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Measuring Uncertainty and its Impact on the Economy*

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Abstract

We propose a new model for measuring uncertainty and its effects on the economy, based on a large vector autoregression with stochastic volatility driven by common factors representing macroeconomic and financial uncertainty. The uncertainty measures reflect changes in both the conditional mean and volatility of the variables, and their impact on the economy can be assessed within the same framework. Estimates with U.S. data show substantial commonality in uncertainty, with sizable effects of uncertainty on key macroeconomic and financial variables. However, historical decompositions show a limited role of uncertainty shocks in macroeconomic fluctuations.

Keywords: Bayesian VARs, stochastic volatility, large datasets

J.E.L. Classification: E32, E44, C11, C55

*Corresponding author: Todd E. Clark, todd.clark@researchfed.org. The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System. We benefitted from suggestions from editor Yuriy Gorodnichenko, three referees, Brent Bundick, Josh Chan, Soojin Jo, Gary Koop, Haroon Mumtaz, Rodrigo Sekkel, Minchul Shin, Stephen Terry, Molin Zhong, and audiences at the NBER Summer Institute, Federal Reserve Bank of Cleveland, SBIES conference in Philadelphia, John Hopkins University, and the Barcelona summer meeting. We are particularly grateful to Drew Creal for both comments on the paper and his advice on the particle Gibbs sampler. Carriero and Marcellino gratefully acknowledge support for this work from, respectively, the Economic and Social Research Council [ES/K010611/1] (Carriero) and the Baffi-Carefin center (Marcellino).

1 Introduction

In the aftermath of the 2008 financial crisis and the Great Recession, the interest of economists and policymakers is markedly focused on the analysis of macroeconomic and financial uncertainty and their effects on the economy. Reflecting such an interest, the literature on the topic has mushroomed in the last few years. Econometric studies on measuring uncertainty and its effects on the economy started with the seminal paper by Bloom (2009), and other relevant contributions include, among others, Bachmann, Elstner, and Sims (2013), Baker, Bloom and Davis (2016), Basu and Bundick (2016), Berger, Grabert, and Kempa (2016), Caggiano, Castelnuovo and Groshenny (2014), Gilchrist, Sim and Zakrajsek (2014), Jurado, Ludvigson, and Ng (2015), and Ludvigson, Ma, and Ng (2016); Bloom (2014) surveys related work.

As noted in Creal and Wu (2016), in most of the literature, measures of uncertainty (either macroeconomic or financial, or both) are estimated in a preliminary step and then used as if they were observable data series in the subsequent econometric analysis of its impact on macroeconomic variables. For example, Bloom (2009) and Caggiano, Castelnuovo and Groshenny (2014) use the VIX, Basu and Bundick (2016) the VXO, Bachmann, Elstner, and Sims (2013) the disagreement in business expectations, Jurado, Ludvigson, and Ng (2015) an average of the volatilities of the residuals of a set of factor-augmented regressions, Jo and Sikkel (2015) the common factor in the forecast errors resulting from the use of SPF forecasts for a few variables, Baker, Bloom and Davis (2016) an index based on newspaper coverage frequency, and Gilchrist, et al. (2014) a sequence of estimated time fixed effects capturing common shocks to (constructed) firm-specific idiosyncratic volatilities. They all then include their preferred uncertainty measure, together with a small set of macroeconomic variables, in a homoskedastic vector autoregression (VAR) and compute the responses of the macro variables to the uncertainty shock.

While the approach outlined above has the merit of bringing to the fore the effects that uncertainty can have on the macroeconomy, the fact that the uncertainty measure is not fully embedded in the econometric model at the estimation stage inevitably can complicate the task of making statistical inference on its effects, for several reasons. First, the two-step approach treats uncertainty — which

is estimated in the first step — as an observable variable in the second step. It follows that the second step can potentially suffer from measurement errors in the regressors, which might lead to an endogeneity bias.[1] A related problem is that the uncertainty around the uncertainty estimates is not easily accounted for in such a setup, since the proxy for uncertainty is treated as data. Second, even if in the first step a large enough cross section of variables is considered in estimating uncertainty, the second step invariably relies on rather small systems, typically including a handful of macroeconomic variables. The use of small VAR models to assess the effects of uncertainty can make the results subject to the common omitted variable bias and non-fundamentalness of the errors, besides the obvious shortcoming of providing results on the impact to just a few economic indicators. Third, the models used in the first and second step are somewhat contradictory. While the estimation of the uncertainty measure(s) in the first step is predicated on the assumptions that macroeconomic data feature time-varying volatilities, the vector autoregression (VAR) used in the second step features homoskedastic errors. Moreover, in the first step volatilities are assumed not to affect the conditional means of the variables (even though the final goal is to actually assess the conditional mean effects of uncertainty on economic variables), while in the second step the uncertainty measure only affects the conditional means, but not the conditional variances (which as mentioned above are assumed to be constant over time).

Motivated by these considerations, in this paper we develop an econometric model and method for jointly and coherently (1) constructing measures of uncertainty (macroeconomic and financial)

[1]Carriero, et al. (2015) provide a Monte Carlo experiment showing that the attenuation bias stemming from measurement error in the uncertainty measures can be sizable. One might worry less about this in the case of factor based uncertainty measures using a cross-section of observable data so large that factor estimation uncertainty is negligible (a typical condition being $\sqrt{T}/N$ converging to zero). However, if the uncertainty factors are based on generated rather than observable data, as in for example Jurado, Ludvigson, and Ng (2015), the proper conditions for treating the factors as known are not available. Moreover, even if one is not concerned with such complications, it is preferable to have an approach which works well also in smaller cross sections.

and (2) conducting inference on its impact on the macroeconomy in a way that avoids all of the issues highlighted above. Specifically, we build a large, heteroskedastic VAR model in which the error volatilities evolve over time according to a factor structure. The volatility of each variable in the system is driven by a common component and an idiosyncratic component. Changes in the common component of the volatilities of the VAR's variables provide contemporaneous, identifying information on uncertainty.

