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Macroeconomic Uncertainty Through the Lens of Professional Forecasters

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Abstract

We analyze the evolution of macroeconomic uncertainty in the United States, based on the forecast errors of consensus survey forecasts of various economic indicators. Comprehensive information contained in the survey forecasts enables us to capture a real-time subjective measure of uncertainty in a simple framework. We jointly model and estimate macroeconomic (common) and indicator-specific uncertainties of four indicators, using a factor stochastic volatility model. Our macroeconomic uncertainty has three major spikes aligned with the 1973–75, 1980, and 2007–09 recessions, while other recessions were characterized by increases in indicator-specific uncertainties. We also show that the selection of data vintages affects the estimates and relative size of jumps in estimated uncertainty series. Finally, our macroeconomic uncertainty has a persistent negative impact on real economic activity, rather than producing "wait-and-see" dynamics.

Keywords: Factor stochastic volatility model; Survey forecasts; Uncertainty
JEL classification: C38, E17, E32

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1 Introduction

The literature on the impacts of uncertainty on real economic activity has expanded rapidly following the Great Recession.[1] Many studies have aimed at empirically quantifying the effect of uncertainty. Central to them is a need for a measure of time-varying uncertainty, since uncertainty is not directly observable. Accordingly, a number of proxies for uncertainty have been used. Bloom (2009) has pioneered the use of the VIX, the implied stock market volatility based on the S&P index. Alternatively, Bloom et al. (2012) use the cross-sectional dispersion of total factor productivity shocks. Another popular proxy is the cross-sectional disagreement of individual forecasts, as in Bachmann et al. (2013). Finally, the Baker et al. (2013) Economic Policy Uncertainty index combines news article counts with the number of federal tax code provisions set to expire in additional to forecast disagreement.

This paper uses consensus survey forecasts to analyze the evolution of macroeconomic uncertainty in the United States as perceived by professional forecasters. We define macroeconomic uncertainty as the conditional time-varying standard deviation of a factor that is common to the forecast errors for various macroeconomic indicators from the Survey of Professional Forecasters (SPF). An increase in macroeconomic uncertainty thus implies a higher probability that various economic variables simultaneously deviate from their conditional consensus forecasts. This idea is effectively captured by a factor stochastic volatility (FSV) model, first developed by Pitt and Shephard (1999).[2] In our application, we use stochastic volatility processes in a factor model structure to provide time-varying common (macroeconomic) and indicator-specific uncertainty indexes, which are jointly modeled and consistently estimated in one step.

A long strand of literature uses survey forecasts to quantify uncertainty; many studies have focused on *ex-ante* uncertainty measures that draw on dispersions of point forecasts or subjective probability distributions of individual forecasters. In contrast, we introduce a

[1]See, for example, Bloom (2009), Jurado et al. (2015), Caldara et al. (2016) Caggiano et al. (2014), Carriero et al. (2016), among many others.

[2]The stochastic volatility process has been widely adopted in finance literature (e.g., Collin-Dufresne and Goldstein 2002, Heston 1993, and Kim et al. 1998) and more recently in macroeconomic analysis to model the time-varying volatility of macroeconomic variables, (e.g, Caldara et al. 2012, Jo 2014, Mumtaz and Zanetti 2013, Primiceri 2005, and Justiniano and Primiceri 2008, among others).

new framework for measuring *ex-post* uncertainty from forecast errors calculated using the first (and a few other later) data releases and the median of participants' point forecasts. Hence, we differ from studies that identify key sources of forecast disagreement (e.g., Patton and Timmermann 2010), consider individual forecasters' subjective probabilities as a measure of uncertainty (Boero et al. 2015), or investigate the relationship between *ex-ante* and *ex-post* forecast uncertainty (e.g., Clements 2014 and Lahiri and Sheng 2010).

Using survey forecasts provides several advantages for measuring subjective and real-time uncertainty. First, the forecasts are not tied to any particular econometric models, and thus can flexibly capture perceived uncertainty surrounding agents' expectations. The perceived uncertainty likely matters for the agents' decision making process more than model-based objective uncertainty that agents cannot directly observe, as Scotti (2016) points out. Economic agents, in particular, professional forecasters, base their forecasts on various econometric models, leading indicators and surveys, as well as on a variety of available macroeconomic and financial data, encompassing a wide range of information sources (see Zarnowitz and Braun 1993). Consequently, survey forecasts naturally incorporate necessary time-variations and/or any potential structural changes in the economy. They, hence, reflect uncertainty perceived by the agents at the time of the survey more closely than forecasts formed by an econometric model. Second, subjective forecasts have often been found to be more accurate than the forecasts from econometric models.[3] Therefore, survey forecasts provide an effective way of removing expected variations in macroeconomic series. As emphasized by Jurado et al. (2015), it is crucial to remove the foreseeable component of macroeconomic series when estimating uncertainty so as not to attribute some of the predictable variability to unpredictable shocks. Finally, survey forecasts simplify the overall uncertainty estimation procedure to a great extent, since the selection and estimation of a specific forecasting model to obtain forecast errors are not necessary.

Our baseline macroeconomic uncertainty estimated from one-step-ahead forecast (i.e., nowcast) errors for four economic indicators from the SPF (GDP, unemployment rate, industrial production and housing starts) is significantly more persistent than traditional

[3]For example, Ang et al. (2007) and Faust and Wright (2013) document the advantage of surveys over forecasting models for inflation. Aiolfi et al. (2011) study the optimal combinations of survey and model-based forecasts, and find that while the combinations always improve over model-based forecasts, they do not systematically do so over the survey forecasts.

proxies of uncertainty (e.g., the VIX).[4] In particular, all major spikes of uncertainty are associated with episodes of economic recessions, i.e., the 1973–75, 1980, and 2007–09 recessions, similar to the findings in Jurado et al. (2015) and Carriero et al. (2016). Other recessions (i.e., the 1990–91 and 2001 recessions) are still notable in the dynamics of some of the idiosyncratic uncertainty, but were not picked up by the macroeconomic uncertainty series. This suggests that increases in uncertainty during these periods were not as broad-based as during the 1973–75, 1980, and 2007–09 recessions. By contrast, uncertainty estimated using forecast errors of longer-run horizons show increases associated with most recessions in the sample to higher levels than the baseline index. In addition, recursive estimates of our macroeconomic uncertainty series, though certainly more volatile than full sample estimates, are broadly in line with our baseline index.

A large literature has examined the importance of real-time data issues for evaluating the forecasting power of econometric models. However, few papers have examined the role data revisions play when estimating volatility. Similar in spirit to Clark (2012) and Clements (2015), we also examine the impact of data revisions on the estimation of economic uncertainty. As macroeconomic variables are constantly revised, uncertainty measures based on the most recent data vintage use a different information set than was previously available to professional forecasters. Our findings suggest that, while overall dynamics of both macroeconomic and idiosyncratic uncertainties remain robust, they exhibit differences, especially in the relative size of major peaks over time. For instance, macroeconomic uncertainty based on the final vintage data likely underestimates the actual volatility faced by professional forecasters in the 1970s and 1980s relative to the level during the Great Recession.

Finally, vector autoregressions (VAR) show that innovations to macroeconomic uncertainty generate negative effects on real economic activity. The impact is fairly sizable and persistent, in line with the evidence in Jurado et al. (2015) and Carriero et al. (2016). This is in contrast to VAR analysis using traditional proxies for macroeconomic uncertainty, such as the VIX in Bloom (2009) and Caggiano et al. (2014), where the negative effects of uncertainty dissipate quickly.

[4] In subsection 4.5, we show that enlarging our panel of forecast errors with other real activity indicators added to the SPF in the early 1980's does not have a material impact on our estimates.

Our paper shares similarities with recent studies focusing on estimating macroeconomic uncertainty. For example, Jurado et al. (2015) employ a factor model setup for a large cross-section of variables to generate forecasts; the volatilities of individual forecast errors then follow univariate stochastic volatility process, whose average becomes macroeconomic uncertainty. Carriero et al. (2016) explicitly fit a factor model to the stochastic volatilities of forecast errors from a large VAR, where two unobservable factors drive comovements across individual volatilities. Rossi and Sekhposyan (2015) use forecast surveys and econometric models for GDP and inflation to construct an uncertainty index from the unconditional historical distribution of forecast errors. Scotti (2016) exploits survey forecasts and creates an uncertainty index as the weighted sum of the squared forecast errors for different indicators. Our approach complements this literature by combining survey forecasts of different indicators in a factor model structure with stochastic volatility.

Our paper is also related to the literature that applies FSV models to financial and macroeconomic analysis. The FSV model has been widely used in the finance literature as it parsimoniously captures the variance and covariance of various financial time series using a low-dimensional common factor (Kastner et al. 2014).[5] On the macroeconomic side, Mumtaz and Theodoridis (2015) estimate a dynamic factor model with stochastic volatility with a panel of OECD countries to decompose the time-varying volatilities of macro and financial variables to internationally-common, country-specific and variable-specific uncertainties. Del Negro and Otrok (2008) develop a dynamic factor model with time-varying factor loadings and stochastic volatility to study international business cycles. One common feature in the previous studies is that the evolution of the conditional means of the variables is parametrically linked to the factors. In contrast, our approach fits the FSV model directly to survey forecast errors without jointly modeling the conditional mean along with conditional volatilities, for the first time in the literature, to the best of our knowledge. We instead outsource the modelling of the conditional mean to professional forecasters. Hence, we provide an estimate of common and idiosyncratic uncertainties through the perspective of professional forecasters.

