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How Well Does Economic Uncertainty Forecast Economic Activity?*

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*The views expressed here are solely our own and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

How Well Does Economic Uncertainty Forecast Economic Activity?

Abstract

Despite the enormous reach and influence of the literature on economic and economic policy uncertainty, one surprisingly under-researched topic has been the forecasting performance of economic uncertainty measures. We evaluate the ability of seven popular measures of uncertainty to forecast in-sample and out-of-sample over real and financial outcome variables. We also evaluate predictive content over different quantiles of the GDP growth distribution. Real-time data and estimation considerations are highly consequential, and we devote considerable attention to them. Four main findings emerge. First, there is some explanatory power in all uncertainty measures, with relatively good performance by macroeconomic uncertainty (Jurado et al. (2015)). Second, macro uncertainty has additional predictive content over the widely-used excess bond premium of Gilchrist and Zakrajšek (2012) and the National Financial Conditions Index (NFCI). Third, quantile regressions for GDP growth indicate strong predictive power, especially at the lower ends of the distribution, for all uncertainty measures except the VIX. Finally, we construct new real-time versions of both macroeconomic and financial uncertainty and compare them to their ex-post counterparts used in the literature. Real-time uncertainty measures have comparatively poor forecasting performance, even to the point of overturning some of the conclusions that emerge from using ex-post uncertainty measures.

"It's difficult to make predictions, especially about the future."

— Yogi Berra

1 Introduction

Research on economic uncertainty over the last decade has been ubiquitous. As made plain from a glance at www.policyuncertainty.com, research on uncertainty is devoted to macroeconomic phenomenon such as inflation and GDP growth, microeconomic issues concerning firm-level investment and export market entry and exit, and finance topics such as corporate strategy and equity returns. New measures reflect uncertainty in the minds of consumers, traders, managers, and policymakers about possible futures, and cover events like terrorism, natural disasters, war and climate change. It is difficult to overstate the reach and influence of this literature. As of this writing, Google scholar citation counts for four prominent articles in this literature are approaching ten thousand (Bloom (2009), Baker et al. (2016), Bloom et al. (2007), and Bloom et al. (2018)).

Surprisingly, little work has focused on the *forecasting* performance of the various measures of economic uncertainty.[1] We fill that gap in the literature in this paper. We consider both in-sample and out-of-sample forecasting, both real and financial outcome variables, and sub-sample stability. We also devote attention to real-time considerations, and find that conclusions concerning forecasting performance depend significantly on them.

Our measures of uncertainty, all for the U.S., sample from the different types that have emerged from this large literature:

[1] We recently became aware of two exceptions written concurrently: Hengge (2019) and Kalamara et al. (2019). In addition, like us, Jovanovic and Ma (2019) focus on quantiles of the output distribution, though with a much different focus than ours. Many papers identify shocks to measures of uncertainty in VARs and estimate their transmission effects in-sample. In addition, Caldara et al. (2016) examine the interaction between economic uncertainty and financial conditions, also using VARs, while Leduc and Liu (2016) estimate VARs using alternative measures of uncertainty, and match impulse responses with a DSGE model. These estimation strategies are quite different from the forecasting exercises we perform.

Newspaper-based: economic policy uncertainty (EPU) from Baker et al. (2016) and monetary policy uncertainty (MPU) from Husted et al. (forthcoming);

Regression-based: macroeconomic uncertainty (MU) from Jurado et al. (2015), and financial uncertainty (FU) from Ludvigson et al. (forthcoming);

Market-based: the VIX as in Bloom (2009); and

Survey-based: the consumer uncertainty measure of Leduc and Liu (2016) and the professional forecasters uncertainty index of Rossi and Sekhposyan (2015).[2] [3]

Our measures are available at a monthly frequency with the exception of SPF uncertainty, which is quarterly. We benchmark the forecasting performance of the uncertainty measures by comparing it to the performance of the excess bond premium (EBP) of Gilchrist and Zakrajšek (2012) and the Chicago Fed's National Financial Conditions Index (NFCI), which have been shown to have high predictive power over many macroeconomic variables.[4]

We examine the marginal explanatory power of uncertainty over a baseline forecast from a dynamic factor model of the type used extensively in the literature with success (Bai and Ng (2002)). We begin by casting a wide net, examining how well our uncertainty measures forecast each of 128 variables in the updated McCracken and Ng (2016) data set. We show that there is substantial explanatory power, both in-sample and out-of-sample, based on comparison of the baseline dynamic fac-

[2]The Leduc and Liu (2016) measure is constructed from the monthly Michigan Survey question: "Speaking now of the automobile market–do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van or sport utility vehicle?" and the follow-up question as to why. The Leduc-Liu measure is the fraction of respondents who report that "uncertain future" is a reason why it will be a bad time over the next 12 months.

[3]The index Rossi and Sekhposyan (2015) propose is constructed from the Philadelphia Fed's Survey of Professional Forecasters (SPF). Their construct compares the SPF realized forecast error of real GDP growth with the SPF historical forecast error distribution. If the realization is in the tails of the distribution, it is deemed to be very difficult to predict from all available information, implying that the macroeconomic environment is highly uncertain then.

[4]The NFCI provides a comprehensive weekly update on U.S. financial conditions in money markets, debt and equity markets, and the traditional and "shadow" banking systems. The index is constructed to have an average value of zero and a standard deviation of one over a sample period extending back to 1971. Positive values of the NFCI have been historically associated with tighter-than-average financial conditions, while negative values have been historically associated with looser-than-average financial conditions.

tor model to the model augmented with one of the uncertainty measures. Macro uncertainty (MU) does particularly well, on par with EBP and NFCI.[5]

Following these initial explorations, we then examine whether uncertainty has any additional predictive content over the widely-used excess bond premium of Gilchrist and Zakrajšek (2012). We find that there is added predictability, though only for macro uncertainty. Adding MU to the regressions used by Gilchrist-Zakrajsek, we find that it has the expected sign and is statistically significant in regressions for employment, unemployment, industrial production, non-residential investment, and inventories, even controlling for EBP. The other uncertainty proxies do poorly, while the predictive content of EBP and NFCI remains high.

Next we use quantile regressions to examine whether the forecasting performance of uncertainty measures varies over different parts of the GDP growth *distribution*. For example, does uncertainty forecast recessionary conditions better than expansions? There is good reason to expect that it might, in light of important recent work on "Growth at Risk" as well as our Figures 4 and 5, which we return to below.[6] We find both in sample and out of sample that several measures of uncertainty show strong predictive power, especially at lower quintiles. In this exercise, MU out-performs all competitors, including EBP and the NFCI measure emphasized by Adrian et al. (2019) in their examination of U.S. GDP growth quintiles.

Finally, we demonstrate that real-time data construction and estimation issues are highly important for reaching conclusions about forecasting performance. Sev-

[5] We also examined the variance risk premium (Bollerslev et al. (2009)) and a measure of equity return skewness across S&P 500 firms (RT Ferreira (2018)). Furthermore, we examined both EPU and all of its sub-indexes: monetary policy, fiscal policy, taxes, government spending, health care, national security, entitlement programs, regulation, financial regulation, trade policy and sovereign debt (currency crises). We find, but do not report, that uncertainty concerning monetary policy, regulation, and financial regulation have similar in-sample performance as does the general EPU index. For out-of-sample forecasting, sub-categories such as monetary policy, regulation, financial regulation, and trade policy perform even better than overall EPU.

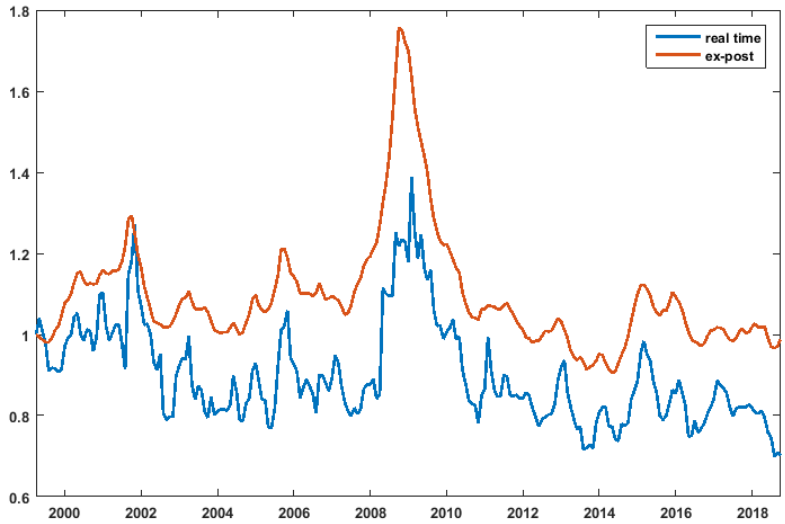
[6] Adrian et al. (2019) model the distribution of future U.S. GDP growth as a function of current financial and economic conditions. They show that the estimated lower quantiles exhibit strong variation as a function of current financial conditions, while the upper quantiles are stable over time. Adrian et al. (2018) extend this analysis to 11 advanced and 10 emerging market economies.

eral of our uncertainty measures do not contain values that were, strictly speaking, available in real time. MU, FU, and EBP are all regression based. Their magnitudes are residuals derived through estimation using a full-sample-period data set. The NFCI, an index constructed from 46 weekly, 33 monthly, and 26 quarterly indicators, is also subject to revisions. Furthermore, the data set includes many series that are themselves continuously revised. This is true of GDP growth, of course, implying that the forecast errors in the SPF are also not strictly-speaking real-time measures. Rossi and Sekhposyan (2015) provide a real-time version of their uncertainty measure, which we examine as well.

