional variation in the average values of β^{UNC}; the average uncertainty beta increases from -0.62 to 0.72. Another notable point in Table 1 is that for the equal-weighted portfolio, the next-month average excess return decreases monotonically from 1.13% to 0.62% per month, when moving from the lowest to the highest β^{UNC} decile. The average return difference between decile 10 (high-β^{UNC}) and decile 1 (low-β^{UNC}) is -0.51% per month with a Newey-West (1987) t-statistic of -3.81.[14] This result indicates that stocks in the lowest β^{UNC} decile generate 6.12% higher annual returns compared to stocks in the highest β^{UNC} decile.

[14]Newey-West (1987) adjusted standard errors are computed using six lags.

In addition to the average raw returns, Table 1 presents the magnitude and statistical significance of the risk-adjusted returns (alphas) from four different factor models: (i) α_5^1 is the intercept from the regression of the excess portfolio returns on a constant, excess market return (MKT), a size factor (SMB), a book-to-market factor (HML), a momentum factor (UMD), and a liquidity factor (LIQ); (ii) α_5^2 is the alpha relative to the market (MKT), size (SMB), book-to-market (HML), investment ($R_{I/A}$), and profitability (R_{ROE}) factors; (iii) α_4 is the alpha relative to the market (MKT), size (SMB), investment ($R_{I/A}$), and profitability (R_{ROE}) factors; and (iv) α_7 is the alpha relative to all factors, including the market (MKT), size (SMB), book-to-market (HML), momentum (UMD), liquidity (LIQ), investment ($R_{I/A}$), and profitability (R_{ROE}) factors.

As shown in the third column of Table 1, for the equal-weighted portfolio, α_5^1 decreases monotonically from 0.28% to -0.28% per month, when moving from the lowest to the highest β^{UNC} decile. The difference in alphas between the high-β^{UNC} and low-β^{UNC} portfolios is -0.56% per month (or -6.72% per annum) with a Newey-West t-statistic of -4.55. Next, we investigate the source of the 6.72% annualized risk-adjusted return difference between the high-β^{UNC} and low-β^{UNC} portfolios: Is it due to outperformance by low-β^{UNC} stocks, underperformance by high-β^{UNC} stocks, or both? For this, we focus on the economic and statistical significance of the risk-adjusted returns of decile 1 versus decile 10. As reported in Table 1, α_5^1 of decile 1 (low-β^{UNC} stocks) is significantly positive, whereas α_5^1 of decile 10 (high-β^{UNC} stocks) is significantly negative. Hence, we conclude that the significantly negative alpha spread between high-β^{UNC} and low-β^{UNC} stocks is due to both the outperformance by low-β^{UNC} stocks and the underperformance by high-β^{UNC} stocks.

The next three columns in Table 1 present similar alpha results from alternative factor models. For the equal-weighted portfolio, α_5^2, α_4, and α_7 decrease almost monotonically when moving from the lowest to the highest β^{UNC} decile. The difference in alphas between the high-β^{UNC} and low-β^{UNC} portfolios is $\alpha_5^2 = -0.47$% per month (t-stat. = -2.93); $\alpha_4 = -0.50$% per month (t-stat. = -3.09) for the four-factor model; and α_7 = -0.42% per month (t-stat. = -3.04) for the combined seven-factor model. This indicates that after controlling for the well-known market, size, book-to-market, momentum, liquidity, investment, and profitability factors, the return difference between the high-β^{UNC} and low-β^{UNC} stocks remains negative and statistically significant.

The last five columns of Table 1 present evidence from the value-weighted portfolios of β^{UNC}. Consistent with the equal-weighted portfolio results, stocks with negative β^{UNC} (decile 1) generate a value-weighted average excess return of 0.93% per month, whereas stocks with positive β^{UNC} (decile 10) generate a lower value-weighted average excess return of 0.53% per month. The average return spread between the value-weighted high-β^{UNC} and low-β^{UNC} portfolios turns out to be negative and significant; -0.40% per month with a Newey-West t-statistic of -1.93. Similar to our findings from the equal-weighted portfolios, the alpha differences between the value-weighted high-β^{UNC} and low-β^{UNC} portfolios are also negative and statistically significant: $\alpha_5^2 = -0.56\%$ per month (t-stat. = -2.45); $\alpha_5^2 = -0.67\%$ per month (t-stat. = -2.35); $\alpha_4 = -0.69\%$ per month (t-stat. = -2.40); and $\alpha_7 = -0.62\%$ per month (t-stat. = -2.56).[15]

These results are consistent with a well-established literature that distinguishes risk and uncertainty. Due to their negative uncertainty betas, the returns of individual stocks in decile 1 correlate negatively with increases in economic uncertainty, hence uncertainty-averse investors would demand extra compensation in the form of higher expected return to hold these stocks with negative β^{UNC}. On the other hand, with their positive uncertainty betas, the returns of individual stocks in decile 10 correlate positively with increases in economic uncertainty. Since stocks with positive β^{UNC} would be viewed as relatively safer assets at times of increased economic uncertainty, investors are willing to pay higher prices for these stocks and accept lower returns.

Of course, the uncertainty betas documented in Table 1 are for the portfolio formation month and, not for the subsequent month over which we measure average returns. Investors may pay high prices for stocks that have exhibited high uncertainty beta in the past in the expectation that this behavior will be repeated in the future, but a natural question is whether these expectations are rational. To address this question, we examine the persistence of β^{UNC} by running firm-level cross-sectional regressions of β^{UNC} on lagged β^{UNC}

[15] Unless otherwise stated, we present results from the seven-factor alpha (α_7) in our follow-up tables.

and lagged cross-sectional predictors. Specifically, for each month in the sample we run a regression across firms of 12-month-ahead β^{UNC} ($\beta_{i,t}^{UNC}$) on the lagged β^{UNC} ($\beta_{i,t}^{UNC}$) and 13 lagged control variables that are defined in Section 3.2−the market beta (β^{MKT}), the market capitalization (SIZE), the book-to-market ratio (BM), the return in the previous month (REV), the return over the 11 months prior to that month (MOM), a measure of illiquidity (ILLIQ), co-skewness (COSKEW), the idiosyncratic volatility (IVOL), the analyst earnings forecast dispersion (DISP), the market volatility beta (β^{VXO}), annual growth of book assets (I/A), operating profitability (ROE), and lottery demand (MAX). The first row in Table 2 reports the average cross-sectional coefficients on $\beta_{i,t}^{UNC}$ from the univariate and multivariate cross-sectional regressions. In the univariate regression of 12-month-ahead β^{UNC} on lagged β^{UNC}, the coefficient is positive, quite large, and extremely statistically significant. In other words, stocks with high β^{UNC} also tend to exhibit similar features in the following 12 months. When the 13 control variables are added to the regression, the coefficient on 12-month lagged β^{UNC} remains large and significant. We also investigate the persistence of β^{UNC} for two, three, four, and five years ahead. The last four rows in Table 2 show that β^{UNC} remains highly persistent up to five years into the future.

[Table 2 about here.]

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

4.2. Average stock characteristics

In this section, we examine the average characteristics of stocks with low vs. high uncertainty beta based on the Fama and MacBeth (1973) cross-sectional regressions. We present the time-series averages of the slope coefficients from the regressions of the uncertainty beta (β^{UNC}) on the stock-level characteristics and risk factors. Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$\beta_{i,t}^{UNC} = \lambda_{0,t} + \lambda_{1,t} X_{i,t} + \varepsilon_{i,t}, \tag{6}$$

where $\beta_{i,t}^{UNC}$ is the uncertainty beta of stock i in month t and $X_{i,t}$ is a collection of stock-specific variables observable at time t for stock i (market beta, market volatility beta, size, book-to-market, momentum, short-term reversal, illiquidity, co-skewness, idiosyncratic volatility, analyst dispersion, investment, profitability, and MAX). The cross-sectional regressions are run at a monthly frequency from July 1977 to December 2014.

Column 1 of Table 3 shows that the average slope coefficient on $\beta_{i,t}^{MKT}$ is positive and significant, implying that stocks with high uncertainty beta (and low returns/alpha) have high market beta. This result is consistent with Frazzini and Pedersen (2014), providing evidence that stocks with higher $\beta_{i,t}^{MKT}$ generate lower one-month-ahead returns and alpha. Columns 3 and 4 report that the average slope coefficients on SIZE and BM are significantly positive and negative, respectively. This indicates that stocks with low uncertainty beta (and high returns/alpha) are small and value stocks, consistent with the findings of Fama and French (1992, 1993) that small/value stocks generate higher one-month-ahead returns and alpha than big/growth stocks.

[Table 3 about here.]

As presented in Column 7, the average slope on ILLIQ is negative and significant, indicating that stocks with low uncertainty beta (and high returns/alpha) are illiquid. This result is in line with Amihud (2002) and a number of follow-up studies that small and illiquid stocks generate higher one-month-ahead returns and alpha. Columns 8, 9, and 13 show that the average slopes on COSKEW, IVOL, and MAX are positive and significant, indicating that stocks with low uncertainty beta (and high returns/alpha) are negatively skewed, and they have low volatility and low MAX. These results are in agreement with Harvey and Siddique (2000), Ang et al. (2006), and Bali et al. (2011), presenting evidence that stocks with high co-skewness, high volatility, and high MAX generate lower one-month-ahead returns and alpha.