The rest of the paper is organized as follows. Section 2 introduces the data set. Section

[5]See, e.g., Aguilar and West (2000) and Chib et al. (2009).

3 provides an exposition of our econometric model. The next section presents results. A VAR analysis in Section 5 shows the responses of real economic activity to innovations in our uncertainty measure. Finally, Section 6 concludes.

2 Data

We use data from the SPF, the oldest quarterly survey of macroeconomic forecasts in the U.S. The National Bureau of Economic Research and the American Statistical Association initially introduced the survey in 1968. The Federal Reserve Bank of Philadelphia took it over in June 1990. Survey panelists include forecasters from large corporations, Wall Street financial firms, economic consulting firms, and university research centers. We use four variables that have been part of the survey since its inception: real GDP, unemployment rate, industrial production (IP) and housing starts. With the selected variables, we obtain a long time-series of uncertainty from 1968Q4 to 2016Q1.

Forecasters are surveyed on a quarterly basis; the most recent quarter of data in their information set is the previous quarter. Survey questionnaires are sent after the Bureau of Economic Analysis (BEA) *advance report* of the national income and product accounts (NIPA), which contains the first estimates of the previous quarter's GDP. The survey's forecast submission deadline tends to occur around the second to third week of the middle month of a quarter. Thus, before the survey is submitted, forecasters may have access to the first month's of data for initial quarter of the survey.[6] We use their one-step-ahead forecasts, namely, their nowcasts, to construct the forecast errors.

The calculation of forecast errors at any point in time is contingent on the realized value of the series, and thus, data revisions can ultimately affect our measurement of uncertainty through revisions to the forecast errors. We use the first release and revised data available in one and five quarters after the initial release, as well as the final 2016Q1 vintage data to compute four possible values of forecast errors. It is worthwhile to note here that the

[6]For instance, the Bureau of Labor Statistics releases the unemployment rate in the first week of a month; hence, it will be in the survey respondant's information set. By comparison, housing starts compiled by the Census Bureau have been released during the third week of each month in recent years. It then becomes less clear whether the first month's value in each quarter is included. Similarly, IP has been released near mid-month by the Federal Reserve System Board of Governors during our sample period, and, thus, the inclusion of the first month's value may not occur depending on particular dates in each month.

degree of the revisions may differ across variables. For example, while revisions to the unemployment rate are known to be relatively small and confined to changes in seasonal factors, other indicators may be revised substantially reflecting newly available related data series, late-arriving or revised values, and updated measurement methodology. In addition, other than the first release, each variable from the same vintage may have been revised a different number of times.[7]

When obtaining forecast errors, we use the consensus forecasts, i.e., the median across forecasters, to minimize potential influences from individual forecasting biases.[8]

3 Factor Stochastic Volatility Model

We use the FSV model of Pitt and Shephard (1999) to estimate macroeconomic as well as idiosyncratic uncertainty indexes. First, we define the forecast error of a variable i in period t, denoted as $\varepsilon_{i,t}$, as follows:

$$\varepsilon_{i,t} = x_{i,t} - \text{median}\{E_1[x_{i,t}|I_t], \cdots, E_J[x_{i,t}|I_t]\}, \tag{1}$$

where $x_{i,t}$ is the realization of variable i in time t, $E_j[x_{i,t}|I_t]$ is forecaster j's expectation of variable i for quarter t, and $\text{median}\{E_1[x_{i,t}|I_t], \cdots, E_J[x_{i,t}|I_t]\}$ captures the median forecast across total J forecasters in each quarter. Again, a key difference of our measure from other uncertainty indexes based on a particular forecasting model is that we obtain $E[x_{i,t}|I_t]$ from subjective consensus survey forecasts instead of a specific econometric model. The information set (I_t) also has the same time-subscript t, as it contains information obtained to the middle of quarter t. That is, I_t includes the first NIPA estimate of GDP in $t-1$,

[7]For instance, BEA releases three vintages of the current quarterly estimate for GDP, while the Board of Governors of the Federal Reserve System announces each month a preliminary estimate of the previous month's IP and revised estimates of five proceeding months. In one quarter after the first release, GDP would be revised twice after the first "advance" estimate, while the first month value of IP in the previous quarter may have gone through four to five revisions.

[8]We use the median, and not the mean forecast across survey respondents to minimize the effect of outliers, especially in the earlier part of the sample. A number of previous studies consider the median as standard consensus projections. See Engelberg et al. (2009) and Croushore (2010), for example. Uncertainty indexes based on the 25th-percentile, mean, and 75th-percentile forecasts are very close to the benchmark estimated using the median, with the average correlation coefficient of 0.93, as shown in the Appendix.

while for the other monthly indicators, the first month's value in quarter t may also be included in I_t in addition to all monthly values in the previous quarter.

Next, we postulate that the forecast error of a macroeconomic series i has a factor structure:

$$\varepsilon_t = \lambda f_t + u_t, \tag{2}$$

where $\varepsilon_{i,t} = [\varepsilon_{1,t}, \cdots, \varepsilon_{n,t}]'$ is a $(n \times 1)$ vector of forecast errors; $\lambda = [\lambda_1, \cdots, \lambda_n]'$ is a vector of factor loadings; f_t is a common factor across different i's; and $u_t = [u_{1,t}, \cdots, u_{n,t}]'$ is a vector of idiosyncratic errors, capturing indicator-specific variations.[9] Equation (2) implies a common factor that drives a shock to all n economic indicators and, thus, affects the size of forecast errors. The remaining indicator-specific variations is captured by u_t.[10]

As in a standard FSV model (e.g., Pitt and Shephard 1999 and Chib et al. 2006), we further assume that u_t and f_t are conditionally independent Gaussian random vectors.

$$\begin{pmatrix} u_t \\ f_t \end{pmatrix} \mid \mathcal{I}_t \sim N\left(0, \begin{bmatrix} \Sigma_t & 0 \\ 0 & h_{f,t} \end{bmatrix}\right), \tag{3}$$

where Σ_t are a $n \times n$ diagonal matrix of time-varying idiosyncratic volatilities and $\mathcal{I}_t$ is information available in time t. In other words,

$$\Sigma_{n,t} = \begin{bmatrix} h_{1,t} & 0 & \cdots & 0 \\ 0 & h_{2,t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & h_{n,t} \end{bmatrix}.$$

The common as well as indicator-specific volatilities follow independent stochastic volatility

[9] The first principal component explains 52% of the variability in forecast errors, supporting such a factor structure. We provide various statistical information regarding the comovements in forecast errors as well as their volatilities in the Appendix.

[10] Some previous studies used density forecasts of variables such as GDP and inflation in the SPF to quantify uncertainty (see, for example, Lahiri and Liu (2006), Lahiri and Sheng (2010), and Clements (2014), among others). In comparison to the studies where individual forecast errors are decomposed into common and idiosyncratic errors, our model decomposes consensus forecast errors of the four variables into economy-wide and variable-specific errors.

processes:

$$\log h_{f,t} = \log h_{f,t-1} + \sigma_f \eta_{f,t}$$
$$\log h_{i,t} = \log h_{i,t-1} + \sigma_i \eta_{i,t}, \tag{4}$$

where σ_f and σ_i's are time-invariant parameters determining the variability of the volatilities, and $\eta_{f,t}$ and $\eta_{i,t}$ capture innovations to volatility. One reason that the stochastic volatility model has been widely adopted in literature is its flexibility due to the innovation term in the volatility process in addition to that of the first moment. Applied to our set-up, it is possible to examine shocks to the volatility process, which can be uncorrelated with unexpected variations in the level of forecast errors.[11]

The key estimate of interest is the time-varying standard deviations of the factor, i.e., $\{\sqrt{h_{f,t}}\ \}$, which we define as a measure of the macroeconomic uncertainty: The time series of macroeconomic uncertainty captures the volatility of a common driver that simultaneously affects the magnitude of forecast errors across different real activity indicators. Other important estimates are the time-varying standard deviations of idiosyncratic errors, i.e., $\{\sqrt{h_{i,t}}\ \}$. These idiosyncratic volatility series will capture the size of indicator-specific shocks, which are orthogonal to the common factor by construction. It is worthwhile to note again that our framework yields both common and indicator-specific uncertainty indexes, which are consistently modeled and estimated in one step. In addition, the estimation procedure generates the posterior distribution of uncertainties, through which we can infer the size of the uncertainty surrounding uncertainty estimates. Another point to note: Our current framework further implies a factor structure in the *volatility* processes of forecasts errors as well. That is, squaring both sides of equation (2) and taking expectations yields $var(\varepsilon) = E(\varepsilon^2) = E(\lambda f_t + u_t)^2 = E(\lambda^2 f_t^2) + E(u_t^2)$, as we assume the factor and idiosyncratic errors are independent from each other. Here $E(f_t^2)$ can be viewed as a factor of volatilities. With additional modeling assumptions, such as a static factor and unit root SV process, the squared factor estimates $(\{\hat{f}_t^2\}_{t=1}^T)$ and the estimated common (macroeconomic) uncertainty $(\{\hat{h}_{f,t}\}_{t=1}^T$ do not precisely overlap, yet are quite highly correlated (with

[11]The resulting shock processes can be included in a univariate regression framework to gauge the effects of uncertainty shocks in a straightforward way. For example, the shock processes can be used to obtain impulse responses to an uncertainty shock by local projections à la Jordà (2005).

the correlation coefficient of 0.68).

