Stock returns and macroeconomic uncertainty

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Abstract

This paper provides a comprehensive review of various measures of uncertainty and their asset pricing implications in the cross-section of U.S. stock returns. With a focus on survey-based uncertainty, we add to the list of uncertainty measures previously studied in the literature with novel measures of forecast disagreement sourced from three professional forecast datasets. Through portfolio analyses and stock-level cross-sectional regressions over the sample period between 1989 and 2020, we observe that exposure to uncertainty can explain a significant portion of the cross-sectional dispersion in future stock returns. For survey-based uncertainty, the negative relation between uncertainty and future returns persists over long-term investment horizons, extending up to 36 months, and cannot be explained by the well-established return-predicting factors. Our subsample analysis also reveals that for the uncertainty measures heavily dependent on macroeconomic data, the return predictive power of uncertainty is significantly more prominent in the later subperiod.

Keywords: *Macroeconomic uncertainty; Cross section stock returns; Forecast disagreement; Economic Policy Uncertainty*

1 Introduction

Uncertainty is embedded in many aspects of our lives. It is a broad concept, encompassing uncertainty surrounding economic phenomena like inflation and economic growth, as well as non-economic events such as geopolitical instability and climate change. Introduced as an economic concept more than a century ago by Knight (1921), uncertainty describes a situation where future outlook is difficult to predict, and where objective, quantifiable probabilities cannot be easily assigned to the possible outcomes. Efforts have since been made both in the literature at large and in practice, by investors and policymakers alike, to quantify the concept of uncertainty and to explore its far-reaching implications. This paper sets out to provide a thorough overview of different proxies of uncertainty and to study their asset pricing potential in the U.S. equity markets.

The main intuition behind our paper is that an increase in uncertainty raises concerns about future wealth, which leads investors to hedge changes in future wealth and consumption. Stocks that are positively correlated with uncertainty can serve as a hedging instrument, as they perform better when uncertainty increases. The demand for such stocks should therefore raise their prices and diminish their expected returns, leading to an uncertainty risk premium. More importantly, one may argue that this risk premium is time-varying, meaning that both the exposure to uncertainty as a state variable as well as the impact that uncertainty has on future wealth may change over time (Barroso et al., 2021).[1]

Driven by this theoretical insight, our analysis spans a broad set of uncertainty indicators, with a focus on survey-based measures. We use three separate professional forecast datasets. The first two, Consensus Forecast (CF), and BlueChip Economic Indicators (BCE), cover principal macroeconomic variables such as real GDP growth and unemployment rate. The third set of data, the BlueChip Financial Indicators (BCF), provides expectations of the direction and level of U.S. interest rates. The same procedure applies to obtain the uncertainty measure for all three datasets. Starting with forecasts of individual economic or financial variables, we calculate the variable-specific forecast disagreement, measured as the cross-sectional standard deviation of survey responses in a given month. Next, we correct these dispersion series for seasonality and variation in the sizes of the forecast panel. Finally, we average the seasonally-adjusted, normalised dispersion series across variables within each dataset to arrive at the aggregate, dataset-specific, uncertainty measure.

Measuring uncertainty with survey disagreement provides four major advantages. First, it is intuitive, as dispersion in beliefs is a direct reflection of the differing views by economists about macroeconomic and financial conditions. Second, it employs only real-time forecasts, making it valuable in out-of-sample testing and as a potential return predictor. Third, it is model-free, meaning there is no need to specify an economic or statistical model to arrive at the final uncertainty measure. Finally, it captures uncertainty concerning both unexpected shifts in macroeconomic conditions as

[1]The intertemporal capital asset pricing model (ICAPM) proposed by Merton (1973) provides further insights into this intuition. Under ICAPM, risk-averse investors with long-term investment goals hold intertemporal hedges against unfavorable shifts in future investment opportunities and may accept lower expected returns for assets that perform better when investment opportunities worsen. Economic uncertainty is a promising candidate for proxies of innovations in future macroeconomic activity and drivers of consumption and investment opportunity. Assets with high exposure to uncertainty, therefore, should command a risk premium. If uncertainty risk is indeed priced, this risk premium could be a manifestation of a precautionary savings effect or real options. Evidence in the literature at large also supports the notion of macroeconomic uncertainty as a relevant state variable influencing future consumption and investment opportunities

well as the models used to predict the macroeconomic conditions.[2]

We expand our asset pricing evaluation, by incorporating four popular measures of uncertainty: (i) the news-based Economic Policy Uncertainty (EPU) of Baker et al. (2016), which measures the frequency of uncertainty references in newspapers; (ii) the econometric measure of macroeconomic uncertainty by Jurado et al. (2015) (JLN), which measures the forecastable component of the innovations in macro-financial time series; (iii) the CBOE option-implied volatility index (VIX); and (iv) the realized stock market volatility (RVOL).[3] As a result, our battery of indicators covers the four categories of survey-based, news-based, market-based, and econometric-based[4] of uncertainty.

Equipped with this broad set of uncertainty measures, we assess the asset pricing implications linked to each index using the same empirical design and period, ranging from October 1989 to December 2020. In the first step, we estimate uncertainty beta with a 60-month rolling window regression of excess stock returns against each uncertainty measure. We then form the uncertainty-based portfolios to unveil potential patterns in excess and risk-adjusted returns linked to these factors.[5] Next, cross-sectional regressions according to Fama and MacBeth (1973) methodology are employed to test for the significance of uncertainty risk premia, simultaneously controlling for exposure to factors other than uncertainty. The rolling window regressions applied throughout this paper allows us to track the evolving uncertainty exposures, thus addressing the potential changes in the relationship between uncertainty measures and stock returns over time. In addition to our primary analyses, we conduct several robustness checks to adequately evaluate the performance of these uncertainty measures.

We find evidence of a significant negative relation between survey-based uncertainty measures and future stock returns. This relation persists over holding periods longer than one month and is present during recessions and expansions. Subperiod analysis reveals that survey-based uncertainty measures predict stock returns over the subperiod of 2005-2020, but not in the earlier subperiod of 1989-2004. Additionally, we find that the forecasting power of uncertainty series based on BCE and BCF is linked to size and liquidity. The BCE measures do not forecast large and liquid stock returns and the BCF-based fails to forecast the returns of the 1000 largest stocks. These results indicate that for BCE and BCF uncertainty series, the negative correlation between uncertainty and returns may be driven by the performance of small and illiquid stocks. In addition, when employing stock-level Fama and MacBeth (1973) regressions, we do not identify any significant pricing effect from the survey-based measures. This suggests that while survey-based uncertainty measures hold predictive power for future stock returns, they may not directly translate into pricing effects at the stock level.

We also confirm the results of previous works regarding the significance of the EPU index by Baker et al. (2016) and market-based measures of uncertainty. We show these results are robust to sample and period selections, as well as the different empirical pricing tests. Finally, for the JLN index by Jurado et al. (2015), we observe a negative correlation between uncertainty exposure and future stock returns. However, this negative relation is sensitive to the choice of the sample period and is

[2]One concern with regards to the use of survey forecasts, however, is the lack of objectivity, as forecasters can be driven by reputational, monetary, and other external incentives.

[3]The two latter measures are also referred as market-based measures of uncertainty.

[4]Econometric-based measures are also referred to in the literature as structural- or model-based

[5]Throughout our analysis we control for the well-known return-predicting factors, including market sensitivity, size, value, investment, profitability, liquidity, and momentum.

not quite as strong as some of the relations examined in this paper. While we find excess returns and uncertainty premium comparable in an economic sense to the findings in Bali et al. (2017), our results carry less statistical significance.

Together, the result is consistent with the hypothesis that uncertainty represents a systematic risk factor that is priced in the cross-section of stock returns. In both univariate and bivariate portfolio analyses, the average monthly excess returns increase when going from the top decile (high uncertainty) to the bottom decile (low uncertainty) portfolios. The average coefficient (risk loading) of uncertainty exposure in Fama and MacBeth (1973) cross-sectional regressions is negative for all uncertainty measures examined in this paper. The significance of our findings cannot be explained by other well-known return-predicting factors, such as market sensitivity, size, value, momentum, and liquidity. The pricing effects persist over longer holding period horizons than just one month but prove to vary substantially across industries. Notably, the return-predicting ability of uncertainty across different measures is more established in the subperiod spanning from 2005 to 2020 compared to the earlier subperiod from 1989 to 2004. This suggests an increasing role of uncertainty as a source of systematic risk within the U.S. equity market.

This paper makes three contributions. First, we contribute to the growing body of literature on macroeconomic uncertainty and ambiguity aversion by introducing three novel survey-based measures of uncertainty. The uncertainty indicators that we develop in this study provide major advantages thanks to their real-time forecasting capability, long-term forecasting horizon, and model-free property, while still proving to be competitive to the other well-recognized uncertainty measures in terms of predictive performance. Second, our paper acts as a comprehensive review and robustness check to the measures previously examined in prior literature. By covering all four major categories of uncertainty measures, we bridge the gap left by previous survey papers on the topic. We further strengthen the evidence of the ability to predict future returns of the EPU index, implied volatility, and realised volatility, while demonstrating that the pricing effect of the popular measure of macroeconomic uncertainty of Jurado et al. (2015) is not as pronounced as previous empirical studies have shown. Lastly, with the use of BCF survey, we are the first to examine the potential of uncertainty in key interest rates as a stock return predictor. The forecast disagreement on interest rates, while commonly employed in the context of term structure models and fixed-income asset pricing, offers a novel perspective for stock market cross-section analysis.

The remaining of the paper proceeds as follows. Section 2 reviews the related literature. Section **??** introduces the theoretical foundation to our model. Section 3 provides the data and variables, and goes more in details on the empirical designs behind our analysis. Section 4 presents the main findings while Section 5 discusses the robustness of these findings. Section 6 concludes the paper.

2 Literature

This paper lies in the crossroad between the well-studied multifactor asset pricing literature and the growing body of research on economic uncertainty. Within the literature in macroeconomic uncertainty, a large part is dedicated towards the use of survey forecasts, with a strong tendency for measuring uncertainty from an ex-post lens as realized forecast errors. Rossi and Sekhposyan (2015) use the likelihood of the realization of forecast errors to arrive at a measure of uncertainty. The paper zeroes in on real GDP growth as the single macroeconomic variable of interest, and introduces also a broad uncertainty index for the Euro area based on variable-specific components.

The paper by Abel et al. (2016) constructs measures of uncertainty for output growth, inflation rate, and the unemployment rate in the EU, based on both ex-ante forecast dispersion and ex-post forecast accuracy. Ozturk and Sheng (2018) take a different route and decompose global uncertainty, measured as forecast errors, into a common volatility and idiosyncratic volatility component. Using survey data of business conditions for manufacturing firms in Germany and the US, Bachmann et al. (2013) find strong correlation between ex-ante disagreement and dispersion in ex-post forecast errors, thus providing further evidence of forecast disagreement as a valid proxy for general uncertainty. Building on these works, we construct ex-ante measures of uncertainty based on forecast disagreement, using three novel data sets not yet employed in similar literature.

Separately, the literature on macroeconomic uncertainty involves also objective measures of uncertainty, derived from time series models of macroeconomic variables. Notable research on this topic includes Bloom (2009), Bloom (2014), and Christiano et al. (2014). One of the most well-known is the work by Jurado et al. (2015) on macroeconomic uncertainty as the ex-ante conditional volatility of the unexpected component of the macroeconomic series. The methodology used in this paper has since been further refined and extended in a number of other research papers, such as those by Moramarco (2023), Berger et al. (2017), and Scotti (2016).

Next to the research on survey-based and model-based uncertainty, the seminal work by Baker et al. (2016) on EPU stands out for its unique contributions. The paper introduces a novel approach to measure EPU in the U.S. using text-based analysis of newspapers. The approach relies on archives of 10 selected newspapers and measures uncertainty as newspaper coverage frequency of key words that are associated with EPU. Their methodology has seen been applied in numerous papers on uncertainty and more specifically the uncertainty risk premium, both for the U.S. market and extending the case to other countries[6].

Given the abundant and active research in macroeconomic uncertainty measures, a broad review of these various measures is much needed. Cascaldi-Garcia et al. (2023) provide an extensive overview of the uncertainty measures in the literature. The survey article by David and Veronesi (2022) compares the performance of all four categories of uncertainty measures in explaining the fluctuations in stock volatility and Treasury bond market volatility. Xu and Rogers (2023) examine whether uncertainty measures found in the literature hold forecasting power over economic activity at large. Their findings suggest that there is explanatory power in all measures considered, with some yielding more significant results than others. However, they also find that the real-time equivalents of these ex-post macro and financial uncertainty measures perform poorly in the same tests.

