Macroeconomic Uncertainty Through the Lens of Professional Forecasters

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Abstract

We propose a novel framework for using consensus survey forecasts to estimate economic uncertainty, defined as the conditional volatility of unanticipated fluctuations. Comprehensive information contained in survey forecasts enables us to capture the unanticipated fluctuations in a parsimonious but efficient way. We jointly estimate macroeconomic (common) and indicator-specific uncertainties of nine indicators in a framework that extends a Factor Stochastic Volatility model to incorporate different starting dates of indicators. 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 demonstrate for the first time in the literature that the selection of data vintage affects the relative size of jumps in estimated uncertainty series substantially. Finally, our macroeconomic uncertainty has a persistent negative impact on real economic activity, rather than producing "wait-and-see" dynamics.

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1 Introduction

The literature on the impacts of uncertainty on real economic activity has recently witnessed a rapid growth following the last Financial Crisis and Great Recession.[2] Several studies have aimed at empirically quantifying the effect of uncertainty. Central to these studies is a need for a measure of time-varying uncertainty, as uncertainty is not directly observable. Bloom (2009) has pioneered the use of the VIX, the implied stock market volatility based on the S&P index. Others have used different approaches to quantify uncertainty. For example, Bloom et al. (2012) use the cross-sectional dispersion of total factor productivity shocks. Another popular proxy for uncertainty is the cross-sectional dispersion of individual forecasts, as in Bachmann et al. (2013). A proxy constructed using word searches from newspaper articles is proposed in Alexopoulos and Cohen (2009), and Baker et al. (2013)'s Economic Policy Uncertainty index combines news article counts with the number of federal tax code provisions set to expire as well as the forecast dispersions.

This paper proposes a novel framework for using consensus survey forecasts to estimate subjective and real-time measures of common, as well as idiosyncratic uncertainties. 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 such as unemployment, industrial production, consumption expenditure, among others. In other words, an increase in the macroeconomic uncertainty implies the higher probability of many economic variables to deviate from their expectations simultaneously. This idea is effectively captured by a Factor Stochastic Volatility (FSV) model, first developed by Pitt and Shephard (1999). The stochastic volatility process is widely adopted in finance literature, as it is parsimonious, yet efficiently quantifies time-varying volatility.[3] More recently, it has also been employed often in macroeconomic analysis to model the time-varying volatility of macroeconomic indicators.[4] Combined with a factor model structure, it provides a straightforward approach to jointly model common (macroeconomic) as well as indicator-specific uncertainties.

[2]See, for example, Bloom (2009), Arellano et al. (2012), Caggiano et al. (2014), Aastveit et al. (2013), and Mumtaz and Surico (2013), among many others.

[3]See Kim et al. (1998).

[4]See Primiceri (2005) and Justiniano and Primiceri (2008), among others.

We use total nine economic indicators from the Survey of Professional Forecasters (SPF) conducted by the Federal Reserve Bank of Philadelphia, with which we calculate forecast errors to estimate uncertainty series. Using survey forecasts provide the following advantages. First, they are not tied to any particular econometric models. Hence, it is not necessary to select and estimate a specific forecasting model in order to obtain forecast errors. Second, they provide an effective way of removing expected variations in macroeconomic series. As highlighted by Jurado et al. (2015), it is crucial to remove the predictable component of macro series when estimating macroeconomic uncertainty, in order not to attribute some of the predictable variability to unpredictable shocks. Subjective forecasts have been shown to be at least as accurate as forecasts from econometric models.[5] Therefore, survey forecasts are good candidates to control for the predictable variations in economic indicators.

On the methodological side, our contribution is to extend the standard FSV model to incorporate the forecasting errors of economic indicators whose histories differ in length.[6] The SPF has expanded its coverage beyond the six variables that were included in the initial form of the survey in 1968. To capture a common factor that can span a larger number of indicators, we augment the FSV model to easily include forecasts for new indicators as they become available. The augmented FSV model allows us then to estimate the longest possible common and idiosyncratic uncertainty series, while continuously incorporate information from new indicators that were appended to the survey over time.

Our paper shares similarity with recent studies focusing on estimating macroeconomic uncertainty, as well as papers using stochastic volatility with a factor structure. For example, Jurado et al. (2015) fit a factor model to a variety of macro and financial variables to generate forecasts. They assume that the volatilities of individual forecast errors follow a univariate stochastic volatility process, whose average becomes macroeconomic uncer-

[5] 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 combination of the two types of forecasts for different indicators, and find that combinations always improve over time series models, but still fail to systematically improve on the survey forecasts alone.

[6] Stambaugh (1997) demonstrates that utilizing information from longer series benefits overall parameter estimation for portfolio analysis using return histories of different starting dates. In a factor model setup, citestock2002macroeconomic and Bańbura and Modugno (2014) investigated how to deal with missing observations in a panel data set when estimating common factors under the assumption of constant volatilities. Thus, we differ in that our main interest is to estimate the time-varying conditional volatility series with in a factor framework, rather than the common factors.

tainty. Rossi and Sekhposyan (2015) use the SPF for GDP to construct an uncertainty index from the unconditional historical distribution of forecast errors. Carriero et al. (2015) develop a vector autoregressive (VAR) model where macroeconomic variables share a common stochastic volatility factor. Contrary to our framework, idiosyncratic volatility is not modeled, since the variations of individual volatilities over time are completely determined by the common factor. Scotti (2013) exploits survey forecasts and creates an uncertainty index as the sum of the squared forecast errors for different indicators. The squared forecast errors are weighted by the loadings taken from a factor model estimated to construct a business condition index as in Aruoba et al. (2009). The most distinct feature of our approach is that it postulates a factor structure explicitly for an increasing set of survey forecast errors over time, which *jointly* estimates time-varying common and idiosyncratic volatilities as well as factor loadings. As a result, our proposed framework is parsimonious, yet provides consistent indexes of both macroeconomic and indicator-specific uncertainties in one step.

Our estimated uncertainty measure shows persistent dynamics. 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). However, other recessions (i.e. the 1990-91 and 2001 recessions) are still notable in the dynamics of idiosyncratic uncertainty, but were not picked up by the macroeconomic uncertainty series, suggesting that increases in uncertainty during these periods were not as broad-based as during other recessions.

We also examine the impact of data revisions on the estimation of economic uncertainty. To the best of our knowledge, ours is the first paper to do so. As macroeconomic variables are constantly revised, uncertainty measures based on the most recent data vintage use a different information set than that previously available to professional forecasters. We find large quantitative differences in the uncertainty series with real-time and revised forecast errors. More specifically, the 1973-75 and 1980 recessions exhibit the largest jumps in our baseline uncertainty index with forecast errors based on the initial release. Yet, data revision conducted within one quarter after the initial release pushes the uncertainty jump accompanying the 1980 recession further up, leaving its peak at the highest level throughout

the entire sample period. On the contrary, uncertainty is at its highest in the Great Recession when the data available five quarters after the initial release is used, although overall dynamics remain similar. Hence, the use of a specific data vintage can be very important especially when the interest lies in estimating the relative level of macroeconomic uncertainty over time.

We compare our measure to another popular survey-based proxy of uncertainty, namely forecast disagreement. We construct a common disagreement factor using the same set of variables as in our uncertainty index. The most notable difference is that a common disagreement factor is significantly more volatile and less persistent than our uncertainty index. A further investigation of the dynamic relationship between the two shows that while common disagreement reacts strongly to uncertainty shocks, shocks to common disagreement actually lead to a small decreases in uncertainty.

In addition, VAR analysis show that shocks to our uncertainty measure have significant and negative effects on a variety of real economic variables: investment, non-durable and durable consumptions and GDP retract after an increase in macroeconomic uncertainty. The impact of uncertainty shocks are not only sizable, but also highly persistent. This is in stark 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 dissipates quickly.

The rest of the paper is organized as follows. Section 2 introduces the dataset. Section 3 provides an exposition of our econometric model. The next section presents our estimates of common, as well as idiosyncratic uncertainties. We also study the effects of data revisions to our uncertainty estimates, as well as compare our measure to forecast disagreement. A VAR analysis show the impact of shocks to our uncertainty measure to real economic activity in section 5. Finally, section 6 concludes.

2 Data

We use the data from the U.S. Survey of Professional Forecasters (SFP). The survey was initially introduced by the National Bureau of Economic Research and the American Statistical Association in 1968, which was then taken over by the Federal Reserve Bank of

Philadelphia in June, 1990. An important feature of the survey is that the set of economic indicators for which professional forecasters provide forecasts for has expanded significantly since the survey began. While the survey started with a handful of variables in 1968Q4 (*e.g.*, Gross Domestic Product (GDP), Industrial Production, Unemployment Rate), others variables have been added over time (*e.g.*, expenditure side components of GDP in 1981Q3, Nonfarm Payroll in 2003Q4). We use total nine variables which are added in three sub-groups. Three variables, industrial production, unemployment rate and housing starts, span the longest periods starting from 1968Q4; next, five additional variables representing components of GDP (consumption, non-residential investment, residential investment, federal government spending and local government spending) are added from 1981Q3 and onwards; finally, we add non-farm payroll employment in 2003Q4. The final data point of our sample is 2015Q1. Table 1 summarizes the variables in our dataset, as well as their starting date.