The model is estimated using Bayesian methods, since it features high dimensionality as well as non-linearity. Bayesian methods deal with such features by separating parameters into several blocks, which greatly simplifies the estimation process. In particular, the Markov Chain Monte Carlo (MCMC) algorithm groups the parameters into several blocks and repeatedly draws from their conditional posterior distributions in order to simulate the joint posterior distribution. We collect $5,000$ draws by storing every 10th draw in order to avoid potential autocorrelation across draws, after discarding the first $30,000$ draws of parameters. We follow the common identification scheme of a factor model that sets the first factor loading (of GDP) equal to unity. The choice of prior distributions and their parameter values is very similar to that of Pitt and Shephard (1999). We provide a detailed description of the prior distribution setup and the MCMC algorithm in the Appendix.

4 Results

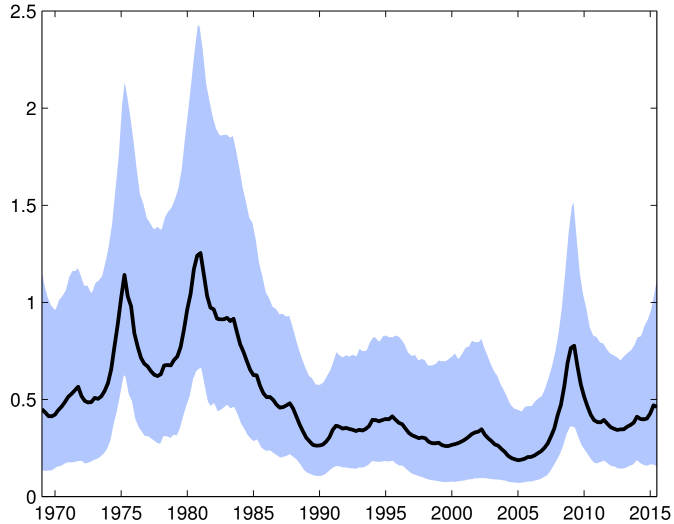
4.1 Estimated Macroeconomic and Idiosyncratic Uncertainties

We plot our baseline macroeconomic uncertainty series in Figure 1: the solid line is the median posterior draw ($\{\sqrt{h_{f,t}}\}_{t=1}^{T}$) and the shaded area represents the 95 percent posterior credible set. For our baseline estimates, we use the first data release to calculate the forecast errors.[12] In line with Carriero et al. (2016), the posterior credible set is fairly wide, suggesting that the uncertainty around uncertainty estimates is large.

There are three main spikes in macroeconomic uncertainty, all associated with deep recessions. The first spike was observed during the 1973–75 recession, the second during the 1980 recession, and the last one during the recent Great Recession. The greatest increase in macroeconomic uncertainty occurred during the 1980 recession. It is also clear from the figure that, in general, the level of macroeconomic uncertainty was significantly higher in the 1968–85 period than from 1985 until the Great Recession, consistent with the findings in Kim and Nelson (1999) and McConnell and Perez-Quiros (2000). The index shows some increase around the 1991 recession, but it is a small one in comparison with

[12]We assess the effect of data revisions on our uncertainty measure in Section 4.3.

Figure 1: Estimated Macroeconomic Uncertainty Series



Note: Figure plots the baseline macroeconomic uncertainty series estimated using the first-released data. The solid black line is the median posterior draws of the time-varying standard deviation of a common factor across forecast errors of four macroeconomic indicators. The shaded area is the 95 percent posterior credible set.

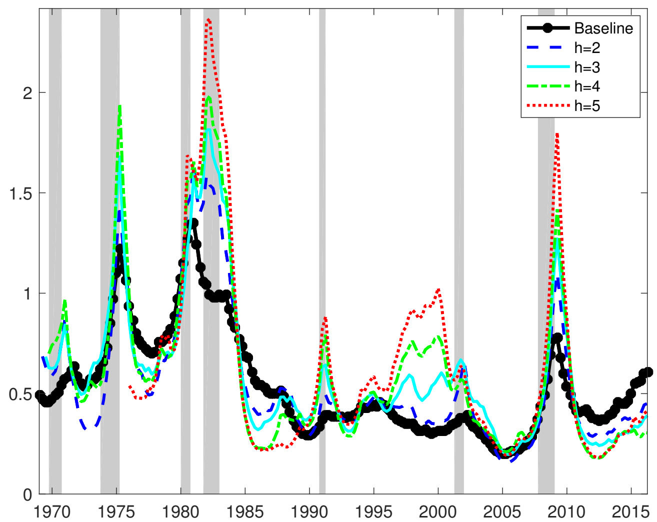
the three critical spikes. The 2001 recession was also accompanied by very mild increases in uncertainty.

While our baseline index is estimated using one-step-ahead forecasts, namely the nowcasts, the SPF also collects forecasts for longer horizons, e.g., h-step-ahead quarterly forecasts for $h = 2, 3, 4$ and 5. These longer-run forecasts can be used as a basis for measuring long-run macroeconomic uncertainty under our framework. Figure 2 plots median posterior draws of all h-step-ahead uncertainty along with the baseline measure.[13] A couple of differences are noticeable. The size of the uncertainty spikes increase with the forecast horizon h, suggesting that greater perceived uncertainty encompass longer-run survey forecasts. Additionally, the 1991 and 2001 recessions as well as their interim period are more pronounced in the longer-horizon estimates relative to the baseline index. However, since the overall dynamics of these longer horizon macroeconomic uncertainties are very similar to nowcast uncertainty, we focus on our baseline index below.

Table 1 reports the median posterior draws of factor loadings. For identification, loading

[13]The five-step-ahead uncertainty series starts in 1975Q3 due to some missing values in earlier periods.

Figure 2: Uncertainty Estimated using Longer-Run Forecasts



Note: Figure plots estimated longer-run uncertainty series. We use two- to five-step-ahead forecasts ($h = 2, 3, 4$ and 5) from the SPF to calculate forecast errors to attain corresponding longer-run uncertainty estimates, and compare those to our baseline nowcast uncertainty series based on nowcasts.

Table 1: Summary Statistics of Posterior Draws of Factor Loadings

	GDP	IP	UR	HS
Median	1	1.25	-0.96	0.41
Std. Dev.	-	0.25	0.20	0.14

Note: Table shows the median and standard deviations calculated from the posterior draws of four factor loadings. Since our identification strategy is to set the loading of GDP to unity, the standard deviation is not reported for GDP.

of GDP is set to unity, as mentioned in the previous section. However, the relative sizes of the factor loadings and subsequently the estimated series of uncertainty are robust to different normalization.[14] We find that housing starts load least on the common factor, while the loadings of the other three variables are in a comparable range.

Using the median posterior draws, we further examine how much of the total variation in the forecast errors of each indicator is driven by the common versus idiosyncratic volatilities.

[14]In addition, while the medians change depending on which vintage is used to calculate forecast errors, the relative sizes of most factor loadings are also robust to the choice of data vintage. The factor loading estimates based on different data vintages are available upon request.

This is calculated by using the factor structure of our model. In particular, our model implies a total variance of each variable in each period, $var(\varepsilon_{i,t})$, to be

$$\begin{aligned} var(\varepsilon_{i,t}) &= var(\lambda_i f_t + u_{i,t}) \\ &= \lambda_i^2 var(f_t) + var(u_{i,t}) \\ &= \lambda_i^2 h_{f,t} + h_{i,t}, \end{aligned} \tag{5}$$

as the factor and idiosyncratic error terms are assumed to be uncorrelated. We then measure the size of the total common variation driven by macroeconomic uncertainty in each period as $\lambda_i^2 var(f_t) = \lambda_i^2 h_{f,t}$, incorporating the heterogeneity due to the difference in factor loadings. Next, we compare $\sqrt{var(\varepsilon_{i,t})}$ and $\lambda_i\sqrt{h_{f,t}}$ to investigate the contributions of the common and idiosyncratic uncertainties.