The importance of these real-time considerations is foreshadowed in figures 1 and 2. In Figure 1, we display the Jurado-Ludvigson-Ng measure of macroeconomic uncertainty along with our recalculation of that series using a real-time data set and rolling estimation window, as explained in section 6. Both series are scaled such that the index equals 1.0 in January 2000. Notice that real-time macro uncertainty fell between 2000 and 20008, while ex-post uncertainty rose. In JLN's original series, uncertainty peaks at a level nearly 80% above the starting point, but with our real-time series that rise is greatly attenuated, only about 40% above starting point. In Figure 2 we display quantiles 1 through 5 of the distribution of GDP growth against macroeconomic uncertainty. All series are normalized to have a mean of zero and standard deviation equal to 1.0. We display these quantiles for the real-time estimates of the two series (in blue) and for the ex-post measures (in red). The first red bar on the left, for example, displays the average level of ex-post macro uncertainty (vertical axis) when ex-post GDP growth was in its lowest quantile, and what the mean GDP growth was in that quantile (horizontal axis). Although for both ex-post and real-time cases uncertainty is much higher in the lowest growth quantile than the higher ones, the ex-post GDP growth distribution is noticeably "stretched", with larger values at both the low end and high end, compared to the real-time quantiles. Furthermore, using the ex-post measures, the relationship between uncertainty and growth is monotonically negative for the first four quan-

tiles, but using the real-time counterparts gives rise to a see-saw pattern (down, up, down, up) across quantiles. What appears to be unusually high or low uncertainty (and growth) with the benefit of hindsight, was not as evident in real time.

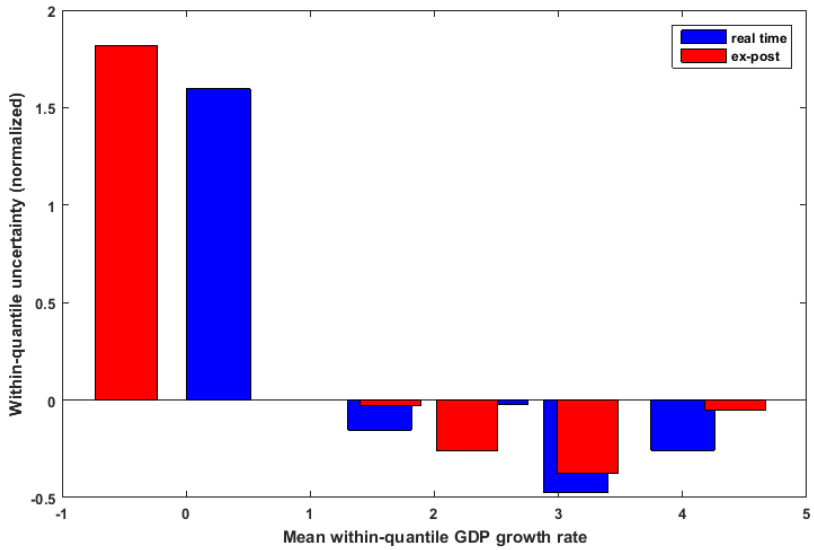
Figure 1 Real time MU v.s. Ex-post MU



The figures suggest that considering how much uncertainty existed in real time versus how much is measured ex-post may affect forecasting performance significantly. The newspaper-based EPU and MPU measures, as well as the market-based measures, are closest to real-time series. We level the playing field in our forecast comparison exercises by using our newly-constructed real-time MU and FU measures, as well as the real-time SPF measure. We find that the real-time uncertainty measures, especially MU, fare much worse than their ex-post revised counterparts. This is arguably the main take-away of the paper. To rephrase the great Yankee catcher, we find that, ”Making predictions, even about the future, is less difficult when you observe part of that future.”[7]

[7]Related to this, in the forecasting exercises below, we use one month ahead MU and FU to forecast variables at time t+h for h=1,3,12. There is a potential “look-ahead bias” for the case of h=1, however, because the 1-step ahead MU and FU at time t contain information at t+1 by

Figure 2 Quantiles of real-time GDP growth with real-time MU and ex-post GDP growth with ex-post MU 2002:I-2018:III



In the next section, we further describe our data and the in-sample predictive exercises, and follow that with a description of the out-of-sample forecast tests. In section 3, we estimate the marginal predictive content of uncertainty and NFCI when added to the Gilchrist-Zakrajsek regressions. In section 4, we estimate quantile regressions that allow us to compare predictability across the GDP growth distribution. The final section we devote to comparison of the predictive content of the results above to those using uncertainty measures based on real-time vintage data.

construction. Hence the importance of our analysis of $h > 1$ and our real time exercises.

2 Uncertainty Measures and their Predictive Power over a Large Macroeconomic Data Set

2.1 Race horses: seven uncertainty measures plus EBP and NFCI

In Figure 3 and Table 1, respectively, we depict our measures of uncertainty and the correlations among them. Notice the large spikes around 2008-09 in most measures. Correlations are typically quite large for all measures except MPU. Both NFCI and EBP are highly correlated with most of the uncertainty measures.[8] We begin with the "kitchen sink", examining the predictive power of these uncertainty measures over the 128 monthly macroeconomic and financial time series from the (updated) data set of McCracken and Ng (2016).

2.2 In-sample predictive regression

We define "predictability" of a particular uncertainty measure as its marginal contribution to the dynamic factor model represented by equation (1):

$$y_{i,t+h} = \alpha_i + \phi_i^y(L)y_{i,t} + \beta_i\varphi^F(L)\hat{F}_t + \gamma_i' Z_t + \varepsilon_{i,t+h}^y \tag{1}$$

where $y_{i,t}$ is the transformed variable of interest, one of the time series from the McCracken and Ng (2016) data set. Similarly, we transform $y_{i,t+h}$, the h-step ahead forecast, also according to the McCracken-Ng code.[9] The $\hat{F}_t$ are estimated factors from the dynamic factor model, with the number of factors selected using the criteria of Bai and Ng (2002). Our benchmark, workhorse dynamic factor model is

[8] The results for MPU suggest at least that the Fed's commitment to a zero interest rate policy and pre-announced large-scale asset purchases were effective in keeping uncertainty about monetary policy from exploding in an environment that was otherwise replete with uncertainty.

[9] This is an unbalanced monthly data set spanning 1959:1-2018:12. We apply specific transformations to the raw series before estimation and construct the factors according to the transformation code provided in the data file. For example, real personal income (RPI), the first variable in the monthly data set, is transformed by $\triangle \ln(x_t)$. y_{t+h} is defined as $y_{t+h} = \frac{C}{h}(\ln(x_{t+h}) - \ln(x_t))$, with $C = 1200$ for monthly data and $C = 400$ for quarterly data. For details, see the data appendix of McCracken and Ng (2016).

a formidable one, as the literature has shown it to have great forecasting success (Stock and Watson (2006) provide an early survey.). The Z_t term contains, alternately, one of the seven uncertainty measures described above, EBP, and NFCI.[10]

The predictive regression (1) is estimated by OLS, with 4 lags of $y'_{i,t}s$ and 2 lags of $\hat{F}_t$.[11] The in-sample predictive content of the aforementioned uncertainty indexes is measured by the t-statistics of γ_i computed using HAC standard errors. Table 2 summarizes the number of series with significant indexes for $h = 1, 3, 12$.[12] Each column reports the number of significant series for different forecast horizons h. MU does well across all horizons, while EBP and NFCI also have good predictive content. EPU has relatively less predictive power than other indexes, but it does improve as the horizon increases.

2.3 Out-of-sample forecasting

In our out-of-sample forecasting exercise we use data from 1990:1-1999:12 for in-sample estimation and model selection, and the rest of the data for out-of-sample forecast accuracy evaluation. We compute the h-step ahead mean squared forecast error (MSFE) for each model j and series i.

$$MSFE^h_{i,j} = \frac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2-h} (y_{i,t+h} - \hat{y}^j_{i,t+h|t})^2$$

where $\hat{y}^j_{i,t+h|t}$is the h-step ahead forecast of $y_{i,t}$ in model j computed using the direct approach. Parameter estimation, factor estimation and model selection are fully recursive. The first simulated out of sample forecast is made in 1999:12. To construct this forecast, we use only data available from 1990:1. Thus regressions were

[10]We also compute the first principal component from the set of uncertainty measures and label the resulting series PC1 in the tables. This turns out not to have much predictive power and so we do not focus on its performance.