Since forecasters are surveyed on a quarterly basis, the most recent quarter of data in their information set would be the previous quarter. The forecast submission deadline of the survey tends to occur close to the middle of the quarter (after the Bureau of Economic Analysis' *advance report* of the national income and product accounts (NIPA), which contains the first estimates of the previous quarter's GDP), so for macroeconomic variables released on a monthly basis, forecasters would have access to the first month's realized data for the current forecast horizon, before the survey is submitted. We use their one-step-ahead forecasts, namely their nowcasts, in order to construct the forecast errors.

The calculation of forecast errors at any point in time is contingent on the realized value of the series. The NIPA data go through substantial revisions, and these revisions can ultimately affect our measurement of uncertainty. Thus, we use the first release, and revised data available in one and five quarters after the initial release to compute three possible values of forecast errors. When calculating the forecasting errors, we take consensus forecasts, i.e., averages of individual professional forecasters' forecasts, to minimize potential influences from individual forecasting biases.[7]

[7] Arai (2014) finds that the SPF consensus forecasts for GDP growth present no systematic biases.

3 Factor Stochastic Volatility Model

In order to estimate macroeconomic as well as idiosyncratic uncertainty indexes from forecasting errors whose histories differ in length, we build on the FSV model developed in Pitt and Shephard (1999). We start by defining the forecasting error of a variable i in period t, denoted as $\varepsilon_{i,t}$, as follows:

$$\varepsilon_{i,t} = x_{i,t} - E[x_{i,t}|I_t], \tag{1}$$

where $x_{i,t}$ is the realization of variable i in time t, and $E[x_{i,t}|I_t]$ is a conditional mean of forecasts of variable i for the quarter t across different forecasters (i.e., consensus forecast). One of the key differences of our measure from other uncertainty indexes based on a particular forecasting model is that we obtain $E[x_{i,t}|I_t]$ from the consensus forecasts, instead of using forecasts from a specific econometric model. The information set (I_t) also has the same time-subscript t, as it contains information obtained until the middle of the quarter t. As discussed in the previous section, for monthly macroeconomic indicators such as industrial production and the unemployment rate, the first month's value in the quarter t is included in I_t along with the first NIPA release of $x_{i,t-1}$. For indicators of quarterly frequency, I_t includes the first NIPA estimate of $x_{i,t-1}$ which is only available in the middle of the quarter t.

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

$$\varepsilon_{i,t} = \lambda_i f_t + u_{i,t}, \tag{2}$$

where f_t is a common factor across different i's, λ_i is a factor loading, and $u_{i,t}$ is an idiosyncratic error, capturing indicator-specific variations. Equation (2) implies that there is a factor that drives the common dynamics across the forecasting errors of total n economic indicators.

One distinct feature of our model compared to standard factor models is that the forecasting errors have different lengths of history. In other words, the starting period of $\tilde{\varepsilon}_{i,t}$ can vary for each i, making the available number of observations of forecasting errors

differ across n economic indicators. This is due to the expansion of the SPF over time to include more variables, as noted in the previous section: the first set of variables has been surveyed since 1968Q4, others have been added starting from 1981Q3. If we were to restrict the model to use the SPF data with equal and longest histories, only a couple of indicators would remain at our disposal. Or, if we focus on the period during which most variables are available, we would discard a considerable number of observations in earlier periods, which is not desirable given that the main purpose of this paper to construct a historical time series of uncertainty. Therefore, we develop a factor model which can easily add economic indicators to the model as they become available in the SPF. The proposed framework incorporates as much information as possible and does not require discarding data in early periods. In this fashion, we can properly construct a long time series of the volatility of a common component that simultaneously drives cross-sectional variations in various economic indicators.

Based on a factor model framework, our main interest is to estimate common and idiosyncratic uncertainty series, defined as time-varying conditional volatilities. Here we follow the FSV model in Pitt and Shephard (1999), and postulate that the volatilities of the factor f_t and idiosyncratic errors $u_{i,t}$'s evolve as stochastic volatility processes. For demonstration, here we assume that variables in the data are divided into two groups only depending on their starting dates.[8] Let the vector $\varepsilon_{n_1,t}$ contain forecasting errors of n_1 variables in period t and $\varepsilon_{n_1,t}$ have T observations are available for periods $t = 1, \ldots, T$. Let $\varepsilon_{n_2,t}$ denote the vector of n_2 forecasting errors that are observed for periods $s, \ldots, T$ where $s \geq 1$. Hence, the total number of indicators available from time s is $n = n_1 + n_2$.

As in the standard FSV model (e.g., Pitt and Shephard 1999 and Chib et al. 2006), we assume that $u_{n,t}$ and f_t are conditionally independent Gaussian random vectors. That is, for periods before s

$$\begin{pmatrix} u_{n_1,t} \\ f_t \end{pmatrix} | \Sigma_{n_1,t}, h_{f,t} \sim N\left(0, \begin{bmatrix} \Sigma_{n_1,t} & 0 \\ 0 & h_{f,t} \end{bmatrix}\right), \tag{3}$$

[8] However, it is straightforward to extend the model to include a number of different starting dates. In the application of the model, we have three groups of economic indicators that start in 1968Q4, 1981Q3 and 2003Q4.

and from $s+1$

$$\begin{pmatrix} u_{n,t} \\ f_t \end{pmatrix} | \Sigma_{n,t}, h_{f,t} \sim N\left(0, \begin{bmatrix} \Sigma_{n,t} & 0 \\ 0 & h_{f,t} \end{bmatrix}\right), \tag{4}$$

where $\Sigma_{n,t}$ are a $n \times n$ diagonal matrix of time-varying idiosyncratic volatilities,

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

and $\Sigma_{n_1,t}$ is a diagonal sub-matrix containing the first $n_1 \times n_1$ elements of $\Sigma_{n,t}$. The factor structure of our model simplifies incorporating variables of different starting dates, since comovements across variables in each period are captured by the common factor by definition. This implies that we do not need to consider the covariance among idiosyncratic variations separately. The common as well as indicator-specific volatilities follow independent stochastic volatility processes:

$$\begin{aligned} \log h_{f,t} &= \log h_{f,t-1} + \sigma_f \eta_{f,t} \\ \log h_{i,t} &= \log h_{i,t-1} + \sigma_i \eta_{i,t}, \end{aligned} \tag{5}$$

where σ_f and σ_i's are time-invariant parameters determining the variability of the volatilities.

Based on multivariate Gaussianity and conditional independence, the likelihood func-

tion becomes,

$$
\begin{aligned}
(6) \qquad p(\varepsilon|\lambda,\sigma) &= \prod_{t=1}^{s-1} \int p(\varepsilon_{n_1,t}|h_t, f_t, \lambda, \sigma)\, \mathrm{d}h_t\, \mathrm{d}f_t \\
&\qquad \times \prod_{t=s}^{T} \int p(\varepsilon_{n_1,t}, \varepsilon_{n_2,t}|h_t, f_t, \lambda, \sigma)\, \mathrm{d}h_t\, \mathrm{d}f_t \\
&= \prod_{t=1}^{s-1} \int p(\varepsilon_{n_1,t}|h_t, f_t)\, p(h_t, f_t|\mathcal{F}_{t-1}, \lambda, \sigma)\, \mathrm{d}h_t\, \mathrm{d}f_t \\
&\qquad \times \prod_{t=s}^{T} \int p(\varepsilon_{n_1,t}, \varepsilon_{n_2,t}|h_t, f_t)\, p(h_t, f_t|\mathcal{F}_{t-1}, \lambda, \sigma)\, \mathrm{d}h_t\, \mathrm{d}f_t,
\end{aligned}
$$

where $\mathcal{F}_{t-1}$ denotes the history of the $\{\varepsilon_t\}$ process up to time $t-1$ and $p(h_t, f_t|\mathcal{F}_{t-1}, \lambda, \sigma)$ the density of the latent variables conditioned on $(\mathcal{F}_{t-1}, \lambda, \sigma)$.

In this setup, one salient estimate of interest is the time-varying standard deviations of the factor, i.e., $\{\sqrt{h_{f,t}}\ \}$ which we define as our measure of the macroeconomic uncertainty index: the time series of macroeconomic uncertainty captures the volatility of a common driver that simultaneously affects the magnitude of forecasting errors across different variables, by determining the magnitude of common variations across all 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. It is worthwhile to note again that our framework hence yields both common and indicator-specific uncertainty indexes, which are consistently modeled and estimated in one step.

Our model is estimated using Bayesian methods, since the model features high dimensionality as well as non-linearity. The 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 breaks the parameters into several blocks and repeatedly draws from conditional posterior distributions, in order to simulate the joint posterior distribution. Thus, instead of using the likelihood function directly, this efficiently summarizes the joint posterior distribution, once blocks are carefully selected. While details regarding the MCMC algorithm is provided in Appendix A, here we briefly summarize steps in the estimation procedure as follows:

1. Assign initial values for λ, $\{f^T\}$, σ_f, $\{h_f\}$, and σ_i and $\{h_i\}$ 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 $\{h_f\}$, and $\{h_i\}$'s from $p(h|\varepsilon^T, f^T, \sigma_f, \sigma_i)$
6. Go to step 2.