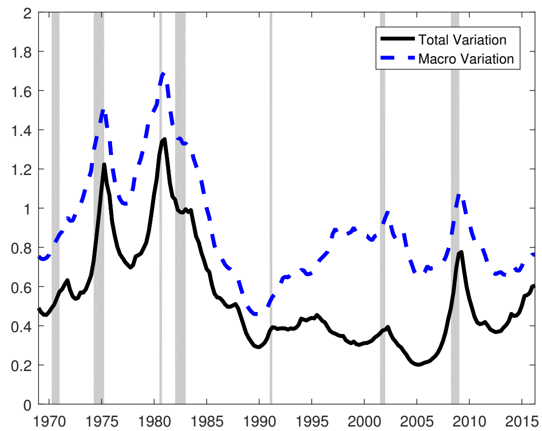
Figure 3 plots the estimated total variation and the share explained by macroeconomic uncertainty for each indicator. For most variables except housing starts, the most notable spikes in the total variation are largerly driven by macroeconomic uncertainty. Moreover, recessions that were not accompanied by distinct increases in macroeconomic uncertainty, as in the 1991 and 2001 recessions, show up in the total variations of unemployment and, to a lesser extent, GDP and industrial production.

During the period of 1985 to 2007, when the baseline macroeconomic uncertainty index was relatively subdued, idiosyncratic volatilities explain a large fraction of the total volatilities of the different series. In the case of GDP, the share of idiosyncratic volatility takes more than 50 percent of the total variation of GDP forecast errors during this period. Finally, it is interesting to note that the variation of housing starts contributes the least to the macroeconomic uncertainty, and it leads the total volatility of the other indicators. Interestingly, the idiosyncratic uncertainty of housing starts was on an increasing trend from the mid-1990s to the Great Recession.

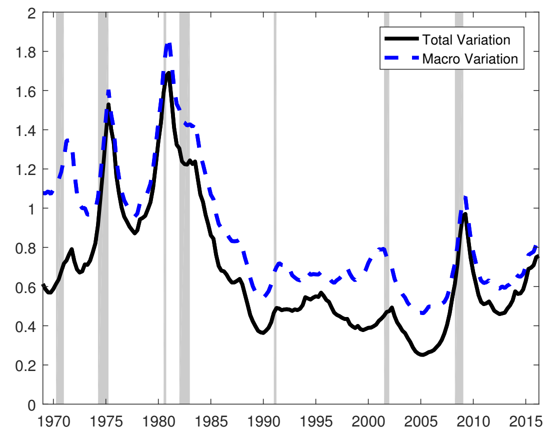
4.2 Macroeconomic Uncertainty from a Larger Panel

Our baseline index is based on the forecast errors for four economic indicators that have been part of the SPF since its inception in 1968Q4. This is intended to recover uncertainty

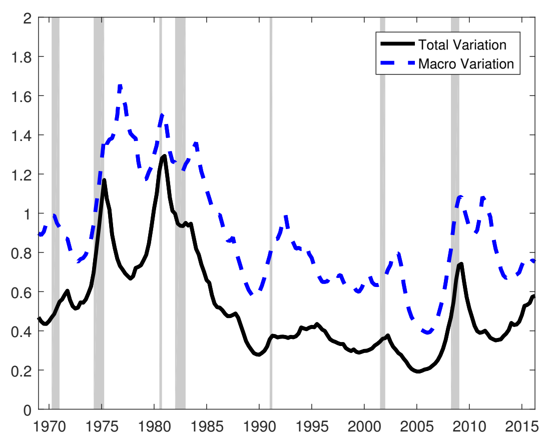
Figure 3: Total Variation versus Macro Variation



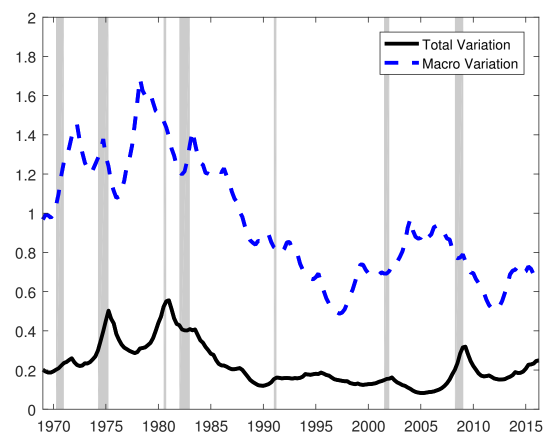
(a) GDP



(b) IP



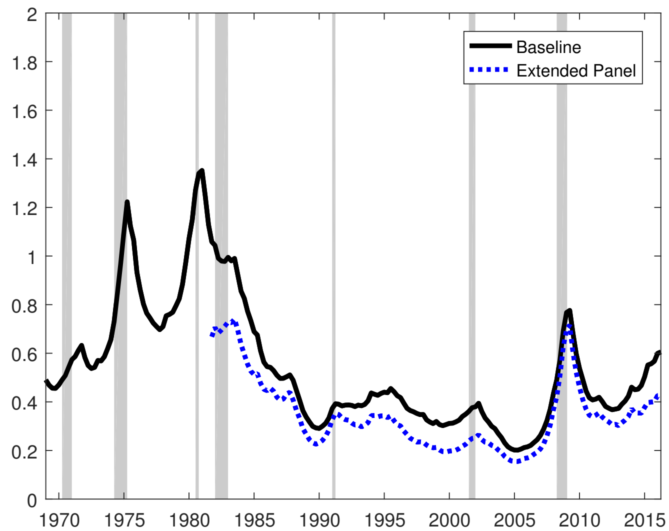
(c) Unemployment



(d) Housing Starts

Note: This figure shows how much of total variation of each variable is explained by the macroeconomic uncertainty. The blue dashed line is the total variation of one variable (defined as standard deviation), and the black line is the macroeconomic uncertainty multiplied by a factor loading. All calculations are based on the median posterior draws.

Figure 4: Uncertainty with a Larger Panel of Indicators



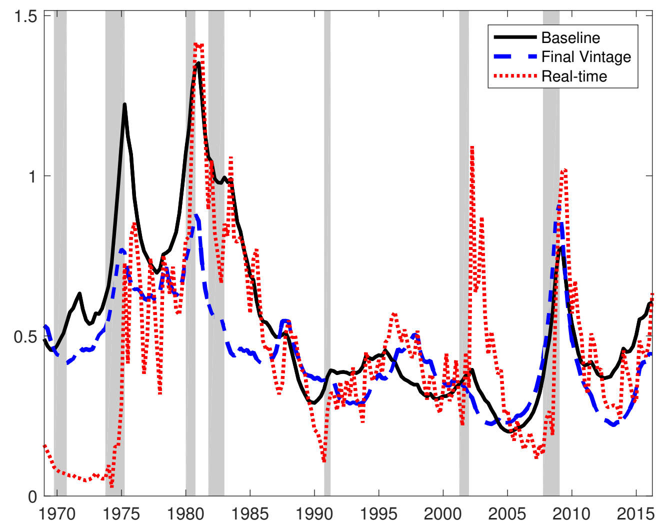
Note: Figure plots the uncertainty series estimated from a panel of nine economic indicators (blue-dotted line) starting in 1981Q3. The benchmark uncertainty estimate (black line) is shown for comparison.

estimates for the longest period possible. However, the SPF has increased its coverage over time; for instance, it included forecasts for various components of GDP (e.g., real personal consumption expenditures and real residential investment) and financial variables (three-month Treasury bill rate and Moody's AAA corporate bond yield) in 1981Q3, and continued to expand in subsequent years. To see how our index changes once we include more variables, we add the forecast errors of five economic indicators to the vector ε_t in equation (1) and re-estimate our macroeconomic uncertainty series. In particular, we add forecast errors for real personal consumption, real residential fixed investment, real nonresidential fixed investment (i.e., business fixed investment), real federal government consumption and gross investment, and real state and local government consumption and gross investment, and re-estimate the model from 1981Q3 onward.[15]

Figure 4 plots the estimates of macroeconomic uncertainty based on the large panel of real economic variables since 1981Q3, as well as our main estimates based on the smaller set of forecast errors starting in 1968Q4. It is clear from the figure that both series co-

[15]We restrict ourselves in this paper to the modelling of the volatility of real activity indicators, in the same spirit as Aruoba et al. (2012) and Scotti (2016). We thus leave the joint modelling of real and nominal volatilities for future work.

Figure 5: Uncertainty Estimated Recursively in Real Time with Expanding Samples



Note: This figure plots the uncertainty series estimated recursively after the first 20 quarters with expanding sample periods (in red) along with the baseline uncertainty index (in black) based on the first data release and the index using the final vintage data (in blue).

move very closely. The results show that our four variables chosen for the baseline model summarizes information well regarding the state of macroeconomic uncertainty.

4.3 Recursively-Estimated Uncertainty with Expanding Samples

Although forecast errors used to estimate the FSV model are calculated in real time, we obtain our baseline index by estimating the above model once, after collecting the errors for the entire sample. Hence, the macroeconomic index is smoothed full-sample estimates and model parameters and state variables, such as factor loadings and factors, are not updated with each additional observation. In this section, we instead run another set of estimation with expanding samples. In other words, we add one set of observations (i.e., real-time quarterly forecast errors for the four indicators) at a time after the first 20 quarters, and re-estimate the factor loadings and other parameters recursively. We then retain the median draw of macroeconomic uncertainty for the latest period added to the sample.