[11]We always keep 4 lags of $y_{i,t}$'s in the regression and leave out those insignificant regressors in F_t and its lag. We report t-statistics of Z_t in the screened regression.

[12]The t-statistics for all of the 128 series are not reported due to space constraint but available upon request.

run for t = 1990:1,...,1999:12$-h$, then the values of the regressors at t = 1999:12 were used to forecast $y_{1999:12+h}$. All parameters, factors, and so forth were then re-estimated, information criteria were recomputed, and models were selected using data from 1990:1 through 2000:1, and forecasts from these models were then computed for $y_{2000:1+h}$. The final simulated out of sample forecast is made in 2018:6$-h$ for $y_{2018:6}$.

Forecast accuracy is evaluated via the significance of Clark-West test statistics by comparing MSFEs of the competing model j with the benchmark model 0. $\hat{y}{}^{0}_{i,t+h|t}$ is the h-step ahead forecast of $y_{i,t}$ using the factor-based benchmark model (2).The competing model j is a nested model with additional uncertainty index j, $j \in$\{EPU, MU, FU, MPU, VIX, CarU, EBP, NFCI\}.

$$y_{i,t+h} = \alpha_i + \phi_i^y(L)y_{i,t} + \beta_i\varphi^F(L)\hat{F}_t + \varepsilon^y_{i,t+h} \tag{2}$$

We choose the same forecasting horizons as above for the in-sample predictive regressions $(h = 1, 3, 12)$. In Table 3, we report the number of series with significantly smaller out-of-sample MSFE than the benchmark model.[13] By analogy to Table 2, we summarize the number of significant out-of-sample MSFE, by column for the different horizons h. MU again does well, while EBP and NFCI also have strong forecasting power. They perform better than the benchmark in nearly half of the 128 series, an impressive finding in light of results in the literature that the factor-based or diffusion index forecasting model is difficult to beat empirically. As the forecasting horizon increases, EPU tends to perform better and can beat the benchmark in approximately 1/3 of the 128 series.

The conclusions from our kitchen sink analysis that evaluates the marginal performance of each measure in isolation are that (a) all measures of uncertainty have some predictive content, both in-sample and out-of-sample, and (b) among the uncertainty measures, MU does best, equivalent to EBP and NFCI.

[13]Out-of-sample MSFE for the individual series are not reported but available upon request.

3 Marginal Predictability of Uncertainty over EBP

In this section, we examine if there is marginal predictive power of uncertainty over EBP and NFCI in the Gilchrist-Zakrajsek (GZ) key regressions (their regression 2, Table 6) with a specific uncertainty measure added. We also add NFCI, which was not in the original GZ regressions, because of the strong evidence presented in Adrian et al. (2019) of its predictive power, including over EBP.

The in-sample predictive regression is:

$$\bigtriangledown^h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \bigtriangledown Y_{t-i} + \gamma_1 TS_t + \gamma_2 RFF_t + \gamma_3 \hat{S}_t^{GZ} + \gamma_4 EBP_t + \gamma_5 NFCI_t + \gamma_6 UI_t + \varepsilon_{t+h}$$

where $\bigtriangledown^h Y_{t+h} \equiv \frac{C}{h+1} \ln(\frac{Y_{t+h}}{Y_{t-1}})$, $h \geq 0$ is the forecast horizon. Here TS_t denotes the "term spread"—defined as the difference between the three-month constant-maturity Treasury yield and the ten-year constant-maturity yield; RFF_t denotes the real federal funds rate. The credit spread index is decomposed into two parts: a component that captures systematic movements in default risk of individual firms and a residual component—the excess bond premium, we denote $\hat{S}_t^{GZ}$ and EBP_t respectively. $UI \in \{$EPU, MU, FU, MPU, CarU, VIX$\}$

The full sample data is from 1990:1-2018:6. The complete results are in tables 4 and 5, where we report the coefficients and t-statistics for the uncertainty measure, EBP, and NFCI (the other three variables noted above are included, as in Gilchrist and Zakrajšek (2012), but not reported in order to save space). The Y_t in monthly regressions are EMP, UER and IPM, representing private non-farm payroll employment; civilian unemployment rate; and index of manufacturing industrial production. In Table 4, we see that NFCI has marginal predictive power over EBP for all three series at all horizons $(h = 1, 3, 12)$. In addition, note that all of the uncertainty measures except MU are insignificant for all forecasted series and at all horizons. In Table 5, we run regression (2) using quarterly data for GDP and its main components. In the table, C-D (C-NDS) is personal consumption expenditures on durable (non-durable) goods; I-RES is residential investments; I-NRS is business fixed in-

vestment in structures. The full sample is from 1990:Q1 to 2018:Q2, and forecast horizon is 4 steps. Once again, we see that MU performs quite well, while the other measures of uncertainty have no marginal predictive content and sometimes enter with the wrong sign, as with the VIX. Macroeconomic uncertainty has an impressive degree of predictability for all components, frequencies, and prediction horizons. MU knocks out the significance of EBP in several cases.[14]

4 GDP Growth Distribution and Uncertainty

In this section, we estimate quantile regressions to assess the correlation and predictive content of uncertainty indexes with GDP growth at different quantiles. In Figures 4 and 5 we display the unconditional correlations between GDP growth at different quantiles with our uncertainty indexes. On the horizontal axis, we display the average annualized quarterly GDP growth rates at $\tau = 0.1, 0.3, 0.5, 0.7, 0.9$; on the vertical axis, we show the mean value for each uncertainty index in those quarters when GDP growth is in that particular quantile. The figures show that when GDP growth is low and even negative ($\tau = 0.1$), all uncertainty indexes are quite high, and conversely, when GDP growth is high, the uncertainty indexes are typically low. This negative relationship is monotonically so for EPU and MU.

Next, we further analyze whether uncertainty indexes provide additional predictive power, over factors estimated from large macro data set, for different parts of the growth distribution. In order to do so, we run predictive quantile regression of y_{t+h} on x_t, where x_t is a vector containing a constant, current and lagged values of y_t, estimated factors $\hat{F}_t$, and uncertainty indexes. The quantile coefficients β_τ are chosen to minimize the quantile weighted absolute value of errors:

[14] Husted, Rogers, and Sun (2019), show that MPU has strong predictive power for the cross-section of *firm-level* investment. Other measures of uncertainty may also.

$$\hat{\beta}_\tau = \underset{\beta_\tau \in R^k}{\arg\min} \sum_{t=1}^{T-h} \left(\tau \cdot 1_{(y_{t+h} \geq x_t\beta)} |y_{t+h} - x_t\beta_\tau| + (1-\tau) \cdot 1_{(y_{t+h} < x_t\beta)} |y_{t+h} - x_t\beta_\tau| \right)$$

where $1_{(.)}$ denotes the indicator function. We use FRED-QD for factor estimation in this section.[15] There are in total 248 series, out of which 125 are used for factor estimation. We exclude EPU from the dataset for factor estimation, and so use 124 series for factor estimation. The $\hat{F}_t$ are estimated using the complete unbalanced panel from 1959:I to 2018:IV.

In Table 6, we report the quantile regression coefficients and t-statistics for each of the uncertainty indexes, including the quarterly SPF uncertainty now, at $\tau = 0.1, 0.3, 0.5, 0.7, 0.9$ and for $h = 1, 4, 8$. Most uncertainty series are significantly and negatively related to 1-quarter or 4-quarter ahead GDP growth rate at the lower quantiles. MU, EBP, and NFCI have the strongest negative relationships at the lowest quantiles, while EPU and the VIX have the weakest.

5 Summary of the Sub-sample Analysis

Macroeconomic time series cover a long time span and when it comes to forecast evaluation, it is usually crucial to consider time variation in parameters. This often leads to improved performance in sub-samples (see Clements and Hendry (1999) and Hendry and Mizon (2005)). Stock and Watson (2009) split data into pre and post 1984 sub-samples and found substantial in-sample predictive fit improvements in sub-periods after 1984. In this section, we discuss sub-sample results both before and after the 2008 beginning of the financial crisis. The results are reported in Appendix tables.

In the "kitchen sink" analysis, EPU performs particularly well in the pre-2008 period but has less predictive content after 2008. Several other indexes perform

[15] FRED-QD can also be downloaded at http://research.stlouisfed.org/econ/mccraken/. It is updated every quarter.

better in the post-2008 period, with the number of series with significant indexes even increasing as the forecast horizon increases. When $h = 12$, MU, FU and NFCI are significant in over 75 out of 128 regressions. The out-of-sample results are mostly consistent with in-sample results: EPU performs better before 2008, as do FU and EBP. The best performing indexes pre and post 2008, respectively, are EPU and NFCI. EPU improves upon the benchmark in about 40 out of 128 series. EBP outperforms the benchmark in 44 out of 128 cases.