Our paper addresses the gap in the literature in two respects. One, we add to the growing list of uncertainty measures in the literature with multiple forecast dispersion measures based on the survey databases of CE and BCE and BCF Indicators. To the best of our knowledge, no attempt has been made to assess the potential of interest rate forecasts as pricing factors in the equity market. Additionally, we expand the application of interest rate forecast disagreement, a metric employed in a host of recent research in bond risk premia and fixed income asset pricing, to serve as a return predictor in the stock market domain. Two, we go beyond the contributions of existing survey papers (Cascaldi-Garcia et al., 2023, Xu and Rogers, 2023, David and Veronesi, 2022), by examining the ability of different uncertainty measures as a return predictor in the stock market.

[6] For further reading: application to UK market (Gao et al., 2019), Australian market (Chen et al., 2021), Chinese market (Lin et al., 2021)

While these works take on various routes to assess the economic implications of macroeconomic uncertainty, the cross-sectional relationship between uncertainty and equity returns has not yet been explored.

The paper closest to ours is by Lee et al. (2022), who investigate the significance of an uncertainty risk premium among the indices by Jurado et al. (2015), Bekaert et al. (2022), Baker et al. (2016), and two market-based volatility indices (implied and realized volatility). We distinguish our study in two key aspects: (i) we focus on survey-based uncertainty, which was not part of the uncertainty measures examined in their paper, and (ii) we perform a different set of asset pricing tests and provide a more thorough robustness analysis. On the other hand, our work with survey-based uncertainty and their asset pricing implications is also closely related to the study by Lee et al. (2019), who demonstrate that ambiguity, measured as forecast dispersion in GDP growth, can negatively predict future stock returns. The main difference is our forecast dispersion covers a wide range of macroeconomic and financial variables and thus is able to better capture uncertainty in the market and the real economy. There is also a difference in terms of forecast horizon and the frequency of the forecast: we look at monthly one-quarter-ahead and one-year-ahead forecasts, while the data set used in Lee et al. (2019) covers quarterly one-quarter-ahead forecasts.

With regards to the empirical design, our paper builds on a specific strand of literature that studies asset pricing implications of non-fundamental factors, more specifically economic uncertainty. Boons (2016) studies the risk premium of state variables that forecast macroeconomic activity and finds that exposure to business cycle risk is in fact priced in the cross-section of stock returns. Xyngis (2017) decomposes the uncertainty index as in Jurado et al. (2015) into layers with different heterogeneous degrees of persistence, and then proceeds to analyze the asset pricing implications of each of these layers. The paper finds evidence of a negative price of risk for uncertainty components with persistence ranging from 32 to 128 months. Aramonte (2014) attempts the same, but for the equity option market, interpreting uncertainty as the changes in implied volatility surrounding macroeconomic announcements. The author also finds significant results. Bali et al. (2021) examine the pricing implications of the uncertainty index as in Jurado et al. (2015) for the corporate bond market. Our empirical approach mirrors that of Bali et al. (2017), who evaluate the explanatory ability of the uncertainty index by Jurado et al. (2015) in a series of asset pricing tests. The specific implementation also takes notes from the work of Lambert et al. (2018), who provide a methodological review of portfolio construction techniques in different asset pricing tests and their effect on the evaluation of the priced factor.

3 Data and variables

3.1 Uncertainty measures

3.1.1 Survey-based uncertainty

We work with three separate survey data sets. Below, we provide descriptions of each data set and outline the process for constructing the uncertainty measures.

The first survey data set that we use is the Consensus Forecast (CF), sourced from Consensus Economics Inc. The monthly survey covers key economic variables for the U.S., spanning the period between 1989 and 2020. The availability of forecast and the forecasters participating vary over time and across the different macroeconomic indicators. Each monthly survey consists of a mix of fixed-event and fixed-horizon forecasts. Fixed-event forecasts show the projections of the variables for the same events: e.g. the current calendar year, or the first quarter of the next year. They are available for a range of indicators, including real GDP change (gdp), real personal consumption change (cons), real business investment change (invest), nominal before-tax corporate profits change (profit), real industrial production change (prod), consumer prices change (cprice), producer prices change (pprice), auto and truck sales (auto), housing starts (housing), unemployment rate (unrate), current account (account) and budget balance (budget). Fixed-horizon forecasts show the projections of the variables in the next three and twelve months. They are available for: global oil price (oil), three-month interest rate (m3), and 10-year government bond yield (y10). Transformations from fixed-event to fixed-horizon forecasts are needed to make use of the forecasts for the first group of variables. Given the nature of the survey, we only work with the 12-month ahead forecast horizon.

The second data set is the BlueChip Economic Indicators (BCE). This contains the monthly professional forecasts of macroeconomic indicators of the U.S. economy, with each panel providing their estimate for the current and next year. There is some overlap between the BCE dataset and the CF survey regarding variables and participating panelists. The list of indicators comprises of real GDP change (rgdp), nominal GDP change (ngdp), CPI change (cpi), industrial production change (prod), disposable personal expenditures change (dpe), non-residential fixed investment change (invest), corporate profits before taxes change (profit), 3-month Treasury Bill rate (m3), 10-year Treasury Bond rate (y10), unemployment rate (unrate), housing starts (housing, U.S. auto and truck sales (auto), and net export (ne). Similarly to CF, the BCE survey also contains fixed-event forecasts that need to be transformed into fixed-horizon forecasts of 12-months ahead.

The third set of data is the BlueChip Financial Indicators (BCF), which provides expectations of direction and level of U.S. interest rates, also from a panel of professional analysts. This data set is available on a monthly basis. The interest rates consist of Federal funds (fed), Prime bank (prime), one-month Commercial Paper (cp), Treasury Bills of three-month (m3), six-month (m6), and one-year (1y), Treasury notes of two-year (y2), five-year (y5), and ten-year (y10), AAA-rated (aaa) and BAA-rated (baa) corporate bonds, and three-month LIBOR (libor). Next to the interest rates, the forecasts are also available for real GDP change (rgdp), GDP price index change (gdppi), and CPI change (cpi). All of the forecasts are fixed-event, covering the current quarters up to the next six quarters. To facilitate our analysis, we transform these forecasts from fixed-event (current and next quarter) to fixed-horizon (one-quarter-ahead).

To transform fixed-event forecasts to the more useful format of fixed-horizon forecasts, we adopt the same methodology as Dovern and Weisser (2009). For the sake of space, we only demonstrate using the example of CF, where the target horizon is 12-months ahead. Let the fixed-event forecasts for the current and next year of a specific indicator made in month $m = 1, ..., 12$ of year y be F_m^y and F_m^{y+1}, respectively. The equivalent 12-month ahead forecast is calculated as the interpolated value of the other two forecasts:

$$F_m^{12m} = F_m^y \left(\frac{12 - m + 1}{12} \right) + F_m^{y+1} \left(\frac{m - 1}{12} \right)$$

The same procedure is applied to the BCE Indicators data set. With the BCF Indicators survey, we apply the interpolation for the current and next quarter's forecasts, to arrive at a fixed-horizon forecast of 3-months ahead [7].

[7] Alternatives to transform fixed-event forecasts to fixed-horizon are well studied in literature, but most

An additional concern is the (strong) seasonal patterns observed in many macroeconomic series. Even though we are looking at one-year ahead and three-month ahead forecast values which in theory should already exclude any of the forecast horizon bias, the inconsistency in target dates that result from the transformation introduces unwanted seasonality effects. These seasonal patterns emerge as a result of the seasonal changes in the panel size (e.g. holiday season), macroeconomic news release, information availability, among others. Additionally, variation in the forecast panel outside of seasonality also gets picked up in the disagreement measure. However, the seasonality issue with the uncertainty/forecast dispersion measures is not often addressed in the previous studies. We choose to correct the seasonal and panel size effects by running the following regressions:

$$D_{it} = \sum_{m=1}^{12} \beta_m S_m + \lambda F_{it} + \epsilon_{it}$$

where D_{it} is the dispersion among forecasters for indicator i at time t, S_m the month of the year corresponding to time t, and F_{it} the number of forecasters that report their prediction. Since there have been no structural changes in the survey throughout the sample period, no adjustment was needed to account for that.

Lastly, with regards to missing data, we interpolate between two adjacent forecasts of variable i made by the same forecaster f to fill in the gap, given that the two forecasts are the same. That is, we set the missing forecast $F_{i,f,t}$ equal to its neighbors, if $F_{i,f,t-1} = F_{i,f,t+1}$. This is the same approach as used by Dovern and Weisser (2009).

The variable-specific dispersion is measured as the standard deviation among forecasters for a specific macroeconomic indicator. This dispersion is then standardized for each variable by means of series normalization to ensure the dispersion measures are comparable across indicators. The aggregated uncertainty index is measured as the simple average of all variable-specific measures[8].

3.1.2 Other uncertainty measures

In our paper, we incorporate an econometric-based uncertainty measure known as the one-month macroeconomic uncertainty index (JLN) developed by Jurado et al. (2015). The index is constructed as the ex-ante conditional volatility of the unexpected component of macroeconomic time series for the U.S. The second uncertainty measure from the literature that we include in our analysis is the economic policy uncertainty (EPU) index developed by Baker et al. (2016). This index measures the newspaper coverage frequency of keywords appointing to policy-related uncertainty. We further scale the entire index by dividing it by 100 for ease of interpretation.

Lastly, we consider two measures of market volatility as candidates for the uncertainty risk state variables: implied volatility (VIX) and realized volatility (RVOL). The monthly implied volatility is calculated as the average of the daily values of the CBOE VIX index within the month. The VIX index reflects expectations of future volatility in the stocks market, derived from option prices on the

require the use of forecast errors (which, in turn, require realizations of the macroeconomic variables), or an additional fixed-horizon forecast series. For further details, see for example Ganics et al. (2020), Knüppel and Vladu (2016)

[8] As a robustness check, we use also the first principal component of the forecast disagreement across variables, and find similar results. This is in line with evidence in the literature (Ozturk and Sheng, 2018, Bali et al., 2015).

S&P 500 index. The monthly stock volatility, or realized volatility, is calculated as the annualized standard deviation of the daily (log) price of the market portfolio, proxied by the S&P500, over a one-month lookback period. The formula for realized volatility is:

$$RVOL_t = 100 \times \frac{252}{N} \sum_{i=1}^{N} \left(\ln \frac{S_{t-i+1}}{S_{t-i}} \right)^2$$

where S_t denotes the index price at time t, and N denotes the number of observations within the lookback period.

Figure 1 plots the uncertainty measures examined in this paper for the whole sample of October 1989 to December 2020. Across all measures, the most notable spikes tend to coincide with major economic crises, including the COVID-19 pandemic, the 2008 financial crisis, and the 2001 dot-com bubble. Table 1 reports the correlation among the uncertainty measures. Among the measures based on professional forecasts, the correlations are positive and significant. These professional survey-based measures also exhibit high correlation with the JLN series. This positive correlation can be explained by the fact that they all serve to measure the underlying volatility of macroeconomic and financial time series, whether via measuring analysts' dispersion, or via modelling the unforecastable component of the volatility. As expected, the two market-based measures, VIX and RVOL, are closely related. The EPU index, on the other hand, only has a mild positive correlation to these market-based measures.

3.2 Cross-sectional return predictors

Our dependent variable is stock excess returns, obtained from the CRSP database. The return data contains monthly returns of common stocks traded on NYSE, NASDAQ, or AMEX[9] over the period between October 1989 and December 2020. To account for survivorship bias in CRSP data, we adjust for the return of delisted stocks, following the approach in Shumway (1997)[10].

Macroeconomic uncertainty, denoted UNC, takes on the values of the different uncertainty measures. The market, size, value, profitability, investment pattern, and momentum factor returns (denoted MKT, SMB, HML, RMW, CMA, MOM respectively) are obtained from Kenneth French's website, based on CRSP and Compustat data sets. The liquidity factor (denoted LIQ) is obtained from the data library of Professor Lubos Pastor. Lastly, risk-free returns are the one-month Treasury bill rate, also obtained from Kenneth French website (from Ibbotson Associates). These risk-free returns are subtracted from stock monthly returns to arrive at excess returns.