Figure 5 plots the resulting recursive uncertainty estimates along with the baseline index, as well as the one based on the final-vintage data. Not surprisingly, the recursive estimates of uncertainty are more volatile than the other two series. Except for a large uncertainty jump following the 2001 recession that is rather muted by the other two measures, the recursive uncertainty series closely follows the dynamics of the other two. The correlation coefficient after the first 20 quarters is higher between the recursively-estimated index and the baseline series (0.71) than that with the final-vintage estimates (0.56). In sum, the recursive estimates of uncertainty are largely consistent with the smoothed full-sample estimates of macroeconomic uncertainty.

4.4 The Impact of Data Revisions

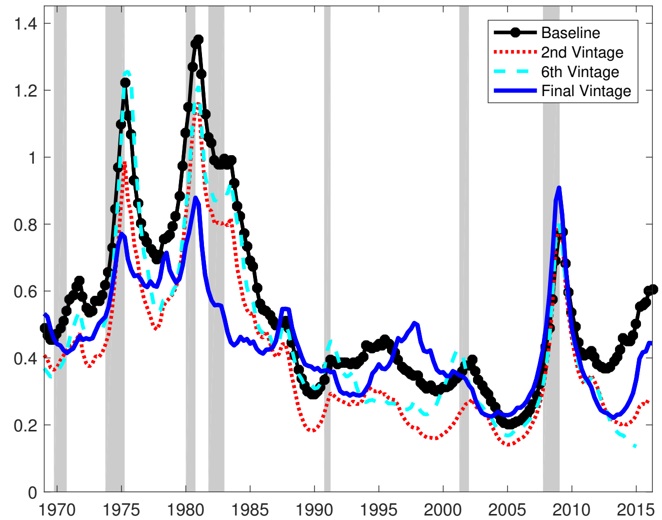
Macroeconomic data go through substantial revisions after initial release.[16] Likewise, macroeconometric analysis using latest available vintage data often results in different conclusions from work that takes real-time issues into account (Orphanides 2001 and Orphanides and Van Norden 2002, for example). A large body of papers has also shown that real-time data issues are particularly important for evaluating the forecasting power of econometric models (Diebold and Rudebusch 1991, Faust et al. 2003, and Ghysels et al. 2014, among many others). However, previous studies focus on the effects on point forecasts (i.e., the conditional mean); likewise, not much attention has been paid to the effect of data revision on the estimation of conditional second moments.[17] Nonetheless, data revisions can also have a potentially important impact on the measurement of volatility, since they directly affect the magnitude of forecast errors. Our baseline measure is estimated with forecast errors computed using the first data release; in this section, we also examine to what extent our macroeconomic uncertainty index differs if we use vintages available in one and five quarter(s) after the initial release as well as the final 2016Q1 vintage to calculate the forecast errors.

Figure 6 shows the macro uncertainty indexes based on the first-released data (the baseline measure), the data revised in one and five quarter(s) after the initial release, and

[16]See Faust et al. (2005) and Aruoba (2008) for more details on the empirical properties of data revisions in GDP as well as other macroeconomic data, respectively.

[17]Clark (2012) is one of few exceptions documenting nontrivial variations in volatility estimates due to data revisions, based on a VAR model with SV. Using survey forecasts, Clements (2015) also demonstrates how the accuracy of forecast intervals is affected by the revisions and how such problems can be resolved if one uses real-time vintage data when estimating a forecasting model.

Figure 6: Macroeconomic Uncertainty Based on the Different Vintages



Note: Figure compares the baseline macroeconomic uncertainty factor (based on the first release) with the uncertainty factor estimated with data from different vintages. The black line with circles is our baseline uncertainty index; the red dotted line is the one where forecast errors of each variable are computed using the revised data available in one quarter after the initial release; the cyan dash line, the 6th vintage, and the blue solid line, the final vintage data.

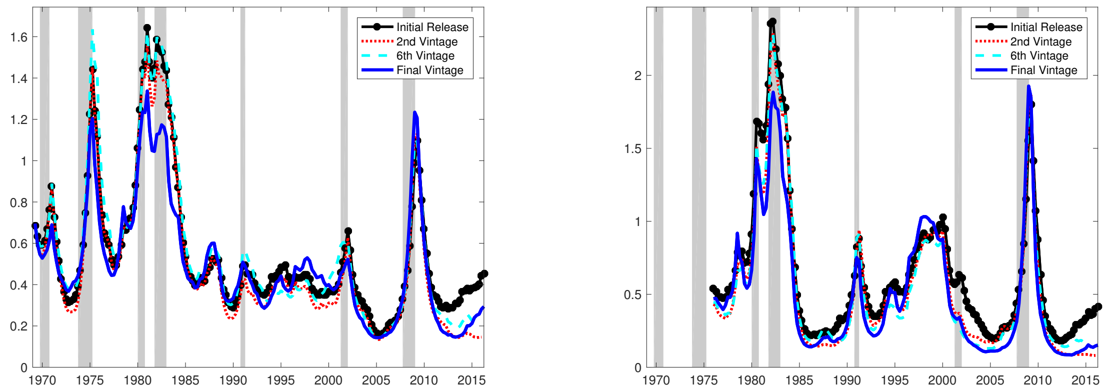
the final vintage data. The final vintage data differ from others, as each data point has gone through different numbers of revisions. That is, data from the more distant past have been revised multiple times, while more recent data may have undergone only a few revisions.

The correlations among all four indexes are high, peaking substantially at the same periods as the baseline index, i.e., the 1973–75, 1980, and 2008–09 recessions. Therefore, we find that the estimated series of uncertainty using different data vintages largely coincide under our framework. Nonetheless, we find quantitative differences across the four series. First, when we focus on the estimates based on the initial release and the second vintage, the overall level of the second vintage-based index is lower than that of the first release-based index, although the difference is rather small. One factor contributing to the difference may be that professional forecasters are well-aware of issues associated with the first, preliminary release such as noise and mismeasurement, and they may accordingly target revised values. Second, the relative size of the peaks changes depending on the data vintage used to calculate forecast errors. In other words, with the forecast errors based on the initial release and the sixth vintage, the uncertainty hikes during the recessions in the pre-Great Moderation periods, i.e., the 1973–75 and 1980 recessions, are comparable to each other. In contrast, the uncertainty based on the second vintage during the 1980 recession reaches the highest level, pushing the peak during the 1973–75 recession downward. Finally, the difference is most stark when the final vintage data are used to compare relative levels of uncertainty in the Great Recession and the two recessions in the pre-Great Moderation periods. With the final vintage data, the Great Recession is associated with the largest jump in uncertainty since the beginning of the series, more in line with the dynamics of uncertainty captured by the VIX and the Jurado et al. (2015) index. However, uncertainty during the recessions in the pre-Great Moderation periods are higher than that in the Great Recession by the other three measures.

We further investigate how data revisions affect the long-horizon uncertainty estimates for two- and five-period-ahead forecasts. Similar to Figure 6, Figure 7 shows the long-horizon macroeconomic uncertainty indexes based on the first-released data, the data revised in one and five quarter(s) after the initial release, and the final vintage data. We find that the size of differences across the indexes is much smaller for both longer-run horizons than nowcasts. Although the impacts of data revision is less pronounced, the key findings based on the nowcast uncertainty indexes still apply. In other words, the level of the second vintage-based index tends to be slightly lower than that of the first release-based index, and the relative size of the peaks changes depending on the data vintage.

In sum, our findings suggest that, while overall dynamics of both macroeconomic and idiosyncratic uncertainties remain robust, they exhibit differences, particularly in the relative size of major peaks over time, depending on a particular data vintage chosen. For instance, macroeconomic uncertainty based on the final vintage data will likely underestimate the actual volatility faced by professional forecasters in the 1970s and 1980s in comparison with the level during the Great Recession.

Figure 7: Effects of Data Revisions on Uncertainties of Longer-Run Horizons



(a) h =2 (b) h = 5

Note: Figure compares estimated h-step-ahead macroeconomic uncertainty factor based on the first release with those based on data from different vintages, for h = 2, and 5. The black line with circles is the uncertainty index based on the initial release, the red dotted line is the one where forecast errors of each variable are computed using the revised data available in one quarter after the initial release, the cyan dashed line, the 6th vintage, and the blue solid line, the final vintage data.

4.5 How Important Is the Information in the Survey?

It is important to remove predictable components from the economic indicators when estimating macroeconomic uncertainty so as not to attribute the predictable variation to unpredictable shocks. As highlighted by Jurado et al. (2015), the most-commonly used proxies of uncertainty —such as stock market volatility (i.e., VIX) and forecast dispersions —do not account for this fact.

Several papers have documented that the predictive ability of survey forecasts is a difficult benchmark for econometric forecasting models to beat, especially at short horizons (see Ang et al. 2007; Faust and Wright 2013; Aiolfi et al. 2011). Consequently, survey forecasts efficiently control for predictable variation in the economic indicators.[18] To examine the effects of using survey forecasts to remove predictable variations, we re-estimate our FSV

[18] It is worthwhile to note that the forecast ability, and thus information content, of the SPF may vary conditional on forecasting horizons. For instance, Rudebusch and Williams (2009) and Lahiri et al. (2013) document that professional forecasters do not appear to incorporate information from the yield curve, and thus do worse at predicting economic downturns than model-based forecasts a few quarters out. In addition, Carriero et al. (2015) find that a mixed-frequency forecast model with stochastic volatility, which combines within-the-quarter observations of monthly indicators and financial variables, can generate GDP growth nowcasts comparable to survey forecasts. In sum, the analysis in this section may not be directly extendable to SPFs of all forecast horizons particularly compared to state-of-the-art forecast models.