We also examine the Gilchrist and Zakrajšek (2012) regressions for two sub-samples: 1985:1-2007:12 and 2008:1-2018:12. EPU has significant predictive power and largely displaces that of EBP and NFCI especially for $h = 1, 3$ during 1985:1-2007:12. We also replicate the GZ Table 7 (quarterly series) for sub-samples 1985:Q1-2007:Q4 and 2008:Q1-2018:Q4. EPU is statistically significant and of the correct sign for I-NRS in the pre-2008 sub-period, but overall does not appear to have much predictive content. The predictive power of NFCI decreases in this period. In the post-2008 crisis period, all three indexes lose their predictive power compared to the full sample.

We also estimate the quantile regressions over sub-samples. In general, the results are quite similar to the full sample results. Slight differences exist at $h = 8$. In-sample quantile predictive regression results during 1973:I-2007:IV show that EPU is positively related to GDP growth at quantiles lower than 0.5; EBP is positively related at the lowest quantile. MU and EBP at other quantiles are negatively related to GDP growth. Results for GDP growth during 2008:I-2018:IV indicate that MU, FU and EBP are all significantly and negatively related to GDP growth, especially at short or medium forecast horizons. Overall, the performance of MU is the best.

6 Real-time Data Issues

6.1 Uncertainty in Real-time

Our analysis above indicates that MU has strong predictive content, almost always better than influential uncertainty measures like EPU and MPU. However, as noted above, MU, FU, and EBP are unavailable in real time, as these series are residuals derived through estimation using a full-sample-period data set. Furthermore, the data set underlying construction of these uncertainty measures includes many series that are themselves continuously revised. The newspaper-based EPU and MPU measures, as well as the survey measures and market-based VIX, are closest to real-time series. In this section, we level the playing field by constructing real-time indexes for MU and FU and comparing their performance to the others.

We begin by reconstructing MU from all vintages of the McCracken-Ng data set, beginning in 1999:08 and ending in 2019:01. Since financial data are never revised, we use only the one financial data set vintage updated to 2018:12.[16] All macro and financial series except for 'MZMSL', 'DTCOLNVHFNM', 'DTCTHFNM', 'INVEST' are used for factor estimation. For each vintage, we construct a balanced panel starting from 1978:06 and ending in the corresponding month. Due to data availability, for vintages from 2004:01 and moving forward, we include 120 out of 132 macroeconomic series used in Jurado et al. (2015).[17] We also exclude some series no longer reported in earlier vintages of FRED-MD.[18] We use the Matlab

[16]Thanks to Sai Ma for providing us the updated financial data in Ludvigson et al. (forthcoming).

[17]We exclude 'HWI', 'HWIURATIO', 'NAPMPI', 'NAPMEI', 'NAPM', 'NAPMNOI', 'NAPMSDI', 'NAPMII', 'NAPMPRI', 'VXOCLSx', 'Agg wkly hours', 'Currency', 'ACOGNO' from the original raw data set for various reasons. 'VXOCLSx' is excluded from macro data set but included in the financial data set to calculate financial uncertainty. In historical vintage data before 2014:12, all 'HWI' and "NAPM' related series are not reported. Also 'Agg wkly hours' and 'Currency' are not found in the FRED-MD data set. Vintage data for 'ACOGNO' starts late, in 1992:02, so we delete it to preserve a long panel.

[18]For vintages from 2003:12 and going back, 'DPCERA3M086SBEA' (Real personal consumption expenditures) is removed. For vintage from 2003:05 and going back, 'USTPU' (All Employees: Trade, Transportation Utilities) is removed. For vintages from 2002:11 going back, some series related to industrial production such as 'IPDCONGD','IPNCONGD', 'IPBUSEQ', 'IPDMAT', 'IPNMAT', 'IPB51222S', 'IPFUELS' are removed. For vintages from 2000:07, series related to personal

and R code posted on Serena Ng's website to reconstruct the MU index. The estimation and construction procedures are repeated every month on a new vintage of data. We collect the last observation of each MU series, estimated vintage by vintage starting with 1999:08, to form the real time MU series. In Figure 6, we plot the 1-step, 3-step, and 12-step ahead real time MU (top panel) together with the ex-post MU updated in 2019:02 (bottom panel). The real-time MU series is much smoother than the original JLN measure. What appears to be high uncertainty about the macroeconomy in hindsight, was not as apparent in real time. We display the analogous real time and ex-post FU series in Figure 7.

Next, we compare the "kitchen sink" predictive content of real-time and ex-post measures. In Table 7, we report comparison results of the in-sample (top panel) and out-of-sample (lower panel) exercises.[19] We reproduce the results for our other uncertainty measures in the lower part of each panel, for comparison purposes. Real time MU and FU consistently have much weaker forecasting power relative to their ex-post variants. Unlike the analysis of earlier sections, which documented the superior forecasting performance of the original, ex-post measures of MU and FU over alternatives like EPU, we find that the real-time variants of MU and FU do no better that the alternative measures of uncertainty.

6.2 Forecasting real time macro data

A separate, but related, question concerns forecasting real-time versions of the *outcome* variables. As is well-known, macroeconomic time series are forever subject to revision. In Table 8 we perform the analogous (to table 7) comparison of real-time uncertainty and ex-post uncertainty, but now for forecasting *real-time vintages* of the series in the McCracken-Ng database. We first constructed a real-time balanced

consumption expenditure such as 'PCEPI', 'DDURRG3M086SBEA', 'DNDGRG3M086SBEA', 'DSERRG3M086SBEA' are removed.

[19] For out-of-sample forecasting, we use data from 1999:7-2007:12 for in-sample estimation. The rest of the data are used for out-of-sample forecasting evaluation.

panel of the macro series in the dataset, over the period 1999:7-2018:12. This is the first announced vintage data for each month. Due to data availability, 105 series are included in the real-time panel, instead of 128 in the ex-post panel.[20] Similar to the above exercises, we run both in-sample predictive regressions and out-of-sample forecasting for those real time macro series. The factors are extracted from the combined real-time macro and financial dataset, along with the relevant uncertainty indexes such as EPU, real-time MU/FU and ex-post MU/FU. The results, presented in table 8, once again show a sharp deterioration in forecasting with real-time uncertainty measures.

Finally, we analyze the in-sample predictability of uncertainty measures over the real-time GDP growth distribution. We carried out a similar factor-based quantile regression as in section 4, but now with factors extracted from our newly-constructed real-time monthly macro dataset (converted to quarterly frequency). The results are presented in table 9. The top panel displays results for the distribution of real-time GDP growth quantiles while the bottom panel is for ex-post growth quantiles as the outcome variable.[21] The results again reveal a decline in forecasting performance of real-time uncertainty measures compared to their ex-post counterparts. EPU, which is effectively a real-time measure, forecasts real-time GDP growth quantiles much better than it forecasts ex-post quantiles. In the real-time exercise of the top panel, EPU has more explanatory power than either real-time or ex-post MU and often outperforms real-time FU and SPF.

[20]The series excluded from the real-time panel are 'DPCERA3M086SBEA', 'IPDCONGD', 'IPNCONGD', 'IPBUSEQ', 'IPDMAT', 'IPNMAT', 'IPB51222S', 'IPFUELS', 'HWI', 'HWIURATIO', 'USTPU', 'ACOGNO', 'WPSFD49207', 'WPSFD49502', 'WPSID61', 'WPSID62', 'CUSR0000SAD', 'CUSR0000SA0L2', 'PCEPI', 'DDURRG3M086SBEA', 'DNDGRG3M086SBEA', 'DSERRG3M086SBEA', 'VXOCLSx'.

[21]The bottom panel is thus analogous to Table 6, but with a shorter sample due to the (un)availability of all vintages.

7 Conclusion

As influential as the literature on economic, financial, and economic policy uncertainty has been, surprisingly little attention has been devoted to the pure forecasting performance of uncertainty measures. We evaluate the ability of seven popular measures of uncertainty to forecast in-sample and out-of-sample over real and financial outcome variables. We also assess sub-sample stability and examine real-time considerations, as well as examining predictive content over different quantiles of the GDP growth distribution. We find some explanatory power in all uncertainty measures, especially macroeconomic uncertainty (Jurado, Ludvigson, and Ng (2015)). Both traditional regression analysis and quantile regressions for GDP growth indicate that most uncertainty measures have strong predictive power, especially at the lower ends of the growth distribution. A crucial take-away from our analysis is that real-time data considerations are very important in reaching conclusions about forecasting with uncertainty measures. We construct real-time versions of both macroeconomic and financial uncertainty, and show that they have poorer forecasting performances than their ex-post counterparts. Our paper suggests an addendum to the famous quote of the former New York Yankees catcher: ”It is difficult to make predictions, especially about the future, but less difficult when you see part of the future first.”