In our setup, uncertainty and its effects are estimated in a single step within the same model, which avoids both the estimated regressors problem and the use of two contradictory models typical of the two-step approach. The model uses a large cross section of data and allows for time variation in the volatilities, which reduces problems of omitted variable bias, and non-fundamentalness.

In the discussion so far we have generically referred to uncertainty. More specifically, we consider both macroeconomic and financial uncertainty. Each is modeled as the common component of the volatilities of macroeconomic and financial variables, respectively. The vector containing the two measures of uncertainty is assumed to depend on its own past values as well as past values of macroeconomic and financial variables. Hence, macroeconomic uncertainty can affect financial uncertainty and vice versa, and both can be affected by the business cycle and financial fluctuations. Moreover, both macro and financial uncertainty enter the conditional mean of the large VAR. As a consequence, macro and financial uncertainty are allowed to contemporaneously affect the macroeconomy and financial conditions.

The model is estimated via a new, computationally efficient MCMC algorithm for estimating large nonlinear VARs with unobserved variables. Since uncertainty is explicitly treated as an unobservable random variable, the estimation procedure returns its entire posterior distribution, which is readily available for inference and allows us to measure uncertainty around uncertainty. The model can be also interpreted as a factor model, or a factor augmented VAR (FAVAR), in which the factor affects not only the levels but also the conditional volatility of the variables. As such, it relates to the vast literature on factor models; see, e.g., Stock and Watson (2015) for an overview.

We apply our proposed model to monthly U.S. data for the period 1959-2014, finding substantial

evidence of commonality in volatilities, as well as not-negligible idiosyncratic movements in the volatilities. Uncertainty around estimated uncertainty is sizable. Yet, a clear and significant pattern of time variation emerges, with increases in macro uncertainty associated with economic recessions. However, we find less evidence of the "Great Moderation." This appears to be mainly due to the use of a large information set.

Our estimates of impulse responses indicate that macroeconomic uncertainty has large, significant effects on real activity, but has a limited impact on financial variables, whereas financial uncertainty shocks directly impact financial variables and subsequently transmit to the macroeconomy. Shocks (surprise increases) to macroeconomic and financial uncertainty both lead to significant and persistent declines in economic activity. But a shock to financial uncertainty does not affect some measures of economic activity (notably, housing and consumption) as much as a shock to macro uncertainty does. Both types of shocks also cause the credit spread to rise. However, for other financial variables, results are more mixed: surprise increases to financial uncertainty reduce aggregate stock prices and returns, whereas the effects of increases in macro uncertainty are not significant. We show that these estimated uncertainty shocks are not significantly correlated with conventional measures of shocks to monetary policy, fiscal policy, productivity, or oil prices. Hence the impulse response functions we present appear to be capturing a "variance" phenomenon rather than masking some kind of conventional "level" shocks.

Although shocks to uncertainty have significant effects, estimates of historical decompositions indicate that they are not a primary driver of fluctuations in macroeconomic and financial variables. For example, over the period of the Great Recession and subsequent recovery, shocks to uncertainty made small to modest contributions to the paths of economic and financial variables, whereas shocks to the VAR's variables played a much larger role.

The paper is structured as follows. Section 2 discusses model specification and estimation. Section 3 presents the data. Section 4 presents our estimates of aggregate uncertainty. Section 5 studies its effects on the economy. Section 6 summarizes our main findings and concludes. A supplemental appendix contains additional details on the priors, estimation algorithm, and results.

2 A joint model of uncertainty and business cycle fluctuations

The model for the macroeconomic and financial variables of interest — collected in the vector y_t — is a heteroskedastic VAR, similar to those widely used in macroeconomic analysis since the contributions of Cogley and Sargent (2005) and Primiceri (2005). However, rather than using a small cross section and assuming that volatilities for each variable evolve independently, we use a large cross section of variables, and we assume that volatilities follow a factor structure, i.e. have a common and an idiosyncratic component.[2]

Our measures of macroeconomic and financial uncertainty are defined as the common components in the volatility of either macroeconomic or financial variables. These common components are state variables of the model, and they are assumed to follow a bivariate VAR augmented with lags of the macroeconomic and financial variables of interest. Hence, the economic and financial variables of y_t are allowed to have a feedback effect on uncertainty. The measures of uncertainty enter the conditional mean of the VAR in y_t. Actually, the latter is the key idea in this literature, but often the relationship is only imposed in a separate auxiliary model and not used at the uncertainty estimation level, so that the estimated measure of uncertainty only reflects the conditional second moments of the variables. In our specification, instead, the measure of uncertainty reflects information in the levels of the variables as well.[3]

[2]The literature on forecasting with large datasets — see, e.g., Banbura, Giannone and Reichlin (2010) and Stock and Watson (2002) — has shown that typically the size of the information set matters and can reduce forecast errors and their volatility, even though there is a debate on how large "large" is; studies such as Koop (2013) and Carriero, Clark and Marcellino (2015) suggest that about 20 selected macroeconomic and financial variables could be sufficient.

[3]Conditional heteroskedasticity in-mean was introduced by French, et al. (1987) with the GARCH-in-mean model. Koopman and Uspensky (2002) and Chan (2017) introduce univariate stochastic volatility-in-mean models. Mumtaz (2011), Mumtaz and Zanetti (2013), Jo (2014) and Shin and Zhong (2015) consider multivariate extensions with independent volatility processes.