Figure 8: Macroeconomic Uncertainty: Forecast Errors from AR Models

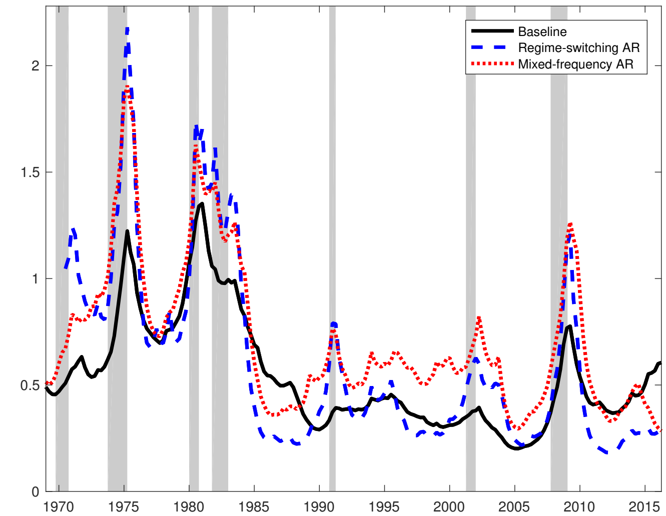


Figure compares the baseline macroeconomic uncertainty index (estimated with survey forecast errors) with the ones estimated using errors obtained from AR models. The black solid line is the baseline index, and the blue dashed and red dotted lines are the index based on forecast errors from the regime-switching and mixed-frequency AR models, respectively.

model using forecast errors from two different autoregressive (AR) models:

$$\text{(AR1)} \qquad y_{i,t} = \alpha_i + \sum_{j=1}^{p} \beta_{i,j} y_{i,t-j} + \gamma_1 y_{i,t}^1 + \gamma_2 y_{i,t-1}^2 + \gamma_3 y_{i,t-1}^3 + \epsilon_{i,t}^{AR1}, \tag{6}$$

$$\text{(AR2)} \qquad y_{i,t} = \alpha_i(s_t) + \beta_i y_{i,t-1} + \epsilon_{i,t}^{AR2}. \tag{7}$$

AR1 is an unrestricted mixed-frequency model. The lag length p is chosen based on the Akaike information criterion with a rolling fixed window of 60 observations. For the variables released at a monthly frequency, the monthly values reported, i.e., the second- and third-month values of quarter $t-1$ ($y_{i,t-1}^2$ and $y_{i,t-1}^3$), and the first-month value in quarter t ($y_{i,t}^1$, only if the release date is before the survey deadline) are augmented, to closely mimic information available to professional forecasters at the time of the survey.[19] It is important to note that the real-time data available in each quarter t are used to match our baseline index closely. In addition, AR2 is an expanding-sample Markov-switching model where the

[19]The forecast errors from AR1 are available at the Federal Reserve Bank of Philadelphia website. Stark (2010) provides a detailed description regarding the model and real-time available information sets.

regime-switching feature shows up in the intercept that may better capture nonlinearities associated with business cycles.[20] Forecasts are made using a pseudo-real-time quarterly data set: for indicators that are available monthly, we take a quarterly average, as soon as a third-month value in a quarter is released.[21]

We then estimate stochastic volatility of a common factor using $\hat{\epsilon}_{i,t}^{AR1}$ and $\hat{\epsilon}_{i,t}^{AR2}$, the forecast errors from the above AR models for each of our four variables. Figure 8 plots the estimated macroeconomic uncertainty with forecast errors from both AR models. The AR-based macroeconomic uncertainty indexes are considerably higher throughout the whole sample period and more volatile than our baseline index based on survey forecasts. Although regime-switching models move more closely with our baseline uncertainty measure during the Great Moderation period, the difference between the two AR models is rather small. The result implies that a significant share of the forecast errors from the AR models are indeed captured by consensus forecasts, especially during recessions. Similarly, statistical models such as AR that have larger and volatile forecast errors likely attribute predictable variations to higher macroeconomic uncertainty. More importantly, this analysis shows that using a consensus survey forecast is a parsimonious and effective way of eliminating the predictable variations from economic variables, thereby providing a more accurate measure of uncertainty faced by economic agents.

5 Innovations to Uncertainty and Macro Dynamics

In this section, we examine the dynamic relationship between our measure of macroeconomic uncertainty and macroeconomic indicators using a standard recursively-identified VAR model proposed by Christiano et al. (2005), augmented with our macroeconomic uncertainty estimates. Previous studies using proxies for macroeconomic uncertainty, such as the VIX in Bloom (2009), tend to find a significantly negative, but short-lived impact of uncertainty on economic activity, followed by an overshoot. In contrast, studies that estimate macroeconomic uncertainty, such as Jurado et al. (2015) and Carriero et al. (2016),

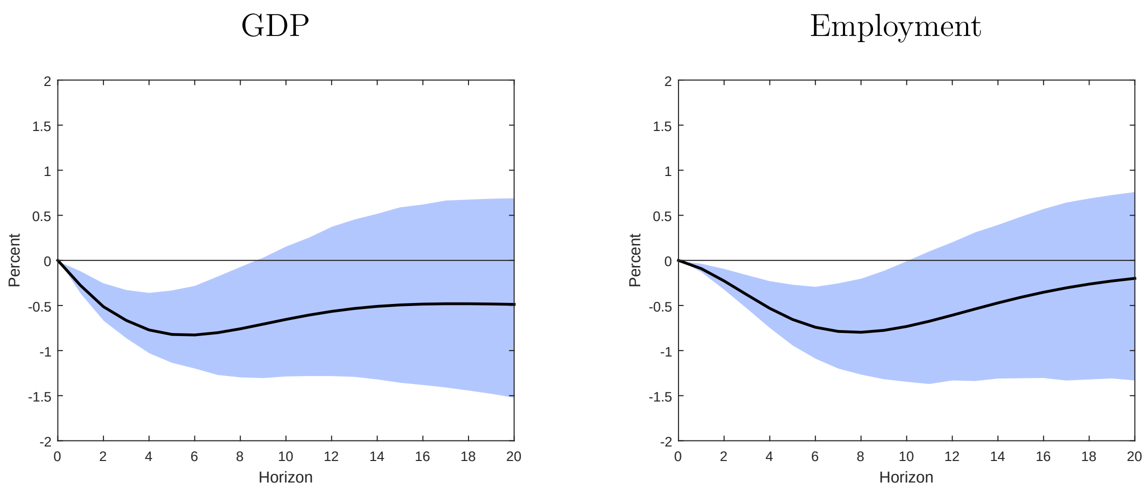
[20]We choose the specification based on its superior forecast ability compared with models with a regime-switching slope and/or regime-switching variance.

[21]For housing starts, some vintages have missing observations in the early period of the sample. Where this occurs, we replace the missing values by observations from the next vintage.

find a much more persistent effect and no evidence of a strong rebound or overshoot.[22]

Our VAR comprises 11 variables in the following order: GDP, employment, consumption, investment, wages, hours, the fed funds rate, profits, M2 and our baseline macroeconomic uncertainty index. The VAR is estimated in levels with three lags. All variables, except the fed funds rate and our uncertainty index, are in logs. A natural choice of the ordering of variables is not clear, as our uncertainty measure should react to real activity shocks within a quarter, while it is also possible that other real variables respond to uncertainty during the same quarter. By placing the uncertainty series last, these estimates should be viewed as a lower bound.

Figure 9: Responses to Innovations to Macroeconomic Uncertainty



Note: Figure shows the response of GDP and Nonfarm Payroll Employment to a four-standard-deviation shock to macroeconomic uncertainty. The shaded area represents one standard deviation bands using Kilian (1998)'s bootstrap-after-bootstrap method.

Figure 9 presents the estimated dynamic responses of GDP and employment to a four-standard-deviation innovation to macroeconomic uncertainty, following Bloom (2009) and Jurado et al. (2015). Both variables show significant and persistent declines following the shock, supporting the findings of long-lived negative effects of uncertainty as in Jurado et al. (2015), and Carriero et al. (2016). In contrast to Bloom (2009), we find no evidence of overshooting in economic activity as the uncertainty shock dissipates.

[22]Caldara et al. (2016) provides a detailed comparative analysis of the impact of different uncertainty measures on economic activity.

Table 2: Variance Decomposition

Quarters	2	4	8	20
GDP	2.34	2.57	3.79	4.28
Employment	1.39	2.14	3.41	4.80

Note: Table shows forecast error variance decomposition for our baseline 11-variable VAR with macroeconomic uncertainty ordered last.