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Table 1 Correlations among Uncertainty measures: 1990:1-2018:6

	EPU	MU	FU	MPU	VIX	CarU	EBP	NFCI
EPU	1.00	0.27***	0.33***	0.47***	0.41***	0.57***	0.38***	0.35***
MU		1.00	0.68***	-0.09*	0.60***	0.33***	0.67***	0.85***
FU			1.00	-0.02	0.85***	0.23***	0.73***	0.77***
MPU				1.00	0.07	0.03	0.07	-0.11**
VIX					1.00	0.26***	0.68***	0.77***
CarU						1.00	0.32***	0.44***
EBP							1.00	0.76***
NFCI								1.00

Note: The table reports Pearson correlation coefficients between different uncertainty measures from 1990:1-2018:6. ***,**,* denote 1%, 5%, and 10% significance levels, respectively.

Table 2 Summary table of in-sample predictive regression results

	h=1	h=3	h=12
EPU	21	22	33
MU	33	29	41
FU	33	27	30
MPU	20	15	13
VIX	21	12	18
CarU	24	27	26
EBP	38	47	51
NFCI	38	39	23
PC1	34	29	38

Note: This table reports the number of series for which the index is significant in in the predictive regression. We use the complete data span for each measure: EPU from 1985:1-2018:12; MU and FU 1960:7-2018:12; MPU 1985:1-2018:6; VIX 1990:1-2018:12; CarU 1978:2-2018:12. EBP 1973:1-2018:12; NFCI 1971:1-2018:12. PC1 stands for the first principle component from a dataset containing all uncertainty measures from 1990:1-2018:6 except for EBP and NFCI. The factors are estimated using 128 macro and 147 financial variables from 1960:1-2018:12.

Table 3 Summary table of out-of-sample forecasting

	h=1	h=3	h=12
EPU	35	44	45
MU	56	54	35
FU	34	43	20
MPU	26	14	25
VIX	38	29	28
CarU	34	44	49
EBP	48	45	50
NFCI	55	48	35

Note: This table reports the number of series with significantly smaller MSFE relative to the benchmark model, i.e. reject the Clark-West test at the 10% significance level. The pseudo out-of-sample forecasting values are computed from 2000:1 to 2018:6. Data from 1990:1 to 1999:12 are used for in-sample estimation. The parameter estimation, model selection, and lag orders are estimated recursively. The multiple step ahead forecasts are computed using the direct approach.

Table 4 Monthly in-sample predictive regression in Gilchrist & Zakrajsek (2012): 1990:1-2018:6

	h=1			h=3			h=12		
	EMP	UER	IPM	EMP	UER	IPM	EMP	UER	IPM
EBP	-0.38***	10.42***	-3.47***	-0.47***	11.14***	-2.87***	-0.56***	7.93***	-1.48**
	(-2.61)	(2.89)	(-3.72)	(-2.79)	(3.53)	(-3.24)	(-2.40)	(3.39)	(-1.81)
NFCI	-0.67**	14.69**	-3.70*	-0.77**	14.32**	-3.59*	-0.75	10.70**	-3.27
	(-2.05)	(2.07)	(-1.61)	(-1.91)	(2.18)	(-1.46)	(-1.25)	(1.83)	(-1.28)
EPU	-0.002	0.04	-0.005	-0.001	0.003	-0.0002	0.002	-0.03	0.01
	(-0.98)	(1.03)	(-0.37)	(-0.48)	(0.09)	(-0.01)	(0.79)	(-0.90)	(0.61)
EBP	-0.41***	9.76***	-3.49***	-0.48***	9.92***	-2.76***	-0.51**	6.45***	-1.24*
	(-2.64)	(3.02)	(-3.92)	(-2.77)	(3.59)	(-3.11)	(-2.08)	(2.80)	(-1.46)
NFCI	-0.36	4.07	-2.78*	-0.39	4.39	-1.96	-0.24	2.62	-1.90
	(-0.99)	(0.52)	(-1.41)	(-0.91)	(0.66)	(-1.09)	(-0.40)	(0.45)	(-0.79)
MU	-4.62***	121.65***	-10.78	-5.45***	106.66***	-17.46	-6.36***	81.79***	-13.14*
	(-2.74)	(3.86)	(-0.81)	(-2.62)	(3.75)	(-1.20)	(-2.83)	(3.25)	(-1.29)
EBP	-0.46***	12.31***	-4.45***	-0.54***	12.49***	-3.24***	-0.60**	8.65***	-1.54*
	(-2.99)	(3.55)	(-4.16)	(-3.00)	(4.05)	(-2.82)	(-2.17)	(3.23)	(-1.59)
NFCI	-0.75**	16.65**	-4.72**	-0.84**	15.70***	-3.97**	-0.80	11.42**	-3.33
	(-2.17)	(2.20)	(-2.12)	(-2.03)	(2.34)	(-1.81)	(-1.22)	(1.85)	(-1.18)
FU	0.40	-10.41	7.28**	0.51	-12.25	2.99	0.80	-11.47	1.72
	(0.74)	(-0.84)	(2.13)	(0.74)	(-1.10)	(0.79)	(0.57)	(-0.88)	(0.30)
EBP	-0.39***	10.32***	-3.21***	-0.47***	11.09***	-2.69***	-0.49**	7.37***	-1.11
	(-2.57)	(2.72)	(-3.48)	(-2.65)	(3.38)	(-2.92)	(-1.96)	(2.93)	(-1.19)
NFCI	-0.73**	16.76***	-4.29**	-0.81**	14.52**	-3.86**	-0.74*	10.27**	-3.40*
	(-2.26)	(2.41)	(-1.94)	(-2.06)	(2.26)	(-1.68)	(-1.30)	(1.89)	(-1.42)
MPU	-0.001	0.03	-0.01**	-0.001	0.003	-0.01	-0.001	0.002	-0.01
	(-0.61)	(1.10)	(-1.81)	(-0.63)	(0.20)	(-1.00)	(-0.48)	(0.13)	(-1.02)
EBP	-0.49***	13.06***	-4.20***	-0.61***	13.23***	-3.59***	-0.76***	9.85***	-2.29***
	(-3.02)	(3.36)	(-4.23)	(-3.25)	(3.96)	(-3.74)	(-3.28)	(4.53)	(-3.00)
NFCI	-0.85**	19.01***	-4.86**	-1.01**	18.19***	-4.77**	-1.16**	14.68***	-4.69*
	(-2.31)	(2.53)	(-1.93)	(-2.31)	(2.70)	(-1.78)	(-1.70)	(2.34)	(-1.57)
VIX	0.02*	-0.56**	0.15*	0.03**	-0.62***	0.17*	0.06***	-0.73***	0.22**
	(1.58)	(-2.03)	(1.53)	(2.20)	(-2.64)	(1.64)	(2.54)	(-2.96)	(1.95)
EBP	-0.42***	11.65***	-3.57***	-0.49***	11.43***	-2.82***	-0.47**	7.39***	-1.26*
	(-2.79)	(3.20)	(-4.03)	(-2.89)	(3.70)	(-3.15)	(-1.86)	(3.04)	(-1.52)
NFCI	-0.65**	10.30*	-3.74*	-0.77**	11.52*	-4.44*	-0.97*	10.67*	-4.07*
	(-1.82)	(1.31)	(-1.51)	(-1.72)	(1.58)	(-1.59)	(-1.46)	(1.64)	(-1.48)
CarU	-0.02	1.38**	-0.01	-0.005	0.75*	0.21	0.08**	-0.12	0.24**
	(-0.47)	(2.09)	(-0.07)	(-0.12)	(1.29)	(0.99)	(1.83)	(-0.30)	(1.66)

Note: This table reports the predictive regression coefficients and t-statistics. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Table 5 Quarterly In-sample predictive regression in Gilchrist & Zakrajsek (2012): 1990:I-2018:II