Column 11 shows that the average slope on I/A is positive and highly significant, indicating that stocks with high uncertainty beta (and low returns/alpha) have high growth of book assets. This result is in agreement with Fama and French (2015) and Hou, Xue, and Zhang (2015).[16]

The results in Columns 5 and 6 provide no evidence of a significant relation between the uncertainty beta and past return characteristics (momentum and short-term reversal) since the average slopes on MOM and REV turn out to be statistically insignificant. Similarly, the average slope on β^{VXO} in Column 2 is positive but statistically insignificant, indicating a positive but insignificant relation between β^{UNC} and β^{VXO}. Columns 10 and 12 report that the average slope coefficients on DISP and ROE are, respectively, positive and negative, but they are marginally significant. This indicates that stocks with low uncertainty beta (and high returns/alpha) may have low analyst dispersion and high operating profitability, consistent with the findings of Diether et al. (2002), Fama and French (2015), and Hou, Xue, and Zhang (2015).

As expected, the univariate cross-sectional regressions in Table 3 indicate that stocks with high uncertainty beta are big, growth, liquid, and volatile stocks with high market beta, high skewness, high MAX, and high investment characteristics. Whereas, stocks with low uncertainty beta are small, value, and illiquid stocks with low volatility, low market beta, low skewness, low MAX, and low investment characteristics.[17]

The last column in Table 3 shows that when we include all variables simultaneously, the cross-sectional relations between the uncertainty beta and most of the aforementioned firm characteristics become weaker or insignificant. The only variables that remain significantly connected to the uncertainty beta are ILLIQ,

[16]For further theoretical and empirical evidence on asset growth and investment-based explanation of the cross-sectional differences in expected returns, see Cooper, Gulen, and Schill (2008), Liu, Whited, and Zhang (2009), Li, Livdan, and Zhang (2009), Li and Zhang (2010), Lin and Zhang (2013), and Hou, Xue, and Zhang (2016).

[17]These results suggest that stocks with high (low) uncertainty beta have low (high) average returns, possibly because of the interactions between the uncertainty beta and the aforementioned firm characteristics. We address this potential concern in the following two sections by testing whether the negative relation between the uncertainty beta and the cross-section of expected returns still holds once we control for these variables using bivariate portfolio sorts and Fama-MacBeth regressions.

COSKEW, and I/A, indicating that stocks with low uncertainty beta are illiquid and have low co-skewness and low investment characteristics after controlling for all other variables.

4.3. Bivariate portfolio-level analysis

This section examines the relation between the uncertainty beta and future stock returns after controlling for the well-known cross-sectional return predictors. We perform bivariate portfolio sorts on the uncertainty beta (β^{UNC}) in combination with the market beta (β^{MKT}), the log market capitalization (SIZE), the log book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), the market volatility beta (β^{VXO}), investment (I/A), profitability (ROE), and lottery demand (MAX). Table I of the online appendix reports the equal-weighted and value-weighted portfolio results from these conditional bivariate sorts.

We control for the market beta (β^{MKT}) by first forming decile portfolios ranked based on β^{MKT}. Then, within each β^{MKT} decile, we sort stocks into decile portfolios ranked based on the uncertainty beta (β^{UNC}) so that decile 1 (decile 10) contains stocks with the lowest (highest) β^{UNC} values. The first column of Table I, Panel A, averages equal-weighted portfolio returns across the ten β^{MKT} deciles to produce decile portfolios with dispersion in β^{UNC} but that contain all the stocks' market betas. This procedure creates a set of β^{UNC} portfolios with very similar levels of market beta, and hence these β^{UNC} portfolios control for differences in market beta. The row (High−Low) in the first column of Table I shows that after controlling for the market beta, the seven-factor alpha (α_7) difference between the high-β^{UNC} and low-β^{UNC} equal-weighted portfolios is about -0.38% per month with a Newey-West t-statistic of -3.24. Similar results are obtained from the value-weighted portfolios. The first column in Panel B of Table I shows that after controlling for the market beta, the seven-factor alpha difference between the high-β^{UNC} and low-β^{UNC} value-weighted portfolios is -0.62% per month with a t-statistic of -3.46. Thus, the market beta does not explain the high (low) returns on low uncertainty (high uncertainty) beta stocks.

Panel A of Table I shows that after controlling for the other cross-sectional return predictors (size, book-to-market, momentum, short-term reversal, illiquidity, co-skewness, volatility, analyst dispersion, market volatility beta, investment, profitability, and MAX), the seven-factor alpha differences between the high-β^{UNC} and low-β^{UNC} portfolios are in the range of -0.30% and -0.46% per month and highly significant. As shown in Panel B of Table I, somewhat stronger results are obtained from the value-weighted bivariate portfolios. These findings indicate that the well-known cross-sectional effects cannot explain the significant uncertainty premium.

4.4. Stock level cross-sectional regressions

So far we have tested the significance of the 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 the uncertainty beta and future returns. The portfolio-level analysis also has two potentially significant disadvantages. First, it throws away a large amount of information in the cross-section via aggregation. Second, it is a difficult setting in which to control for multiple effects or factors simultaneously. Consequently, we now examine the cross-sectional relation between the uncertainty beta and expected returns at the stock level using the Fama and MacBeth (1973) regressions.

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

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t} \cdot \beta_{i,t}^{UNC} + \lambda_{2,t} \cdot \beta_{i,t}^{MKT} + \lambda_{3,t} \cdot \beta_{i,t}^{VXO} + \lambda_{4,t} \cdot X_{i,t} + \varepsilon_{i,t+1}, \tag{7}$$

where $R_{i,t+1}$ is the realized excess return on stock i in month $t+1$, $\beta_{i,t}^{UNC}$ is the uncertainty beta of stock i in month t, $\beta_{i,t}^{MKT}$ is the market beta of stock i in month t, $\beta_{i,t}^{VXO}$ is the market volatility beta of stock i in month

t, and $X_{i,t}$ is a collection of stock-specific control variables observable at time t for stock i (size, book-to-market, momentum, short-term reversal, illiquidity, co-skewness, idiosyncratic volatility, analyst dispersion, investment, profitability, and MAX). The cross-sectional regressions are run at a monthly frequency from July 1977 to December 2014.

Panel A of Table 4 reports the time-series averages of the slope coefficients and the Newey-West t-statistics in parentheses. The univariate regression results reported in the first column indicate a negative and statistically significant relation between the uncertainty beta and the cross-section of future stock returns. The average slope from the monthly regressions of realized returns on $\beta_{i,t}^{UNC}$ alone is -0.504 with a Newey-West t-statistic of -3.12.

[Panel A of Table 4 about here.]

To determine the economic significance of this average slope coefficient, we use the average values of the uncertainty betas in the decile portfolios. Table 1 shows that the difference in $\beta_{i,t}^{UNC}$ values between average stocks in the first and tenth deciles is $1.34[= 0.72-(-0.62)]$. If a stock were to move from the first 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 -0.504 on $\beta_{i,t}^{UNC}$ in Panel A of Table 4 represents an economically significant decrease of 0.68% per month, $[-0.504 \times 1.34 = -0.68\%]$, in the average stock's expected return for moving from the first to the tenth decile of $\beta_{i,t}^{UNC}$.

The second column in Panel A of Table 4 controls for the market beta ($\beta_{i,t}^{MKT}$) and the average slope on $\beta_{i,t}^{UNC}$ remains negative and highly significant, whereas the average slope on $\beta_{i,t}^{MKT}$ is economically and statistically insignificant. The third column controls for the market beta ($\beta_{i,t}^{MKT}$) and the market volatility beta ($\beta_{i,t}^{VXO}$) simultaneously. Similar to our findings in Columns 1 and 2, the average slope on $\beta_{i,t}^{UNC}$ is negative and highly significant, whereas the average slope on $\beta_{i,t}^{MKT}$ remains insignificant. Consistent with Ang, Hodrick, Xing, and Zhang (2006), the average slope on $\beta_{i,t}^{VXO}$ is negative but marginally significant. Column 4 includes three additional controls; market capitalization (SIZE), the book-to-market (BM), and momentum (MOM), a cross-sectional regression specification corresponding to the four-factor model of Fama and French (1993) and Carhart (1997). In this specification, the average slope on $\beta_{i,t}^{UNC}$ is negative and highly significant after controlling for $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{VXO}$, SIZE, BM, and MOM.

Column 6 in Table 4, Panel A, controls for all variables simultaneously, including $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{VXO}$, size, book-to-market, momentum, short-term reversal, illiquidity, co-skewness, idiosyncratic volatility, analyst dispersion, investment, profitability, and MAX. In this more general specification, the average slope of $\beta_{i,t}^{UNC}$ remains negative, -0.253, and highly significant with a Newey-West t-statistic of -2.52. The average slope coefficient of -0.253 for $\beta_{i,t}^{UNC}$ implies that a portfolio short-selling stocks with the highest uncertainty beta (stocks in decile 10) and buying stocks with the lowest uncertainty beta (stocks in decile 1) generates a return in the following month of 0.34%, controlling for all else.