2.1 Model specification

Let y_t denote the $n \times 1$ vector of variables of interest, split into n_m macroeconomic and $n_f = n - n_m$ financial variables. Let v_t be the corresponding $n \times 1$ vector of reduced form shocks to these variables, also split into two groups of n_m and n_f components. The reduced form shocks are:

$$v_t = A^{-1}\Lambda_t^{0.5}\epsilon_t,\ \epsilon_t \sim iid\ N(0, I), \tag{1}$$

where A is an $n \times n$ lower triangular matrix with ones on the main diagonal, and Λ_t is a diagonal matrix of volatilities, with the log-volatilities following a linear factor model:

$$\ln \lambda_{jt} = \begin{cases} \beta_{m,j} \ln m_t + \ln h_{j,t},\ j = 1, \ldots, n_m \\ \beta_{f,j} \ln f_t + \ln h_{j,t},\ j = n_m + 1, \ldots, n. \end{cases} \tag{2}$$

We discuss below the rationale for the block specification of (2), in which only the factor m enters the λ process of macro variables, and only the factor f enters the λ process of financial variables. The variables $h_{j,t}$ — which do not enter the conditional mean of the VAR, specified below — capture idiosyncratic volatility components associated with the j-th variable in the VAR, and are assumed to follow (in logs) an autoregressive process:

$$\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1} + e_{j,t},\ j = 1, \ldots, n, \tag{3}$$

with $\nu_t = (e_{1,t}, ..., e_{n,t})'$ jointly distributed as $i.i.d.\ N(0, \Phi_\nu)$ and independent among themselves, so that $\Phi_\nu = diag(\phi_1, ..., \phi_n)$. These shocks are also independent from the conditional errors ϵ_t.

The variable m_t is our measure of (unobservable) aggregate *macroeconomic* uncertainty, and the variable f_t is our measure of (unobservable) aggregate *financial* uncertainty. Although our specification does not rule out the inclusion of additional uncertainty factors, we believe two factors to be appropriate. One reason is that we are interested in *aggregate* uncertainty, which suggests the use of a single macro factor and a single financial factor, in keeping with the concepts of studies

such as Jurado, Ludvigson and Ng (2015) [hereafter, JLN] and Ludvigson, Ma, and Ng (2016) [hereafter, LMN]. A second reason is that two dynamic factors appear sufficient. As we note below, there does not appear to be a common component remaining in the estimated idiosyncratic components of our model. Moreover, Carriero, Clark, and Marcellino (2016b) estimate a Bayesian VAR (BVAR) with stochastic volatility with 125 variables (including macroeconomic indicators, an array of interest rates, some stock return measures, and exchange rates). Their factor analysis of innovations to volatility indicates two components account for the vast majority of innovations to volatilities.

Together, the two measures of uncertainty (in logs) follow an augmented VAR process:

$$\begin{bmatrix} \ln m_t \\ \ln f_t \end{bmatrix} = D(L) \begin{bmatrix} \ln m_{t-1} \\ \ln f_{t-1} \end{bmatrix} + \begin{bmatrix} \delta_m' \\ \delta_f' \end{bmatrix} y_{t-1} + \begin{bmatrix} u_{m,t} \\ u_{f,t} \end{bmatrix}, \tag{4}$$

where $D(L)$ is a lag-matrix polynomial of order d. The shocks to the uncertainty factors $u_{m,t}$ and $u_{f,t}$ are independent from the shocks to the idiosyncratic volatilities $e_{j,t}$ and the conditional errors ϵ_t, and they are jointly normal with mean 0 and variance $\text{var}(u_t) = \text{var}((u_{m,t}, u_{f,t})') = \Phi_u = \begin{bmatrix} \phi_{n+1} & \phi_{n+3} \\ \phi_{n+3} & \phi_{n+2} \end{bmatrix}$. The specification in (4) implies that the uncertainty factors depend on their own past values as well as the previous values of the variables in the model, and therefore they respond to business cycle fluctuations. Importantly, financial uncertainty affects macro uncertainty and vice-versa, and the error terms $u_{m,t}$ and $u_{f,t}$ are allowed to be correlated, with correlation ϕ_{n+3}, reflecting the idea that a common shock can affect both uncertainties.

For identification, we set $\beta_{m,1} = 1$ and $\beta_{f,n_m+1} = 1$ and assume $\ln m_t$ and $\ln f_t$ to have zero unconditional mean.[4] In addition, we deliberately include the block restrictions of factor loadings in

[4]More precisely, identification simply requires fixing the values of at least one of the loadings β_m and at least one of the loadings β_f to some value. This will uniquely pin down the state variables. The choice of fixing the loadings $\beta_{m,1}$ and β_{f,n_m+1} as well as the choice of 1 for their value is simply an arbitrary normalization that sets up the units of the unobservable state variables.

the volatilities specification of (2) in order to allow the comovement between uncertainties captured in the VAR structure and correlated innovations of (4). Conceptually, these block restrictions are consistent with broad definitions of uncertainty: macro uncertainty is the common factor in the error variances of macro variables, and financial uncertainty is the common factor in the error variances of finance variables. However, these uncertainties may move together due to correlated innovations to the uncertainties, the VAR dynamics of uncertainty captured in $D(L)$, and responses to past fluctuations in macro and finance variables (y_{t-1}).