To test whether our uncertainty measures are valid proxies of uncertainty risk and that exposure to uncertainty earns a negative risk premium, we follow two approaches: (i) perform the Fama and MacBeth (1973) procedure to estimate the risk premium, and (ii) construct an uncertainty mimicking portfolio and run a battery of tests on its implications for assess returns. Both methods are based on a two-step procedure.

[9]We filter on share code 10 or 11 for common stocks, and exchange code 1-3 and 31-33 for NYSE, NASDAQ, and AMEX.

[10]More specifically, the returns are adjusted according to the following logic: if not delisted, use the normal return; if there exists a delisted return, use the delisted return; if delisted code is among 500, 520, 580, 584, 551-574, (i.e. stock was dropped), set return to -30%; otherwise, set return to -100%.

The first step, common to both approaches, consists in running time-series regressions of individual stocks' excess returns against factor values:

$$\begin{aligned} R_{i,t} =& \alpha_{i,t} + \beta_{i,t}^{UNC} UNC_t + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t \\ &+ \beta_{i,t}^{MOM} MOM_t + \beta_{i,t}^{RMW} RMW_t + \beta_{i,t}^{CMA} CMA_t + \beta_{i,t}^{LIQ} LIQ_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

Here, time-series regressions are carried out in a rolling window fashion instead of on the whole sample, since the exposures to different state variables may vary over time. Following Bali et al. (2017) who work with a similar sample size, we set the rolling window to 60 months, such that at each month t, each exposure $\beta_{i,k}$ of stock i to factor k is estimated using data from month $t-59$ to month t. We repeat the 60-month rolling-window regressions for the returns data between Dec 1989 and Dec 2020. Accounting for the initial rolling-window, this leaves us with exposure coefficients for each month in the period between October 1994 and December 2020. At each monthly regression, we further require a minimum of 24 available observations in each rolling window for the regressions to take place.

With Fama and MacBeth (1973) procedure, the second stage derives the prices of risk factors with cross-sectional regressions:

$$R_{i,t+1} = \alpha_t + \lambda_t^{UNC} \hat{\beta}_{i,t}^{UNC} + \lambda_t^{MKT} \hat{\beta}_{i,t}^{MKT} + \sum_{k=1}^{K} \lambda_t^k X_{i,t}^k + \varepsilon_{i,t+1} \tag{2}$$

where $R_{i,t+1}$ is the next-month excess return, $X_{i,t}^k$ are the stock-specific control variables observed in month t, $\hat{\beta}_{i,t}^{MKT}$ and $\hat{\beta}_{i,t}^{UNC}$ are the exposure estimated in month t of stock i to the market portfolio and the uncertainty factor, respectively. The uncertainty risk premium follows as the average value over time of the estimated risk prices:

$$\bar{\lambda}^{UNC} = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_t^{UNC}$$

Thus, estimating the risk premium of macroeconomic uncertainty (and of other factors) reduces to computing the time-series average of the cross-sectional coefficients. The significance of this risk premium is tested using a Newey-West adjusted t-statistic with a 6-month lag to account for potential autocorrelation and heteroskedasticity.

The second stage of the portfolio analysis, begins with the formation of the portfolios based on the $\beta_{i,t}^{UNC}$ of Equation 1. Specifically, decile portfolios are created, where stocks in decile 1 have the lowest uncertainty exposures, and stocks in decile 10 the highest. Portfolio characteristics are calculated as a simple average of the stocks making up the portfolios. We further construct an uncertainty-mimicking portfolio based on a long-short strategy of holding the highest uncertainty beta portfolio and shorting the one with the lowest uncertainty exposure. This difference portfolio is referred to as the High-Low (High minus low) portfolio.[11] In our analysis, we focus on (i) the next month's average excess returns of the High-Low portfolio and (ii) the persistence of abnormal

[11] It is important to note that the same trade-off when choosing between a portfolio-level and stock-level pricing test applies when choosing the number of portfolios. The portfolio-level regressions help reduce idiosyncratic noise and thus deliver more accurate estimates at the cost of decreased dispersion among assets' betas in the cross-sectional regressions, thus reducing the accuracy of the pricing error and risk price estimates.

returns by running the following time-series regressions:

$$R_{p,t} = \alpha_{p,f} + \sum_{f}^{F} \beta^f R_t^f + \varepsilon_t \tag{3}$$

The intercept $\alpha_{p,f}$ of the time-series regressions of portfolio excess returns on the control factors is the abnormal or risk-adjusted return, representing the return that cannot be explained by existing risk factors. We carry out tests for jointly non-zero alpha's over time for each uncertainty measure with respect to four different factor models. These regressions result in the following alpha's estimates: (1) α_3 with respect to market, size, and value factors (Fama-French 3-factor model), (2) α_4 with respect to market, size, value, and momentum factors (Fama-French-Carhatt 4-factor model), (3) α_5 with respect to market, size, value, momentum, and liquidity factors, (4) α_7 with respect to market, size, value, momentum, liquidity, investment, and profitability factors.

While the uncertainty mimicking portfolio that results from the long-short strategy can help net out other passive exposures, this is only appropriate if there is no significant relationship between uncertainty exposure and another risk exposure or characteristic. Thus, in addition to univariate portfolio sorting, we perform a bivariate portfolio-level analysis to examine (i) whether the patterns in returns of the low and high uncertainty portfolios persist when controlling for an additional variable, and (ii) whether there exists some cross-sectional relationship between the uncertainty beta and the control variable. Similar rolling-window regressions of excess returns on uncertainty series provide the uncertainty betas to be used in ranking the stocks and forming the double-sorted portfolios. The main difference with the univariate analysis lies in the double-sorting method to form portfolios. We carry this out with preconditioning sequential sorting, by first sorting the stocks into groups based on one control variable, and then sorting within each group based on the uncertainty betas[12]. The control variables are stock-specific: market beta, market capitalization (size), and book-to-market ratio (value).

Theoretically, investors with uncertainty aversion are willing to pay more for decile 10, as the stocks in this decile perform relatively better in times of heightened uncertainty, and therefore can be used to hedge against macroeconomic uncertainty risk. On the other hand, investors will demand a compensation to hold stocks with lower (negative) uncertainty exposures. In line with Merton's ICAPM, we expect that if macroeconomic uncertainty predicts negatively towards future consumption and/or investment opportunity set, then the risk premium from exposure to macroeconomic uncertainty must carry a negative sign also.

4 Main results

This section presents the results of our analysis and their implications. The aim is to explore whether a cross-sectional relationship exists between stocks returns and the different candidates of economic uncertainty. We first provide our findings from the univariate portfolio analysis for the main uncertainty measures. This is followed by the bivariate portfolio analysis as further examinations of the return characteristics of the uncertainty-ranked portfolios when controlled for market beta, size, and value. Next, we carry out the two-stage regressions in the spirit of Fama and

[12]Lambert et al. (2018) discuss the benefit of this approach in comparison to independent sorting and post-conditioning sorting, where stocks are first sorted based on priced variable and then control variable

MacBeth (1973) to test for the existence and significance of an uncertainty risk premium. Lastly, we assess the robustness of these findings in a number of additional checks.

4.1 Univariate portfolio-level analysis

We begin with univariate portfolio-level analysis to examine the return characteristics of the portfolios constructed based on uncertainty beta and from there infer the relationship between uncertainty exposure and future stock returns. We estimate uncertainty betas from 60-month rolling window regressions, as shown in Equation 1. The resulting uncertainty betas from these monthly multifactor time-series regressions form the basis on which decile portfolios are constructed. At every month, we form the portfolios, hold them for one month, and then repeat the process using the same procedure. The total sample spans the period between October 1989 and December 2020. We present in Table 2 the average pre-ranking uncertainty betas for the top (high uncertainty) decile portfolio and the bottom (low uncertainty) decile portfolio. These uncertainty betas range from negative for the bottom to positive for the top decile portfolio. The cross-sectional variation in the estimated uncertainty exposures for all measures appears to be symmetrical between the top and bottom deciles.

Table 2 further reports the average excess returns and average abnormal returns of the High-Low (top-minus-bottom) portfolios. The factor alphas ($\alpha_3, \alpha_4, \alpha_5$, and α_7), also referred to as abnormal returns or risk-adjusted returns, are the intercepts of the time-series regressions in Equation 3 with respect to the factors: (i) market, size, value, (ii) market, size, value, momentum, (iii) market, size, value, momentum, liquidity, and (iv) market, size, value, momentum, liquidity, investment, and profitability, respectively. These alphas thus reflect the returns not yet explained by the different combinations of factors. All return values refer to monthly returns and are expressed in percentage. Newey-West statistics for the significance test are reported in parentheses[13].

Starting with CF uncertainty series, we find a difference in α_7 of -0.45% (t-statistic of -2.32) between the top and bottom decile portfolio. The uncertainty mimicking (High-Low) portfolio constructed based on CF disagreement yields on average a significant, negative risk-adjusted return of -0.45% per month. Similar results are found for α_4 and α_5, but not for the excess returns spread and α_3, which is the abnormal returns with respect to market, size, and value. The aggregate forecast dispersion measure based on BCF shows milder evidence of having a priced impact with respect to α_7 (-0.35%, t-statistic of -1.87), but stronger for excess returns and other risk-adjusted returns. Among the survey-based measures, the BCE uncertainty displays the strongest priced effect, with a monthly average difference in excess return of -0.45% (t-statistic of -2.30) and risk-adjusted return α_7 of -0.47% (t-statistic of -2.37). Together, these results suggest that the priced impact from exposure to survey forecast dispersion exists and is not driven by exposures to the well-known factors.

Consistent with previous empirical works, the EPU index of Baker et al. (2016) and the two market-based volatility measures (VIX and RVOL) exhibit strong predicting power over future stock returns. The excess returns for all three measures are not only economically large, being the most negative across measures, but also statistically significant at 1% level. The risk-adjusted returns for these uncertainty measures are also statistically significant and negative, indicating that the excess returns cannot be explained by the common factors. In the case of the EPU index, a strategy consisting of buying stocks in the bottom decile and shorting stocks in the top decile would

[13] Newey-West t-statistics are calculated with six lags.

yield on average a risk-adjusted return of 0.59% per month, or 7.31% per year. Regarding the asset pricing implications of the econometric-based measure JLN of Jurado et al. (2015), our results are comparable in economic sense to the findings of Bali et al. (2017), though ours carry less statistical significance (excess returns of -0.47%, t-statistic of -2.18; α_7 of -0.51%, t-statistic of -2.22).

Importantly, the return spread between the high- and low-uncertainty portfolios is negative for all uncertainty measures. This confirms our hypothesis of a negative relationship between negative relationship between exposure to uncertainty risk and future stock returns. Stock returns increase as stocks move from the highest uncertainty beta decile to the lowest, reflecting the compensation that investors demand for holding investment that bears more uncertainty risk.

4.2 Bivariate portfolio-level analysis

We carry out bivariate portfolio-level analysis to get a better understanding of the nature of the cross-sectional relations between macroeconomic uncertainty and other risk factors. More specifically, we control for market beta (β^{MKT}), market capitalization (*size*), and book-to-market ratio (bm) in examination of the cross-sectional relations between the control variables and uncertainty. This extra control step is done in the form of dependent, pre-conditioning sorting, where we first sort stocks into deciles based on market beta (or market capitalization, book-to-market ratio) before sorting stocks within each of these dciles further based on uncertainty beta. This step ensures that when we evaluate the return spread between the low- and high-uncertainty portfolios, these portfolios pairs carry the same market beta (market capitalization, book-to-market ratio). Bivariate analysis results can be found in Table 3. We only display the average excess returns and risk-adjusted returns for the High-Low portfolios.

For the uncertainty measures that have a statistically significant relation with equity returns, i.e. BCE, JLN, EPU, VIX, and RVOL, this negative relation persists after controlling for market beta, market capitalization, and book-to-market ratio. The resulting excess and risk-adjusted returns hold more statistical significance than what we see with univariate portfolio analysis, with most values significant at the 1% level. For the two survey-based measures based on CF and BCF, although uncertainty exposure does not hold as much predictive power over the entire sample–as indicated in the univariate test–it does explain a significant portion of the cross-sectional dispersion in equity returns within sample of similar market beta, size, and value.

The main takeaway here is that the uncertainty premium is not a result of firm-specific characteristics. However, this does not imply that these firm characteristics do not correlate with the firm's exposure to uncertainty. Further analysis reveals that the relationship between uncertainty beta and the control variables follow a U-shape pattern. The top and bottom decile portfolios would exhibit the highest market beta, the lowest size, and the lowest book-to-market ratio out of all decile portfolios[14]. The often-time contradicting effects between other risk factors and uncertainty can be responsible for the less evident return signal that we see in the univariate analysis.