Generally, the coefficients of the individual control variables are also consistent with prior empirical evidence. Column 5 shows that the size effect is negative and significant, whereas the value effect is positive but statistically insignificant. Stocks exhibit strong intermediate-term momentum and short-term reversals, whereas the liquidity and co-skewness effects are weak. The average slopes of idiosyncratic volatility and analyst dispersion are negative and significant. Similarly, investment and profitability significantly predict cross-sectional variation in future returns. Column 6 includes MAX as an additional control variable and consistent with the findings of Bali et al. (2011) and Conrad et al. (2014), the idiosyncratic volatility effect disappears and analyst dispersion becomes weaker, while high MAX predicts low future returns. As shown in Column 6, including MAX does not affect the predictive power of the other control variables.

In the last six columns of Panel A in Table 4, we control for the industry effect. For each month, we assign each stock to one of the ten industries based on the four-digit SIC code and replicate our firm-level cross-sectional regressions with and without the large set of firm characteristics and risk factors. A notable point in Columns 7−12 is that controlling for the industry effect has almost no influence on the economic significance of the cross-sectional relation between the uncertainty beta and future stock returns. In all regression specifications, the average slope coefficients on $\beta_{i,t}^{UNC}$ are negative, highly significant, and have magnitudes very similar to those reported in Columns 1−6 in Panel A of Table 4.

Panel B of Table 4 examines the long-term predictive power of the uncertainty beta and shows that the negative relation between β^{UNC} and future stock returns is not just a one-month affair. The multivariate Fama-MacBeth regression results show that controlling for all firm characteristics and risk factors, the average slopes on β^{UNC} remain negative and highly significant when predicting two-month to 11-month-ahead returns. The significance of β^{UNC} disappears when predicting 12-month-ahead returns in multivariate regressions.

[Panel B of Table 4 about here.]

4.5. Nonlinear time-varying behavior of uncertainty premium

We have so far provided an average estimate of the uncertainty premium over the period 1977−2014. In this section, we test if the cross-sectional relation between the uncertainty beta and future stock returns is state-dependent (nonlinear) and changes over time. Specifically, we first investigate whether the uncertainty premium varies over time by plotting the monthly estimates of the uncertainty premia along with an index of economic activity. Then, we test if the uncertainty premium is higher during recessions and periods of high economic uncertainty.

We determine the states of the economy based on the Chicago FED National Activity Index (CFNAI).[18] In Fig. 2, the solid line depicts the three-month moving averages of the monthly slope coefficient of the uncertainty beta (Column 1 in Table 4) and the dashed line depicts the three-month moving averages of the monthly CFNAI index. A notable point in Fig. 2 is that the monthly slope coefficients move very closely with the CFNAI and become negative and large in absolute magnitude when the CFNAI takes negative

[18]The CFNAI is a monthly index designed to assess overall economic activity. It is the weighted average of 85 monthly economic indicators and is constructed to have an average value of zero and a standard deviation of one. Since economic activity tends toward the trend growth rate over time, a positive index reading corresponds to growth above the trend and a negative index reading corresponds to growth below the trend. The Federal Reserve Bank of Chicago defines economic recessions based on the three-month moving average of the CFNAI. An index value below −0.7 indicates the increasing likelihood that a recession has begun.

values indicating economic downturns. We also run a time-series regression of the monthly slope coefficients of β^{UNC} on the CFNAI and find a positive and significant coefficient; 0.43 (t-stat. = 2.69). Since the standard deviation of the CFNAI is about 0.80, this result implies that a decrease in the CFNAI by two standard deviations is associated with an average increase in the uncertainty premium by 0.69% per month.

[**fig.** 2 about here.]

We also examine if the return and alpha spreads in β^{UNC}-sorted portfolios are higher during periods of high economic uncertainty. We determine high vs. low uncertainty periods using the median JLN index and we find that the average return spread between the high-β^{UNC} and low-β^{UNC} portfolios is -0.33% per month (t-stat. = -2.66) during low uncertainty periods (JLN $\leq$ Median), whereas the average return spread is much higher, -0.70% per month (t-stat = -2.93), during high uncertainty periods (JLN $>$ Median). Similar results are obtained from the risk-adjusted returns; the alpha spreads are in the range of -0.30% and -0.33% per month and significant during periods of low uncertainty, whereas the alpha spreads are much higher, in the range of -0.56% and -0.69% per month, and highly significant during periods of high uncertainty.

Overall, these portfolio-level and firm-level regression analyses indicate that the uncertainty premium is higher during recessions and periods of high uncertainty, also validating the nonlinear time-varying nature of the economic uncertainty premia.

These results are also consistent with the theoretical prediction that the uncertainty premium is higher during bad states of the economy. During recessions, economic uncertainty is much higher and the returns of individual stocks with negative uncertainty beta decrease substantially with increases in economic uncertainty. Hence, uncertainty-averse investors would demand extra compensation in the form of higher expected return to hold these stocks with negative β^{UNC}. On the other hand, during economic downturns, the returns of individual stocks with positive uncertainty beta increase with increases in economic uncertainty. Since stocks with positive β^{UNC} would be viewed as relatively safer assets at times of increased economic uncertainty, investors would be willing to pay higher prices for these stocks with positive β^{UNC} and accept lower returns during economic downturns.[19] Finally, these results are also consistent with the limited participation explanation. During recessions and periods of high uncertainty, investors with relatively high aversion against economic uncertainty cease or significantly reduce their participation in a stock. As a result of this limited participation during downturns with high ambiguity, stocks with high uncertainty beta are held only by investors with low aversion against economic uncertainty. Hence, stocks with high uncertainty beta require low uncertainty premium during economic downturns.

4.6. Equity portfolios as test assets

Having demonstrated the important role that the uncertainty beta plays in predicting the cross-sectional variation in individual stock returns, we proceed by generating a factor capturing the returns associated with the uncertainty beta and examining the ability of well-known factors to explain the returns associated with the uncertainty beta. We form an uncertainty beta factor, using the factor-forming technique pioneered by Fama and French (1993). At the end of each month, we sort all stocks into two groups based on market capitalization (size), with the breakpoint dividing the two groups being the median market capitalization of stocks traded on the NYSE. We independently sort all stocks into three groups based on an ascending sort of the uncertainty beta (β^{UNC}) using the NYSE 30th and 70th percentile values of β^{UNC}. The intersections of the two size groups and the three β^{UNC} groups generate six portfolios. The uncertainty beta factor return is taken to be the average return of the two value-weighted high-β^{UNC} portfolios minus the average return of the two value-weighted low-β^{UNC} portfolios. As such, the uncertainty beta factor is designed to capture returns associated with uncertainty premium while maintaining neutrality to market capitalization.

Panel A of Table 5 shows that the value-weighted uncertainty beta factor generates an average monthly return of -0.28% with a Newey-West t-statistic of -2.50. We also estimate the alpha of the uncertainty

[19] This explanation is also consistent with the ICAPM since investors are more concerned about potential declines in their consumption and investment opportunities during economic downturns. Because of elevated fear and uncertainty during downturns of the economy, investors increase their intertemporal hedging demand even further when economic uncertainty is high during recessions and are willing to accept lower expected returns from stocks with positive β^{UNC} for hedging purposes.

beta factor with respect to four different factor models. The alphas remain negative, in the range of -0.31% and -0.33% per month, and statistically significant with t-statistics ranging from -2.46 to -2.82. Similar results are obtained when the uncertainty beta factor is formed based on the 2×3 equal-weighted bivariate portfolios of size and β^{UNC}. As shown in the second row of Table 5, Panel A, the equal-weighted uncertainty beta factor generates an average monthly return of -0.31% with a t-statistic of -3.20. The alphas remain significantly negative, in the range of -0.33% and -0.35% per month, with t-statistics ranging from -2.85 to -3.30. These results indicate that the uncertainty beta factors obtained from the value-weighted and equal-weighted bivariate portfolios of size and β^{UNC} are not explained by the well-known factors.

[Panel A of Table 5 about here.]

Harvey, Liu, and Zhu (2016) indicate that due to data mining and the large amount of research examining the cross-section of expected returns, a five percent level of significance is too low a threshold and argue in favor of using much more stringent requirements for accepting empirical results as evident of true economic phenomena.[20] Specifically, Harvey et al. (2016) emphasize that a new factor needs to clear a much higher hurdle, with a t-statistic greater than 3.0. As shown in Table 4, the Fama-MacBeth cross-sectional regression indicates that the uncertainty beta factor passes this test with a t-statistic of 3.12 (3.31 controlling for industry effects), and dips just below this level controlling also for momentum. Sorting stocks into bivariate portfolios based on their size and uncertainty betas, we find in Table 5 that the equal-weighted uncertainty beta factor passes the high hurdle with a t-statistic of 3.20. Although the value-weighted uncertainty beta factor fails to pass the bar with a t-statistic of 2.50, we provide comprehensive evidence that our results are not driven by small and illiquid stocks and prevail in the cross-section of large, liquid, and S&P500 stocks. More importantly, the pricing power of the uncertainty beta is motivated by the long-established theoretical models based on economic first principles and hence it is subject to a relatively lower hurdle, as pointed out by

[20] Harvey, Liu, and Zhu (2016) investigate 316 documented factors related to cross-sectional pricing effects and find that many of the documented predictors of stock returns capture the same underlying economic phenomena. Thus, the number of orthogonal drivers of expected stock returns is likely to be substantially lower. As Harvey et al. (2016) explain, heterogeneity in testing methods may blur interpretation of their results. Their results are calibrated on the basis of portfolio tests that as Lewellen, Nagel, and Shanken (2010) observe can exaggerate the explanatory power of cross-sectional tests. Our Fama and MacBeth results reported in Table 4 are based on the cross-section of individual stock returns.