The uncertainty variables m_t and f_t can also affect the levels of the macro and finance variables contained in y_t, contemporaneously and with lags. In particular, y_t is assumed to follow:

$$y_t = \Pi(L)y_{t-1} + \Pi_m(L)\ln m_t + \Pi_f(L)\ln f_t + v_t, \tag{5}$$

where p denotes the number of y_t lags in the VAR, $\Pi(L) = \Pi_1 - \Pi_2 L - \cdots - \Pi_p L^{p-1}$, with Π_i an $n \times n$ matrix, $i = 1, ..., p$, and $\Pi_m(L)$ and $\Pi_f(L)$ are $n \times 1$ lag-matrix polynomials of order p_m and p_f. This model allows the business cycle to respond to movements in uncertainty, both through the conditional variances (contemporaneously, via movements in v_t) and through the conditional means (contemporaneously and with lag, via the coefficients collected in $\Pi_m(L)$ and $\Pi_f(L)$).[5]

Note that, as a general matter of identification, our modeling strategy separates the total variance of the residual $Av_t = \Lambda_t^{0.5}\epsilon_t$ into three orthogonal components: a common component, an idiosyncratic component (both reflected in the matrix $\Lambda_t^{0.5}$), and a component due to the conditionally

Different normalizations would provide different units for the states and hence different values for the loadings, but would still provide exactly the same results in terms of likelihood of the system, and hence all the results presented in the paper are independent from this normalization choice.

[5]In line with the macroeconomic literature, we use log-states instead of levels, as this choice allows us to efficiently impose positivity of m_t and f_t, and it makes the system composed of the VAR and the factor dynamics linear in y and $ln(m_t)$ and $ln(f_t)$. Hence, it is straightforward to perform structural analysis and compute impulse responses in the standard fashion.

independent shock ϵ_t.[6] When a large shock (represented by $\Lambda_t^{0.5}\epsilon_t$) hits the economy, we let the data distinguish whether this is a large shock in the conditional error ϵ_t (so an outlier in a standard normal distribution, with a variance that is not moving) or rather a relatively ordinary shock (in terms of size of ϵ_t) accompanied by an increase in the variance $\Lambda_t^{0.5}$.

The model above differs some in timing with respect to Creal and Wu (2016). In our model, volatility and uncertainty are contemporaneous with y_t, in line with some other studies of macroeconomic uncertainty (e.g., Alessandri and Mumtaz 2014).[7] In contrast, in Creal and Wu (2016), the volatility that affects the size of shocks to y_t and the conditional mean of y_t is from period $t-1$. We find our approach natural for assessing the effects of macro and financial uncertainty, but other approaches are certainly feasible. Other contributions in the literature have also proposed the inclusion of volatility in the conditional mean of a small VAR, without resorting to a common factor specification for the volatilities, notably Jo (2014) and Shin and Zhong (2015).

The model in (1)-(5) is related to several other previous specifications in the literature. These precedents include Cogley and Sargent (2005) and Primiceri (2005), who impose $\Pi_m(L) = \Pi_f(L) = 0$ and have no factor structure in the volatilities, which amounts to setting $\beta_j = 0$.[8] The model in (1)-(5) is also related to parametric factor models, such as Stock and Watson (1989), where $\Pi(L) = 0$ and $v_t \sim iid\ N(0, \Sigma)$, or Marcellino, Porqueddu and Venditti (2016), who allow for

[6]The errors Av_t are structural in the sense that they are mutually uncorrelated, and conditionally (on $\Lambda_t^{0.5}$) independent. However, they are unconditionally mutually dependent because their conditional variances co-move.

[7]Our model also differs in timing with respect to some finance models. The inclusion of y_{t-1} in the volatility factor processes can be seen as a version of the leverage effect in some stochastic volatility models of financial returns. Whereas volatility and uncertainty are contemporaneous with y_t in our model, in finance applications such as Omori, et al. (2007), volatility is lagged.

[8]However, Primiceri's (2005) model permits the innovations to the volatilities to be correlated across variables, while in our specification they are not, and any correlation among volatilities are forced onto the common factor, a restriction that is standard in factor model analysis.

stochastic volatility both in v_t and in the error driving the common factor, u_t. In another precedent, Carriero, Clark and Marcellino (2016a) impose $\Pi_m(L) = \Pi_f(L) = 0$ and consider a small model for computational reasons. However, as discussed in the introduction and emphasized in JLN, when measuring uncertainty it is necessary to allow n to be large. In addition, we believe it is important to permit direct effects of uncertainty on the endogenous macroeconomic and financial variables ($\Pi_m(L) \neq 0,\ \Pi_f(L) \neq 0$).[9] In an analysis of a four-variable model, Alessandri and Mumtaz (2014) assume that $\beta_j = 1$ and $\ln h_{j,t} = 0$ for all j. Augmented by allowing the common volatility factor to affect the conditional mean of y_t, this corresponds to the CSV specification of Carriero, Clark and Marcellino (2016a), which, however, is not suitable in this context, as with n large both restrictions are not likely to hold in the data. Finally, Creal and Wu (2016) develop a model of bond yields and a small set of macro variables that jointly treats uncertainty about monetary policy as a factor in volatility and in conditional means of macro variables and interest rates.

Working with a model as general as (1)-(5) substantially complicates estimation, as we discuss in the next subsection.[10] The reader not interested in technicalities can skip to Section 3.

In implementation with monthly data, we set the VAR lag order at $p = 6$, the lag order for the uncertainty factors in the VAR's conditional mean (p_m and p_f) at 2, and the lag order of the

[9]Although other work, noted above, has emphasized the importance of a large cross section, it is not the case that estimation error surrounding our factor vanishes as the cross-section becomes very large. As a check, we estimated a single-factor macro model with different numbers of variables. Precision of the uncertainty estimate increased as the number of variables went from relatively small to mid-sized but didn't change much as the number went from mid-sized to large. Therefore, a methodology which takes into account such estimation error is needed in order to make proper inference on uncertainty and its effects.