[14]The portfolio characteristics of the 10 decile portfolios based on the different uncertainty measures are not reported. Our findings on this mirror the findings of Bali et al. (2015), who also develop a survey-based uncertainty index based on the quarterly Survey of Professional Forecasts.

4.3 Fama-Macbeth stock-level regressions

As further examination of asset pricing implications of the uncertainty measures, we turn to the two-stage regressions in the spirit of Fama-Macbeth (1973) to test for the existence and significance of an uncertainty risk premium. Table 4 reports the time-series averages of the slope coefficients of the cross-sectional regressions in Equation 2. The risk premium λ^{UNC} represents the average coefficients of the multivariate Fama-Macbeth regressions, which control for market, size, value, profitability, investment, liquidity, and momentum factors. The Newey-West adjusted statistics are reported in parentheses underneath the estimated coefficients.

Table 4 reports an economically large and statistically significant risk premium associated with EPU (-0.04%, t-statistic of -2.57), once again confirming the results found in similar empirical works that involve the index. We find risk premiums of marginal statistical significance in the case of the two market-based uncertainty measures: implied-volatility VIX (-0.83%, t-statistic of -1.91) and realized volatility RVOL (-0.23%, t-statistic -1.82). For the survey-based measures, there is no evidence of a significant cross-sectional relationship between uncertainty exposure β^{UNC} and future excess returns. Table 4 detects no priced effect for the macroeconomic uncertainty measure JLN. The risk premium of -0.01% (t-statistic -1.54) found for JLN is in contrast with the findings by Bali et al. (2017), who show that the same one-month macroeconomic uncertainty measure can significantly predict future stock returns in the same Fama-Macbeth procedure, albeit with a different data set[15]. This result indicates that the ability of JLN uncertainty to predict future stock returns is not robust to settings and sample period. Across all measures, the average coefficients of the control factors are not statistically different from zero for all but the momentum (MOM) factor, and only with very marginal statistical significance.

For survey-based and econometric-based measures, the absence of statistical significance in uncertainty premium with stock-level analysis reveals that while there is a significant spread between stocks in the top and bottom uncertainty deciles, the negative relation between uncertainty and future returns does not necessarily hold for individual stocks. One explanation is the idiosyncratic noise of individual stock returns, as unlike portfolio analysis, this noise is not averaged out in the stock-level pricing tests. It is also important to take note of the possible effects from errors-in-variables bias that result from the two-stage regressions, and how portfolio analysis can help address this bias. The other explanation for the difference in findings between portfolio analysis and stock-level cross-sectional regressions is that the relationship between uncertainty and future stock returns is non-linear. In fact, we find that while the bottom decile portfolios consistently perform the best, the portfolios with lowest excess and abnormal returns are the 8th or 9th deciles and not the top decile. When this is the case, the linear relationship that is inherently assumed with Fama-Macbeth cross-sectional regressions will appear weaker.

Adding to that, the results in Fama-Macbeth regressions are in general much less significant than in portfolio analysis for all measures we examine in this paper, and not limited to only survey-based and econometric-based measures. The differences seen in the two approaches can be boiled down to two main points: (i) The linearity assumption of Fama-Macbeth regressions, and (ii) The aggregation effect of portfolio analysis, which helps reduce idiosyncratic noise and makes it easier to detect the effect of uncertainty risk.

[15] Our sample spans the period between October 1989 and December 2020, and we use as control variables risk factor exposure. Bali et al. (2017) use a sample that spans between 1972 and 2014, and a range of stock-specific characteristics as control variables

In summary, the estimated uncertainty risk premiums are negative across the different uncertainty measures. This is again consistent with our expectations and the underlying restrictions on ICAPM's state variables. Stocks that are highly correlated with uncertainty and thus have a large (positive) uncertainty beta will perform better when uncertainty increases, providing a hedge against uncertainty risk. The demand for such hedging instruments will diminish the expected returns on these stocks, eventually leading to a negative cross-sectional relationship between uncertainty beta and excess returns.

That said, the Fama-Macbeth pricing test provides a crucial perspective to interpret the results and highlights the importance of understanding the limitations of the two different approaches.

5 Robustness checks

5.1 Subperiod analysis

It is interesting to study whether the pricing implications of uncertainty exist throughout our sample period, and how sensitive these findings are to sample period selection. To do this, we first divide our sample into two periods: from October 1989 to December 2004, and from January 2005 to December 2020. Table 5 reports the results of this subperiod analysis.

Looking at the individual uncertainty measures, the survey-based measures demonstrate particularly strong explanatory power over future returns for the subperiod of 2005-2020, outperforming all other uncertainty measures. This result is not unimportant, as despite our efforts at outlier correction for all three survey databases, we still have some concerns over data quality in the early 1990s when collecting the survey answers and constructing the survey-based measures. The ability of the macroeconomic uncertainty index JLN to predict future returns is insignificant in the first subperiod, and marginally significant in the second. On the other hand, we detect for the EPU index a clear and significant negative correlation between next-month returns and uncertainty in both subperiods, albeit a weaker relation in the first subperiod. Similar results are found for realised volatility as a market-based uncertainty measure. The only uncertainty measure that does not demonstrate any pricing effect in the second subperiod is the implied volatility index VIX. This implies that the pricing effect of the VIX has disappeared after 2004. A potential explanation for this finding is the apparent popularity of the VIX as a return predictor.

Overall, we observe much stronger degree of predictive power across measures for the subperiod of 2005-2020 than for the subperiod of 1989-2004. This may be the signal that investors have either become growingly concerned about macroeconomic uncertainty, or simply grown more aware of uncertainty in recent years. Improved access to information, coupled with the advancements in data analysis, means that investors react more strongly and quickly to new information and therefore uncertainty shocks. The increasing level of policy uncertainty, market complexity, and globalisation also expedite the pathways by which macroeconomic variables and policy influence stock prices, thus amplifying the role of uncertainty as a systematic risk. The stronger priced impact in the second subperiod can also be attributed to the two significant spikes in uncertainty observed during the 2008 financial crisis and the 2020 COVID pandemic.

Perhaps the most interesting observation from this analysis is that the measures with the weakest return predicting signal in the earlier subperiod (CF, BCE, BCF, and JLN) are all heavily dependent on contemporaneous information and macro-financial data: the three survey-based measures use non-revised analyst forecasts, and Jurado et al. (2015) use macroeconomic and financial time series in their uncertainty index construction. This lends supporting evidence for our conjecture that the lack of information availability and data quality is responsible for the less significant results in the first subperiod.

Along the same line of subperiod analysis, we want to also assess whether this risk premium is contingent upon underlying economic conditions or a particular stage in the business cycle. We divide our sample into recession and expansion periods, as defined by the National Bureau of Economic Research (NBER), and report on the findings. Table 6 shows that there exists in general a negative relation between uncertainty and stock returns during both recessions and expansions. The return spread between stocks with high and low uncertainty exposure is economically a lot larger during recessions. We also observe less range in uncertainty exposure, measured by β^{UNC} during recessions than expansions.

The smaller range in β^{UNC} can attributed to the fact that the uncertainty measures experience more extreme movements during recessions, thus relatively lessening the comovement between stock returns and uncertainty. Meanwhile, return spread between high and low portfolios widens despite the smaller range in uncertainty beta. This shows that investors demand more for holding stocks that are negatively correlated to uncertainty during bad states of the economy, once again consistent with the underlying ICAPM theory.

5.2 Subsample analysis

In our prior analyses, we find that the return spread between high and low uncertainty exposure stocks is more apparent among stocks of similar market sensitivity, size, and book-to-market value. As further robustness checks, we examine whether our findings are only limited to certain stock samples of similar characteristics. As a first step, we look at the following subsamples: (i) NYSE-listed stocks, (ii) large stocks, defined as those with a market capitalization higher than the 50th percentile of NYSE-listed stocks, prior to portfolio formation month, (iii) the 1000 largest stocks in CRSP universe in terms of market capitalization, and (iv) the 1000 most liquid stocks, according to Amihud (2002) illiquidity measure. Table 7 reports the risk-adjusted returns relative to 7-factor model (α_7) for the uncertainty mimicking portfolios, formed on the aforementioned subsamples.

As we can see in Table 7, whether a stock is listed in NYSE or NASDAQ and AMEX does not seem to negate our previous findings. However, subsamples of large and liquid stocks demonstrate differing results. In fact, the only measures that display significant negative relation with future stock returns across the subsamples are the survey-based CF, econometric-based JLN, and the news-based EPU. The return predicting power disappears among large stocks for BCF, VIX, and RVOL, and among large and liquid stocks for BCE.

These results may be influenced by a number of factors. First, large cap and liquid stocks are generally more stable and have lower exposure to uncertainty. Compared to smaller firms, these companies' stock prices are often more driven by fundamentals and long-term prospects, and less so by macroeconomic and policy ambiguity. Additionally, these large cap and liquid stocks tend to attract institutional investors, who may have a different attitude or perception of uncertainty risk and operate at a different investment horizon compared to the average investor. Lastly, large and liquid stocks are more efficiently priced in the market, leaving less room for an uncertainty risk premium.

As the next step to subsample analysis, we assess the pricing implications of uncertainty measures for different industry groups to see whether any pattern emerges. To do this, we divide all stocks into 12 industry groups according to their SIC codes, as provided by the CRSP database. These industries are: Non-durables, Durables, Manufacturing, Energy, Chemicals, Business Equipment, Telecom, Utilties, Shops, Healthcare, Finance, and Others. The industry definitions can be found on Kenneth French's website.

The results reported in Table 8 show that uncertainty does not impact the different industries similarly. For Durables, Telecom, and Utilities, there is no significant relation with any of the uncertainty measures. These industries have long been seen as defensive stocks due to their high dividends, stable earnings, and resilience to fluctuations in business cycles. On the other hand, we find that Energy is the industry group most sensitive to uncertainty exposure, particularly with regards to the survey-based measures. The average α_7 spread within Energy industry group is -1.76% (t-statistic of 2.96) for CF, -1.55% (t-statistic of 2.85) for BCF, and -1.23% (t-statistic of 2.48) for BCE. The most likely driver behind this finding is the high sensitivity of Energy sector to macroeconomic conditions, particularly inflation and interest rates. The Energy sector as a whole is also highly cyclical in comparison to sectors such as Utilities and Telecommunications, which typically have more predictable cash flows, steady demand, and less exposure to uncertainty.

5.3 Long-term predictability

So far, we have established that uncertainty exposure can predict one-month-ahead stock returns. Now, we examine the predictive power of the different uncertainty measures over longer investment horizons. At the first step, we follow the same procedure as for the main results: we estimate uncertainty exposure of each stock at each month based on 60-month rolling window regressions, controlling for the common return-predicting factors. We then form ten decile portfolios based on these uncertainty betas, and measure the x-month-ahead returns on these portfolios. The average monthly α_7's over the different holding periods of the High-Low portfolios are reported in Table 9.

For CF uncertainty, the negative relation between Consensus Forecast and the cross-sectional stock returns disappear initially, but pick up at 12-month and above holding periods. For BCF uncertainty , the returns on the High-Low portfolio are negative and significant for all holding periods examined, but more or less fade away after 18-months. For the uncertainty series based on BCE, the average risk-adjusted returns are also statistically significant for all holding periods, remaining at -0.23% (t-statistic of -2.13) after 36 months. That is, the negative relation between the BCE index and future stock returns persists even with the longest investment horizons used in this study.

The EPU index, the JLN macroeconomic uncertainty, the implied volatility index VIX, and the realized volatility index RVOL all exhibit the ability to negatively predict stock returns over investment horizons longer than 1 month. This predictive ability remains valid after 12 months for JLN and VIX, 18 months for RVOL, and 24 months for EPU.

Most notably, all three survey-based measures display the longest predictive power. This can be attributed to the longer forward-looking horizons (one-quarter-ahead and one-year-ahead) that are embedded in these surveys. Meanwhile, both JLN and VIX convey uncertainty over the next month, and EPU and RVOL does not possess any forward-looking feature. All in all, the results presented here demonstrate the persistence of uncertainty as a stock return predictor over the longer-term investment horizons. Uncertainty exposure continues to explain a large portion of cross-sectional dispersion in stock returns beyond just the one-month-ahead horizon. Our results with regards to the survey-based measures also highlight the usefulness of dispersion in beliefs as a measure of uncertainty.