Harvey et al. (2016).

We now investigate the predictive power of the uncertainty beta using the cross-section of equity portfolios as test assets. We download from Kenneth French's data library the monthly returns on 49-industry portfolios and 100 portfolios (10×10 bivariate) formed on size and book-to-market, size and investment, and size and profitability (total of 349 portfolios). We should note that individual stocks are sorted into portfolios based on the industry and powerful firm characteristics (size, book-to-market, investment, and profitability) that result in significant cross-sectional differences in the expected returns of these equity portfolios.

To be consistent with our earlier findings from individual stocks, we first estimate the uncertainty beta (β^{UNC}) using Eq. (1) and then form decile portfolios for the same period, July 1977 − December 2014. Panel B of Table 5 presents the magnitude and statistical significance of the alphas from four different factor models. The first four columns of Panel B show that when β^{UNC} is estimated based on the one-month-ahead uncertainty index (UNC^m), the alphas (α_5^1, α_5^2, α_4, and α_7) decrease almost monotonically when moving from the lowest to the highest β^{UNC} decile. The difference in alphas between the high-β^{UNC} and low-β^{UNC} portfolios is $\alpha_5^1 = -0.28\%$ per month (t-stat. $= -2.52$); $\alpha_5^2 = -0.33\%$ per month (t-stat. $= -2.14$) for the five-factor model; $\alpha_4 = -0.32\%$ per month (t-stat. $= -2.11$) for the four-factor model; and $\alpha_7 = -0.30\%$ per month (t-stat. $= -2.30$) for the combined seven-factor model.

[Panel B of Table 5 about here.]

The last eight columns in Panel B of Table 5 present similar evidence from β^{UNC}, estimated with the three-month (UNC^q) and 12-month-ahead (UNC^y) uncertainty indices. Overall, these results indicate that after controlling for the well-known market, size, book-to-market, momentum, liquidity, investment, and profitability factors, the return difference between the high-β^{UNC} and low-β^{UNC} equity portfolios remains negative and statistically significant. Thus, we conclude that the uncertainty beta is priced not only in the cross-section of individual stocks, but in the cross-section of equity portfolios as well.

4.7. Robustness check

We provide a battery of robustness checks in this section. First, we investigate if our results are driven by small, illiquid, and low-priced stocks. As shown in Table II of the online appendix, the uncertainty premium is highly significant in the cross-section of the S&P500 stocks and the 1,000 largest and most liquid stocks in the CRSP universe.[21] Specifically, the seven-factor alpha (α_7) spread between the low-β^{UNC} and high-β^{UNC} portfolios is -0.64% per month (t-stat. = -3.20) for the S&P500 stocks, -0.38% per month (t-stat. = -2.35) for the 1,000 biggest stocks, and -0.43% per month (t-stat. = -2.28) for the 1,000 most liquid stocks. Another notable point in Table II is that the seven-factor alpha of decile 1 (low-β^{UNC} stocks) is significantly positive, whereas the seven-factor alpha of decile 10 (high-β^{UNC} stocks) is statistically weak or insignificant. Hence, we conclude that, in the sample of S&P500, large and liquid stocks, the significantly negative alpha spread between the low-β^{UNC} and high-β^{UNC} stocks is due to the outperformance by low-β^{UNC} stocks.

Second, we test whether alternative measures of the uncertainty beta predict future stock returns. As discussed in Section 3.2, we estimate the uncertainty beta controlling for the market, size, book-to-market, momentum, liquidity, investment, and profitability factors simultaneously based on Eq. (1). In this section, we generate two alternative measures of β^{UNC} based on the following specifications:

$$
\begin{aligned}
Model\ 1: R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{SMB} \cdot SMB_t + \beta_{i,t}^{HML} \cdot HML_t + \beta_{i,t}^{UMD} \cdot UMD_t + \beta_{i,t}^{PS} \cdot PS_t + \varepsilon_{i,t}, \\
Model\ 2: R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC} \cdot UNC_t + \beta_{i,t}^{MKT} \cdot MKT_t + \beta_{i,t}^{SMB} \cdot SMB_t + \beta_{i,t}^{HML} \cdot HML_t + \beta_{i,t}^{R_{I/A}} \cdot R_{I/A,t} + \beta_{i,t}^{R_{ROE}} \cdot R_{ROE,t} + \varepsilon_{i,t}.
\end{aligned}
$$

Once we estimate β^{UNC} from these two alternative specifications, we form the equal-weighted and value-weighted portfolios and compute the five-factor and seven-factor alphas (α_5^1, α_5^2, and α_7) of each decile.

[21] The largest 1,000 stocks in the CRSP universe are determined based on their market capitalization. The most liquid 1,000 stocks in the CRSP universe are determined based on the Amihud (2002) illiquidity measure.

Table 6 shows that when β^{UNC} is estimated with Model 1, α_5^1 and α_7 spreads between the low-β^{UNC} and high-β^{UNC} portfolios are, respectively, -0.57% per month (t-stat. = -4.24) and -0.32% per month (t-stat. = -2.30) for the equal-weighted portfolios and -0.54% per month (t-stat. = -2.24) and -0.56% per month (t-stat. = -2.10) for the value-weighted portfolios. When β^{UNC} is estimated with Model 2, α_5^2 and α_7 spreads between the low-β^{UNC} and high-β^{UNC} portfolios are, respectively, -0.47% per month (t-stat. = -2.75) and -0.41% per month (t-stat. = -2.80) for the equal-weighted portfolios and -0.61% per month (t-stat. = -2.05) and -0.55% per month (t-stat. = -2.22) for the value-weighted portfolios. These results along with those reported in Table 1 indicate that alternative measures of the uncertainty beta remain a significant predictor of future stock returns.

[Table 6 about here.]

Third, we examine if our findings are sensitive to alternative measures of the uncertainty index. We have so far presented results from the one-month-ahead uncertainty index of Jurado, Ludvigson, and Ng (2015) who construct indices of different time periods ranging from one month to a year. As shown in Fig. 1 and discussed in Section 3.1, the one-month, three-month, and 12-month-ahead economic uncertainty indices are highly correlated. However, there might be periods when things are very uncertain and periods when the economy seems relatively predictable. In that case, the market price of uncertainty might be very low for long periods and then very high. Hence, we estimate β^{UNC} by replacing the one-month-ahead uncertainty index with the three-month and 12-month-ahead uncertainty indices and replicate Table 1.

The results from these two alternative measures of the uncertainty beta are reported in Table III of the online appendix. A notable point in Table III is that when β^{UNC} is estimated with the three-month (UNC^q) and 12-month-ahead (UNC^y) uncertainty indices, the return and alpha spreads between the low-β^{UNC} and high-β^{UNC} portfolios are negative and highly significant for both equal-weighted and value-weighted portfolios. Another notable point is that the uncertainty premia reported in Table III (where β^{UNC} is estimated with UNC^q and UNC^y) are in most cases larger in magnitude and statistical significance than those reported in Table 1 (where β^{UNC} is estimated with UNC^m).

Finally, we examine the significance of uncertainty premium for stocks in each of the ten industries determined based on the four-digit SIC code; Non-durable, Durable, Manufacturing, Energy, Hi-Tech, Telecom, Shops, Health, Utilities, and Other. The seven-factor alpha (α_7) spreads presented in Table 7 provide evidence of a significantly negative link between the uncertainty beta and risk-adjusted stock returns for eight industries out of ten.[22] More specifically, the uncertainty premium is statistically significant and economically largest for stocks in Durable, Energy, Hi-Tech, Telecom, Shops, and Other industry groups (in the range of -0.35% and -1.62% per month with t-statistics ranging from -2.31 to -3.25). The uncertainty premium is found to be negative, but statistically weak for stocks in Health and Non-durable industry groups; -0.37% per month (t-stat. = -1.77) and -0.29% per month (t-stat. = -1.73).[23]

[Table 7 about here.]

5. Conclusion

This paper investigates the role of economic uncertainty in the cross-sectional pricing of individual stocks and equity portfolios. Economic uncertainty is quantified with the one-, three-, and 12-month-ahead uncertainty indices of JLN (2015), defined as the conditional volatility of the unforecastable component of a large number of economic indicators. We estimate stock exposure to the uncertainty index and find that the resulting uncertainty betas predict a significant proportion of the cross-sectional dispersion 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 an annualized risk-adjusted return of 6%. We find that this uncertainty premium is driven by the outperformance by stocks with negative

[22] Since there is not a large number of stocks in all industry groups, we present results from quintile (instead of decile) portfolios in Table 7.