[10]More general specifications would feature time-variation in the conditional means, in the A^{-1} matrix, and in the factor loadings. However, these modifications are computationally very demanding with a large model. We have evaluated the effects of a time-varying A^{-1} matrix in a smaller model and found very limited differences in the responses to uncertainty shocks.

bivariate VAR in the uncertainty factors (d) to 2.[11]

2.2 General steps of MCMC algorithm

We estimate the model using an MCMC sampler. All results in the paper are based on 5,000 retained draws, obtained by sampling a total of 30,000 draws, discarding the first 5,000, and retaining every 5th draw of the post-burn sample. The inefficiency statistics provided in the supplemental appendix indicate the efficiency and mixing of the algorithm are reasonably good.

Our exposition of priors, posteriors, and estimation makes use of the following additional notation. The vector a_j, $j = 2, \ldots, n$, contains the j^{th} row of the matrix A (for columns 1 through $j-1$). We define the vector $\gamma = \{\gamma_1, ..., \gamma_n\}$ as the set of coefficients appearing in the conditional means of the transition equations for the states $h_{1:T}$, and $\delta = \{D(L), \delta'_m, \delta'_f\}$ as the set of the coefficients in the conditional means of the transition equations for the states $m_{1:T}$ and $f_{1:T}$. The coefficient matrices Φ_v and Φ_u defined above collect the variances of the shocks to the transition equations for the idiosyncratic states $h_{1:T}$ and the common uncertainty factors $m_{1:T}$ and $f_{1:T}$, respectively. In addition, we group the parameters of the model in (1)-(5), except the vector of factor loadings β, into $\Theta = \{\Pi, A, \gamma, \delta, \Phi_v, \Phi_u\}$. Finally, let $s_{1:T}$ denote the time series of the mixture states used (as explained below) to draw $h_{1:T}$.

We use an MCMC algorithm to obtain draws from the joint posterior distribution of model parameters Θ, loadings β, and latent states $h_{1:T}$, $m_{1:T}$, $f_{1:T}$, $s_{1:T}$. Specifically, we sample in turn from the following two conditional posteriors (for simplicity, we suppress notation for the dependence of each conditional posterior on the data sample $y_{1:T}$): (1) $h_{1:T}$, $\beta \mid \Theta$, $s_{1:T}$, $m_{1:T}$, $f_{1:T}$, and (2) Θ, $s_{1:T}$, $m_{1:T}$, $f_{1:T} \mid h_{1:T}$, β.

[11]These choices balance data fit with parsimony and computational time. In a simple Normal-Wishart BVAR in our 30 variables, with parameter priors similar to those of our complicated model, over a lag choice range of 1 through 6, the model with 6 lags yields the highest marginal likelihood. For the other lags, as these relate to latent states, we follow studies such as Alessandri and Mumtaz (2014) and Creal and Wu (2016) in using low-order processes.

The first step relies on a state space system. Defining the rescaled residuals $\tilde{v}_t = Av_t$, taking the log squares of (1), and subtracting out the known (in the conditional posterior) contributions of the common factors yields the observation equations ($\bar{c}$ denotes an offset constant used to avoid potential problems with near-zero values):

$$\begin{cases} \ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{m,j} \ln m_t = \ln h_{j,t} + \ln \epsilon_{j,t}^2, \ j = 1, \ldots, n_m \\ \ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{f,j} \ln f_t = \ln h_{j,t} + \ln \epsilon_{j,t}^2, \ j = n_m + 1, \ldots, n. \end{cases} \tag{6}$$

For the idiosyncratic volatility components, the transition and measurement equations of the state-space system are given by (3) and (6), respectively. The system is linear but not Gaussian, due to the error terms $\ln \epsilon_{j,t}^2$. However, $\epsilon_{j,t}$ is a Gaussian process with unit variance; therefore, we can use the mixture of normals approximation of Kim, Shepard and Chib (1998) to obtain an approximate Gaussian system, conditional on the mixture of states $s_{1:T}$. To produce a draw from $h_{1:T}, \beta \mid \Theta, s_{1:T}, m_{1:T}, f_{1:T}$ we then proceed as usual by (a) drawing the time series of the states given the loadings using $(h_{1:T} \mid \beta, \Theta, s_{1:T}, m_{1:T}, f_{1:T})$, following Del Negro and Primiceri's (2015) implementation of the Kim, Shepard and Chib (1998) algorithm, and by then (b) drawing the loadings given the states using $(\beta \mid h_{1:T}, \Theta, s_{1:T}, m_{1:T}, f_{1:T})$, using the conditional posterior detailed below in (16).

The second step conditions on the idiosyncratic volatilities and factor loadings to produce draws of the model coefficients Θ, common uncertainty factors $m_{1:T}$ and $f_{1:T}$, and the mixture states $s_{1:T}$. Draws from the posterior $\Theta, s_{1:T}, f_{1:T} \mid h_{1:T}, \beta$ are obtained in three sub-steps from, respectively: (a) $\Theta \mid m_{1:T}, f_{1:T}, h_{1:T}, \beta$; (b) $m_{1:T}, f_{1:T} \mid \Theta, h_{1:T}, \beta$; and (c) $s_{1:T} \mid \Theta, m_{1:T}, f_{1:T}, h_{1:T}, \beta$. More specifically, for $\Theta \mid m_{1:T}, f_{1:T}, h_{1:T}, \beta$ we use the posteriors detailed below, in equations (14), (15), (17), (18), (19), and (20). For $m_{1:T}, f_{1:T} \mid \Theta, h_{1:T}, \beta$, we use the particle Gibbs step proposed by Andrieu, Doucet, and Holenstein (2010). For $s_{1:T} \mid \Theta, m_{1:T}, f_{1:T}, h_{1:T}, \beta$, we use the 10-state mixture approximation of Omori, et al. (2007).