5.4 Variable-specific forecast dispersion

We now extend the univariate portfolio analysis to the dispersion measures of individual variables within the three professional survey data sets: CF, BCF, and BCE. Table 10 presents (i) the average uncertainty beta β^{UNC} of the High and Low portfolios, (ii) the average one-month-ahead excess returns of the High-Low portfolios, and (iii) the risk-adjusted returns relative to different factor models of the High-Low portfolios. We find statistically significant returns for High-Low portfolios formed based on the forecast disagreement of these variables:

- CF: budget balance *budget* (-0.63%, t-statistic of -2.63), auto and truck sales *auto* (-0.35%, t-statistic of -1.8), before-tax corporate profits *profit* (-0.37%, t-statistic of -2.11);
- BCE: real GDP *rgdp* (-0.35%, t-statistic of -1.83), nominal GDP *ngdp* (-0.28%, t-statistic of -1.65), unemployment rate *unrate* (-0.36%, t-statistic of -2.34), industrial production *prod* (-0.46%, t-statistic of -2.28), auto and truck sales *auto* (-0.35%, t-statistic of -1.67), disposable personal income *income* (-0.37%, t-statistic of -2.13), and net exports *ne* (-0.42%, t-statistic of -2.19);
- BCF: consumer price index *cpi* (-0.3%, t-statistic of -1.89), and yield on five-year Treasury Notes *y5* (-0.3%, t-statistic of -1.96).

6 Conclusions

This paper provides a comprehensive review of various measures of uncertainty and their asset pricing implications in the cross-section of stock returns. With a focus on survey-based uncertainty, we construct three separate measures based on forecast disagreement using the survey data from Consensus Forecast, BlueChip Financial Indicators, and BlueChip Economic Indicators. All three survey-based measures examined in this paper exhibit a negative relationship with future stock returns that cannot be explained by other risk factors and remains evident through a number of robustness checks. Importantly, the survey-based measures demonstrate return predicting power comparable to that of the measures popular in the literature. With improvement in data availability and forecasting model, survey-based measures provide superior risk-adjusted returns compared to other measures in the period between 2005 and 2020. Most notably, thanks to the forward-looking horizon of the forecasts, these survey-based measures offer forward-looking property that is evident in their outperformance in long-term predictability tests compared to alternative uncertainty indices.

Through our analysis, we also find compelling evidence for the other uncertainty measures as a priced risk factor in the cross-sectional returns of U.S. stocks. The Economic Policy Uncertainty index by Baker et al. (2016) emerges as a robust predictor of stock returns, with a sizable and statistically significant risk premium associated with exposure to this index across different sample periods and over longer-term investment horizons. The econometric measure of Jurado et al. (2015) also exhibits some return predicting capability, albeit with less statistical significance. The market-based measures of implied volatility and realised volatility demonstrate a consistent negative relation with future stock returns. Our findings confirm that uncertainty is indeed a priced risk factor and exposure to uncertainty commands a risk premium.

These findings emphasize the need for policymakers and investors to recognize uncertainty as a key risk factor, given its impact on stock returns and broader financial stability. Our results reveal that investors show respond to uncertainty by requiring a lower return for stocks that can act as uncertainty hedging instruments. As such, firms with more uncertainty exposure enjoy a lower cost of equity (and cost of capital) thanks to the hedging appeal of their stocks. This lower cost of capital lowers financing costs of these firms, making it less expensive for them to finance new projects.

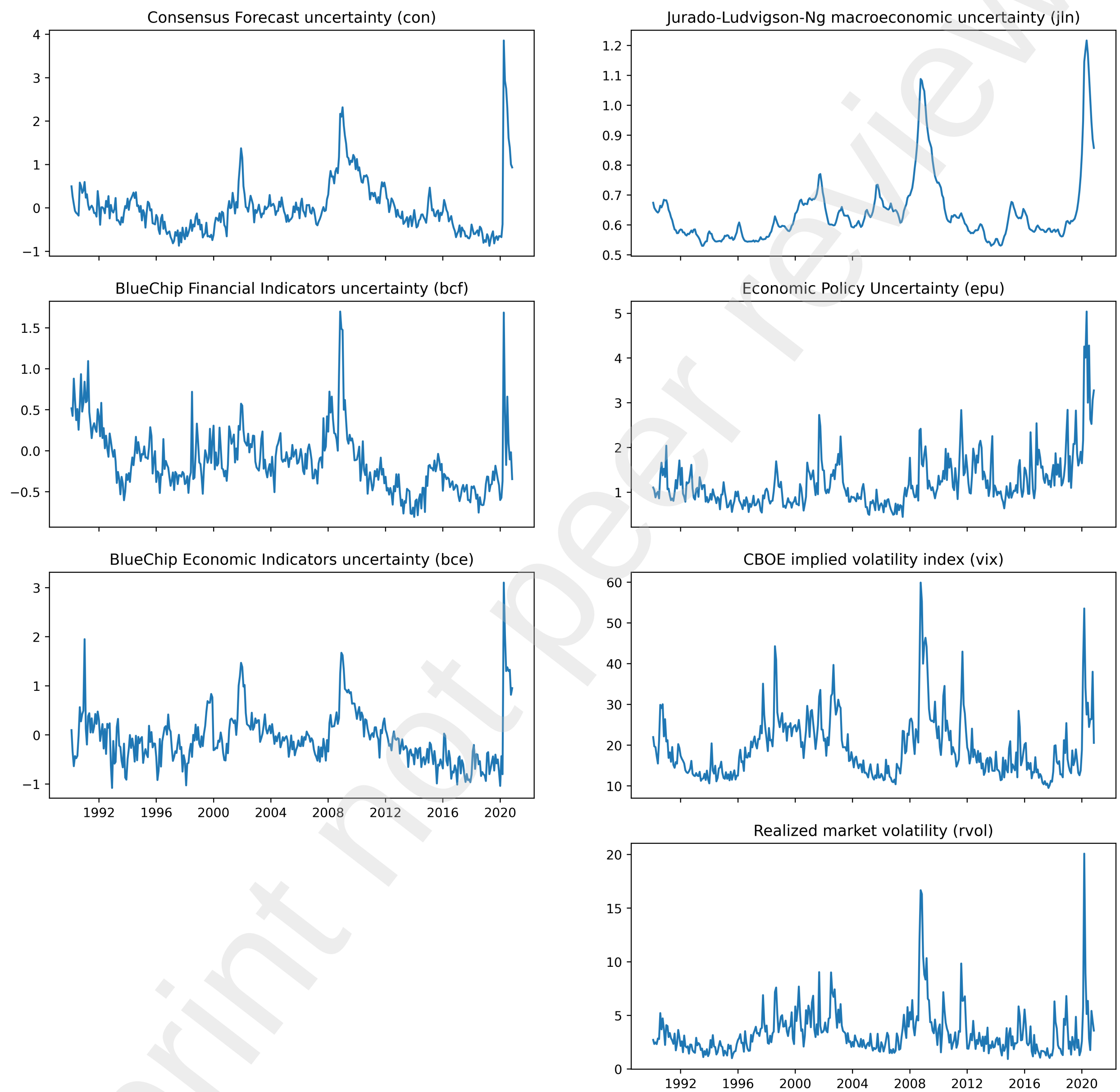
For policymakers, these insights provide several key takeaways. As uncertainty increases, capital may flow towards uncertainty-hedge stocks or sectors. This shift can affect the structure of the economy. Recognizing and understanding these dynamics can help policymakers address potential vulnerabilities and identify the sectors or firms that are in need during times of heightened uncertainty. Our results also demonstrate the need for better tools for measuring and incorporating uncertainty, allowing both policymakers and investors to make better informed decisions. Lastly, of particular interest is the result linked to interest rate uncertainty. The strong negative relationship between stock returns and uncertainty surrounding key rates highlights the sensitivity of investment to interest rate uncertainty. Our results indicate that an environment of high interest rate uncertainty could therefore lead to delayed investment and spending, pointing towards a broader economic effect of uncertainty on growth and stability.

There are two main limitations to this study. First, our analysis on individual decile portfolios reveals that while the lowest uncertainty beta portfolios always earn the highest average excess returns, it is usually the 8th or 9th decile (second or third highest uncertainty beta) portfolios that have the lowest returns. Second, while we find strong return predicting power for most measures in univariate and bivariate portfolio analyses, this predicting power diminishes substantially in the stock-level Fama-Macbeth regressions. This observation raises questions about the robustness of the pricing impact of uncertainty risk. In this regard, our study also serves its purpose to provide insights into the applicability of a broad array of uncertainty measures. We highlight the factors in the empirical settings, such as sample period, control factors, and asset pricing tests, that may influence the results. We leave these inquiries for future research.

7 Tables and Figures

7.1 Figures

Figure 1: Uncertainty measures



Left column: (aggregated) uncertainty measures based on three survey data sets: Consensus Forecast, BlueChip Financial Indicators, and BlueChip Economic Indicators. Right column: one-month-ahead macroeconomic uncertainty from Jurado et al. (2015), Economic Policy Uncertainty from Baker et al. (2016), CBOE implied volatility index, and realized volatility index. The aggregated forecast uncertainty is the average of the variable-specific (standardized) forecast dispersion. For each variable, forecast dispersion is calculated as the cross-sectional standard deviation at each monthly survey.

7.2 Tables

Table 1: Correlation matrix.

Variables	CE	BCF	BCE	JLN	EPU	VIX	RVOL
CE	1.00						
BCF	0.56	1.00					
BCE	0.70	0.58	1.00				
JLN	0.75	0.55	0.57	1.00			
EPU	0.16	-0.03	0.09	0.22	1.00		
VIX	0.45	0.38	0.50	0.58	0.35	1.00	
RVOL	0.38	0.31	0.39	0.59	0.39	0.86	1.00

This table reports the correlation matrix of the uncertainty measures: Consensus Forecast (CE), BlueChip Financials Indicators (BCF), Bluechip Economics Indicators (BCE), Jurado-Ludvigson-Ng (JLN), Economic Policy Uncertainty (EPU), VIX index (VIX), realized market volatility (RVOL).

Table 2: Univariate portfolio analysis.

Variable	CF	BCF	BCE	JLN	EPU	VIX	RVOL
Panel A: Average uncertainty beta β^{UNC}							
Low	-13.22	-17.02	-12.07	-103.58	-13.38	-1.00	-3.72
High	14.67	18.88	13.48	120.72	13.79	1.05	3.75
Panel B: Average excess returns (%)							
High-Low	-0.29	-0.31*	-0.45**	-0.47**	-0.59***	-0.61***	-0.54***
	(-1.50)	(-1.80)	(-2.30)	(-2.18)	(-2.89)	(-3.02)	(-2.45)
Panel C: Abnormal returns relative to factor models (%)							
α_{FF3}	-0.26	-0.36**	-0.48***	-0.45**	-0.40**	-0.54***	-0.42**
	(-1.40)	(-2.08)	(-2.68)	(-2.17)	(-2.03)	(-2.77)	(-1.98)
α_{FFC4}	-0.42**	-0.46**	-0.58***	-0.67***	-0.67***	-0.73***	-0.72***
	(-2.19)	(-2.25)	(-2.96)	(-2.75)	(-3.25)	(-3.47)	(-2.92)
α_{F5}	-0.42**	-0.46**	-0.55***	-0.61***	-0.61***	-0.68***	-0.63***
	(-2.18)	(-2.28)	(-2.81)	(-2.71)	(-3.04)	(-3.33)	(-2.78)
α_{F7}	-0.45**	-0.35*	-0.47***	-0.51**	-0.62***	-0.67***	-0.66***
	(-2.32)	(-1.87)	(-2.37)	(-2.22)	(-2.90)	(-2.99)	(-2.65)

This table presents the results of the univariate portfolio analysis for the main uncertainty measures: Consensus Forecast (CF), Bluechip Financials Indicators (BCF), Bluechip Economics Indicators (BCE), Michigan Consumer Survey (mic), Jurado-Ludvigson-Ng (JLN), Economic Policy Uncertainty (EPU), VIX index (VIX), and realized market volatility (RVOL).
At each month, ten decile portfolios are formed based on uncertainty beta (β^{UNC}) estimated via 60-month rolling window regressions, as shown in Equation 1, controlling for 7 factors: market, size, value, investment, profitability, liquidity, and momentum. The excess returns and alpha's ($\alpha_{FF3}, \alpha_{FFC4}, \alpha_{F5}, \alpha_{F7}$) are the average next-month excess returns and risk-adjusted returns of the High-Low portfolios, which are constructed as taking a long-short position in the top and bottom decile portfolios. α_{FF3} is the alpha relative to the market, size, and value factors; α_{FFC4} is the alpha relative to the market, size, value, and momentum factors; α_{F5} is the alpha relative to the market, size, value, momentum, and liquidity factors; and α_{F7} is the alpha relative to the market, size, value, momentum, liquidity, investment, and profitability factors.
The sample size is from October 1989 to December 2020. Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

Table 3: Bivariate portfolio analysis.