	h=1					h=4				
	GDP	C-D	C-NDS	I-RES	I-NRS	GDP	C-D	C-NDS	I-RES	I-NRS
EBP	-0.68*	1.46	-0.11	2.85	-4.40*	-0.12	2.58***	-0.05	2.80*	-7.43***
	(-1.48)	(0.83)	(-0.36)	(1.20)	(-1.61)	(-0.31)	(2.47)	(-0.15)	(1.55)	(-2.64)
NFCI	-2.56**	-9.01**	-0.88*	-9.48**	-5.34	-2.01**	-6.30**	-0.78*	-1.69	-5.64*
	(-2.22)	(-2.30)	(-1.52)	(-1.81)	(-1.13)	(-1.93)	(-2.13)	(-1.36)	(-0.42)	(-1.29)
EPU	0.01	0.04**	-0.002	0.09***	-0.02	0.01	0.02	0.001	0.09***	0.001
	(1.06)	(1.84)	(-0.52)	(2.65)	(-0.45)	(1.16)	(1.20)	(0.14)	(3.16)	(0.04)
EBP	-0.45	2.87*	-0.09	6.82***	-4.61**	0.06	3.43***	0.04	6.57***	-7.17***
	(-0.99)	(1.47)	(-0.31)	(2.62)	(-1.83)	(0.15)	(2.94)	(0.16)	(3.36)	(-2.77)
NFCI	-1.53**	-6.02*	-0.49	-0.20	0.49	-1.01	-3.78	-0.24	7.33**	0.48
	(-1.71)	(-1.61)	(-0.80)	(-0.05)	(0.08)	(-1.03)	(-1.24)	(-0.36)	(1.72)	(0.09)
MU	-13.43**	-33.53***	-4.38**	-93.27***	-60.13**	-13.41***	-34.43***	-5.76**	-88.88***	-59.62***
	(-2.20)	(-2.48)	(-1.89)	(-3.32)	(-1.92)	(-5.03)	(-3.99)	(-2.12)	(-3.42)	(-2.51)
EBP	-0.88*	1.36	-0.40	3.29	-3.57	-0.39	1.43	-0.27	2.05	-5.73**
	(-1.40)	(0.58)	(-1.10)	(1.28)	(-1.25)	(-0.78)	(1.04)	(-0.71)	(0.92)	(-2.01)
NFCI	-2.93***	-10.33***	-1.29**	-8.83**	-4.03	-2.44**	-9.16***	-1.15**	-3.80	-3.46
	(-2.80)	(-2.56)	(-2.19)	(-1.74)	(-0.87)	(-2.01)	(-2.55)	(-2.01)	(-0.86)	(-0.86)
FU	2.47	9.01	2.25**	14.44*	-13.59	2.68	13.46*	2.13*	27.40***	-17.48**
	(0.98)	(1.02)	(2.23)	(1.45)	(-1.26)	(0.99)	(1.63)	(1.54)	(2.59)	(-1.98)
EBP	-0.51	2.36	-0.13	4.24**	-3.54*	0.07	3.22***	0.004	4.17**	-6.49**
	(-1.06)	(1.16)	(-0.41)	(1.65)	(-1.33)	(0.16)	(2.46)	(0.01)	(1.88)	(-2.23)
NFCI	-2.50**	-8.05**	-0.93*	-5.27	-7.37**	-2.05**	-6.18**	-0.82*	2.49	-6.74**
	(-2.08)	(-2.00)	(-1.53)	(-0.90)	(-1.82)	(-1.82)	(-1.93)	(-1.37)	(0.51)	(-1.73)
MPU	-0.001	0.002	-0.001	0.01	-0.04*	-0.002	-0.01	-0.001	0.01	-0.03*
	(-0.12)	(0.11)	(-0.38)	(0.39)	(-1.36)	(-0.57)	(-0.50)	(-0.64)	(0.50)	(-1.42)
EBP	-1.23***	0.49	-0.39*	3.28	-5.08**	-0.62**	1.51*	-0.31	3.06*	-7.39***
	(-2.51)	(0.27)	(-1.31)	(1.26)	(-1.82)	(-1.77)	(1.29)	(-0.98)	(1.36)	(-2.59)
NFCI	-3.96***	-14.62***	-1.52***	-12.85**	-6.16	-3.23***	-10.91***	-1.50***	-5.83	-5.62
	(-3.45)	(-3.27)	(-2.77)	(-1.97)	(-1.26)	(-3.11)	(-3.21)	(-3.13)	(-1.16)	(-1.28)
VIX	0.19***	0.62***	0.08***	0.66***	0.08	0.16***	0.47***	0.09***	0.73***	0.0001
	(3.81)	(3.21)	(4.15)	(2.47)	(0.34)	(3.28)	(3.04)	(3.35)	(3.12)	(0.0008)
EBP	-0.52	2.31	-0.10	4.39**	-4.76*	0.02	3.01***	0.02	4.24**	-7.23***
	(-1.25)	(1.28)	(-0.40)	(1.89)	(-1.62)	(0.04)	(2.46)	(0.09)	(2.12)	(-2.58)
NFCI	-2.28**	-8.84**	-0.59	-7.05	-4.95	-1.73*	-5.96**	-0.46	0.41	-4.39
	(-1.80)	(-2.09)	(-0.95)	(-1.21)	(-0.90)	(-1.57)	(-1.99)	(-0.75)	(0.09)	(-0.80)
CarU	-0.07	0.28	-0.11**	0.39	-0.17	-0.07	0.02	-0.12**	0.48	-0.28
	(-0.53)	(0.69)	(-1.86)	(0.53)	(-0.28)	(-0.74)	(0.08)	(-2.05)	(0.76)	(-0.51)
EBP	-0.79**	1.54	-0.19	3.09*	-5.52**	-0.12	2.78**	0.00	4.30**	-8.38***
	(-1.77)	(0.85)	(-0.63)	(1.52)	(-1.92)	(-0.24)	(2.13)	(0.00)	(2.09)	(-2.83)
NFCI	-1.94*	-6.54*	-0.58	-3.26	-1.09	-1.63*	-4.86*	-0.69	1.31	-0.29
	(-1.54)	(-1.55)	(-1.06)	(-0.64)	(-0.22)	(-1.40)	(-1.52)	(-1.09)	(0.35)	(-0.07)
SPF	-0.69	2.75	-0.15	11.42*	-14.50*	0.51	-0.29	0.12	6.54	-9.55*
	(-0.45)	(0.61)	(-0.24)	(1.60)	(-1.38)	(0.31)	(-0.09)	(0.14)	(1.07)	(-1.54)

Note: This table reports the predictive regression coefficients and t-statistics. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively. SPF stands for the uncertainty in SPF four-quarters-ahead forecasts associated with news or outcomes that are unexpectedly negative.

Table 6 In-sample predictive quantile regression for GDP growth

τ	0.1	0.3	0.5	0.7	0.9
			h=1		
EPU	-0.55**	-0.18	-0.06	-0.18	-0.07
	(-1.71)	(-0.95)	(-0.71)	(-0.99)	(-0.51)
MU	-1.65***	-1.50***	-0.88***	-0.35*	0.60**
	(-4.99)	(-5.54)	(-3.92)	(-1.35)	(1.92)
FU	-0.43	-0.42**	-0.42**	-0.06	0.25
	(-1.17)	(-1.90)	(-2.06)	(-0.54)	(0.86)
EBP	-0.94***	-0.76***	-0.83***	-0.45**	-0.24
	(-2.57)	(-3.20)	(-3.70)	(-1.72)	(-0.82)
NFCI	-1.24***	-1.09***	-0.67***	-0.48**	-0.18
	(-4.89)	(-4.12)	(-2.90)	(-2.05)	(-0.67)
MPU	-0.29	-0.23	-0.32*	-0.31**	-0.38**
	(-1.04)	(-1.27)	(-1.61)	(-1.89)	(-1.94)
VIX	-0.30	0.04	0.38**	0.54***	0.34*
	(-1.03)	(1.24)	(1.73)	(2.98)	(1.46)
CarU	-0.53*	-0.26	-0.24	-0.29	-0.54*
	(-1.30)	(-0.94)	(-1.10)	(-1.10)	(-1.54)
SPF	-0.33	-0.37*	-0.51**	-0.18	-0.18
	(-1.03)	(-1.30)	(-1.99)	(-0.95)	(-0.81)
			h=4		
EPU	-0.04	-0.03	-0.05	-0.03	-0.04
	(-1.27)	(-0.74)	(-0.54)	(-0.63)	(-0.64)
MU	-1.39***	-1.15***	-0.93***	-0.29*	-0.23*
	(-5.89)	(-7.55)	(-5.42)	(-1.46)	(-1.28)
FU	-0.35**	-0.11	-0.05	-0.08	-0.01
	(-2.23)	(-0.86)	(-0.65)	(-0.81)	(-0.98)
EBP	-0.47***	-0.43***	-0.23	-0.01	-0.23*
	(-2.50)	(-2.74)	(-1.18)	(-0.77)	(-1.54)
NCFI	-1.00***	-0.62***	-0.49***	-0.02	-0.06
	(-4.34)	(-4.34)	(-2.81)	(-0.95)	(-0.79)
MPU	-0.22*	-0.20**	-0.31***	-0.23**	-0.18**
	(-1.41)	(-1.74)	(-3.68)	(-2.11)	(-1.71)
VIX	-0.05	-0.11	0.25**	0.31***	0.19*
	(-0.76)	(-1.12)	(1.88)	(2.89)	(1.40)
CarU	0.05	-0.04	-0.10	-0.08	-0.32*
	(0.85)	(-0.66)	(-0.82)	(-0.67)	(-1.62)
SPF	-0.10	-0.09	-0.38***	-0.36**	-0.29**
	(-0.83)	(-0.83)	(-2.43)	(-2.25)	(-1.92)

Note: This table reports the quantile regression coefficients and t-statistics for all uncertainty measures, adding one index to the benchmark model individually. The first five measures are from 1973:I-2018:IV. MPU is from 1985:I-2018:II. VIX are from 1990:I-2018:II. CarU is from 1978:I-2018:IV. SPF stands for four-quarters-ahead uncertainty associated with news or outcomes that are unexpectedly negative. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Table 7 Real-time and ex-post uncertainty predictability for the McCracken-Ng database series.