[23] Our results from individual stocks in Durable and Non-durable industries are consistent with Gomes, Kogan, and Yogo (2009) who find that the demand for Durable goods is more cyclical than that for Non-durable goods, and hence the stock returns of Durable-good producers are exposed to higher systematic risk. Similar to our findings from stocks in Durable industry, their results also indicate a significant countercyclical risk premium on the Durable-good portfolio.

uncertainty beta and the underperformance by stocks with positive uncertainty beta. Consistent with theoretical predictions, these results indicate that uncertainty-averse investors demand extra compensation to hold stocks with negative uncertainty beta and they are willing to pay high prices for stocks with positive uncertainty beta.

Bivariate portfolio-level analyses and stock-level cross-sectional regressions that control for well-known pricing effects, including size, book-to-market, momentum, short-term reversal, liquidity, co-skewness, idiosyncratic volatility, dispersion in analysts' earnings estimates, market volatility beta, investment, profitability, and lottery demand generate similar results. After controlling for each of these variables one-by-one and then controlling for all variables simultaneously, the results provide evidence of a significantly negative link between the uncertainty beta and future stock returns. Moreover, the predictive power of the uncertainty beta is not just a one-month affair. It predicts cross-sectional variation in stock returns 11 months into the future. Our main findings also hold for different stock samples, including the S&P 500 stocks, large and liquid stocks. In line with the well-celebrated theoretical models, the uncertainty premium is found to be significantly higher during economic downturns and periods of high economic uncertainty, compared to non-recessionary and relatively tranquil periods, indicating a nonlinear time-varying nature of the uncertainty premium.

To the extent that the measures of economic uncertainty developed by JLN (2015) closely follow large falls and rises in financial and economic activity, this broad index of uncertainty provides an accurate characterization of the time-series variation in consumption and investment opportunities. The fact that the stock exposure to economic uncertainty successfully predicts the cross-sectional variation in future stock returns also suggests that the uncertainty beta is a good proxy for future consumption-investment risk in the conditional asset pricing model with time-varying uncertainty.

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Table 1

Univariate portfolios of stocks sorted by uncertainty beta

For each month, decile portfolios are formed by sorting individual stocks based on their uncertainty betas (β^{UNC}), where decile 1 (10) contains stocks with the lowest (highest) β^{UNC} during the previous month. The first column reports the average uncertainty beta of individual stocks in each β^{UNC} decile and the remaining columns present the average excess returns (RET−RF) and alphas (α_5^1, α_5^2, α_4, and α_7) for the equal-weighted and value-weighted portfolios separately. α_5^1 is the alpha relative to the market, size, book-to-market, momentum, and liquidity factors; α_5^2 is the alpha relative to the market, size, book-to-market, investment, and profitability factors; α_4 is the alpha relative to the market, size, investment, and profitability factors; and α_7 is the alpha relative to the market, size, book-to-market, momentum, liquidity, investment, and profitability factors. The last row presents the alpha differences between decile 1 (Low) and decile 10 (High). Newey-West adjusted t-statistics are given in parentheses. The sample period is July 1977−December 2014.

			Equal-weighted					Value-weighted			
Decile	β^{UNC}	RET−RF	α_5^1	α_5^2	α_4	α_7	RET−RF	α_5^1	α_5^2	α_4	α_7
Low	-0.62	1.13	0.28	0.34	0.35	0.31	0.93	0.31	0.50	0.49	0.47
		(3.60)	(2.85)	(2.77)	(2.85)	(3.09)	(2.87)	(1.69)	(2.14)	(2.12)	(2.27)
2	-0.29	1.03	0.24	0.20	0.22	0.17	0.73	0.09	0.08	0.10	0.05
		(4.06)	(3.38)	(2.29)	(2.30)	(2.59)	(2.74)	(0.62)	(0.64)	(0.75)	(0.37)
3	-0.18	1.01	0.24	0.17	0.19	0.14	0.72	0.16	0.13	0.14	0.11
		(4.29)	(3.71)	(2.10)	(2.04)	(2.15)	(3.08)	(1.83)	(1.30)	(1.38)	(1.19)
4	-0.09	0.92	0.17	0.07	0.09	0.04	0.75	0.17	0.09	0.10	0.07
		(4.08)	(2.84)	(0.90)	(0.97)	(0.70)	(3.47)	(1.73)	(0.94)	(1.10)	(0.66)
5	-0.03	0.88	0.15	0.04	0.06	0.02	0.55	-0.03	-0.14	-0.14	-0.16
		(4.05)	(2.72)	(0.59)	(0.72)	(0.29)	(2.62)	(-0.33)	(-1.41)	(-1.32)	(-1.65)
6	0.04	0.88	0.15	0.06	0.08	0.04	0.68	0.07	0.03	0.04	0.03
		(4.07)	(3.34)	(1.04)	(1.05)	(0.85)	(3.28)	(1.12)	(0.37)	(0.47)	(0.33)
7	0.11	0.88	0.11	0.00	0.03	-0.01	0.68	0.03	-0.11	-0.11	-0.11
		(3.95)	(1.75)	(0.05)	(0.28)	(-0.18)	(3.32)	(0.50)	(-1.76)	(-1.67)	(-1.67)
8	0.19	0.81	0.02	-0.06	-0.04	-0.07	0.58	-0.10	-0.16	-0.15	-0.15
		(3.56)	(0.35)	(-0.89)	(-0.51)	(-1.11)	(2.69)	(-1.23)	(-1.97)	(-1.90)	(-1.96)
9	0.32	0.78	-0.04	-0.08	-0.07	-0.08	0.62	-0.08	-0.13	-0.13	-0.12
		(3.11)	(-0.63)	(-0.94)	(-0.78)	(-1.04)	(2.57)	(-1.03)	(-1.58)	(-1.53)	(-1.54)
High	0.72	0.62	-0.28	-0.13	-0.15	-0.11	0.53	-0.25	-0.17	-0.19	-0.15
		(2.06)	(-3.83)	(-1.31)	(-1.49)	(-1.06)	(1.72)	(-2.22)	(-1.33)	(-1.46)	(-1.21)
High−Low		-0.51	-0.56	-0.47	-0.50	-0.42	-0.40	-0.56	-0.67	-0.69	-0.62
		(-3.81)	(-4.55)	(-2.93)	(-3.09)	(-3.04)	(-1.93)	(-2.45)	(-2.35)	(-2.40)	(-2.56)

Table 2
Persistence of uncertainty beta
This table examines the persistence of β^{UNC} by running firm-level cross-sectional regressions of β^{UNC} on lagged β^{UNC} and lagged cross-sectional predictors. The first column reports the average slope coefficients on β^{UNC} from the univariate Fama-MacBeth regressions of one-year- to five-year-ahead β^{UNC} on lagged β^{UNC}. The last column presents the average slope coefficients on β^{UNC} from multivariate Fama-MacBeth regressions after controlling for lagged variables: the market beta (β^{MKT}), market capitalization measured in millions of dollars (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), market volatility beta (β^{VXO}), annual growth of book assets (I/A), operating profitability (ROE), and lottery demand (MAX). Newey-West adjusted t-statistics are given in parentheses. The sample period is July 1977−December 2014.

n-year-ahead β^{UNC}	Univariate predictive regressions	Controlling for lagged variables
n=1	0.659	0.637
	(24.12)	(20.29)
n=2	0.406	0.363
	(14.39)	(11.30)
n=3	0.225	0.192
	(8.08)	(6.39)
n=4	0.110	0.081
	(4.47)	(5.19)
n=5	0.023	0.015
	(3.74)	(2.60)

Table 3

Average stock characteristics

This table reports the time-series averages of the slope coefficients from the regressions of the uncertainty beta (β^{UNC}) on the stock-level characteristics and risk factors. Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof:

$$\beta_{i,t}^{UNC} = \lambda_{0,t} + \lambda_{1,t} X_{i,t} + \varepsilon_{i,t},$$

where $\beta_{i,t}^{UNC}$ is the uncertainty beta of stock i in month t and $X_{i,t}$ is a collection of stock-specific variables observable at time t for stock i: the market beta (β^{MKT}), market capitalization measured in millions of dollars (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), market volatility beta (β^{VXO}), annual growth of book assets (I/A), operating profitability (ROE), and lottery demand (MAX). The cross-sectional regressions are run at a monthly frequency from July 1977 to December 2014. Newey-West adjusted t-statistics are given in parentheses.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Intercept	-0.008	0.019	-0.029	0.005	0.025	0.016	0.022	0.027	0.001	0.015	0.014	0.019	-0.003	0.019
	(-1.09)	(3.68)	(-2.79)	(1.18)	(4.02)	(3.78)	(4.91)	(5.54)	(0.16)	(3.65)	(3.33)	(4.58)	(-0.29)	(1.40)
β^{MKT}	0.020													0.012
	(3.61)													(1.69)
β^{VXO}		0.184												-0.018
		(1.55)												(-0.36)
SIZE			0.008											-0.002
			(4.87)											(-1.33)
BM				-0.023										-0.007
				(-4.33)										(-1.05)
MOM					0.000									0.000
					(-0.76)									(-0.23)
REV						0.000								0.000
						(-0.19)								(0.01)
ILLIQ							-0.003							-0.003
							(-3.81)							(-3.58)
COSKEW								0.183						0.175
								(5.43)						(5.25)
IVOL									0.006					0.002
									(2.41)					(0.92)
DISP										0.010				-0.002
										(1.81)				(-0.86)
I/A											0.022			0.019
											(2.59)			(2.35)
ROE												-0.026		-0.010
												(-1.72)		(-0.99)
MAX													0.004	0.003
													(1.93)	(1.30)