The algorithm is iterated a total of $80,000$ times, discarding the first $30,000$ draws of parameters. We collect $5,000$ draws by storing every 10th draw in order to avoid potential autocorrelation across draws.

Hence, the MCMC algorithm proposed for the new model with different starting dates builds on the one introduced in Pitt and Shephard (1999), dividing parameters into blocks in a similar manner. In particular, as in Pitt and Shephard, steps 2, 4 and 5 can further break down to drawing from a univariate process, due to the conditional independence across t and i as well as of f_t and $u_{i,t}$'s. Thus, the conditional independence further makes the extension straightforward in these steps: one only needs to take into account different starting dates of each variable i. For instance, when drawing λ_i, the sub-step becomes regressing the forecast errors $\{\varepsilon_i\}$ on the factor $\{f\}$ for the period $t = s, \ldots, T$. Likewise, step 3, *i.e.* sampling the common factor f_t, is conditioned on available forecast errors and factor loadings in each period t. That is, when $t < s$, the factor is sampled from n_1 forecast errors, but once the algorithm hits the period s, it incorporates all available n forecast errors to extract a common variation. Likewise, when sampling the common factor f_t, the step is conditioned on available forecast errors and factor loadings in each period t. That is, when $t < s$, the factor is sampled from n_1 forecast errors, but once the algorithm hits the period s, it incorporates all available n forecast errors to extract a common variation.[9]

When the volatility states $\{h\}$ are drawn, we incorporate Metropolis methods within the overall Gibbs sampler, following the algorithm by Jacquier et al. (2002). We follow the common identification scheme of a factor model which sets the first factor loading (of

[9]We do not backcast missing observations of the series that start later in the sample, since the main goal of this paper is to estimate the time-varying volatility series of a factor and idiosyncratic errors rather than the factor itself. In addition, filling in the earlier missing forecasting errors using the information on the factor and loadings does not have an impact on the posterior estimation under the conditional independence assumption. See Stock and Watson (2002) and Bańbura and Modugno (2014) for the estimation of a dynamic factor models with missing observations via the EM algorithm.

IP) equal to unity. However, the resulting baseline index of macroeconomic uncertainty is robust to equalizing other factor loadings to one or changing the ordering of variables. The choice of prior distributions and their parameter values is very similar to Pitt and Shephard (1999). A detailed description of the prior distribution setup and the MCMC algorithm is provided in Appendix A.

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 of the common stochastic volatility ($\{\sqrt{h_{f,t}}\}_{t=1}^{T}$), and the shaded area represents the 95% posterior confidence set. For our baseline estimates, we use the first data release to calculate the forecasting errors.[10]

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 highest 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 a small one in comparison with the three critical spikes. The 2001 recession, on the other hand, was accompanied by very mild increases in macroeconomic uncertainty.

Table 2 reports the median posterior draws of factor loadings. For identification of a factor and factor loadings, we set the factor loading of IP 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.[11] We find that

[10] We assess, in the next section, the effect of data revisions on our uncertainty measure.

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

the forecast errors of unemployment rate, non-residential investment and non-farm payroll employment load more on the common factor than other variables. On the contrary, federal government spending and local government spending load least on the common factor, with a extremely high probability of the loading of the local government spending being around zero.

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

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

as the factor and idiosyncratic error terms are assumed to be uncorrelated. We hence 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. Then, 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 2 plots the decomposition of each total variation into components explained by macroeconomic and idiosyncratic uncertainties. For most variables except federal and state/local government spendings, the most notable spikes in the total variances are driven to a large extent by macroeconomic uncertainty. More interestingly, recessions that were not accompanied by distinct increases in macroeconomic uncertainty do show up in the total variations of unemployment (the 1991 and 2001 recessions) and IP and consumption (the 2001 recession), indicating that these two recessions were not as broad-based as the others. Among the nine variables in the sample, IP and unemployment contribute most to the macroeconomic uncertainty series. The volatility of nonresidential investment and employment also largely commove with the common uncertainty, but their respective idiosyncratic uncertainties still account for a sizable share of their total variations. In particular, from 1985 to 2007, when the baseline macroeconomic uncertainty index was relatively subdued,

idiosyncratic volatilities of unemployment and nonresidential investment were still high, peaking in different periods. The forecast errors of state and local government expenditure contributes little to a common factor, and thus, to the macroeconomic uncertainty.

4.2 The Impact of Data Revisions

Macroeconomic data goes through substantial revisions after their initial release.[12] Likewise, macroeconometric analysis using latest available vintage often times 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 have 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, Amato and Swanson 2001, and Ghysels et al. 2014, among many others). However, previous studies focus on the effects on point forecasts, i.e., the conditional mean, and consequently, the effect of data revision on the estimation of the conditional second moments has not been documented. Nonetheless, data revisions should also have an important impact on the measurement of uncertainty, since it directly affects 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 to calculate the forecast errors. To our knowledge, this is the first paper that examines the effect of data revisions for the estimation of volatility.

Figure 3 shows the macro uncertainty index estimated with the data revised in one and five quarter(s) after the initial data release along with the benchmark index. The correlations among the three indexes are high, with the two based on revised data peaking substantially at the same periods as the real-time index, i.e., the 1973-75, 1980, and 2008-09 recessions. Therefore, we find that the estimated series of uncertainty based on different data vintages largely coincide with the one using real-time data, under our framework.

Nonetheless, we find quantitative differences across the three series. Most notably, the relative size of the peaks changes depending on the data vintage used to calculate

[12] See Faust et al. (2005), Aruoba (2008) and Amir-Ahmadi et al. (2015) for more details on the empirical properties of data revisions.

forecasting errors. In other words, the jump in uncertainty during the 1980 recession is shifted upward when the data vintage available in one quarter after the first release is used, pushing the level of uncertainty to an unprecedented level. With the revised data available in five quarters after the initial release, the increase in uncertainty associated with the recent Great Recession is the largest since the beginning of the series. In contrast, with the forecast errors based on the initial data release, the uncertainty during the recessions in the pre-Great Moderation periods, i.e., the 1973-75 and 1980 recessions, are higher than the level of uncertainty during the last recession.

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 later 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.

4.3 Comparison with Measures of Disagreement

A widely-used proxy for uncertainty based on survey forecasts is forecast disagreement, commonly measured as the interquartile range (e.g. Bachmann et al. 2013). Underlying this practice is the assumption that predictions of forecasters are more likely to be close to each other when economic uncertainty is low. However, forecast disagreement may just reflect heterogeneous, but not uncertain, beliefs.[13]

In this section, we investigate the relationship between our macroeconomic uncertainty measure and an analogous, disagreement-based proxy of uncertainty. We first create an unbalanced panel including the disagreement of economic indicators used for our index for the sample period that matches ours as in Table 1. Disagreement is measured as the interquartile ranges, i.e., the 75th percentile minus the 25th percentile of individual forecasts. Next, we take the averages of the interquartile ranges for available variables in each period. The average disagreement series which summarizes disagreements among surveyed forecasters for different variables, is then compared to our baseline macroeconomic

[13]See, for example, Mankiw et al. (2004), Lahiri and Sheng (2010) and Sill (2012) for more detailed discussions of measuring uncertainty using forecast disagreement.

uncertainty series.

Figure 4 presents the resulting average disagreement series. The most notable difference is that the disagreement-based uncertainty index is significantly more volatile than our baseline macroeconomic uncertainty index. Nonetheless, the three major spikes in disagreement coincide with the three main episodes of uncertainty increases in our baseline index. One notable difference is that the relative size of the increment in the average disagreement during the Great Recession is substantially smaller than that of our measure of macroeconomic uncertainty. This suggests that although economic uncertainty was high, point forecasts of different professional forecasters on average had more centered distributions during this period, resulting in an increase of a relatively moderate size. In addition, the average disagreement series peaks during the 2000 - 2001 recession markedly, compared to our baseline index. Furthermore, while our baseline measure dwindles quickly upon the arrival of the Great Moderation in mid-80s, the average disagreement series shows a sizable jump around 1986 comparable to that during the Great Recession, stays at a relatively high level, and then finally drops in 1989.

We further investigate the differences between our measure of uncertainty and the average forecast disagreement in a more formal manner. That is, we examine the dynamic relationship between the two by estimating a bivariate VAR(4) with the average disagreement ordered first for the recursive identification of shocks. Figure 5 shows the impulse response functions to both uncertainty and average disagreement shocks. A few interesting results emerge. First, it is evident that the response to its own shock is significantly more persistent for our measure of macroeconomic uncertainty, compared to that of the common disagreement. Second, we find that while the average disagreement reacts strongly positively to uncertainty shocks, the reverse is not true: shocks to common disagreement actually lead to a small decreases in uncertainty. If the dispersion factor was a close proxy of macroeconomic uncertainty, one would expect a significant and positive impact on uncertainty of a dispersion shock. We thus conclude that, even though we find a high unconditional correlation, an increase in disagreement is likely the result of heightened uncertainty, but not vice versa.