2.2.1 Coefficient priors and posteriors

We specify the following (independent) priors for the parameter blocks of the model (parameterization details are given in the supplemental appendix):

$$\begin{aligned}
\text{vec}(\Pi) &\sim N(\text{vec}(\underline{\mu}_{\Pi}), \underline{\Omega}_{\Pi}), && (7)\\
a_j &\sim N(\underline{\mu}_{a,j}, \underline{\Omega}_{a,j}),\ j = 2, \ldots, n, && (8)\\
\beta_j &\sim N(\underline{\mu}_{\beta}, \underline{\Omega}_{\beta}),\ j = 2, \ldots, n_m, n_{m+2}, ..., n, && (9)\\
\gamma_j &\sim N(\underline{\mu}_{\gamma}, \underline{\Omega}_{\gamma}),\ j = 1, \ldots, n, && (10)\\
\delta &\sim N(\underline{\mu}_{\delta}, \underline{\Omega}_{\delta}), && (11)\\
\phi_j &\sim IG(d_{\phi} \cdot \underline{\phi}, d_{\phi}),\quad j = 1, \ldots, n, && (12)\\
\Phi_u &\sim IW(d_{\Phi_u} \cdot \underline{\Phi_u}, d_{\Phi_u}). && (13)
\end{aligned}$$

Under these priors, the parameters Π, A, β, γ, δ, Φ_v, and Φ_u have the following closed form conditional posterior distributions:

$$\begin{aligned}
\text{vec}(\Pi)|A, \beta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} &\sim N(\text{vec}(\bar{\mu}_{\Pi}), \bar{\Omega}_{\Pi}), && (14)\\
a_j|\Pi, \beta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} &\sim N(\bar{\mu}_{a,j}, \bar{\Omega}_{a,j}),\ j = 2, \ldots, n, && (15)\\
\beta_j|\Pi, A, \gamma, \Phi, m_{1:T}, f_{1:T}, h_{1:T}, s_{1:T}, y_{1:T} &\sim N(\bar{\mu}_{\beta}, \bar{\Omega}_{\beta}),\quad j = 2, \ldots, n_m, n_{m+2}, ..., n, && (16)\\
\gamma_j|\Pi, A, \beta, \Phi, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} &\sim N(\bar{\mu}_{\gamma}, \bar{\Omega}_{\gamma}),\ j = 1, \ldots, n, && (17)\\
\delta|\Pi, A, \gamma, \beta, \Phi, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} &\sim N(\bar{\mu}_{\delta}, \bar{\Omega}_{\delta}), && (18)\\
\phi_j|\Pi, A, \beta, \gamma, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} &\sim IG\left(d_{\phi} \cdot \underline{\phi} + \Sigma_{t=1}^{T} v_{jt}^2,\ d_{\phi} + T\right),\ j = 1, \ldots, n, && (19)\\
\Phi_u|\Pi, A, \beta, \delta, \gamma, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} &\sim IW(d_{\Phi_u} \cdot \underline{\Phi_u} + \Sigma_{t=1}^{T} u_t^2, d_{\Phi_u} + T). && (20)
\end{aligned}$$

Expressions for $\bar{\mu}_{a,j}$, $\bar{\mu}_{\delta}$, $\bar{\mu}_{\gamma}$, $\bar{\Omega}_{a,j}$, $\bar{\Omega}_{\delta}$, and $\bar{\Omega}_{\gamma}$ are straightforward to obtain using standard results from the linear regression model. To save space, we omit details for these posteriors; general solutions are readily available in other sources (e.g., Cogley and Sargent (2005) for $\bar{\mu}_{a,j}$).

In the posterior for the factor loadings β, the mean and variance take a GLS-based form, with dependence on the mixture states used to draw volatility. For the VAR coefficients Π, with smaller models it is common to rely on a GLS solution for the posterior mean (e.g., Carriero, Clark and Marcellino 2015). However, with large models it is far faster to exploit the triangularization — obtaining the same posterior provided by standard system solutions — discussed in Carriero, Clark and Marcellino (2016b) and estimate the VAR coefficients on an equation-by-equation basis.

Specifically, using the factorization given in the supplemental appendix allows us to draw the coefficients of the matrix Π in separate blocks. Let $\pi^{(j)}$ denote the j-th row of the matrix Π, and let $\pi^{(1:j-1)}$ denote all the previous rows. Then draws of $\pi^{(j)}$ can be obtained from:

$$\pi^{(j)} \quad | \quad \pi^{(1:j-1)}, A, \beta, f_{1:T}, m_{1:T}, h_{1:T}, y_{1:T} \sim N(\bar{\mu}_{\pi^{(j)}}, \overline{\Omega}_{\pi^{(j)}}), \tag{21}$$

$$\bar{\mu}_{\pi^{(j)}} = \overline{\Omega}_{\pi^{(j)}} \left\{ \Sigma_{t=1}^{T} X_{j,t} \lambda_{j,t}^{-1} y_{j,t}^{*\prime} + \underline{\Omega}_{\pi^{(j)}}^{-1} (\underline{\mu}_{\pi^{(j)}}) \right\}, \tag{22}$$

$$\overline{\Omega}_{\pi^{(j)}}^{-1} = \underline{\Omega}_{\pi^{(j)}}^{-1} + \Sigma_{t=1}^{T} X_{j,t} \lambda_{j,t}^{-1} X_{j,t}^{\prime}, \tag{23}$$

where $y_{j,t}^{*} = y_{j,t} - (a_{j,1}^{*} \lambda_{1,t}^{0.5} \epsilon_{1,t} + \cdots + a_{j,,j-1}^{*} \lambda_{j-1,t}^{0.5} \epsilon_{j-1,t})$, with $a_{j,i}^{*}$ denoting the generic element of the matrix A^{-1} and $\underline{\Omega}_{\pi^{(j)}}^{-1}$ and $\underline{\mu}_{\pi^{(j)}}$ denoting the prior moments on the j-th equation, given by the j-th column of $\underline{\mu}_{\Pi}$ and the j-th block on the diagonal of $\underline{\Omega}_{\Pi}^{-1}$.