In-sample	h=1	h=3	h=12
real time MU	28	15	35
ex-post MU	46	37	58
real time FU	12	13	43
ex-post FU	29	39	63
EPU	10	20	50
MPU	20	15	15
VIX	36	22	42
CarU	23	32	37
EBP	55	52	69
NFCI	38	46	68

Out-of-sample	h=1	h=3	h=12
real time MU	27	41	25
Ex-post MU	51	56	37
real time FU	30	32	45
Ex-post FU	41	60	50
EPU	35	21	35
MPU	17	11	21
VIX	37	27	37
CarU	23	29	30
EBP	46	41	48
NFCI	55	50	55

Note: The top panel summarizes the number of series with significant indexes from in-sample predictive regressions, using data from 1999:7-2018:6. The bottom panel reports the number of series with significant smaller MSFE relative to the benchmark model, i.e. reject Clark-West test at 10% significance level. The pseudo out-of-sample forecasting values are computed from 2008:1 to 2018:6. Data starting from 1999:7 to 2007:12 are used for in-sample estimation.

Table 8 Real-time and ex-post uncertainty predictability for real-time McCracken-Ng database.

In-sample	h=1	h=3	h=12
EPU	11	20	47
real time MU	28	25	46
ex-post MU	39	42	55
real time FU	24	22	43
ex-post FU	25	30	57
MPU	7	3	16
VIX	38	28	48
CarU	14	20	42
EBP	36	39	57
NFCI	37	48	59

Out-of-sample	h=1	h=3	h=12
EPU	15	25	46
real time MU	41	44	44
ex-post MU	46	52	55
real time FU	26	31	46
ex-post FU	40	48	59
MPU	27	22	20
VIX	32	35	51
CarU	17	25	42
EBP	40	52	58
NFCI	40	57	64

Note: The top panel of this table reports the number of series for which the index is significant in the predictive regression. The full sample is from 1999:9-2018:10. The factors are estimated using full sample data of 105 real time macro and 147 financial variables. The bottom panel reports the number of series with significantly smaller MSFE relative to the benchmark model, i.e. reject the Clark-West test at the 10% significance level. The pseudo out-of-sample forecasting values are computed from 2009:9 to 2018:6. Data from 1999:9 to 2009:8 are used for in-sample estimation. The parameter estimation, model selection, and lag orders are estimated recursively.

Table 9 Real-time and ex-post GDP growth quantile regressions: in-sample prediction

τ	0.1	0.3	0.5	0.7	0.9
			Real-time GDP Growth		
EPU	-0.99***	-0.98***	-0.60***	-0.74***	-0.40***
	(-5.81)	(-4.45)	(-3.22)	(-3.42)	(-2.38)
Real time MU	-0.47*	-0.59**	-0.53**	-0.19	-0.22
	(-1.58)	(-2.18)	(-1.92)	(-1.22)	(-1.05)
Ex-post MU	-0.60***	-0.77***	-0.72***	-0.36*	-0.01
	(-2.47)	(-2.62)	(-2.52)	(-1.48)	(-0.64)
Real time FU	-0.79***	-0.88***	-1.05***	-1.08***	-0.66**
	(-2.48)	(-2.45)	(-3.18)	(-3.32)	(-2.32)
Ex-post FU	-1.73***	-1.62***	-0.71**	-0.004	-0.37*
	(-4.65)	(-5.20)	(-2.07)	(-0.47)	(-1.56)
Real time SPF	-1.49***	-0.77***	-0.26	-0.28*	0.06
	(-3.15)	(-2.52)	(-1.05)	(-1.43)	(0.52)
Ex-post SPF	-1.36***	-0.63**	-0.38**	-0.32*	-0.25
	(-3.33)	(-1.91)	(-1.70)	(-1.47)	(-0.99)
			Ex-post GDP Growth		
EPU	-0.21	-0.18	-0.13	-0.30*	-0.11
	(-1.25)	(-1.18)	(-0.95)	(-1.61)	(-0.93)
Real time MU	-0.65**	-0.07	0.20	-0.12	-0.27
	(-1.70)	(-0.79)	(0.83)	(-0.59)	(-1.21)
Ex-post MU	-0.33	-0.80*	-0.40	-0.51*	-0.33
	(-1.00)	(-1.63)	(-1.00)	(-1.33)	(-0.94)
Real time FU	-0.39	-0.38*	-0.75***	-0.21	-0.14
	(-1.26)	(-1.30)	(-2.88)	(-0.86)	(-0.72)
Ex-post FU	-1.40***	-1.09***	-0.87***	-0.38	-0.46*
	(-3.44)	(-3.62)	(-2.67)	(-1.09)	(-1.42)
Real time SPF	-0.17	-0.29	-0.44**	-0.55***	-0.41**
	(-1.26)	(-1.25)	(-1.66)	(-2.37)	(-1.75)
Ex-post SPF	-0.09	-0.42*	-0.62**	-0.66**	-0.51**
	(-1.17)	(-1.29)	(-1.91)	(-2.21)	(-1.80)

Note: This table reports the h=1 quantile regression coefficients and t-statistics for uncertainty measures, adding one index to the benchmark model individually. In the top panel, the sample is from 2002:I-2018:III. In the bottom panel, data from 1999:III-2018:III are used for estimation. Statistical significance at the 10%, 5% and 1% levels are denoted by *, ** and ***, respectively.

Figure 3 Uncertainty Measures

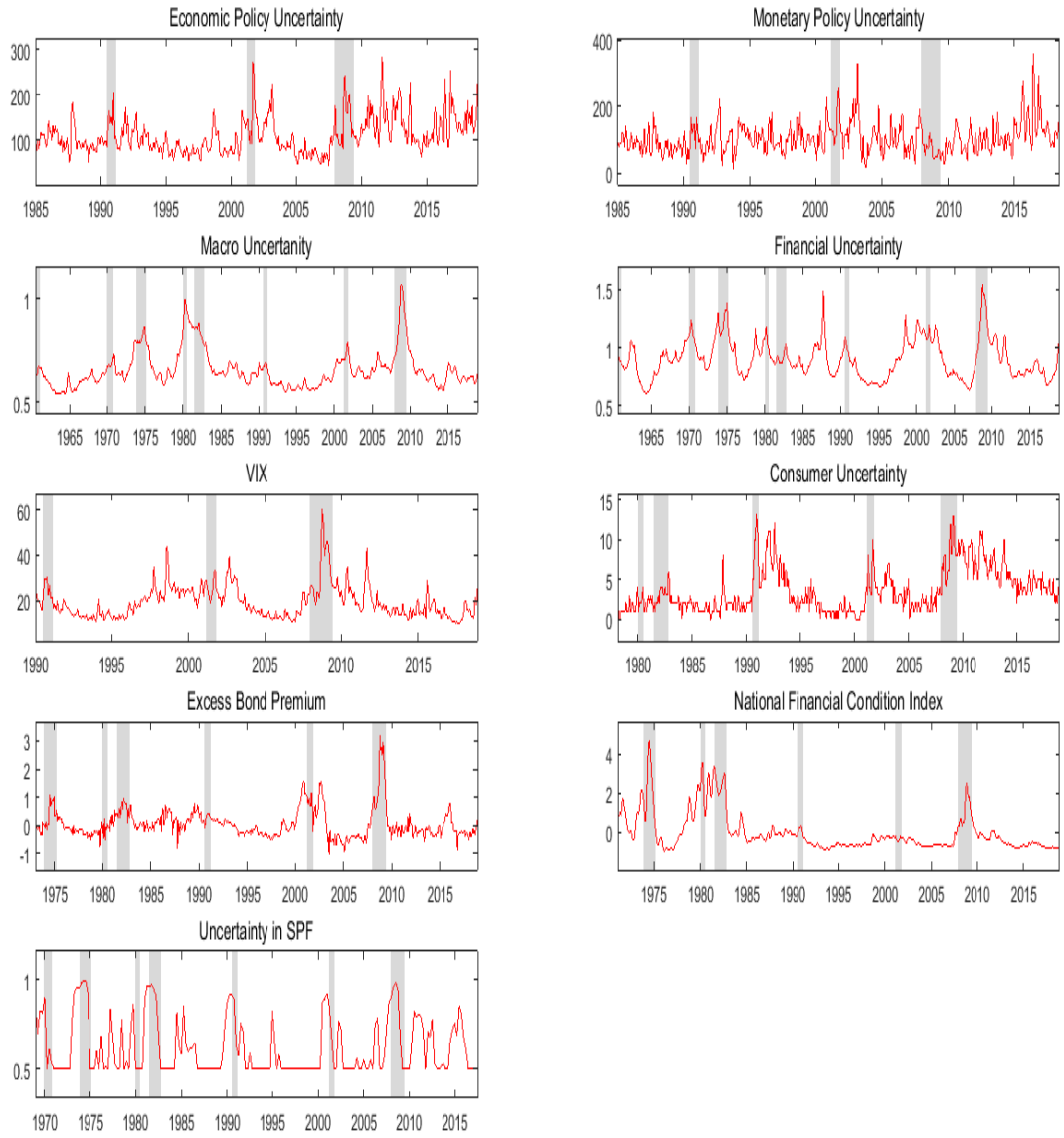

Figure 4 Bar chart of GDP growth with uncertainty measures: Group 1
1978:I-2018:III