5 The Effects of Uncertainty on Economic Activities

In this section, we examine the dynamic relationship between our measure of macroeconomic as well as idiosyncratic uncertainties and a set of macroeconomic indicators using a standard recursively identified VAR. Previous studies using proxies for macroeconomic uncertainty, like the VIX in Bloom (2009), tend to find a significantly negative, but short-lived impact of uncertainty on economic activity. This drop in activity is then followed by an overshoot, as economic activity rebounds. In contrast, studies that estimate macroeconomic uncertainty, as Jurado et al. (2015), find that these shocks have a much more persistent effect on economic activity, and no evidence of a strong rebound and overshooting. We add to the literature by i) revisiting the impacts of an macroeconomic uncertainty shock and ii) distinguishing the effects due to an increase in macroeconomic uncertainty and that in variable-specific uncertainty.

Our benchmark specification of a VAR comprises six variables, with the following order: log(private investment), log(nondurable consumption expenditure), log(durable consumption), log(GDP), log(S&P index), and our macroeconomic uncertainty index. The VAR is estimated in levels and with four lags. A natural choice of the ordering of variables in the VAR 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. Given the above difficulty, we choose to order our uncertainty measure last in our baseline VAR analysis. Hence, we purge innovations to our uncertainty measure from any contemporaneous and past movements in the real activity variables, as well as the S&P index. This choice of ordering implies, by construction, both a zero contemporaneous impact of uncertainty on economic activity and a more conservative estimate of the impact of uncertainty shocks.

Figure 6 presents the estimated dynamic responses of the various economic activity measures to a one standard deviation innovation to macroeconomic uncertainty. All of the economic activity variables show a significant and persistent decline following an uncertainty shock, supporting the findings of long-lived negative effects of uncertainty as in Bachmann et al. (2013) and Jurado et al. (2015). Moreover, we find no evidence of overshooting in economic activity, as the uncertainty shock dissipates.

There is some heterogeneity in how the different economic activity measures respond to innovations in our measure of macroeconomic uncertainty: uncertainty shocks generate a larger fall of durables consumption and investment compared to the responses of non-durables consumption and GDP. These findings are consistent with theoretical models of business investment and durable consumption where irreversibility plays a significant role; any investment or durable consumption is accompanied by a fixed adjustment cost that makes it difficult to reverse such decisions, and as a result, economic agents will postpone investment or durable consumption when uncertainty is high.[14]

To verify the quantitative importance of an uncertainty shock, Table 3 reports the forecast error variance decomposition for the real economic activity variables included in the VAR. As discussed earlier, given our choice of the benchmark VAR with uncertainty ordered last, these estimates should be viewed as a lower bound. The decomposition shows that an uncertainty shock can explain a maximum of 5.58 to 8.08% of the variance of various real economic activity measures within 5 years after the shock. These numbers are near the lower end of those reported by Bachmann et al. (2013), Jurado et al. (2015) and Caggiano et al. (2014).

Next, we investigate the robustness of the findings to the ordering assumption of the VAR. We estimate a VAR with the same set of variables, but now our uncertainty measure is ordered second after the S&P index, before the real economic activity indicators. Figure 7 reports the impulse response functions of the economic activity indicators, and Table 4 the resulting forecast error variance decomposition. As one would expect, this change in ordering results in a larger decline of economic activity, following a positive innovation to uncertainty. Its importance in the variance decomposition of economic activity also rises significantly. Under this ordering, uncertainty shocks account for a maximum of 20.08 to 28.98% of the variance of the real economic activity indicators. Notwithstanding the more pronounced effects, the qualitative evidence is very similar to our baseline ordering choice.

We also conduct a comparison of our impulse response functions to the ones obtained with other estimates and proxies for macroeconomic uncertainty. Figure 8 plots responses to innovations in our baseline uncertainty series, as well as Jurado et al. (2015) estimates

[14]See e.g., Pindyck (1991) and Bertola et al. (2005).

of macroeconomic uncertainty, the common disagreement estimated in Section 4.3 and the VIX. There is a clear divergence in results. Both innovations to our measures, as well as JLN measure of macroeconomic uncertainty result in large and persistent drops in economic activity. On the other hand, innovations to proxies of macroeconomic uncertainty, as the disagreement and the VIX result in very small and short-lived negative impacts on economic activity, followed by strong rebounds.

6 Conclusion

This paper estimates macroeconomic uncertainty from 1968Q4 to 2015Q1 as perceived by professional forecasters. Using a FSV model proposed by Pitt and Shephard (1999), we estimate volatilities of a common factor and idiosyncratic components across consensus forecast errors of different economic indicators. We define the time-varying standard deviation of the factor as a measure of macroeconomic uncertainty, and estimate it jointly with indicator-specific uncertainties.

In general, macroeconomic uncertainty was higher in the 1968-85 period compared to the post-1985 period. Our baseline uncertainty measure is relatively smooth and persistent with all major spikes associated with economics recessions (the 1973-75, 1980, and 2007-09 recessions), consistent with Jurado et al. (2015). Additionally, we find that data revisions have a substantial effect on the estimated macroeconomic uncertainty. In particular, data vintage selection influences the relative size of major uncertainty peaks.

We also compare our baseline measure of uncertainty to another survey-based uncertainty proxy, namely forecast disagreement. The first principal component of disagreement is significantly more volatile than our measure throughout the sample period. Further investigation on the dynamic relationship between the two shows that shocks to common disagreement do not have any meaningful impact on uncertainty, while common disagreement reacts strongly positively to uncertainty shocks.

Finally, we conduct a VAR analysis to investigate the dynamic relationship between uncertainty and real economic variables. A one-standard deviation increase in our baseline uncertainty index results in a significant and persistent decrease in various measures of economic activity such as investment, durable and non-durable consumptions, in line with

the findings in Bachmann et al. (2013) and Jurado et al. (2015). However, this evidence is at odds with the short-lived negative impact followed by a strong rebound, as suggested by Bloom (2009).

Appendix

A Bayesian Estimation Method

A.1 Prior Distributions and Starting Values

Our choice of prior distributions and their parameter values is very similar to Pitt and Shephard (1999) except for the values of the conditional inverse Gamma prior, $\sigma^2 \sim IG(\frac{v_0}{2}, \frac{\delta_0}{2})$. We set $v_0 = 1$ and $\delta_0 = 1$, which makes the conditional prior distribution flatter than the one in Pitt and Shephard (1999) and more so than the ones in other recent studies incorporating stochastic volatility (see e.g., Primiceri 2005 and Baumeister et al. 2013) to allow for a large time variation for stochastic volatilities *a priori*. Compared to the previous studies using time-varying VAR models with stochastic volatility (e.g., Primiceri 2005 and Baumeister and Peersman 2013), the total number of parameters to estimate is substantially smaller in our case. Thus, we use a more diffuse prior and put a larger weight on data.

The prior distribution 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 relatively 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 forecasting errors on the first principal component as a proxy of a factor. Since the factor and loadings are not completely identified in a factor model, we set the loading of the first variable (i.e., IP) to be equal to one, a commonly-used identification strategy of a factor model. Factor loadings of the second variable to the last are drawn from the posterior distribution introduced below.

A diffuse Normal prior is used as the prior distribution for a **factor** conditional on $\{h_{f,t}\}_{t=1}^{T}$, consistent with equation (**??**) (i.e., $f_t \sim N(\theta_0, \Theta_0)$ where $\theta_0 = 0$ and $\Theta_0 = h_{f,t}$). As mentioned above, we use the first principal component for the initial iteration.

The prior for the **variability of volatilities** is the inverse Gamma, i.e., σ_f^2 and σ_i^2 $\sim IG(\frac{v_0}{2}, \frac{\delta_0}{2})$, where $v_0 = 1$ and $\delta_0 = 1$. As discussed above, we choose a larger value of δ_0 compared to a conventional setup to be less informative about the variability of volatilities, allowing for potentially larger time variation of volatilities at the same time.

The prior of each **time-varying volatility** is the log-normal. In particular, for the initial period's stochastic volatility, h_0^2, 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.

A.2 Posterior Distribution Simulation

The MCMC algorithm proposed for the joint posterior distribution of the FSV model with different starting dates extends the one introduced in Pitt and Shephard (1999). We divide the parameters in the model into four blocks; a) the factor loadings (λ), b) the time series of the factor ($\{f_t\}_{t=1}^T$), c) the hyperparameters of volatilities (σ_f and σ_i for all i), and d) the volatility states ($\{h_{f,t}\}_{t=1}^T$ and $\{h_{i,t}\}_{t=s}^T$ for all i where s denotes the starting date of each series).

As will be explained in detail, the conditional independence across t and i as well as of f_t and $u_{i,t}$'s makes the extension straightforward. To be more specific, most steps in the Gibbs sampler, such as drawing factor loadings ($\{\lambda\}$), volatility states ($\{h\}$) and the variance of volatilities ($\{\sigma\}$) further break down to drawing from a univariate process. As a result, one only needs to take into account different starting dates of each variable i, and each sub-step can be conducted given the different length of history. When sampling the common factor f_t, the step is conditioned on available forecast errors and factor loadings in each period t.