Table 4

Fama-MacBeth cross-sectional regressions

This table reports the time-series averages of the slope coefficients obtained from regressing monthly excess returns (in percentage) on the uncertainty beta (β^{UNC}) and a set of lagged predictive variables using the Fama-MacBeth methodology. In Panel A, the control variables are the market beta (β^{MKT}), market volatility beta (β^{VXO}), market capitalization measured in millions of dollars (SIZE), book-to-market ratio (BM), momentum (MOM), short-term reversal (REV), illiquidity (ILLIQ), co-skewness (COSKEW), idiosyncratic volatility (IVOL), analyst dispersion (DISP), annual growth of book assets (I/A), operating profitability (ROE), and lottery demand (MAX). In Panel A, entries under "With control for industry effect" present the same set of regression results controlling for the industry effect. Panel B presents the results from regressing monthly excess returns in two- to 12-months ahead against β^{UNC} after controlling for all other predictive variables. Newey-West adjusted t-statistics are reported in parentheses. The sample period is July 1977−December 2014.

Panel A: Monthly Fama-MacBeth regressions

	Without controlling for industry effect						With controlling for industry effect					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept	0.912	0.821	0.744	0.642	1.392	1.447	0.906	0.813	0.707	0.584	1.371	1.430
	(3.81)	(4.44)	(3.44)	(2.19)	(4.74)	(5.08)	(3.67)	(3.77)	(2.79)	(1.88)	(4.23)	(4.55)
β^{UNC}	-0.504	-0.458	-0.494	-0.333	-0.280	-0.253	-0.487	-0.449	-0.455	-0.317	-0.272	-0.254
	(-3.12)	(-3.22)	(-3.40)	(-2.92)	(-2.76)	(-2.52)	(-3.31)	(-3.33)	(-3.22)	(-2.95)	(-2.90)	(-2.73)
β^{MKT}		0.071	0.102	0.105	0.178	0.205		0.083	0.096	0.090	0.144	0.160
		(0.54)	(0.70)	(0.82)	(1.44)	(1.71)		(0.76)	(0.79)	(0.83)	(1.37)	(1.58)
β^{VXO}			-5.862	-7.107	-4.717	-3.921			-4.074	-5.560	-3.438	-2.927
			(-1.77)	(-1.95)	(-1.56)	(-1.53)			(-1.32)	(-1.88)	(-1.25)	(-1.27)
SIZE				0.004	-0.068	-0.065				0.009	-0.062	-0.060
				(0.16)	(-2.38)	(-2.26)				(0.35)	(-2.26)	(-2.18)
BM				0.126	0.099	0.097				0.169	0.163	0.160
				(1.78)	(1.41)	(1.40)				(2.77)	(2.56)	(2.55)
MOM				0.006	0.005	0.005				0.005	0.004	0.005
				(3.91)	(3.58)	(3.67)				(3.73)	(3.16)	(3.27)
REV					-0.021	-0.014					-0.026	-0.020
					(-5.34)	(-2.59)					(-6.97)	(-3.87)
ILLIQ					-0.024	-0.024					-0.022	-0.022
					(-1.78)	(-1.67)					(-1.70)	(-1.62)
COSKEW					-0.063	-0.042					0.065	0.076
					(-0.42)	(-0.29)					(0.52)	(0.63)
IVOL					-0.144	0.002					-0.150	-0.026
					(-3.94)	(0.03)					(-4.58)	(-0.51)
DISP					-0.065	-0.060					-0.067	-0.062
					(-2.05)	(-1.89)					(-2.26)	(-2.11)
I/A					-0.258	-0.250					-0.253	-0.246
					(-4.72)	(-4.50)					(-4.69)	(-4.50)
ROE					0.750	0.724					0.803	0.778
					(3.03)	(2.95)					(3.38)	(3.32)
MAX						-0.126						-0.109
						(-2.19)						(-2.14)
Obs	2,709	2,709	2,681	2,569	2,310	2,310	2,709	2,709	2,681	2,569	2,310	2,310
Adj. R^2	0.32%	2.51%	2.64%	4.32%	5.76%	6.23%	0.31%	2.50%	2.62%	4.31%	5.75%	6.21%

Table 4 – continued

Panel B: Long-term predictive power of uncertainty beta

	n=2	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10	n=11	n=12
Intercept	1.278	1.044	1.067	0.984	0.903	0.841	0.952	0.722	0.730	0.806	0.785
	(4.63)	(3.94)	(3.83)	(3.48)	(3.25)	(2.83)	(3.34)	(2.45)	(2.64)	(2.77)	(2.64)
β^{UNC}	-0.196	-0.220	-0.174	-0.201	-0.266	-0.289	-0.336	-0.314	-0.269	-0.220	-0.172
	(-2.41)	(-2.62)	(-2.09)	(-2.63)	(-3.60)	(-3.55)	(-3.95)	(-3.93)	(-3.23)	(-2.39)	(-1.78)
β^{MKT}	0.096	0.108	0.093	0.059	0.068	0.115	0.089	0.086	0.098	0.113	0.119
	(0.84)	(0.97)	(0.91)	(0.61)	(0.67)	(1.13)	(0.88)	(0.83)	(0.98)	(1.15)	(1.20)
β^{VXO}	5.492	-8.033	-1.438	4.628	7.141	-5.180	-0.381	-0.080	3.609	2.297	-2.517
	(1.20)	(-1.37)	(-0.92)	(1.14)	(1.27)	(-1.53)	(-0.09)	(-0.04)	(1.43)	(1.58)	(-0.99)
SIZE	-0.052	-0.028	-0.028	-0.020	-0.009	-0.004	-0.018	0.008	0.012	0.005	0.007
	(-1.93)	(-1.04)	(-1.03)	(-0.71)	(-0.33)	(-0.14)	(-0.63)	(0.26)	(0.42)	(0.17)	(0.22)
BM	0.087	0.113	0.095	0.088	0.098	0.105	0.054	0.074	0.093	0.080	0.089
	(1.27)	(1.72)	(1.44)	(1.35)	(1.45)	(1.53)	(0.78)	(1.03)	(1.28)	(1.09)	(1.23)
MOM	0.004	0.002	0.003	0.001	0.000	-0.001	0.000	-0.001	0.000	-0.002	-0.002
	(2.81)	(1.88)	(2.43)	(0.86)	(0.11)	(-0.60)	(-0.27)	(-1.02)	(-0.45)	(-1.88)	(-2.01)
REV	0.008	0.019	0.007	0.006	0.016	0.008	0.007	0.009	0.004	0.013	0.012
	(1.50)	(3.87)	(1.68)	(1.36)	(3.31)	(1.67)	(1.37)	(2.24)	(0.77)	(2.51)	(2.73)
ILLIQ	0.012	0.009	0.019	0.018	0.012	0.005	0.013	0.010	0.006	0.004	0.001
	(0.87)	(0.80)	(1.64)	(1.57)	(1.24)	(0.40)	(1.43)	(0.89)	(0.44)	(0.40)	(0.07)
COSKEW	0.050	-0.039	0.018	0.130	0.186	0.132	0.171	0.171	0.172	0.098	0.104
	(0.37)	(-0.29)	(0.14)	(1.03)	(1.30)	(1.01)	(1.25)	(1.25)	(1.38)	(0.79)	(0.81)
IVOL	-0.108	-0.035	-0.028	-0.154	-0.007	-0.027	-0.065	-0.007	0.013	-0.049	0.039
	(-2.19)	(-0.70)	(-0.57)	(-2.95)	(-0.16)	(-0.45)	(-1.25)	(-0.14)	(0.23)	(-0.97)	(0.75)
DISP	-0.042	-0.054	-0.006	-0.003	0.037	-0.025	0.028	0.005	0.079	0.070	0.016
	(-1.57)	(-1.66)	(-0.19)	(-0.10)	(1.04)	(-0.83)	(0.83)	(0.17)	(2.29)	(1.63)	(0.47)
I/A	-0.218	-0.201	-0.160	-0.190	-0.152	-0.204	-0.175	-0.143	-0.145	-0.186	-0.157
	(-4.23)	(-4.03)	(-3.21)	(-3.69)	(-2.90)	(-4.13)	(-3.80)	(-3.32)	(-3.26)	(-4.01)	(-3.29)
ROE	0.576	0.696	0.787	0.593	0.499	0.509	0.523	0.478	0.293	0.506	0.409
	(2.31)	(2.79)	(3.35)	(2.84)	(3.23)	(2.94)	(2.38)	(2.06)	(1.62)	(3.12)	(2.39)
MAX	-0.039	-0.060	-0.068	0.044	-0.054	0.005	0.004	-0.001	-0.019	0.010	-0.048
	(-0.74)	(-1.19)	(-1.37)	(0.82)	(-1.12)	(0.09)	(0.09)	(-0.02)	(-0.38)	(0.21)	(-0.94)
Obs	2,308	2,297	2,286	2,275	2,265	2,254	2,243	2,233	2,222	2,211	2,200
Adj. R^2	5.78%	5.59%	5.47%	5.24%	5.13%	5.04%	4.93%	4.79%	4.75%	4.59%	4.51%