To verify the quantitative importance of an uncertainty shock, Table 2 reports the forecast error variance decomposition for the two variables. The decomposition shows that an uncertainty shock can explain a maximum of 4.28 percent and 4.80 percent of GDP and employment, respectively, within five years following the shock. These numbers are smaller than those reported by Bachmann et al. (2013) and Jurado et al. (2015).

6 Conclusion

This paper analyzes the evolution of economic uncertainty in the United States from 1968Q4 to 2016Q1 as perceived by professional forecasters. Using a FSV framework proposed by Pitt and Shephard (1999), we jointly model and estimate time-varying macroeconomic and indicator-specific uncertainties from the consensus forecast errors of different economic indicators. Our baseline macroeconomic uncertainty index is persistent with all major spikes associated with deep economic recessions (the 1973–75, 1980, and 2007–09 recessions), consistent with Jurado et al. (2015). Other recessions (i.e., the 1990–91 and 2001 recessions) are still notable in the dynamics of some idiosyncratic uncertainties but were not picked up by the macroeconomic uncertainty. By contrast, the macroeconomic uncertainty series estimated using longer-run horizon forecast errors show additional peaks aligned with the other recessions. Recursive estimates of our macroeconomic series from an expanding sample are more volatile, yet broadly in line with our baseline index.

Using survey forecasts enables us to gauge subjective and real-time macroeconomic uncertainty as perceived by professional forecasters. In addition, they incorporate extensive information, and flexibly account for potential time variations and structural breaks, keeping our framework simple and straightforward. Our baseline macroeconomic uncertainty index shows dynamics similar to Jurado et al. (2015), despite the substantial differences in the number of underlying series. In addition, when we add into the benchmark model more real economic activity indicators that have been included in the SPF since 1981, they did not materially impact our macroeconomic uncertainty estimates. A comparison with objective, model-based uncertainty indexes also confirms the efficiency of using survey forecasts.

We also document how data revisions affect the estimated evolution of macroeconomic uncertainty. In particular, we show that the relative size of major uncertainty peaks changes depending on a specific vintage chosen to calculate forecast errors.

Finally, a VAR analysis demonstrates that a positive innovation to our baseline index as well as longer-run uncertainty indexes results in significant decreases in GDP and employment, in line with the findings in Jurado et al. (2015) and Carriero et al. (2016). However, this evidence is at odds with the short-lived negative impact followed by a strong rebound, as suggested by Bloom (2009).

Appendix

A Prior Distributions and Starting Values

Our choice of prior distributions and their parameter values is very similar to Pitt and Shephard (1999). The prior for **factor loadings** is the Normal distribution, i.e., $\lambda_i \sim N(\lambda_0, \Lambda_0)$ with $\lambda_0 = 1$ and $\Lambda_0 = 25$, as in Pitt and Shephard (1999). The choice of large Λ_0 represents a fair degree of uncertainty around the factor loadings. The initial value of the factor loadings is the OLS estimates of forecast errors on the first principal component as a proxy. Since the factor and loadings are not fully identified in a factor model, we set the loading of the first variable (i.e., GDP) equal to one, a common identification strategy for a factor model. A diffuse Normal prior is used as the prior for the **factor** conditional on $\{h_{f,t}\}_{t=1}^{T}$, consistent with (3) (i.e., $f_t \sim N(\theta_0, \Theta_0)$ where $\theta_0 = 0$ and $\Theta_0 = h_{f,t}$).

The prior for the **variability of volatilities** is the inverse Gamma, i.e., σ_f^2 and σ_i^2 $\sim IG(\frac{v_0}{2}, \frac{\delta_0}{2})$. We set $v_0 = 1$ and $\delta_0 = 1$, which makes the conditional prior distribution flatter than that in Pitt and Shephard (1999) and more so than those in other recent studies applying SV (see, e.g., Primiceri 2005; Baumeister et al. 2013) to allow for a large time variation for volatilities *a priori*. Compared with the above studies, the total number of parameters is substantially smaller in our case. Thus, we use a more diffuse prior and put a larger weight on data. The prior of each **time-varying volatility** is the log-Normal. For the initial period's stochastic volatility, we have $\log h_0 \sim N(\mu_0^h, V_0^h)$, where $\mu_0^h = 1$ and $V_0^h = 10$ to allow a good chance for the data to determine the posterior distribution.

B Posterior Distribution Simulation

The MCMC algorithm for the estimation of the joint posterior distribution of an FSV model closely follows Pitt and Shephard (1999). We divide the parameters into four blocks: (a) the factor loadings (λ); (b) the time series of the factor ($\{f_t\}_{t=1}^T$); (c) the hyperparameters for volatilities (σ_f; and σ_i for all i); and (d) the volatility states ($\{h_{f,t}\}_{t=1}^T$ and $\{h_{i,t}\}_{t=1}^T$ for all i). The conditional independence across t and i as well as of f_t and $u_{i,t}$'s further breaks down most steps in the Gibbs sampler, i.e., drawing factor loadings $\{\lambda\}$, volatility states $\{h\}$ and the variance of volatilities $\{\sigma\}$ to drawing from a univariate process. Finally, the volatility states are drawn via Metropolis methods within the Gibbs sampler. Denoting by z^T the time series of a variable z from $t = 1$ to T, we describe the algorithm below.

Factor loadings. Conditional on all other parameters, this step becomes a simple Bayesian regression of forecast errors on the factor with known heteroskedastic error structures. Moreover, because all correlations are by definition captured by the factor, this step further decomposes into the n sub-steps of drawing each i-th loading separately from $\lambda_i|\varepsilon^T, f^T, \sigma_f, \sigma_i, h_f^T, h_i^T \sim N(\lambda_1, \Lambda_1)$, given the history of variable i, where $\Lambda_1 = (\Lambda_0^{-1} + \sum_{t=1}^T f_t^2/(h_{i,t}))^{-1}$ and $\lambda_1 = \Lambda_1(\Lambda_0^{-1}\lambda_0 + \sum_{t=1}^T f_t \cdot \varepsilon_{i,t}/(h_{i,t}))$.

Factor. Conditional independence also simplifies this step. Given all other parameter values, this step again becomes a Bayesian regression of available forecast errors on factor loadings with known heteroskedasticity for each period t. That is, $f_t|\varepsilon^T, \lambda_i, \sigma_f, \sigma_i, h_f^T, h_i^T \sim N(\theta_1, \Theta_1)$, where $\Theta_1 = \{h_{f,t}^{-1} + \sum_{i=1}^n \lambda_i^2(h_{i,t})\}^{-1}$, and $\theta_1 = \Theta_1(\sum_{i=1}^n \lambda_i \cdot \varepsilon_{i,t}/(h_{f,t}))$.

Innovation variance of volatilities. Since we model each stochastic volatility to follow a unit-root process without a drift, σ^2 is drawn from $\sigma|\varepsilon^T, f^T, h_f^T, h_i^T \sim IG(\frac{v_1}{2}, \frac{\delta_1}{2})$, where $v_1 = v_0 + T$, and $\delta_1 = \delta_0 + \sum_{t=1}^T (h_{i,t} - h_{i,t-1})^2$.

Volatility states. This step further decomposes to the $n + 1$ sub-steps of univariate stochastic volatility draws, based on the Markovian property of stochastic volatility. Following the algorithm by Jacquier et al. (2002) as used in Cogley and Sargent (2005), for each volatility series of an idiosyncratic error i or of the factor, we draws the exponential of volatility ($h_{i,t}^2$) one by one for each $t = 1, \ldots, T$, based on $f(h_{i,t}|h_{i,t-1}, h_{i,t+1}, y_i^T, \lambda, f^T, \sigma)$.

Before sampling the states, we first transform forecast errors to be $\varepsilon_{i,t}^* = \varepsilon_{i,t} - \lambda_{i,t} f_t$. Such transformation is unnecessary for the factor. Then, we apply the Jacquier et al. (2002) algorithm for each date, i.e.,

$$
\begin{aligned}
f(h_{i,t}|(h_i)_{-t}^T, y_i^{*T}, \sigma) &= f(h_{i,t}|h_{i,t-1}, h_{i,t+1}, y_i^{*T}, \sigma) \\
&\propto f(y_{i,t}^*|h_{i,t}) f(h_{i,t}|h_{i,t-1}) f(h_{i,t+1}|h_{i,t}) \\
&= (h_{i,t})^{-1.5} \exp\left(\frac{-y_{i,t}^*}{2h_{i,t}}\right) \exp\left(\frac{-(\log h_{i,t} - \mu_t)^2}{2\sigma_c^2}\right),
\end{aligned}
$$

where μ_t and σ_c^2 are the conditional mean and variance of $\log h_{i,t}$, respectively. Under the unit-root specification of this paper, they can be calculated as

$$
\begin{aligned}
\mu_t &= \frac{(\log h_{i,t-1} + \log h_{i,t+1})}{2}, \\
\sigma_c^2 &= \frac{\sigma_i^2}{2},
\end{aligned}
$$

for $t = 1, \cdots, T-1$. Thus, a trial value of $\log h_{i,t}$ is drawn from the Normal distribution with mean μ_t and variance σ_c^2. For the beginning and end periods of each series i, the following conditional mean and variance are used instead:

$$
\begin{array}{lll}
t = 0: & \sigma_c^2 = \frac{\sigma_i V_0^h}{\sigma_i + V_0^h}, & \mu = \sigma_c^2 \left(\frac{\mu_0^h}{V_0^h} + \frac{\log h_{i,t+1}}{\sigma_i^2}\right), \\
t = T: & \sigma_c^2 = \sigma_i^2, & \mu = \log h_{i,T-1}.
\end{array}
$$

After obtaining a draw, the acceptance probability is evaluate using the conditional likelihood $f(y_{i,t}^*|h_{i,t})$, completing a Metropolis step (see Cogley and Sargent 2005 for details). We can summarize the estimation procedure as follows:

1. Assign initial values for λ, f^T, σ_f, σ_i for all i, h_f^T, and h_i^T for all i.
2. Draw λ from $p(\lambda|\varepsilon^T, f^T, \sigma_f, \sigma_i, h_f^T, h_i^T)$.
3. Draw f^T from $p(f^T|\varepsilon^T, \lambda, \sigma_f, \sigma_i, h_f^T, h_i^T)$.