Finally, the volatility states are drawn via Metropolis methods within the overall Gibbs sampler. Denoting by z^T the time-series of a variable z from $t = 1$ to T, the sampler algorithm is described below.

A.2.1 Factor loadings

Conditional on all other parameters, this step is a simple Bayesian regression of forecasting errors on the factor with known heteroskedastic error structures. Moreover, because all

correlations are captured by the factor by definition, this step further decomposes into the n sub-steps of drawing each i-th loading separately from the following distribution given the history of variable i:

$$\lambda_i | \tilde{\varepsilon}^T, f^T, \sigma_f, \sigma_i, h_f^T, h_i^T \sim N(\lambda_1, \Lambda_1),$$

where $\Lambda_1 = (\Lambda_0^{-1} + \sum_{t=s}^{T} f_t^2/(h_{i,t}))^{-1}$ and $\lambda_1 = \Lambda_1(\Lambda_0^{-1}\lambda_0 + \sum_{t=s}^{T} f_t \cdot \tilde{\varepsilon}_{i,t}/(h_{i,t}))$ with $s \geq 1$ is the starting point of each forecasting error series $\tilde{\varepsilon}_i$.

A.2.2 Factor

Conditional independence also simplifies this step. Given all other parameter values, this step again becomes a Bayesian regression of available forecasting errors on factor loadings with known heteroskedasticity for each period t. That is,

$$f_t | \tilde{\varepsilon}^T, \lambda_i, \sigma_f, \sigma_i, h_f^T, h_i^T \sim N(\theta_1, \Theta_1),$$

where $\Theta_1 = \{h_{f,t}^{-1} + \sum_{i=1}^{n_s} \lambda_i^2 (h_{i,t})\}^{-1}$, $\theta_1 = \Theta_1(\sum_{i=1}^{n_s} \lambda_i \cdot \tilde{\varepsilon}_{i,t}/(h_{f,t}))$, and n_s is the number of variables whose forecast errors are available in period $s = 1 \ldots T$.

A.2.3 Innovation variance of volatilities

Since we model each stochastic volatility to follow a unit-root process without a drift, the conditional posterior distribution of σ can be simplified from the posterior inverse Gamma distribution in Kim et al. (1998). Hence, σ^2 is drawn from

$$\sigma | \tilde{\varepsilon}^T, f^T, h_f^T, h_i^T \sim IG(\frac{v_1}{2}, \frac{\delta_1}{2})$$

where $v_1 = v_0 + S$, $\delta_1 = \delta_0 + \sum_{t=s+1}^{T} (h_{i,t} - h_{i,t-1})^2$, and S is the total number of periods that a series i is available.

A.2.4 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. It follows 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, the algorithm draws the exponential of volatility ($h_{i,t}^2$) one by one for each $t = s, \ldots, T$, 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 forecasting errors to be $\varepsilon_{i,t}^* = \tilde{\varepsilon}_{i,t} - \lambda_{i,t} f_t$. Such transformation is unnecessary for the factor.

Then, we apply Jacquier et al. (2002) 's 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 $t = s, \cdots, T-1$. Hence, 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:

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

After obtaining a draw, the conditional likelihood $f(y_{i,t}^*|h_{i,t})$ is evaluated in order to obtain the acceptance probability, completing a Metropolis step (see Cogley and Sargent 2005 for a detailed description).

We can summarize the estimation procedure as following:

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 $p(\lambda|\tilde{\varepsilon}^T, f^T, \sigma_f, \sigma_i, h_f^T, h_i^T)$
3. Draw f^T from $p(f^T|\tilde{\varepsilon}^T, \lambda, \sigma_f, \sigma_i, h_f^T, h_i^T)$
4. Draw σ_f and σ_is from $p(\sigma|\tilde{\varepsilon}^T, f^T, h_f^T, h_i^T)$
5. Draw h_f^T, and h_i^Ts from $p(h|\tilde{\varepsilon}^T, f^T, \sigma_f, \sigma_i)$
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 of parameters. 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.

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Table 1: Starting Dates of Survey Forecasts

1968Q4	Industrial Production Index (IP)
	Civilian Unemployment Rate (UR)
	Housing Starts (HS)
1981Q3	Real Personal Consumption Expenditures (RCON)
	Real Nonresidential Fixed Investment (RNRESIN)
	Real Residential Fixed Investment (RRESIN)
	Real Federal Government Consumption Expenditures & Gross Investment (RFEDGOV)
	Real State and Local Government Consumption Expenditures & Gross Investment (RSLGOV)
2003Q4	Nonfarm Payroll Employment (EMP)

Note: This table shows the starting date of each of the survey variables in our dataset.

Table 2: Summary Statics of Posterior Draws of Factor Loadings

	IP	UR	HS	RCON	RNRESIN	RRESIN	RFEDGOV	RSLGOV	EMP
Initial Release									
Median	1	−0.97	0.35	0.40	0.73	0.38	−0.33	−0.01	1.07
Std. Dev.	-	0.19	0.16	0.20	0.20	0.24	0.18	0.19	0.44

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

Table 3: Variance Decomposition for the Baseline VAR

Quarters	GDP	RPI	PCE-ND	PCE-D
1	0.00	0.00	0.00	0.00
2	3.42	1.44	1.82	4.71
4	6.30	4.68	6.24	6.91
8	9.52	9.29	10.34	8.39
20	9.65	9.76	7.31	5.77

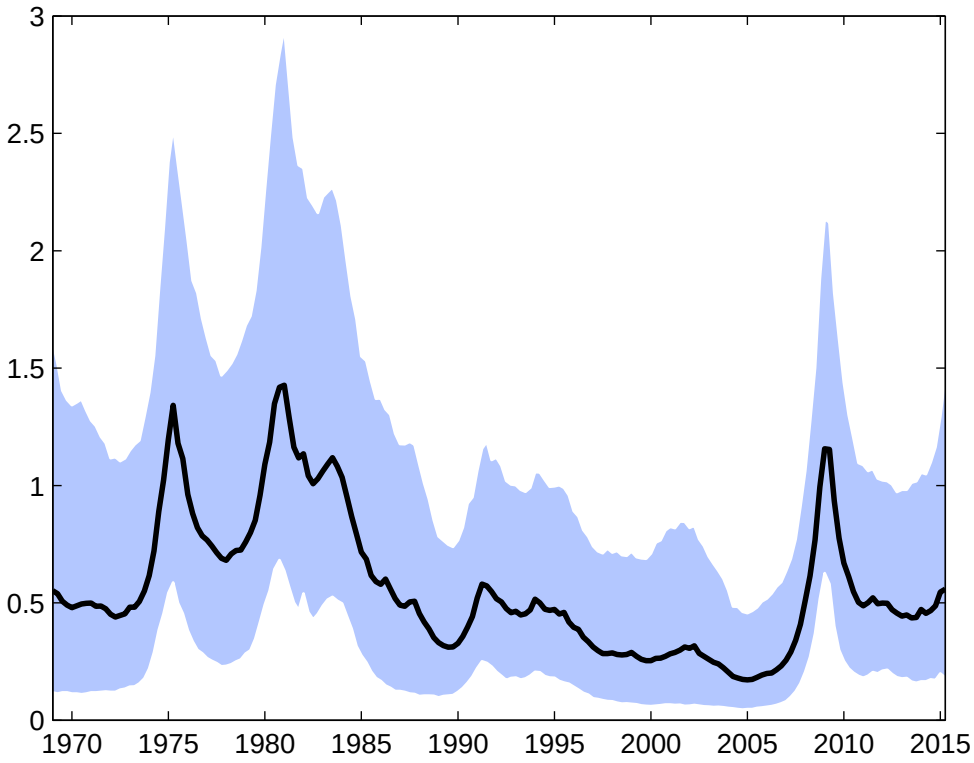
Note: This table shows forecast error variance decomposition for our baseline VAR with the following variables and Cholesky ordering: real private investment (RPI), real personal consumption expenditures on non durables (PCE-ND), real personal consumption expenditures on durables (PCE-D), GDP, S&P index, and our uncertainty measure. The VAR is estimated in levels with 4 lags. All variables, except our uncertainty measure, enter the VAR in logs.