2.2.2 Unobservable states

For the unobserved volatility states f_t, m_t, and $h_{j,t}$, $j = 1, ..., n$, given the law of motion for the unobservable states in (3)-(4) and priors on the period 0 values detailed in the supplemental appendix, draws from the posteriors can be obtained using the algorithm of Kim, Shepard and Chib (1998) for the idiosyncratic volatilities and the particle Gibbs sampler of Andrieu, Doucet, and Holenstein (2010) for the common volatility factors. In the particle Gibbs sampler of the uncertainty factors, we follow Creal and Wu (2016) in using 300 particles.[12]

[12]In the results provided in the appendix, for computational speed we use a setting of 50 particles. Efficiency, mixing, and our baseline results are very similar with 50 and 300 particles.

3 Data

Our results are based on a VAR including 30 macroeconomic and financial variables, which are listed in Table 1. Following common practice in the factor model literature as well as studies such as JLN, after transforming each series for stationarity as needed, we standardize the data (demean and divide by the simple standard deviation) before estimating the model.

Our variable set includes 18 macroeconomic series, chosen for being major indicators within broad categories (production, labor market, etc.). We take these series and some financial indicators from the FRED-MD monthly dataset detailed in McCracken and Ng (2016), which is similar to that underlying common factor model analyses, such as Stock and Watson (2006).

Our variable set also includes 12 financial series, consisting of the return on the S&P 500, the spread between the Baa bond rate and the 10-year Treasury yield, and a set of additional variables made available by Kenneth French.[13] Specifically, we use the French series on CRSP excess returns, four risk factors — for SMB (Small Minus Big), HML (High minus Low), R15_R11 (small stock value spread), and momentum — and sector-level returns for a breakdown of five industries (consumer, manufacturing, high technology, health, other).

This specification reflects some choice as to what constitutes a macroeconomic variable rather than a financial variable. Reflecting the typical factor model analysis, the McCracken-Ng dataset includes a number of indicators — of stock prices, interest rates, and exchange rates — that may be

[13]We obtained similar results when, instead of the 10 additional variables from the French datasets, we used more detailed breakdowns of returns (by industry and portfolios sorted on size and book-to-market) available from his datasets. Although our main results are robust across the choices of the variable set considered, the set of financial variables chosen has some effect on the responsiveness of financial variables to macro shocks (in some specifications, we obtained larger effects on asset returns than we report for the baseline), as well as on the correlation between the estimated macro and financial uncertainty factors (in some specifications, this correlation was modestly higher than in the baseline).

considered financial indicators. In our model specification, the variables in question are the federal funds rate, the credit spread, and the S&P 500 index. As the instrument of monetary policy, it seems most appropriate to treat the funds rate as a macro variable. For the other two variables, the distinction between macro and finance is admittedly less clear. Whereas JLN and LMN treat these indicators as macro variables that bear on macroeconomic uncertainty and not directly on financial uncertainty (in LMN, financial uncertainty is based on the volatilities of various measures of stock returns and risk factors), it seems more natural to consider these indicators as financial variables, in keeping with such precedents as Koop and Korobilis (2014) on the measurement of financial conditions. Accordingly, we instead include the credit spread and the S&P 500 index in the set of financial variables. In the supplemental appendix, we discuss robustness to these choices.

4 Measuring Aggregate Uncertainty

In the following results, we focus on estimates of our baseline model with 30 variables, in monthly data. To save space, we present volatility estimates for a subset of 18 variables; the full set of estimates is shown in the supplemental appendix. The appendix also provides other results, showing, e.g., that most of the factor loadings are clustered around a value of 1.

Figure 1 displays the posterior distribution of the measures of macro (top panel) and financial uncertainty (bottom panel). In these charts, we define macro uncertainty as the square root of the common volatility factor ($\sqrt{m_t}$) and financial uncertainty as the square root of the common volatility factor ($\sqrt{f_t}$), corresponding to standard deviations. In the interest of brevity, we do not compare our uncertainty measures with other proposals in the literature, such as the VIX or the cross-sectional variation in SPF forecasts or in firms' profits; studies such as JLN and Caldara, et al. (2016) provide such comparisons. Although not reported directly in Figure 1, the correlations of our uncertainty estimates with the JLN and LMN estimates are quite high, about 0.76 in each case. However, our estimates are more variable than the JLN and LMN estimates, partly due to the inclusion of y_{t-1} in the VAR process of the factors. Figure 1 also reports the 15%-85% credible set

bands around our estimated measures of uncertainty, which, as mentioned, are correctly considered random variables in our approach. These bands indicate that the uncertainty around uncertainty estimates is sizable.

The estimated macro and financial uncertainties in Figure 1 have some tendency to co-move, with a correlation of 0.39. About the financial uncertainty factor, it is worth noting that it increases during recessions, as does the macro uncertainty factor, as well as in other periods of financial turmoil. This different temporal pattern may help in disentangling macroeconomic and financial uncertainty. As indicated in Figure 1, our estimates of uncertainty show significant increases around some of the political and economic events that Bloom (2009) highlights as periods of uncertainty. For example, financial uncertainty rises sharply with the Black Monday event of 1987.

From a broader macroeconomic point of view, it is interesting that our measures of aggregate uncertainty do not present clear evidence of the sharp decline in volatility commonly referred to as the Great Moderation. This finding is in line with Giannone, Lenza and Reichlin (2008), who stress that the Great Moderation appears smaller with models based on larger datasets than with models based on smaller datasets. However, they do not consider large models with stochastic volatility, as methodology existing before our paper did not make it tractable.