Variable	CF	BCF	BCE	JLN	EPU	VIX	RVOL
Panel A: Control for market sensitivity β^{MKT}							
High-Low	-0.28***	-0.28***	-0.43***	-0.52***	-0.68***	-0.54***	-0.52***
	(-2.58)	(-2.95)	(-3.98)	(-4.59)	(-6.20)	(-4.78)	(-4.46)
α_{FF3}	-0.20	-0.27**	-0.43***	-0.41***	-0.44***	-0.26*	-0.21
	(-1.40)	(-2.06)	(-3.24)	(-2.50)	(-3.00)	(-1.84)	(-1.28)
α_{FFC4}	-0.40***	-0.40***	-0.54***	-0.63***	-0.73***	-0.49***	-0.53***
	(-2.58)	(-2.67)	(-3.72)	(-3.42)	(-4.72)	(-3.25)	(-3.14)
α_{F5}	-0.40***	-0.40***	-0.52***	-0.57***	-0.69***	-0.44***	-0.46***
	(-2.56)	(-2.69)	(-3.60)	(-3.19)	(-4.58)	(-2.96)	(-2.84)
α_{F7}	-0.42***	-0.32**	-0.51***	-0.49***	-0.71***	-0.40***	-0.45***
	(-2.69)	(-2.24)	(-3.36)	(-2.70)	(-4.50)	(-2.61)	(-2.65)
Panel B: Control for market capitalization							
High-Low	-0.31***	-0.28***	-0.25***	-0.41***	-0.52***	-0.55***	-0.48***
	(-3.19)	(-3.03)	(-2.44)	(-3.98)	(-5.37)	(-5.52)	(-5.00)
α_{FF3}	-0.25*	-0.3***	-0.25**	-0.36***	-0.31***	-0.44***	-0.32***
	(-1.90)	(-2.52)	(-2.11)	(-2.44)	(-2.56)	(-3.75)	(-2.52)
α_{FFC4}	-0.39***	-0.39***	-0.32***	-0.51***	-0.54***	-0.55***	-0.53***
	(-2.85)	(-3.03)	(-2.49)	(-3.31)	(-4.40)	(-4.57)	(-3.94)
α_{F5}	-0.39***	-0.39***	-0.30***	-0.46***	-0.50***	-0.53***	-0.47***
	(-2.84)	(-3.02)	(-2.33)	(-2.98)	(-4.15)	(-4.35)	(-3.61)
α_{F7}	-0.40***	-0.29**	-0.22	-0.33**	-0.50***	-0.49***	-0.44***
	(-2.83)	(-2.26)	(-1.62)	(-2.24)	(-4.07)	(-3.97)	(-3.21)
Panel C: Control for book-to-market ratio							
High-Low	-0.18*	-0.26***	-0.34***	-0.63***	-0.64***	-0.65***	-0.59***
	(-1.75)	(-2.66)	(-3.41)	(-5.82)	(-6.17)	(-6.32)	(-5.51)
α_{FF3}	-0.16	-0.33***	-0.37***	-0.64***	-0.48***	-0.57***	-0.48***
	(-1.23)	(-2.74)	(-2.93)	(-4.43)	(-3.60)	(-4.23)	(-3.29)
α_{FFC4}	-0.29**	-0.39***	-0.41***	-0.76***	-0.71***	-0.70***	-0.70***
	(-2.10)	(-2.89)	(-2.87)	(-4.87)	(-5.09)	(-4.94)	(-4.33)
α_{F5}	-0.28**	-0.38***	-0.39***	-0.72***	-0.66***	-0.66***	-0.62***
	(-2.05)	(-2.90)	(-2.79)	(-4.72)	(-4.89)	(-4.81)	(-4.17)
α_{F7}	-0.27**	-0.31***	-0.32**	-0.61***	-0.70***	-0.65***	-0.60***
	(-1.97)	(-2.41)	(-2.24)	(-4.03)	(-5.04)	(-4.58)	(-3.74)

This table presents the results of the bivariate portfolio analysis for the main uncertainty measures: Consensus Forecast (CF), Bluechip Financials Indicators (BCF), Bluechip Economics Indicators (BCE), Jurado-Ludvigson-Ng (JLN), Economic Policy Uncertainty (EPU), VIX index (VIX), and realized market volatility (RVOL).

At each month, we sort stocks into decile based on one of the control variables (β^{MKT}, size, value), and then further sort them into deciles based on uncertainty beta (β^{UNC}), resulting in ten High-Low uncertainty portfolios. Market beta is estimated over the full sample. Uncertainty beta is estimated via 60-month rolling window regressions, as shown in Equation 1. The excess returns and alpha's are the average next-month excess returns and risk-adjusted returns of the High-Low portfolios.

The sample size is from October 1989 to December 2020. Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

Table 4: Fama-Macbeth cross-sectional regressions at stock level.

Variable	CF	BCF	BCE	JLN	EPU	VIX	RVOL
λ^{UNC}	-0.02	-0.01	-0.02	-0.01	-0.04***	-0.83*	-0.23*
	(-1.19)	(-0.83)	(-1.07)	(-1.54)	(-2.57)	(-1.91)	(-1.82)
Constant	0.88***	0.89***	0.89***	0.88***	0.90***	0.84***	0.88***
	(3.80)	(3.85)	(3.87)	(3.78)	(3.90)	(3.60)	(3.78)
λ^{MKT}	0.11	0.12	0.11	0.12	0.10	0.13	0.12
	(0.66)	(0.74)	(0.68)	(0.73)	(0.63)	(0.79)	(0.73)
λ^{SMB}	0.03	0.03	0.04	0.03	0.03	0.01	0.03
	(0.36)	(0.38)	(0.45)	(0.44)	(0.42)	(0.13)	(0.41)
λ^{HML}	0.03	0.03	0.03	0.03	0.04	0.03	0.04
	(0.33)	(0.37)	(0.36)	(0.37)	(0.41)	(0.37)	(0.44)
λ^{RMW}	-0.02	-0.02	-0.01	-0.03	-0.02	-0.02	-0.03
	(-0.23)	(-0.24)	(-0.17)	(-0.39)	(-0.29)	(-0.30)	(-0.33)
λ^{CMA}	-0.04	-0.04	-0.05	-0.05	-0.04	-0.05	-0.04
	(-0.78)	(-0.76)	(-0.88)	(-0.84)	(-0.81)	(-0.81)	(-0.76)
λ^{LIQ}	0.12	0.12	0.12	0.12	0.12	0.13	0.11
	(1.10)	(1.14)	(1.11)	(1.17)	(1.15)	(1.26)	(1.08)
λ^{MOM}	-0.18*	-0.17*	-0.17*	-0.18*	-0.18*	-0.16*	-0.17*
	(-1.80)	(-1.77)	(-1.82)	(-1.86)	(-1.93)	(-1.68)	(-1.80)

This table presents the results of the Fama-Macbeth cross-sectional regressions at Stock level for the main uncertainty measures: Consensus Forecast (CF), Bluechip Financials Indicators (BCF), Bluechip Economics Indicators (BCE), Jurado-Ludvigson-Ng (JLN), Economic Policy Uncertainty (EPU), VIX index (VIX), and realized market volatility (RVOL).
First, we estimate the uncertainty beta's β^{UNC} for each stock via 60-months rolling window time-series regressions, as shown in Equation 1, controlling for 7 factors: market, size, value, investment, profitability, liquidity, and momentum. Second, we regress the next-month excess returns against the estimated uncertainty beta's β^{UNC} while controlling for the exposure to the control factors, according to Equation 2. The risk premiums λ are obtained as time-series averages of the estimated slopes in the cross-sectional regressions.
The sample size is from October 1989 to December 2020. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the risk premiums. Newey-West adjusted t-statistics are provided in parentheses.

Table 5: Subperiod analysis.

Variable	CF	BCF	BCE	JLN	EPU	VIX	RVOL
Panel A. 1989-2004 subsample							
Average uncertainty beta β^{UNC}							
Low	-15.80	-17.78	-12.23	-144.67	-18.08	-1.15	-4.72
High	17.48	22.03	13.03	182.93	18.17	1.04	5.09
Average excess returns (%)							
	(0.23)	(0.12)	(0.16)	(1.25)	(1.66)	(1.59)	(1.30)
Abnormal returns relative to factor models (%)							
α_{FF3}	0.22	0.09	-0.11	-0.38	-0.38	-0.45	-0.53
	(-1.04)	(-0.60)	(0.50)	(1.13)	(1.12)	(1.38)	(1.50)
α_{FFC4}	-0.03	0.08	-0.22	-0.72	-0.79**	-0.88**	-1.00**
	(0.14)	(-0.44)	(1.13)	(1.57)	(2.04)	(2.09)	(2.10)
α_{F5}	-0.05	0.09	-0.21	-0.49	-0.68*	-0.79**	-0.78*
	(0.24)	(-0.43)	(1.07)	(1.20)	(1.92)	(2.10)	(1.86)
α_{F7}	-0.10	0.14	-0.18	-0.53	-0.80**	-1.00***	-0.91*
	(0.53)	(-0.70)	(0.88)	(1.22)	(2.09)	(2.51)	(1.95)
Panel B. 2005-2020 subsample							
Average uncertainty beta β^{UNC}							
Low	-11.07	-16.40	-11.94	-69.94	-9.47	-0.70	-2.90
High	12.31	16.26	13.85	70.34	10.14	0.65	2.63
Average excess returns (%)							
High-Low	-0.50	-0.54**	-0.8***	-0.54*	-0.67***	-0.49*	-0.64**
	(1.64)	(2.14)	(2.74)	(1.93)	(2.38)	(1.67)	(2.11)
Abnormal returns relative to factor models (%)							
α_{FF3}	-0.47*	-0.51**	-0.67***	-0.38	-0.43*	-0.25	-0.38
	(1.69)	(2.20)	(2.74)	(1.62)	(1.74)	(0.95)	(1.33)
α_{FFC4}	-0.50**	-0.55***	-0.70***	-0.43***	-0.48***	-0.29	-0.43*
	(2.00)	(2.80)	(3.07)	(2.33)	(2.51)	(1.26)	(1.80)
α_{F5}	-0.50**	-0.55***	-0.71***	-0.44***	-0.50***	-0.32	-0.46**
	(1.99)	(2.78)	(3.06)	(2.39)	(2.45)	(1.41)	(1.96)
α_{F7}	-0.54**	-0.54***	-0.69***	-0.36*	-0.43*	-0.32	-0.41*
	(2.04)	(2.68)	(2.72)	(1.70)	(1.89)	(1.34)	(1.68)

This table presents the results of subperiod analysis for the main uncertainty measures: Consensus Forecast (CF), Bluechip Financials Indicators (BCF), Bluechip Economics Indicators (BCE), Jurado-Ludvigson-Ng (JLN), Economic Policy Uncertainty (EPU), VIX index (VIX), and realized market volatility (RVOL).
We apply univariate portfolio analysis for each of the two subperiods spanning from October 1989 to December 2004, and from January 2005 to December 2020. We report here the average uncertainty beta's β^{UNC} of the High (top decile) and Low (bottom decile) portfolios. For the High-Low (top minus bottom decile) portfolios, we report the next-month excess returns and the abnormal returns, calculated as the alpha relative to a factor model.
Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