Table 4: Variance Decomposition for alternative VAR ordering: Uncertainty Before Real Activity

Quarters	GDP	RPI	PCE-ND	PCE-D
1	3.57	2.95	5.79	7.17
2	13.52	7.99	12.04	18.21
4	20.63	15.08	22.73	23.73
8	27.25	23.72	30.09	26.58
20	26.96	24.15	23.84	20.14

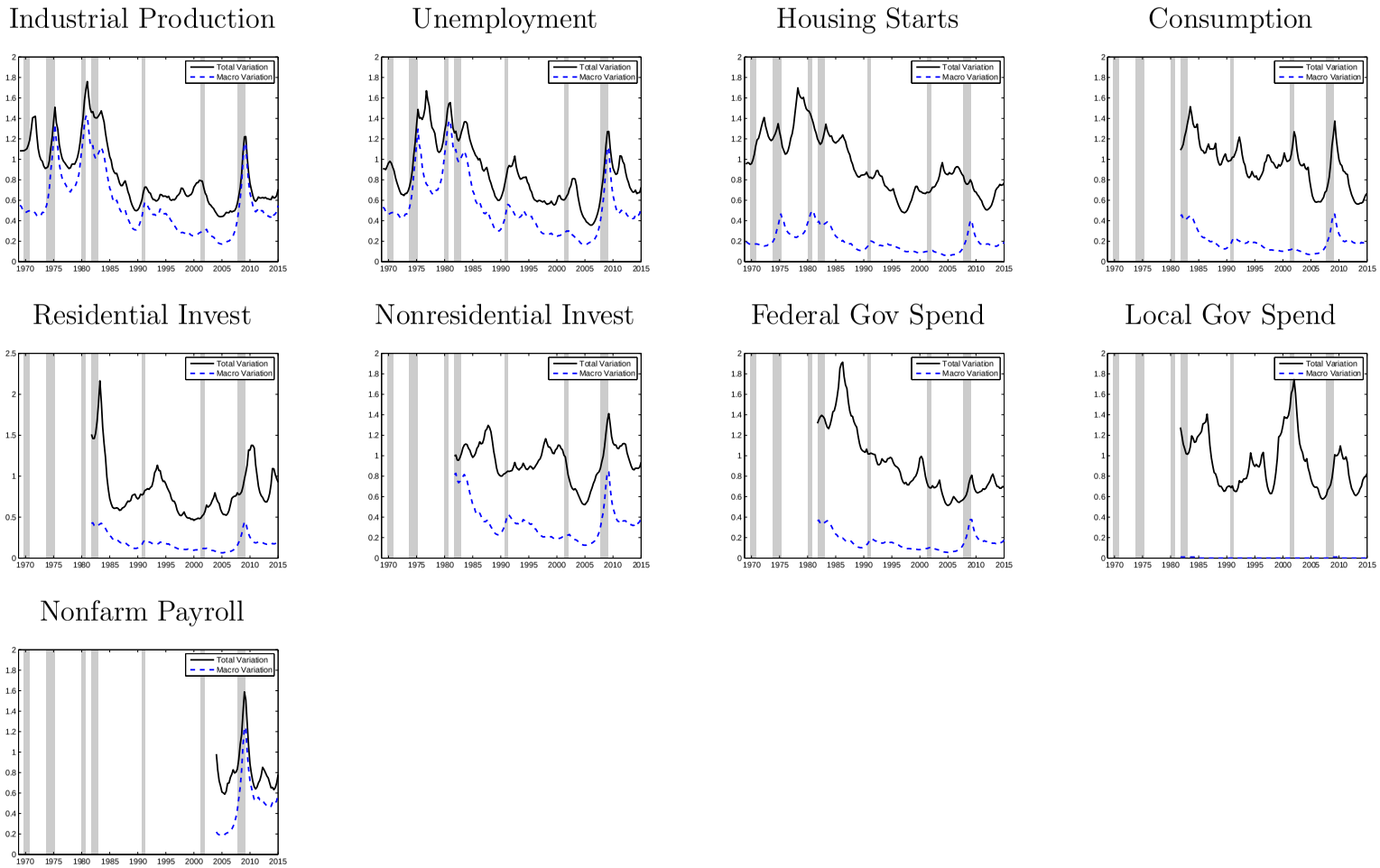
Note: This table shows forecast error variance decomposition for our baseline VAR with the following variables and Cholesky ordering: S&P index, our uncertainty measure, real private investment (RPI), real personal consumption expenditures on non durables (PCE-ND), real personal consumption expenditures on durables (PCE-D), and GDP. The VAR is estimated in levels with 4 lags. All variables, except our uncertainty measure, enter the VAR in logs.

Figure 1: Estimated Macroeconomic Uncertainty Series



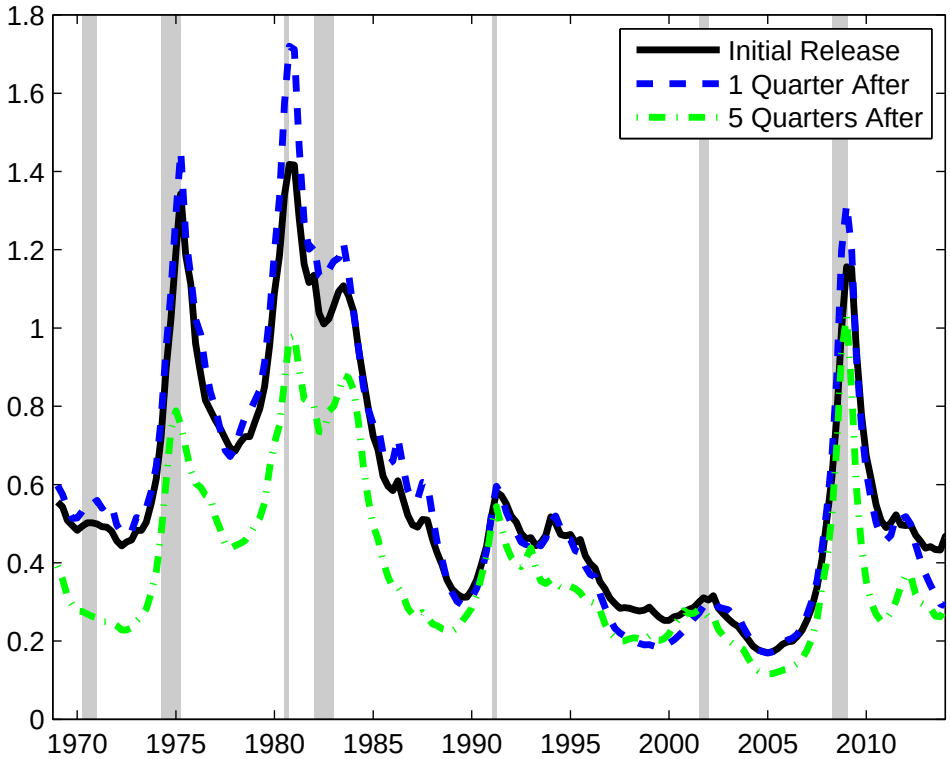
Note: This figure plots the baseline macroeconomic uncertainty series estimated using real-time data. The series is the time-varying standard deviation of a common factor across forecasting errors of four macroeconomic indicators. The black solid line represents the median posterior draws along with the 95% posterior credible set.

Figure 2: Total Variation versus Common Variation



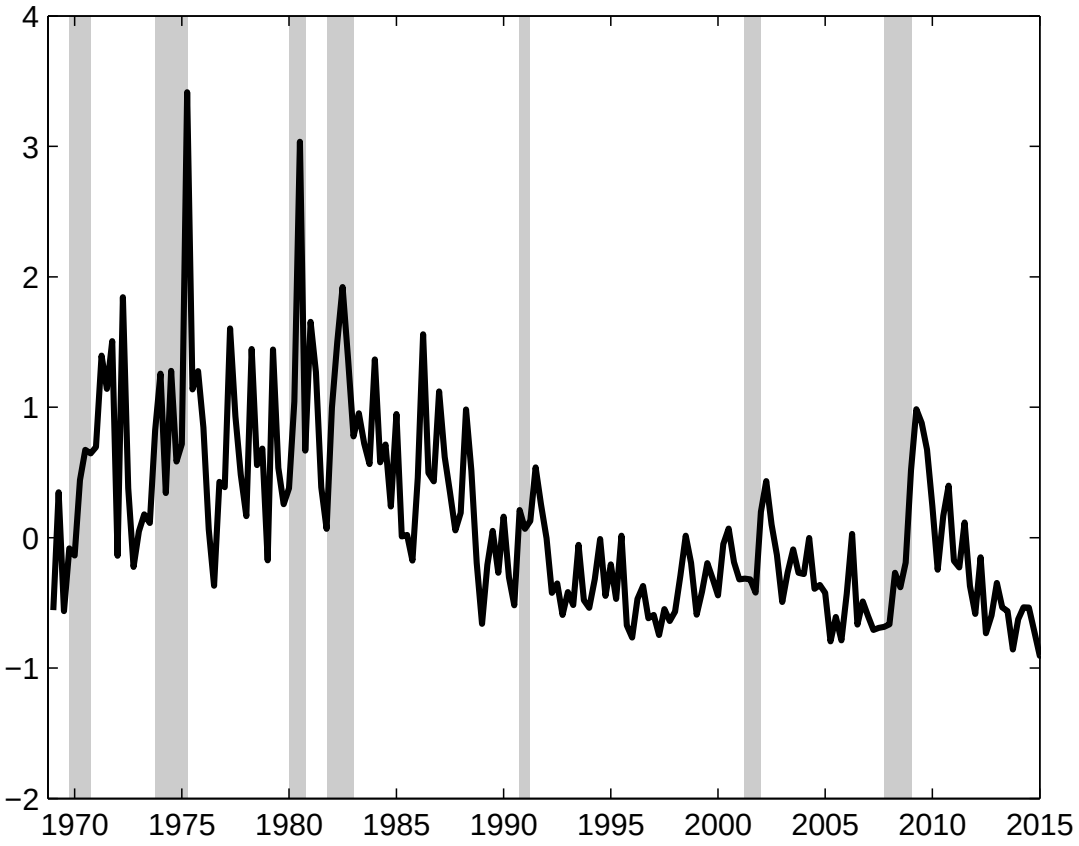
Note: This figure shows how much of total variation of each variable is explained by the macroeconomic uncertainty. The grey line is the total variation of one variable (defined as standard deviation), and the black line is the macroeconomic uncertainty multiplied by a factor loading. All calculations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

Figure 3: Macroeconomic Uncertainty Based on the Different Vintages



Note: This figure compares the baseline macroeconomic uncertainty factor (real-time) with the uncertainty factor estimated with data from different vintages. The solid line is our baseline uncertainty index, the blue dashed line is the one where forecasting errors of each variable are computed using the revised data available in one quarter after the initial release, and the green dash-dot line is the one using the revised value appearing in five quarters after the first release.