4. Draw σ_f and σ_is from $p(\sigma|\varepsilon^T, f^T, h_f^T, h_i^T)$.
5. Draw h_f^T, and h_i^Ts from $p(h|\varepsilon^T, f^T, \sigma_f, \sigma_i)$.
6. Go to step 2.

We iterate over the Metropolis-within-Gibbs sampler a total of $80,000$ times, discarding the first $30,000$ draws. Then we store every 10th draw in order to avoid potential autocorrelation across draws, and finally obtain $5,000$ draws from the joint posterior distribution.

C Uncertainty Based on Different Measures of Central Tendency and Quantiles of Survey Forecasts

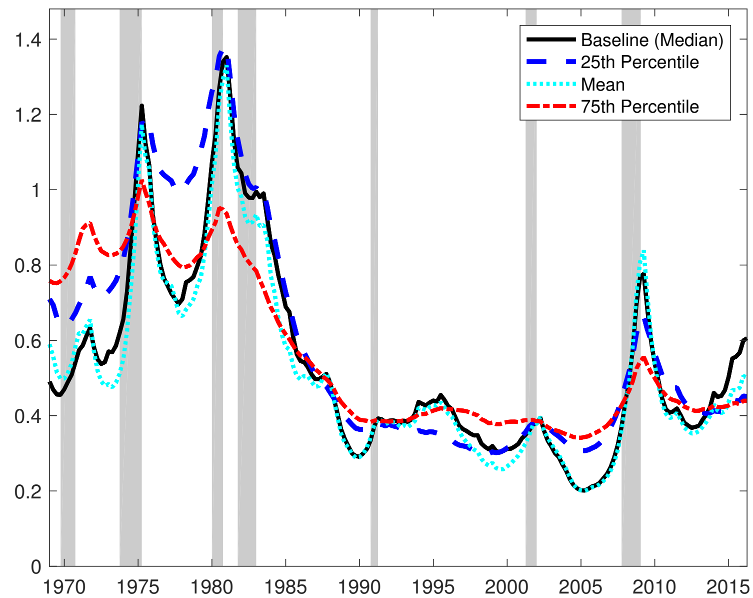
When calculating the forecasting errors for the baseline model, we use the consensus forecasts, i.e., the median across forecasters, to minimize potential influences from individual forecasting biases, as noted in Section 2 of the main paper. Capistrán and Timmermann (2009) provide support for the use of the median; they show that means of survey forecasts performs better than other methods of individual forecast combination when evaluated by root-mean-squared errors. In the case of SPF, the mean and median forecasts are very close to each other, as documented in Croushore (2010). In addition, Arai (2014) finds that the SPF median forecasts for GDP growth present no systematic biases. Hence, a number of previous studies consider the median as standard consensus projections.[23]

However, studies such as Gneiting (2011) show that quantiles might also be optimal forecasts when the loss function is generalized piecewise linear. Therefore, we re-estimate our FSV model using the 25th and 75th percentiles of the forecast error distribution, instead of the median as reported in the main text. In addition, we use the means of forecasts instead of the medians and reestimate the FSV model.

Figure 10 shows the resulting estimates. First, we find that the series based on the mean and our baseline index are very close to each other, with a correlation coefficient of 0.99. This is in line with a notion that the mean and median are very close to each other in the SPF. The uncertainty estimates based on the 25th and 75th percentiles of forecasts have similar dynamics with our baseline index, with the correlation coefficients amounting

[23]See Engelberg et al. (2009) and Croushore (2010), for example.

Figure 10: Uncertainty Based on Different Optimal Forecasts



Note: Figure plots uncertainty estimates based on different quantiles in comparison with our baseline index that is based on median forecast errors. The blue, cyan, and red dashed lines represent the estimates based on the 25th percentile, mean, and 75th percentile forecasts, respectively.

to 0.95 and 0.84, respectively. The differences in index appear to be most notable in the earlier period of the sample, supporting the use of the median as consensus to remove idiosyncratic variations in individual forecasts.

D Evidence of a Factor Structure in Data

We provide more information about the presence of a factor structure in the forecast errors of the four variables used for our benchmark index. First, Table 3 summarizes the correlation coefficients among the forecast errors the four variables. The forecast errors are calculated as the difference between the median of individual forecasts and the initial data release. The correlations between GDP, IP and the unemployment rate forecast errors are in the range of 40 to 57% (negative correlations for the unemployment rate). The correlations are lower for housing, ranging from 8 to 28%. This smaller degree of comovement between housing and the remaining variables is reflected in our estimated factor loading (see Table 1), as well as its higher share of idiosyncratic variance (see Figure 2). More formally, we also estimate principal components and find that the first principal component explains 52% of the variability in forecasting errors. Hence, we conclude that there is a fair degree of co-movement across the forecasting errors of these four variables.

Table 3: Correlation Coefficients of Forecasting Errors

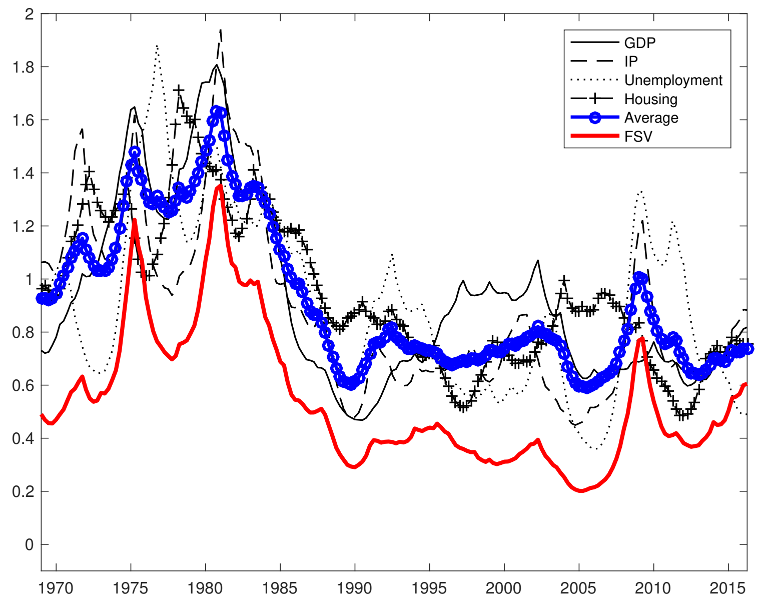
	GDP	IP	UR	HS
GDP	1			
IP	0.57	1		
UR	−0.40	−0.54	1	
HS	0.28	0.14	−0.09	1

In addition, we estimate a univariate Stochastic Volatility (SV) model separately for the four forecasting error series. Our factor model is constructed under the assumption that all comovement is captured by a factor and that innovations to the factor as well as idiosyncratic errors are uncorrelated. Therefore, a factor structure in the levels of forecasting errors implies the same factor structure in volatilities of forecasting errors. Hence, we gauge if there is any similarity across the separately-estimated individual volatility series. We first report in Table 4 the correlation coefficients across the four individually-estimated SV series. The correlations range from 51 to 78%, reflecting close comovements as seen in Figure 11. Moreover, we plot in Figure 11 the average of individually estimated volatility series (in blue): This series shows very similar dynamics to our benchmark macroeconomic uncertainty from the FSV model (in red), with the correlation coefficient of 0.94. The similarity found in the four individually estimated SV series is again consistent with a factor structure imposed in our baseline model.

Table 4: Correlation of Volatility Series Estimated Separately from Univariate SV Models

	GDP	IP	UR	HS
GDP	1			
IP	0.78	1		
UR	0.59	0.65	1	
HS	0.70	0.68	0.51	1

Figure 11: Volatilities from Univariate Stochastic Volatility Models



Note: Figure shows volatility estimates from univariate SV models fitted to each forecasting error of the four macroeconomic indicators (i.e., GDP, IP, unemployment, and housing starts) used in our benchmark model. The blue line represents the average of the four univariate SV series, while the red line plots the benchmark macroeconomic uncertainty index from a FSV model.

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