Table 6: Recessions versus Expansions

Variable	CF	BCF	BCE	JLN	EPU	VIX	RVOL
Panel A. NBER Expansions							
Average uncertainty beta β^{UNC}							
Low	-13.29	-17.15	-11.93	-106.75	-13.37	-0.90	-3.76
High	14.68	18.91	13.37	125.40	13.80	0.83	3.83
Average excess returns (%)							
High-Low	-0.19	-0.19	-0.26	-0.31*	-0.4***	-0.32**	-0.37**
	(1.24)	(1.40)	(1.64)	(1.78)	(2.34)	(2.04)	(2.03)
Average abnormal returns relative to factor models (%)							
α_{FF3}	-0.19	-0.28**	-0.36***	-0.37**	-0.24	-0.26	-0.29
	(1.17)	(2.17)	(2.39)	(2.10)	(1.33)	(1.60)	(1.57)
α_{FFC4}	-0.28*	-0.28*	-0.39***	-0.56**	-0.5**	-0.53**	-0.6**
	(1.70)	(1.92)	(2.62)	(2.15)	(2.25)	(2.21)	(2.19)
α_{F5}	-0.27*	-0.29**	-0.36***	-0.5**	-0.45**	-0.48**	-0.53**
	(1.68)	(1.98)	(2.55)	(2.13)	(2.15)	(2.21)	(2.13)
α_{F7}	-0.27*	-0.21	-0.29**	-0.44*	-0.52**	-0.62***	-0.62**
	(1.70)	(1.48)	(2.01)	(1.81)	(2.28)	(2.64)	(2.29)
Panel B. NBER Recessions							
Average uncertainty beta β^{UNC}							
Low	-12.41	-15.54	-13.67	-71.00	-13.53	-0.87	-3.36
High	14.53	18.44	14.74	76.47	13.62	0.77	2.83
Average excess returns (%)							
High-Low	-1.45	-1.69	-2.67**	-2.52	-2.71	-2.05	-2.54
	(0.99)	(1.24)	(2.08)	(1.52)	(1.58)	(1.11)	(1.34)
Average abnormal returns relative to factor models (%)							
α_{FF3}	-1.43	-1.66	-2.90***	-2.83***	-3.07***	-2.40***	-3.00***
	(1.00)	(1.53)	(3.01)	(2.39)	(3.26)	(2.46)	(2.73)
α_{FFC4}	-1.03	-1.34***	-2.69***	-2.56***	-2.76***	-2.18***	-2.73***
	(1.14)	(2.79)	(4.68)	(2.67)	(4.05)	(2.74)	(2.93)
α_{F5}	-1.04	-1.34***	-2.64***	-2.29***	-2.59***	-1.98***	-2.38***
	(1.22)	(3.14)	(4.49)	(2.35)	(3.80)	(2.44)	(2.62)
α_{F7}	-2.11***	-1.42**	-2.41**	-2.30***	-2.69***	-1.63*	-2.24***
	(2.65)	(2.12)	(2.18)	(2.49)	(3.78)	(1.81)	(2.81)

This table presents the results of univariate portfolio analysis during recessions and expansions for the main uncertainty measures: Consensus Forecast (CF), Bluechip Financials Indicators (BCF), Bluechip Economics Indicators (BCE), Jurado-Ludvigson-Ng (JLN), Economic Policy Uncertainty (EPU), VIX index (VIX), and realized market volatility (RVOL).

At each month, ten decile portfolios are formed based on uncertainty beta (β^{UNC}) estimated via 60-month rolling window regressions, as shown in Equation 1, over the entire sample between October 1989 and December 2020. We then calculate for each decile portfolio the average monthly excess returns and the abnormal returns, measured as the alpha relative to a factor model. We report here the average uncertainty beta's β^{UNC} of the High (top decile) and Low (bottom decile) portfolios, the next-month excess returns and the abnormal returns of the High-Low (top minus bottom deciles) portfolio. The recession and expansion periods are as defined by the National Bureau of Economic Research (NBER).

The sample spans from October 1989 to December 2020. Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

Table 7: Subsample analysis

Subsample/Variable	CF	BCF	BCE	JLN	EPU	VIX	RVOL
NYSE	-0.64***	-0.57***	-0.64***	-0.63***	-0.46**	-0.31*	-0.36**
	(2.88)	(3.36)	(2.84)	(3.25)	(2.30)	(1.80)	(2.00)
Large	-0.41***	-0.14	0.01	-0.58***	-0.32*	-0.17	-0.10
	(2.68)	(1.08)	(-0.04)	(2.91)	(1.80)	(1.07)	(0.57)
1000 Largest	-0.38***	-0.14	0.01	-0.52***	-0.30*	-0.14	-0.11
	(2.62)	(1.13)	(-0.06)	(2.74)	(1.78)	(0.83)	(0.66)
1000 Most liquid	-0.83***	-0.53***	-0.33	-0.63**	-0.48*	-0.45**	-0.43*
	(3.96)	(2.63)	(1.34)	(2.04)	(1.81)	(2.09)	(1.86)

This table presents the results of the subsample analysis for the main uncertainty measures: Consensus Forecast (CF), Bluechip Financials Indicators (BCF), Bluechip Economics Indicators (BCE), Jurado-Ludvigson-Ng (JLN), Economic Policy Uncertainty (EPU), VIX index (VIX), and realized market volatility (RVOL).
At each month, ten decile portfolios are formed based on uncertainty beta (β^{UNC}) estimated via 60-month rolling window regressions, as shown in Equation 1, over the entire sample between October 1989 and December 2020. We then calculate for each decile portfolio the average monthly excess returns and the abnormal returns, measured as the alpha relative to the market, size, value, investment, profitability, momentum, and liquidity factors. We report here the average α_{F7} of the High (top decile), Low (bottom decile), and High-Low (top minus bottom decile) portfolios for the subsamples: (i) NYSE-listed stocks, (ii) large stocks, defined as having a market capitalization larger than the 50th percentile of NYSE-listed stocks, (iii) 1000 largest stocks in terms of market capitalization in the CRSP universe, and (iv) 1000 most liquid stocks in the CRSP universe according to Amihud (2002) illiquidity measure.
Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

Table 8: Industry specific results

Industry/Variable	CF	BCF	BCE	JLN	EPU	VIX	RVOL
Non-durables	-0.63	-0.50	-0.99**	-1.17***	-0.65	-0.91**	-0.80*
	(1.42)	(1.08)	(2.27)	(2.92)	(1.42)	(2.04)	(1.87)
Durables	0.24	-0.74	-0.51	0.31	-0.69	-0.88	-0.54
	(-0.49)	(1.28)	(1.09)	(-0.60)	(1.43)	(1.59)	(1.10)
Manufacturing	-0.47	0.09	-0.27	-0.57*	-0.74***	-0.90***	-0.85***
	(1.52)	(-0.29)	(0.91)	(1.78)	(2.88)	(3.23)	(2.55)
Energy	-1.76***	-1.55***	-1.23***	-0.96*	-0.90*	-0.80	-0.34
	(2.96)	(2.85)	(2.48)	(1.72)	(1.66)	(1.57)	(0.61)
Chemicals	-0.29	0.74*	-1.13*	0.11	-0.23	-0.02	-0.45
	(0.48)	(-1.84)	(1.87)	(-0.27)	(0.49)	(0.05)	(0.85)
Business Equipment	-0.34	-0.03	0.16	-0.43	-0.66**	-0.37	-0.46
	(0.91)	(0.12)	(-0.48)	(1.29)	(2.01)	(1.09)	(1.06)
Telecom	-1.01	-0.62	-0.06	-0.59	-0.88	-1.06	-0.82
	(1.59)	(0.84)	(0.10)	(0.94)	(1.21)	(1.46)	(1.25)
Utilities	0.15	-0.18	0.34	0.23	0.03	0.19	-0.28
	(-0.33)	(0.58)	(-0.80)	(-0.67)	(-0.09)	(-0.59)	(0.81)
Shops	-0.25	-0.43	-0.92***	-0.48*	-0.04	-0.29	-0.43
	(0.87)	(1.19)	(3.24)	(1.71)	(0.16)	(0.88)	(1.27)
Healthcare	-0.18	-0.72	0.01	0.33	-1.16***	-1.10***	-0.67
	(0.32)	(1.55)	(-0.02)	(-0.49)	(2.35)	(2.42)	(1.15)
Finance	-0.05	0.01	-0.38	-0.15	-0.58**	-0.21	-0.40
	(0.21)	(-0.07)	(1.49)	(0.56)	(2.07)	(0.82)	(1.41)
Others	-0.36	-0.25	-0.71**	-0.85***	-0.87***	-1.10***	-0.77**
	(1.25)	(0.76)	(2.31)	(2.34)	(3.09)	(3.87)	(2.22)

This table presents the industry-specific results for the main uncertainty measures: Consensus Forecast (CF), Bluechip Financials Indicators (BCF), Bluechip Economics Indicators (BCE), Jurado-Ludvigson-Ng (JLN), Economic Policy Uncertainty (EPU), VIX index (VIX), and realized market volatility (RVOL).
At each month, ten decile portfolios are formed based on uncertainty beta (β^{UNC}) estimated via 60-month rolling window regressions, as shown in Equation 1, over the entire sample between October 1989 and December 2020. We then calculate for each decile portfolio the average monthly excess returns and the abnormal returns, measured as the alpha relative to the market, size, value, investment, profitability, momentum, and liquidity factors. We report here the average α_{F7} of the 12 industry groups, according to the definitions of 12 industry portfolios on Kenneth French's website.
Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

Table 9: Long-term return predictability.

Horizon/Variable	CF	BCF	BCE	JLN	EPU	VIX	RVOL
3 months	-0.27	-0.33**	-0.44***	-0.37**	-0.46***	-0.34**	-0.41**
	(1.55)	(2.25)	(2.42)	(2.20)	(3.02)	(2.05)	(2.00)
6 months	-0.26	-0.32***	-0.38**	-0.33***	-0.40***	-0.31**	-0.38**
	(1.52)	(2.41)	(2.27)	(2.53)	(2.80)	(2.19)	(2.12)
12 months	-0.22*	-0.28***	-0.29**	-0.22**	-0.28***	-0.21*	-0.30**
	(1.76)	(2.62)	(2.25)	(2.06)	(2.35)	(1.86)	(2.12)
18 months	-0.19**	-0.22***	-0.24**	-0.14	-0.24**	-0.13	-0.23**
	(1.98)	(2.43)	(2.15)	(1.40)	(2.31)	(1.42)	(1.98)
24 months	-0.17*	-0.17*	-0.23**	-0.08	-0.20**	-0.09	-0.17
	(1.81)	(1.92)	(2.04)	(0.79)	(2.01)	(1.02)	(1.64)
36 months	-0.18*	-0.15*	-0.23**	-0.02	-0.12	-0.02	-0.08
	(1.86)	(1.69)	(2.13)	(0.20)	(1.34)	(0.20)	(0.84)

This table presents the average monthly abnormal returns of the High-Low portfolios over longer holding periods for the following uncertainty measures: Consensus Forecast (CF), Bluechip Financials Indicators (BCF), Bluechip Economics Indicators (BCE), Jurado-Ludvigson-Ng (JLN), Economic Policy Uncertainty (EPU), VIX index (VIX), and realized market volatility (RVOL).
The abnormal returns of the High-Low portfolios measure the alpha spread between the top and bottom decile portfolios. The alpha is with respect to 7 factors: market, size, value, investment, profitability, liquidity, and momentum.
At each month, ten decile portfolios are formed based on uncertainty beta (β^{UNC}) estimated via 60-month rolling window regressions, as shown in Equation 1, controlling for 7 factors: market, size, value, investment, profitability, liquidity, and momentum. We then calculate the average monthly excess returns of the decile portfolios over an x-month holding-period, which ranges from 3 to 36 months. We report here the α_{F7} spread between the top and bottom decile portfolios (High-Low portfolio). $alpha_{F7}$ is the alpha relative to the market, size, value, momentum, liquidity, investment, and profitability factors.
The sample size is from October 1989 to December 2020. Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

Table 10: Univariate portfolio analysis for Consensus Forecast indicators.