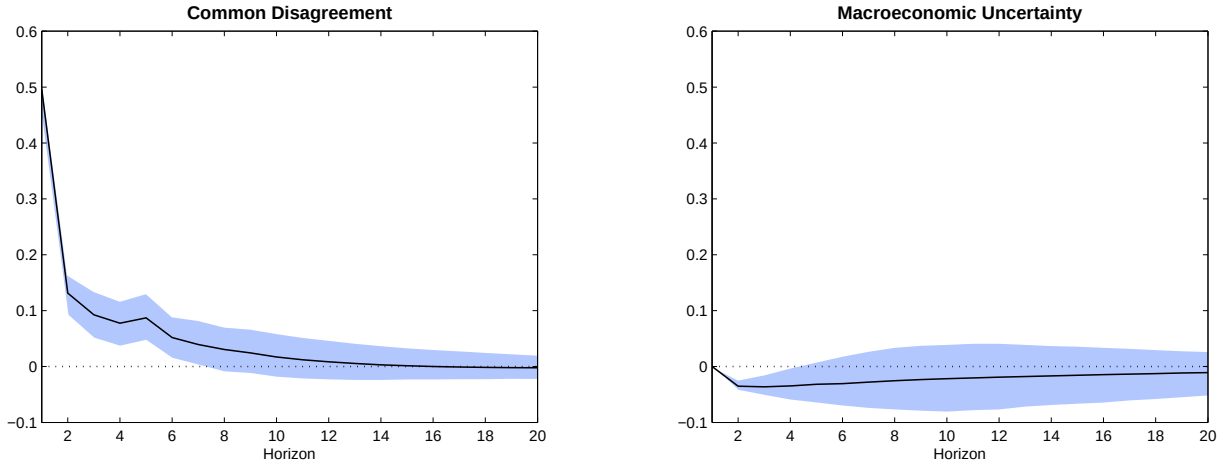
Figure 4: Common Disagreement Factor



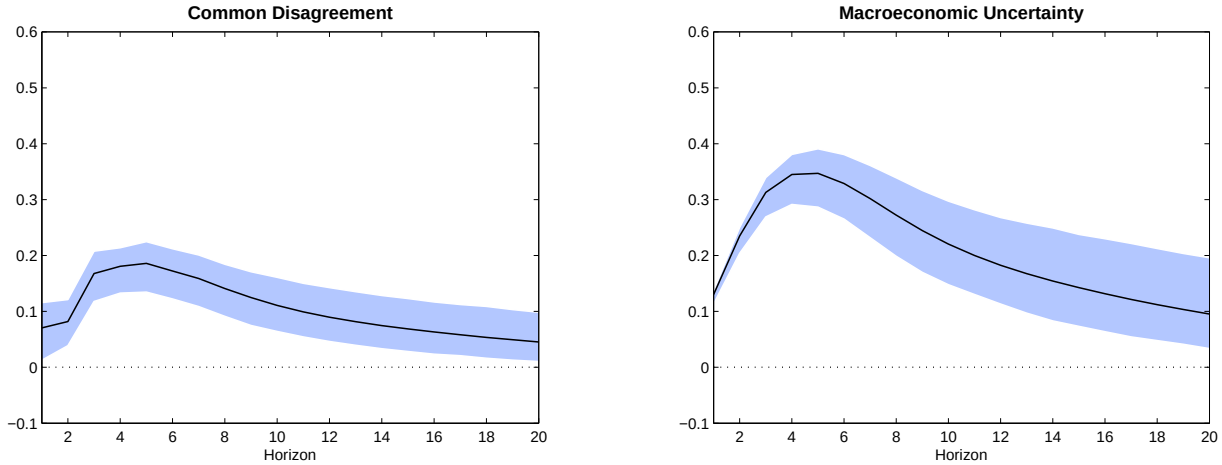
Note: This figure shows the first principal component of the disagreements of the four economic indicators.

Figure 5: Dynamic Relationship between Common Disagreement and Macroeconomic Uncertainty