Table 5

Equity portfolios as test assets

In Panel A, at the end of each month, we independently sort all stocks into two groups based on market capitalization (size) using the median NYSE size breakpoint and three uncertainty beta (β^{UNC}) groups using the NYSE 30th and 70th percentile values of β^{UNC}. The intersections of the two size groups and the three β^{UNC} groups generate six portfolios. The value-weighted return (the first row of Panel A) of the uncertainty beta factor is taken to be the average return of the two value-weighted high-β^{UNC} portfolios minus the average return of the two value-weighted low-β^{UNC} portfolios. The equal-weighted return (the second row of Panel A) of the uncertainty beta factor is measured by the average return of the two equal-weighted high-β^{UNC} portfolios minus the average return of the two equal-weighted low-β^{UNC} portfolios. Panel A reports the average monthly returns of the uncertainty beta factor and the alphas (α_5^1, α_5^2, α_4, and α_7). α_5^1 is the alpha relative to the market, size, book-to-market, momentum, and liquidity factors; α_5^2 is the alpha relative to the market, size, book-to-market, investment, and profitability factors; α_4 is the alpha relative to the market, size, investment, and profitability factors; and α_7 is the alpha relative to the market, size, book-to-market, momentum, liquidity, investment, and profitability factors. In Panel B, for each of the 49-industry portfolios and 100 portfolios (10×10 bivariate) formed on size and book-to-market, size and investment, and size and profitability (total of 349 portfolios), we first estimate the uncertainty beta (β^{UNC}) using Eq. (1). We then form decile portfolios for the period July 1977 – December 2014. Panel B presents the magnitude and statistical significance of the alphas (α_5^1, α_5^2, α_4, and α_7). Newey-West adjusted t-statistics are given in parentheses.

Panel A:Average monthly returns and alphas of the uncertainty beta factors

	Average return	α_5^1	α_5^2	α_4	α_7
VW β^{UNC} factor	-0.28%	-0.33%	-0.31%	-0.31%	-0.32%
	(-2.50)	(-2.62)	(-2.79)	(-2.82)	(-2.46)
EW β^{UNC} factor	-0.31%	-0.35%	-0.33%	-0.33%	-0.34%
	(-3.20)	(-2.97)	(-3.27)	(-3.30)	(-2.85)

Table 5 – continued

Panel B: Univariate sorts of equity portfolios by β^{UNC}

	one-month-ahead uncertainty index				three-month-ahead uncertainty index				12-month-ahead uncertainty index			
Decile	α_5^1	α_5^2	α_4	α_7	α_5^1	α_5^2	α_4	α_7	α_5^1	α_5^2	α_4	α_7
Low	0.25	0.33	0.34	0.28	0.25	0.34	0.35	0.30	0.22	0.32	0.33	0.29
	(2.60)	(2.12)	(2.19)	(2.59)	(2.41)	(2.24)	(2.31)	(2.67)	(2.07)	(2.18)	(2.25)	(2.50)
2	0.22	0.23	0.25	0.20	0.24	0.26	0.28	0.22	0.24	0.26	0.27	0.22
	(2.82)	(1.81)	(1.87)	(2.26)	(2.91)	(1.97)	(2.02)	(2.43)	(2.62)	(1.76)	(1.82)	(2.11)
3	0.19	0.20	0.21	0.16	0.19	0.19	0.21	0.16	0.20	0.20	0.22	0.17
	(2.60)	(1.56)	(1.63)	(1.91)	(2.65)	(1.58)	(1.66)	(1.94)	(2.98)	(1.71)	(1.78)	(2.13)
4	0.17	0.18	0.19	0.14	0.15	0.16	0.17	0.12	0.12	0.13	0.15	0.09
	(2.26)	(1.54)	(1.63)	(1.78)	(2.38)	(1.39)	(1.47)	(1.60)	(1.91)	(1.20)	(1.28)	(1.30)
5	0.13	0.12	0.13	0.09	0.13	0.12	0.13	0.08	0.13	0.11	0.13	0.07
	(2.74)	(1.33)	(1.43)	(1.59)	(2.40)	(1.33)	(1.42)	(1.52)	(2.45)	(1.26)	(1.33)	(1.43)
6	0.11	0.11	0.12	0.08	0.11	0.09	0.11	0.06	0.12	0.11	0.12	0.07
	(2.49)	(1.49)	(1.55)	(1.65)	(2.38)	(1.19)	(1.25)	(1.15)	(2.60)	(1.47)	(1.52)	(1.60)
7	0.10	0.07	0.09	0.04	0.09	0.07	0.09	0.04	0.14	0.09	0.11	0.06
	(2.04)	(0.91)	(1.01)	(0.78)	(1.92)	(0.80)	(0.92)	(0.69)	(2.83)	(1.08)	(1.18)	(1.18)
8	0.11	0.08	0.10	0.05	0.12	0.08	0.10	0.05	0.09	0.06	0.08	0.03
	(2.19)	(1.04)	(1.12)	(1.02)	(2.32)	(0.94)	(1.04)	(0.84)	(1.77)	(0.69)	(0.81)	(0.48)
9	0.01	0.00	0.01	-0.03	0.01	-0.01	0.01	-0.04	0.03	0.01	0.02	-0.02
	(0.18)	(-0.06)	(0.16)	(-0.51)	(0.15)	(-0.19)	(0.07)	(-0.74)	(0.53)	(0.07)	(0.26)	(-0.42)
High	-0.03	0.00	0.02	-0.02	-0.02	0.01	0.03	0.00	-0.01	0.02	0.03	0.00
	(-0.43)	(0.03)	(0.22)	(-0.25)	(-0.27)	(0.20)	(0.37)	(-0.07)	(-0.12)	(0.27)	(0.46)	(0.00)
High−Low	-0.28	-0.33	-0.32	-0.30	-0.27	-0.32	-0.32	-0.30	-0.23	-0.31	-0.30	-0.29
	(-2.52)	(-2.14)	(-2.11)	(-2.30)	(-2.32)	(-2.12)	(-2.09)	(-2.27)	(-1.95)	(-1.98)	(-1.96)	(-2.09)

Table 6

Univariate portfolios of stocks sorted by alternative measures of uncertainty beta

For each month, stocks are sorted into decile portfolios based on their uncertainty betas β^{UNC}, estimated from alternative models:

$$\begin{aligned} Model\ 1: R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC}\cdot UNC_t + \beta_{i,t}^{MKT}\cdot MKT_t + \beta_{i,t}^{SMB}\cdot SMB_t + \beta_{i,t}^{HML}\cdot HML_t + \beta_{i,t}^{UMD}\cdot UMD_t + \beta_{i,t}^{PS}\cdot PS_t + \varepsilon_{i,t}, \\ Model\ 2: R_{i,t} &= \alpha_{i,t} + \beta_{i,t}^{UNC}\cdot UNC_t + \beta_{i,t}^{MKT}\cdot MKT_t + \beta_{i,t}^{SMB}\cdot SMB_t + \beta_{i,t}^{HML}\cdot HML_t + \beta_{i,t}^{R_{I/A}}\cdot R_{I/A,t} + \beta_{i,t}^{R_{ROE}}\cdot R_{ROE,t} + \varepsilon_{i,t}, \end{aligned}$$

where MKT, SMB, HML, UMD, PS, $R_{I/A}$, and R_{ROE} are are the market, size, book-to-market, momentum, liquidity, investment, and profitability factors. This table reports the alphas (α_5^1, α_5^2, and α_7) for the equal-weighted and value-weighted portfolios separately. α_5^1 is the alpha relative to the market, size, book-to-market, momentum, and liquidity factors; α_5^2 is the alpha relative to the market, size, book-to-market, investment, and profitability factors; and α_7 is the alpha relative to the market, size, book-to-market, momentum, liquidity, investment, and profitability factors. The last row presents the alpha differences between decile 1 (Low) and decile 10 (High). Newey-West adjusted t-statistics are given in parentheses. The sample period is July 1977−December 2014.