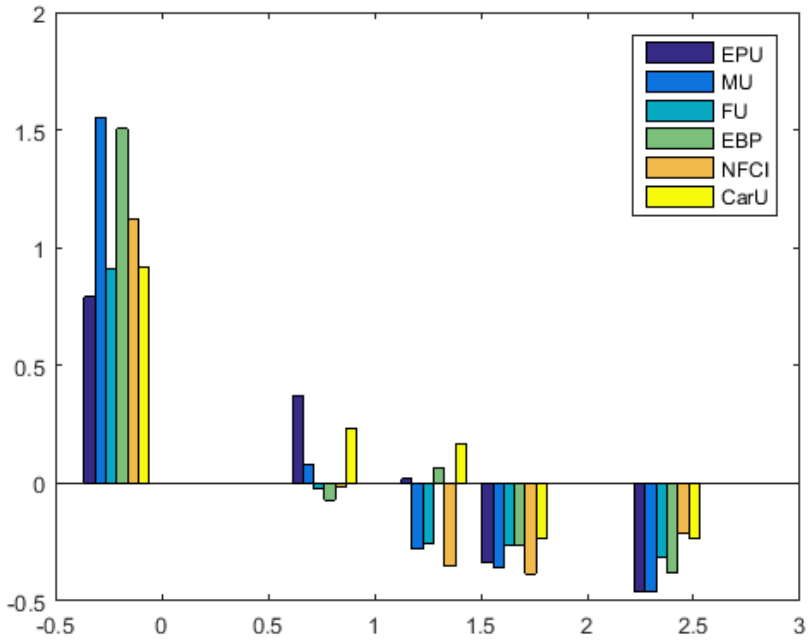

Figure 5 Bar chart of GDP growth with uncertainty measures: Group 2
1990:I-2018:II

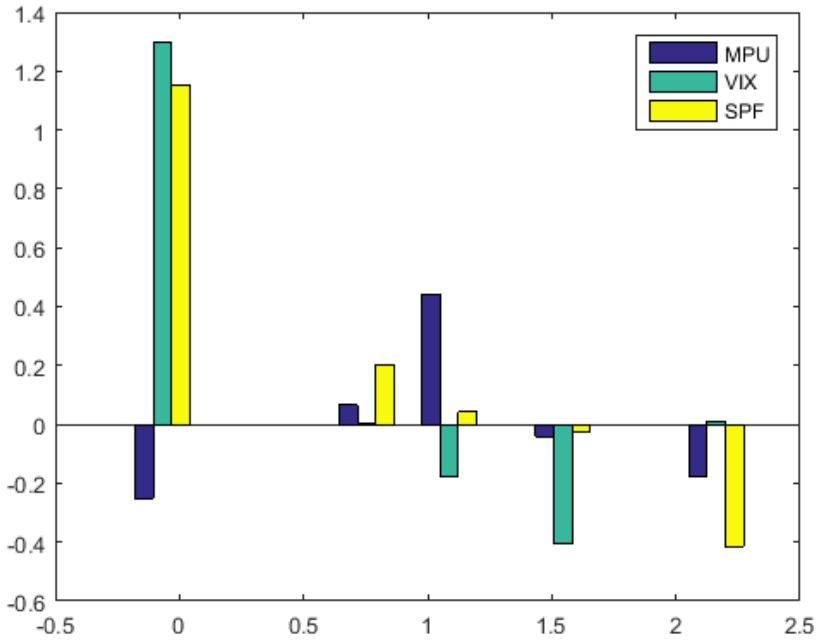

Figure 6 Real time MU v.s. ex-post MU

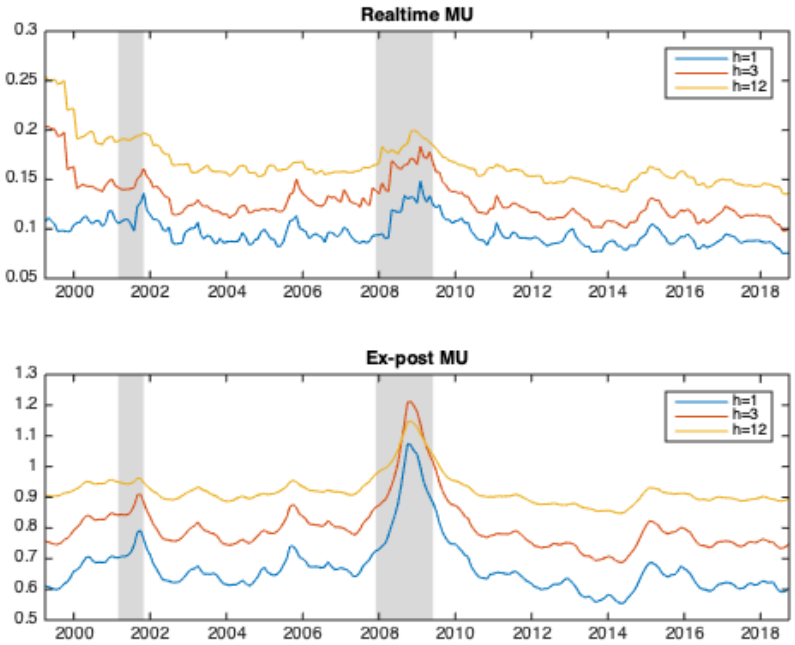

Figure 7 real time FU v.s. ex-post FU

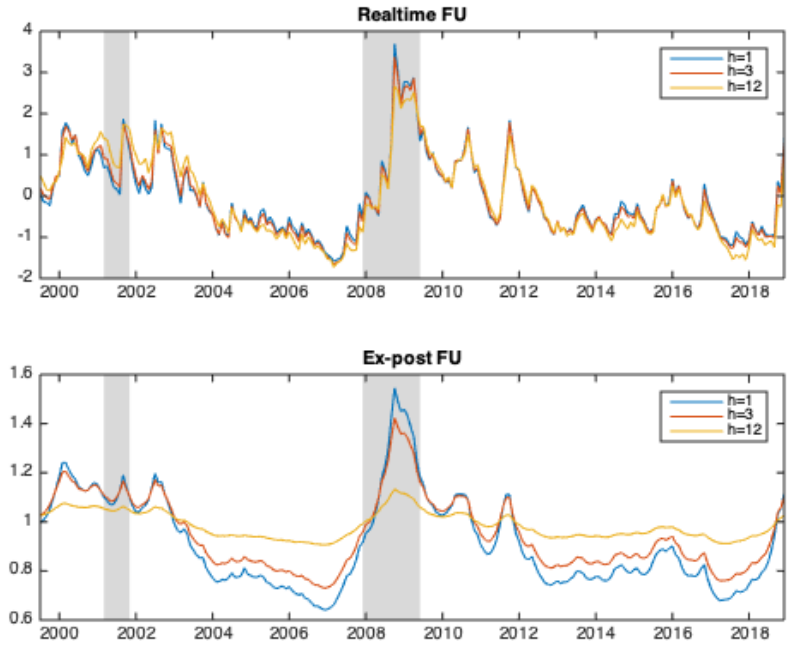
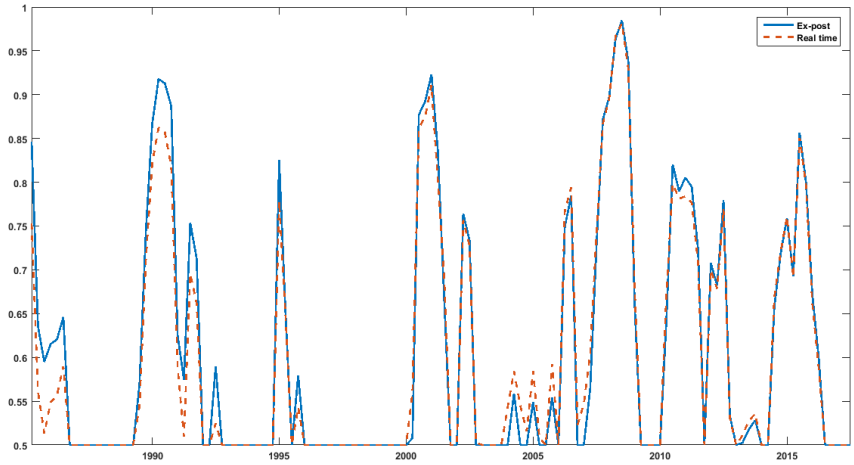
Figure 8 real time v.s. ex-post uncertainty in SPF