(a) Innovation to Common Disagreement

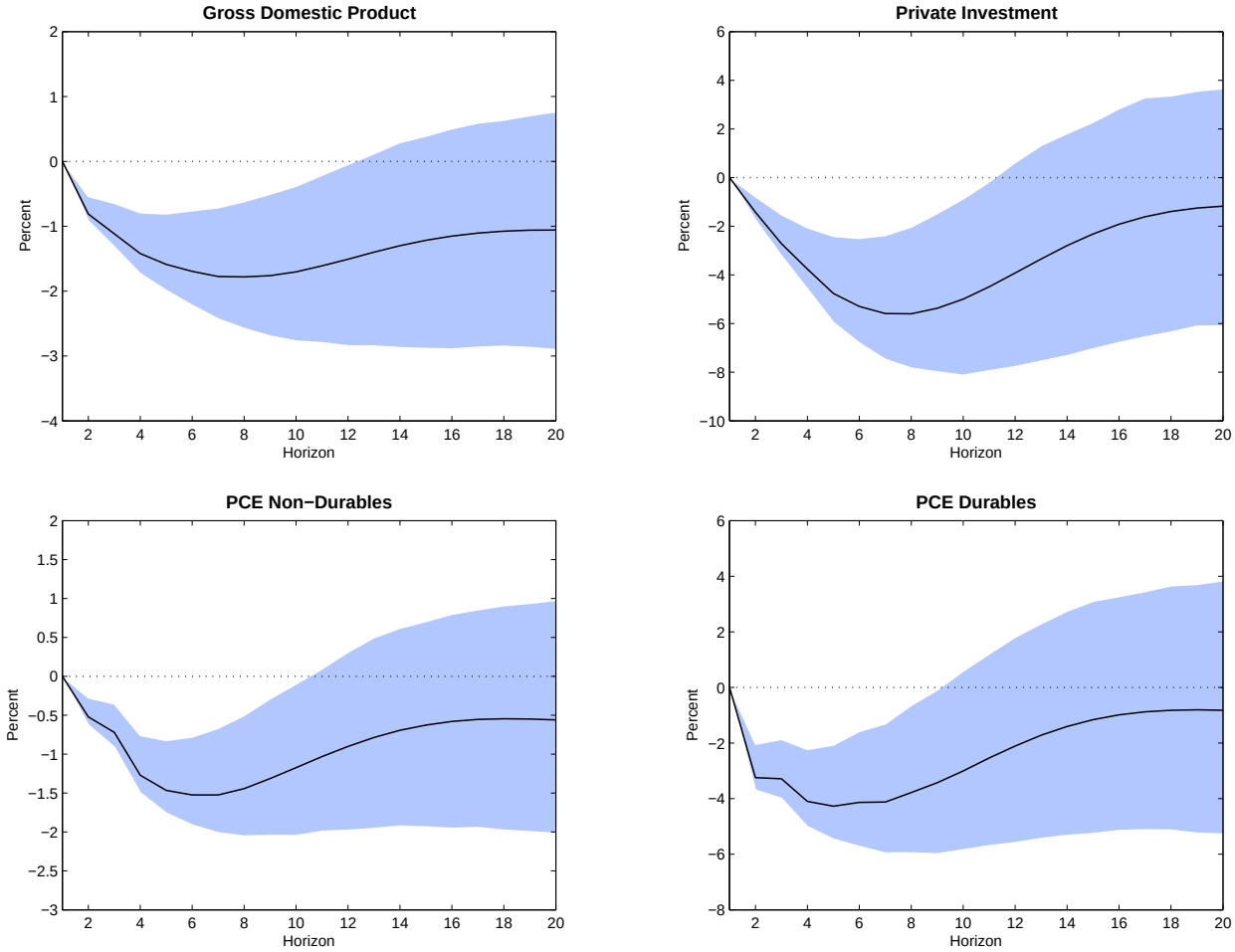


(b) Innovation to Macroeconomic Uncertainty



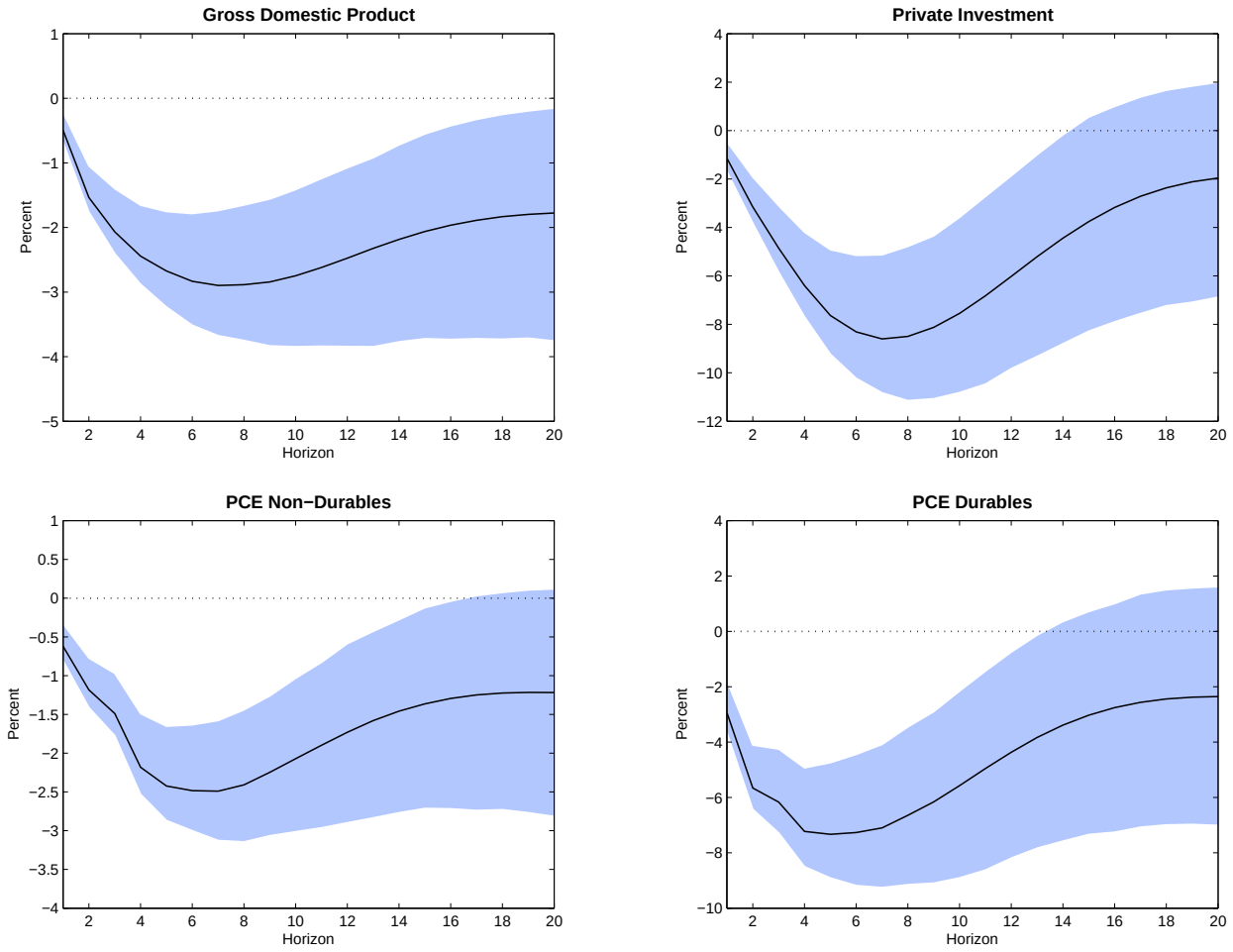
Note: This figure shows the impulse response functions to a bivariate VAR with four lags featuring a common dispersion factor and our baseline measure of macroeconomic uncertainty. The VAR uses a Cholesky factorization for identification with the common dispersion factor ordered first. The shaded area represents one standard deviation bands using Kilian (1998)'s bootstrap-after-bootstrap method.

Figure 6: Responses to Innovations to Macroeconomic Uncertainty



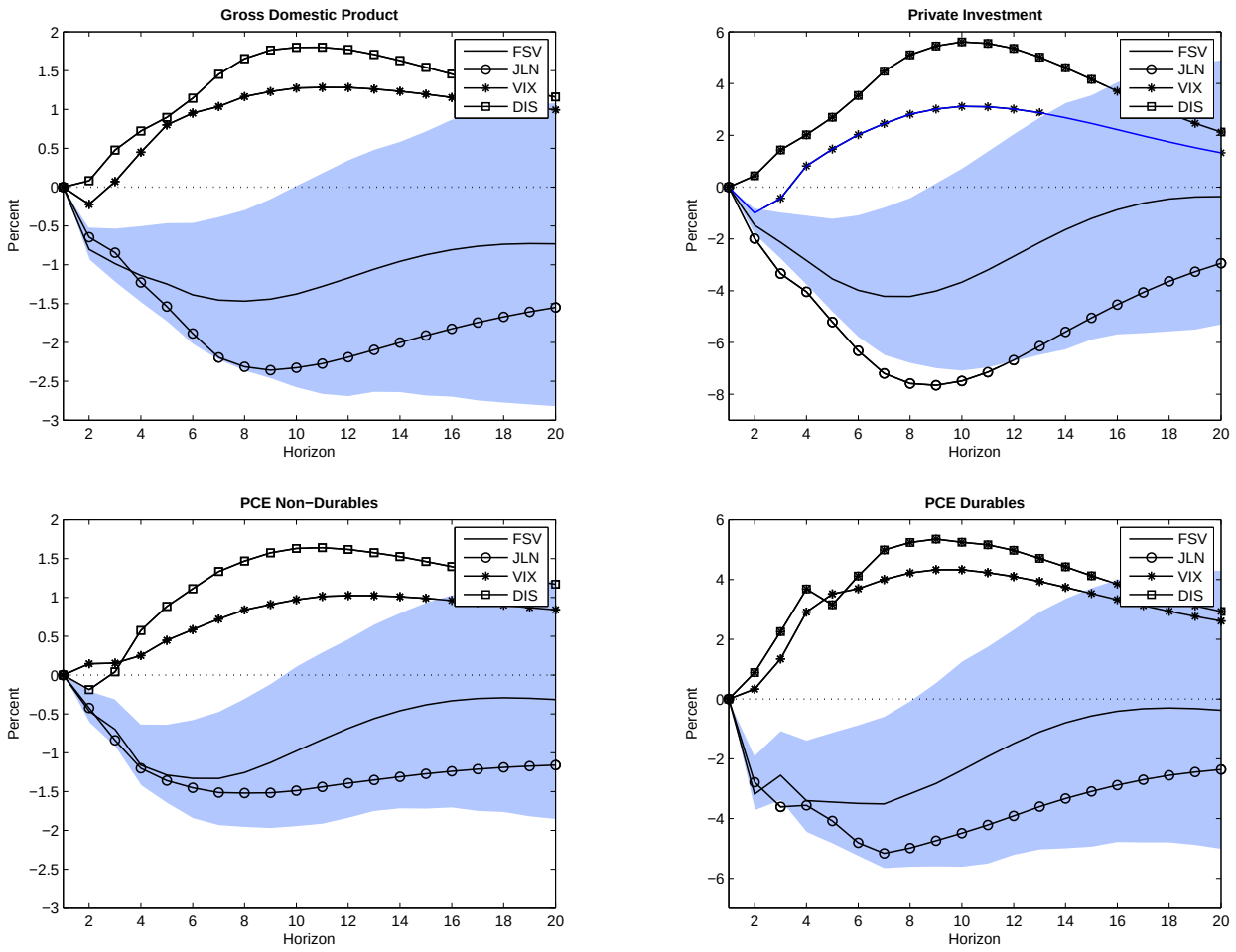
Note: This figure shows the response of various macroeconomic variables to uncertainty shocks in a 6-variable VAR with the following variables and ordering: real private investment, real personal consumption expenditures on non-durables, real personal consumption expenditures on durables, real GDP, S&P index, macroeconomic uncertainty index. The VAR is estimated in levels with 4 lags. All variables, except the uncertainty index, are measured in logs. The shaded area represents one standard deviation bands using Kilian (1998)'s bootstrap-after-bootstrap method.

Figure 7: Responses in the VAR with Alternative Ordering



Note: This figure shows the response of various macroeconomic variables to uncertainty shocks in a 6-variable VAR with the following variables and ordering: S&P index, macroeconomic uncertainty index, real private investment, real personal consumption expenditures on non-durables, real personal consumption expenditures on durables, real GDP. The VAR is estimated in levels with 4 lags. All variables, except the macroeconomic uncertainty, are measured in logs. The shaded area represents one standard deviation bands using Kilian (1998)'s bootstrap-after-bootstrap method.

Figure 8: Responses with Alternative Measures of Uncertainty



Note: This figure shows the response of various macroeconomic variables to uncertainty shocks in a 6-variable VAR using alternative proxies and estimates of macroeconomic uncertainty: FSV is our baseline measure of macroeconomic uncertainty as perceived by professional forecasters; JLN is the measure estimated by Jurado et al. (2015); VIX is the stock market implied volatility used by Bloom (2009); and DIS is our estimate of common disagreement as discussed in section 4.3. The shaded area represents one standard deviation bands using Kilian (1998)'s bootstrap-after-bootstrap method.