Variable	budget	auto	cons	cprice	account	gdp	housing	businv	oil	pprice	prod	profit	y10	tspread	m3	unrate	wage
Average uncertainty beta β^{UNC}																	
Low	-20.73	-6.48	-7.74	-6.61	-11.60	-6.79	-7.56	-5.48	-13.54	-6.79	-7.43	-6.33	-5.08	-4.96	-6.74	-14.22	-5.21
High	19.84	6.69	8.83	6.63	11.93	7.65	7.92	6.33	13.73	7.47	8.56	7.21	5.23	5.05	6.81	15.76	5.56
Average excess returns (%)																	
High-Low	-0.63***	-0.34*	-0.23	-0.04	-0.32	-0.24	-0.07	-0.24	-0.14	-0.18	-0.23	-0.37**	-0.09	-0.21	-0.05	-0.13	-0.11
	(-2.63)	(-1.80)	(-1.43)	(-0.17)	(-1.64)	(-1.38)	(-0.48)	(-1.31)	(-0.65)	(-0.98)	(-1.19)	(-2.11)	(-0.56)	(-1.40)	(-0.27)	(-0.74)	(-0.66)
Abnormal returns relative to factor models (%)																	
α_{FF3}	-0.63***	-0.36**	-0.26	0.08	-0.29	-0.22	-0.16	-0.19	-0.16	-0.15	-0.22	-0.34**	-0.04	-0.11	0.00	-0.07	-0.17
	(-2.88)	(-2.06)	(-1.57)	(0.44)	(-1.64)	(-1.27)	(-1.08)	(-1.15)	(-0.78)	(-0.86)	(-1.21)	(-2.12)	(-0.22)	(-0.82)	(0.03)	(-0.36)	(-1.12)
α_{FFC4}	-0.80***	-0.46**	-0.33	-0.07	-0.49***	-0.31*	-0.15	-0.30*	-0.32	-0.27	-0.37*	-0.48***	-0.15	-0.24	-0.14	-0.07	-0.14
	(-3.29)	(-2.31)	(-1.80)	(-0.38)	(-2.82)	(-1.76)	(-0.94)	(-1.73)	(-1.46)	(-1.45)	(-1.94)	(-3.00)	(-0.82)	(-1.61)	(-0.88)	(-0.28)	(-0.78)
α_{F5}	-0.79***	-0.43**	-0.30*	-0.10	-0.49***	-0.31*	-0.15*	-0.30	-0.28	-0.28*	-0.36***	-0.49	-0.15	-0.24	-0.13	-0.07	-0.13
	(-3.39)	(-2.16)	(-1.66)	(-0.52)	(-2.88)	(-1.74)	(-0.95)	(-1.66)	(-1.35)	(-1.48)	(-1.92)	(-2.99)	(-0.83)	(-1.60)	(-0.79)	(-0.33)	(-0.73)
α_{F7}	-0.87***	-0.36*	-0.26	-0.28	-0.37**	-0.36**	-0.12	-0.37**	-0.16	-0.24	-0.35*	-0.49***	-0.30	-0.37**	-0.15	-0.14	-0.01
	(-3.50)	(-1.89)	(-1.48)	(-1.51)	(-2.13)	(-1.97)	(-0.71)	(-1.97)	(-0.73)	(-1.20)	(-1.83)	(-3.05)	(-1.64)	(-2.21)	(-0.89)	(-0.57)	(-0.10)

This table presents the results of the univariate portfolio analysis for the forecast dispersion of the Consensus Forecast indicators: budget balance (budget), auto and truck sales (auto), personal consumption expenditure (pce), consumer prices (cpi), current account (account), GDP (gdp), housing starts (housing), business investment (invest), oil price (oil), producer prices (pprice), industrial production (prod), corporate profits before taxes (profit), 10-year Treasury Bond yield (y10), term spread (tspread), 3-month Treasury Bill rate (3m), unemployment rate (unrate), employment costs (wage).

At each month, ten decile portfolios are formed based on uncertainty beta (β^{UNC}) estimated via 60-month rolling window regressions, as shown in Equation 1, controlling for 7 factors: market, size, value, investment, profitability, liquidity, and momentum. The excess returns and alpha's ($\alpha_{FF3}, \alpha_{FFC4}, \alpha_{F5}, \alpha_{F7}$) are based on one-month holding period of the High-Low portfolios, which are constructed as taking a long-short position in the top and bottom decile portfolios. α_{FF3} is the alpha relative to the market, size, and value factors; α_{FFC4} is the alpha relative to the market, size, value, and momentum factors; α_{F5} is the alpha relative to the market, size, value, momentum, and liquidity factors; and α_{F7} is the alpha relative to the market, size, value, momentum, liquidity, investment, and profitability factors.

The sample size is from October 1989 to December 2020. Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

Table 11: Univariate portfolio analysis for BlueChip Financials indicators.

Variable	fed	prime	cp	m3	rgdp	cpi	gdppi	libor	m6	y1	y5	y10	y2	aaa	baa
Average uncertainty beta β^{UNC}															
Low	-24.30	-17.12	-13.24	-17.34	-10.15	-6.98	-8.07	-13.94	-12.69	-12.11	-9.62	-11.56	-11.05	-7.78	-6.91
High	22.69	17.64	13.54	18.95	12.17	6.16	8.55	14.64	13.32	13.95	11.09	13.55	12.57	8.37	7.29
Average excess returns (%)															
High-Low	0.07	-0.20	-0.20	-0.05	-0.09	-0.30*	-0.04	-0.11	-0.06	-0.11	-0.30*	-0.26	0.04	-0.27	-0.27
	(0.37)	(-1.29)	(-1.02)	(-0.32)	(-0.61)	(-1.89)	(-0.27)	(-0.54)	(-0.34)	(-0.62)	(-1.96)	(-1.56)	(0.23)	(-1.57)	(-1.38)
Abnormal returns relative to factor models (%)															
α_{FF3}	0.01	-0.19	-0.17	-0.07	-0.11	-0.28**	-0.08	-0.11	-0.08	-0.09	-0.32**	-0.32**	0.00	-0.34	-0.32
	(0.04)	(-1.22)	(-0.83)	(-0.44)	(-0.80)	(-2.06)	(-0.59)	(-0.52)	(-0.50)	(-0.48)	(-2.21)	(-2.00)	(-0.02)	(-2.33)	(-1.82)
α_{FFC4}	-0.09	-0.30*	-0.26	-0.10	-0.13	-0.37***	-0.11	-0.14	-0.14	-0.16	-0.41***	-0.38*	-0.11	-0.35**	-0.38**
	(-0.55)	(-1.94)	(-1.24)	(-0.54)	(-0.83)	(-2.42)	(-0.70)	(-0.53)	(-0.68)	(-0.76)	(-2.45)	(-1.91)	(-0.63)	(-2.23)	(-2.11)
α_{F5}	-0.09	-0.30*	-0.26	-0.08	-0.12	-0.38***	-0.11	-0.13	-0.14	-0.17	-0.42***	-0.39**	-0.12	-0.33**	-0.38**
	(-0.56)	(-1.95)	(-1.26)	(-0.48)	(-0.77)	(-2.46)	(-0.64)	(-0.54)	(-0.71)	(-0.81)	(-2.56)	(-1.99)	(-0.73)	(-2.08)	(-2.11)
α_{F7}	-0.04	-0.24	-0.27	0.03	-0.02	-0.42***	-0.05	0.00	-0.09	-0.06	-0.41***	-0.25	-0.04	-0.26	-0.32*
	(-0.24)	(-1.64)	(-1.28)	(0.16)	(-0.14)	(-2.66)	(-0.29)	(-0.02)	(-0.46)	(-0.31)	(-2.54)	(-1.24)	(-0.23)	(-1.63)	(-1.93)

This table presents the results of the univariate portfolio analysis for the forecast dispersion of the Consensus Forecast indicators: Federal Funds rate (fed), prime bank rate (prime), commercial paper (cp), 3-month Treasury Bill (m3), real GDP (rgdp), consumer price index (cpi), GDP price index (gdppi), LIBOR rate (libor), 6-month Treasury Bill (m6), 1-year Treasury Bill (y1), 5-year Treasury Notes (5y), 10-year Treasury Notes (10y), 2-year Treasury Notes (y2), Aaa-rated corporate bond yield (aaa), Baa-rated corporate bond yield (baa).
At each month, ten decile portfolios are formed based on uncertainty beta (β^{UNC}) estimated via 60-month rolling window regressions, as shown in Equation 1, controlling for 7 factors: market, size, value, investment, profitability, liquidity, and momentum. The excess returns and alpha's ($\alpha_{FF3}, \alpha_{FFC4}, \alpha_{F5}, \alpha_{F7}$) are based on one-month holding period of the High-Low portfolios, which are constructed as taking a long-short position in the top and bottom decile portfolios. α_{FF3} is the alpha relative to the market, size, and value factors; α_{FFC4} is the alpha relative to the market, size, value, and momentum factors; α_{F5} is the alpha relative to the market, size, value, momentum, and liquidity factors; and α_{F7} is the alpha relative to the market, size, value, momentum, liquidity, investment, and profitability factors.
The sample size is from October 1989 to December 2020. Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

Table 12: Univariate portfolio analysis for BlueChip Economics indicators.

Variable	profit	gdppi	t3	rgdp	ngdp	unrate	housing	prod	cpi	auto	invest	income	ne	pce
Average uncertainty beta β^{UNC}														
Low	-7.77	-7.93	-9.25	-6.54	-6.17	-13.98	-12.81	-6.17	-7.19	-7.99	-6.37	-7.45	-13.17	-10.23
High	7.88	8.25	9.13	7.42	6.95	15.33	10.97	7.08	7.35	8.96	7.08	7.83	14.17	10.45
Average excess returns (%)														
High-Low	-0.13	-0.11	-0.02	-0.35*	-0.29*	-0.36***	0.06	-0.46**	-0.18	-0.35*	-0.22	-0.37**	-0.42**	-0.19
	(-0.87)	(-0.59)	(-0.10)	(-1.83)	(-1.65)	(-2.34)	(0.38)	(-2.28)	(-1.05)	(-1.67)	(-1.06)	(-2.13)	(-2.19)	(-1.09)
Abnormal returns relative to factor models (%)														
α_{FF3}	-0.16	-0.11	0.05	-0.39**	-0.35**	-0.29**	-0.03	-0.47***	-0.22	-0.36*	-0.26	-0.43***	-0.38**	-0.26
	(-1.16)	(-0.60)	(0.33)	(-2.17)	(-2.01)	(-2.12)	(-0.20)	(-2.64)	(-1.38)	(-1.86)	(-1.34)	(-2.63)	(-2.14)	(-1.53)
α_{FFC4}	-0.22	-0.21	0.01	-0.47***	-0.43**	-0.34**	-0.03	-0.61***	-0.28	-0.51***	-0.36*	-0.53***	-0.59***	-0.37*
	(-1.47)	(-1.09)	(0.03)	(-2.39)	(-2.20)	(-2.17)	(-0.20)	(-3.23)	(-1.39)	(-2.59)	(-1.71)	(-3.09)	(-3.37)	(-1.92)
α_{F5}	-0.22	-0.20	0.01	-0.46**	-0.43**	-0.32**	-0.04	-0.58***	-0.28	-0.45**	-0.33	-0.52***	-0.56***	-0.33*
	(-1.46)	(-1.05)	(0.08)	(-2.30)	(-2.25)	(-2.05)	(-0.21)	(-3.05)	(-1.34)	(-2.31)	(-1.53)	(-3.03)	(-3.31)	(-1.77)
α_{F7}	-0.09	-0.26	0.06	-0.39*	-0.41**	-0.34**	-0.02	-0.50***	-0.24	-0.32	-0.35	-0.51***	-0.48***	-0.28
	(-0.54)	(-1.37)	(0.34)	(-1.86)	(-2.05)	(-2.00)	(-0.10)	(-2.49)	(-1.10)	(-1.64)	(-1.60)	(-2.91)	(-2.94)	(-1.47)

This table presents the results of the univariate portfolio analysis for the forecast dispersion of the BlueChip Economics (BCE) indicators: corporate profits before taxes (profit), GDP price index (gdppi), 3-month Treasury Bills (m3), real GDP (rgdp), nominal GDP (ngdp), unemployment rate (unrate), housing starts (housing), industrial production (prod), consumer price index (cpi), auto/truck sales (auto), non-residential fixed investment (invest), disposable personal income (income), net exports (ne), personal consumption expenditure (pce).
At each month, ten decile portfolios are formed based on uncertainty beta (β^{UNC}) estimated via 60-month rolling window regressions, as shown in Equation 1, controlling for 7 factors: market, size, value, investment, profitability, liquidity, and momentum. The excess returns and alpha's ($\alpha_{FF3}, \alpha_{FFC4}, \alpha_{F5}, \alpha_{F7}$) are based on one-month holding period of the High-Low portfolios, which are constructed as taking a long-short position in the top and bottom decile portfolios. α_{FF3} is the alpha relative to the market, size, and value factors; α_{FFC4} is the alpha relative to the market, size, value, and momentum factors; α_{F5} is the alpha relative to the market, size, value, momentum, and liquidity factors; and α_{F7} is the alpha relative to the market, size, value, momentum, liquidity, investment, and profitability factors.
The sample size is from October 1989 to December 2020. Returns are expressed as monthly percentage. *, **, *** indicate statistical significance at 10%, 5%, and 1% level, respectively, for the return values. Newey-West adjusted t-statistics are provided in parentheses.

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