	Equal-weighted				Value-weighted			
	Model (1)		Model (2)		Model (1)		Model (2)	
Decile	α_5^1	α_7	α_5^2	α_7	α_5^1	α_7	α_5^2	α_7
Low	0.29	0.27	0.34	0.31	0.31	0.50	0.45	0.41
	(2.85)	(2.61)	(2.70)	(2.95)	(1.65)	(2.30)	(1.84)	(1.97)
2	0.18	0.09	0.24	0.20	0.16	0.09	0.15	0.11
	(2.31)	(1.10)	(2.25)	(2.60)	(0.87)	(0.55)	(0.86)	(0.71)
3	0.26	0.10	0.13	0.11	0.18	0.12	0.08	0.05
	(3.82)	(1.53)	(1.72)	(1.53)	(1.59)	(0.96)	(0.77)	(0.51)
4	0.19	0.07	0.06	0.03	0.06	-0.03	0.09	0.07
	(3.06)	(1.02)	(0.70)	(0.43)	(0.65)	(-0.38)	(1.00)	(0.76)
5	0.20	0.08	0.05	0.03	0.11	0.03	-0.03	-0.04
	(3.66)	(1.67)	(0.68)	(0.50)	(1.68)	(0.35)	(-0.54)	(-0.71)
6	0.10	-0.02	0.03	0.01	0.02	-0.09	-0.04	-0.04
	(1.79)	(-0.39)	(0.49)	(0.18)	(0.38)	(-1.27)	(-0.62)	(-0.67)
7	0.06	-0.06	0.00	-0.02	-0.07	-0.23	-0.13	-0.13
	(1.01)	(-1.00)	(-0.04)	(-0.26)	(-0.99)	(-2.97)	(-1.89)	(-1.83)
8	0.07	-0.01	-0.04	-0.05	0.01	-0.01	-0.12	-0.10
	(1.23)	(-0.08)	(-0.53)	(-0.76)	(0.19)	(-0.14)	(-1.38)	(-1.37)
9	-0.01	-0.02	-0.07	-0.07	-0.11	-0.13	-0.12	-0.12
	(-0.22)	(-0.30)	(-0.96)	(-0.98)	(-1.34)	(-1.37)	(-1.19)	(-1.30)
High	-0.29	-0.05	-0.12	-0.10	-0.23	-0.05	-0.16	-0.14
	(-3.86)	(-0.60)	(-1.26)	(-1.01)	(-1.89)	(-0.44)	(-1.17)	(-1.04)
High−Low	-0.57	-0.32	-0.47	-0.41	-0.54	-0.56	-0.61	-0.55
	(-4.24)	(-2.30)	(-2.75)	(-2.80)	(-2.24)	(-2.10)	(-2.05)	(-2.22)

Table 7
Uncertainty premium of stocks in ten industry Groups
We divide stocks into ten industries determined based on the four-digit SIC code: Non-durable, Durable, Manufacturing, Energy, Hi-Tech, Telecom, Shops, Health, Utilities, and Other. For each month, stocks in each of the ten industry groups are sorted into quintile portfolios based on their uncertainty betas (β^{UNC}), where quintile 1 (5) contains stocks with the lowest (highest) β^{UNC} during the previous month. This table reports seven-factor alphas (in percentage) relative to the market, size, book-to-market, momentum, liquidity, investment and profitability factors (α_7) for each uncertainty beta decile. The last row presents the differences in α_7 between Decile 1 (Low) and Decile 10 (High). Newey-West adjusted t-statistics are given in parentheses. The sample period is July 1977−December 2014.

Decile	Non-durable	Durable	Manufacturing	Energy	Hi-tech	Telecom	Shops	Health	Utilities	Other
Low	-0.02	0.01	0.06	-0.02	0.63	1.24	0.24	0.55	0.39	0.04
	(-0.14)	(0.04)	(0.49)	(-0.05)	(4.00)	(4.17)	(1.66)	(2.64)	(1.41)	(0.33)
2	-0.08	-0.11	-0.05	0.15	0.24	0.41	0.13	0.46	0.18	0.04
	(-0.68)	(-0.73)	(-0.48)	(0.48)	(1.84)	(1.89)	(1.07)	(2.35)	(1.40)	(0.43)
3	-0.14	-0.15	-0.02	-0.12	0.30	0.42	0.06	0.32	0.11	-0.03
	(-1.11)	(-0.99)	(-0.20)	(-0.40)	(2.07)	(1.82)	(0.51)	(1.88)	(0.86)	(-0.38)
4	-0.04	-0.30	-0.24	-0.30	0.32	0.73	-0.10	0.44	0.06	-0.14
	(-0.32)	(-1.59)	(-1.68)	(-0.88)	(2.56)	(2.54)	(-0.72)	(2.83)	(0.40)	(-1.47)
High	-0.31	-0.45	-0.19	-0.78	0.28	-0.37	-0.21	0.18	0.20	-0.31
	(-1.89)	(-2.22)	(-1.44)	(-1.91)	(1.85)	(-0.79)	(-1.47)	(0.96)	(0.86)	(-2.77)
High−Low	-0.29	-0.46	-0.25	-0.76	-0.35	-1.62	-0.46	-0.37	-0.19	-0.35
	(-1.73)	(-1.99)	(-1.63)	(-2.14)	(-2.31)	(-3.25)	(-3.67)	(-1.77)	(-0.50)	(-3.02)

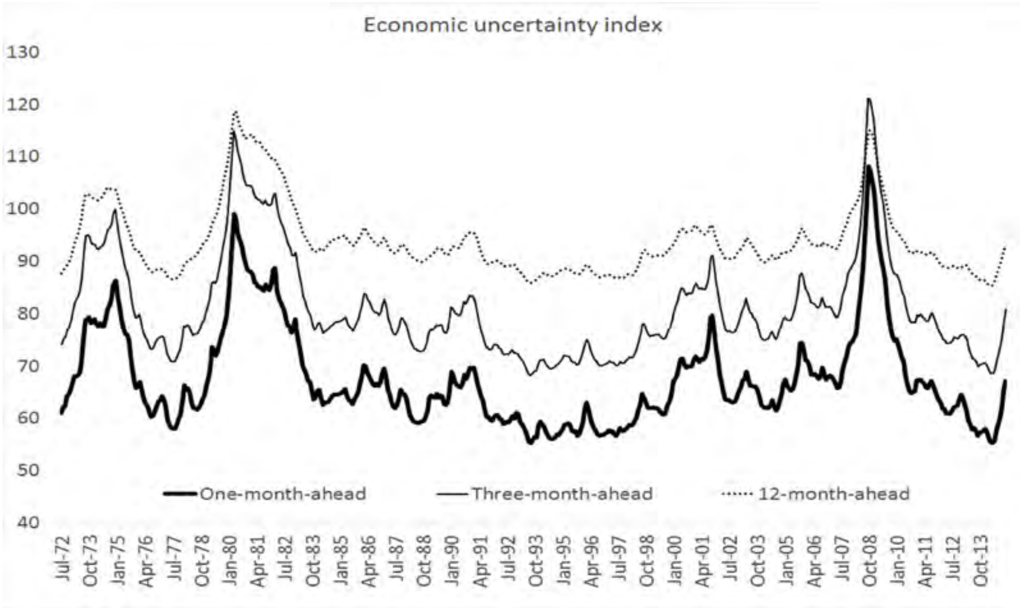

fig. 1. Economic uncertainty index. This figure depicts the one-month, three-month, and 12-month-ahead economic uncertainty indices (multiplied by 100) developed by Jurado, Ludvigson, and Ng (2015). The data for the period July 1972−December 2014 are obtained from Sydney Ludvigson's website.

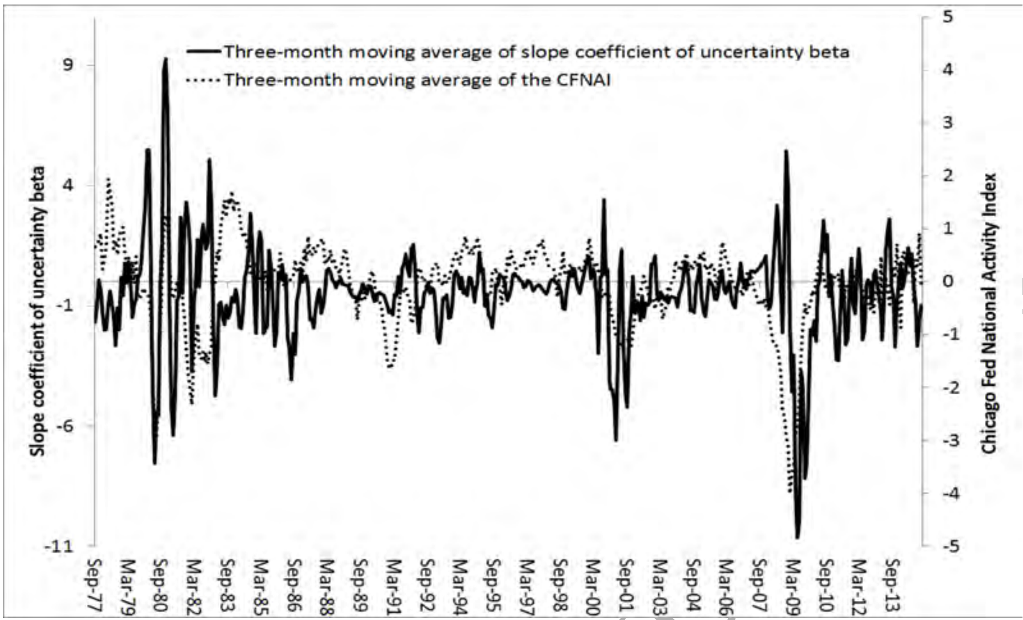

fig. 2. Slope coefficient of uncertainty beta. In the figure, the solid line depicts the three-month moving averages of the monthly slope coefficient of the uncertainty beta (Column 1 in Table 4) and the dashed line depicts the three-month moving averages of the monthly CFNAI index