In **Figure 2** we report the reduced form volatilities of the variables in our model, i.e., the diagonal elements of $\Sigma_t^{0.5}$, which reflect both the common uncertainty factors and idiosyncratic components. Great Moderation effects become evident for some variables, and particularly the volatility of the federal funds rate exhibits a major decrease after the early 1980s, suggesting that a more predictable monetary policy contributed to the stabilization of the other volatilities.

Figure 2 also plots the estimated idiosyncratic volatilities (reported in the chart as $h_{i,t}^{0.5}$). For some variables, notably employment and the federal funds rate, the idiosyncratic variation is preponderant, explaining most of the overall variation in the volatility. In other cases, the variation in the idiosyncratic component is small. Importantly, the estimated pattern of idiosyncratic volatilities shows no residual factor structure, which we consider a reassuring result in favor of our two-factor structure. A principal components analysis on the idiosyncratic volatilities shows that the share of

variance explained by the first principal component is about 11%, indicating that there is no sizable residual factor structure in the idiosyncratic volatilities.

Finally, an important issue is whether the unobserved uncertainty state variables merely pick up some kind of "level" shock rather than isolating uncertainty. For example, Bloom's (2009) uncertainty shocks are thought to be correlated with identified shocks to monetary policy, productivity, etc., estimated in other work. Once these "level" shocks are partialed out from Bloom's uncertainty shocks, the effects of uncertainty shocks seem to be rather reduced. To assess whether the same correlations are evident in our uncertainty estimates, we compute the correlations of our estimated macroeconomic and financial uncertainty shocks with some well-known macro shocks, drawing on comparable exercises in Stock and Watson (2012) and Caldara, et al. (2016). Specifically, we consider productivity shocks (Fernald's updates of Basu, Fernald, and Kimball 2006), oil supply shocks (Hamilton 2003 and Kilian 2008), monetary policy shocks (Gurkaynak, et al. 2005 and Coibion, et al. 2016), and fiscal policy shocks (Ramey 2011 and Mertens and Ravn 2012).[14]

As indicated by the results in Table 2, our uncertainty shocks are not very correlated with "known" macroeconomic shocks. Accordingly, our estimated uncertainty shocks seem to truly represent a second order "variance" phenomenon, rather than a first order "level" shock.

5 Measuring the impact of uncertainty

5.1 Identification

With our uncertainty measures entering each of the equations of the VAR in y_t, we can compute impulse responses for uncertainty shocks. From equation (4) it is clear that the VAR shocks ϵ_t do not appear in the law of motion of the factors. This restriction on the uncertainty dynamics is

[14]The productivity shocks correspond to growth rates of utilization-adjusted TFP. The oil price shock measure of Hamilton (2003) is the net-oil price increase series. The monetary policy shocks of Coibion, et al. (2016) update the estimates of Romer and Romer (2004).

similar to that imposed by other uncertainty VARs (with the recursive ordering as in Bloom 2009 or JLN), and it is somewhat similar to adding an uncertainty proxy to a VAR, ordered first.

Differently from other uncertainty VARs, though, our uncertainty measure is estimated within the model, and the shocks to this measure are orthogonal to the VAR shocks by construction. This means that our identification scheme is very similar to the one typical of factor-augmented VAR models, such as Bernanke, Boivin and Eliasz (2005).

Indeed, a look at equations (1) and (5) makes clear that the model proposed here can be seen as a factor model like that of Bernanke, Boivin and Eliasz (2005), with the additional feature that the factors appear also in the conditional variance of the system. Just as it happens in the factor and FAVAR literatures, there is no contemporaneous correlation between factor shocks and VAR shocks, and there are no VAR shocks in the dynamics of the factors, which provides identification. A shock to an uncertainty factor has a clear interpretation as a contemporaneous, sudden increase of the conditional variance of all the variables in the macroeconomy, but it is orthogonal to the shocks to the variables themselves.

Note that the ordering of the variables within the VAR does not have an effect on impulse responses for shocks to the uncertainty factors. To see this point, consider again our model, which using together expressions (5), (2) , and (1) can be written as

$$y_t = \Pi(L)y_{t-1} + \Pi_m(L)\ln m_t + \Pi_f(L)\ln f_t + A^{-1}\cdot \underbrace{\begin{bmatrix} m_t^{\beta_{m,j}} h_{1,t} & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & f_t^{\beta_{f,j}} h_{n,t} \end{bmatrix}^{0.5}}_{\Lambda_t} \cdot \epsilon_t, \quad (24)$$

and consider the effects of a shock to $\ln m_t$ or $\ln f_t$. In our setup the shocks to uncertainty contemporaneously affect y_t and are orthogonal to ϵ_t. With that orthogonality and with the shocks ϵ_t set to zero when the impulse response from a shock to uncertainty is computed, it follows that the resulting impulse response is independent from the matrix A^{-1}. A shock to uncertainty is transferred onto the y_t only through the matrix $\Pi_m(L)$ on impact, and then it propagates in the future via the other

conditional mean parameters, but at no point does the matrix A^{-1} enter the picture. It follows that the ordering of the variables within the vector y_t is irrelevant as far as impulse responses to shocks to the uncertainty factors are concerned.[15]

However, beyond impulse responses, our model has some features or complexities that differ from those of FAVAR specifications, as well as those of past work on uncertainty (e.g., Bloom 2009, JLN, and Caldara, et al. 2016). In our specification (24), a shock to uncertainty affects not only the conditional mean of y_t but also its conditional variance. Put another way, while the shocks to the factors (u_t) and the shocks to the variables ($v_t = A^{-1}\Lambda_t^{0.5}\epsilon_t$) are uncorrelated, they are not independent: a large positive shock to the uncertainty measures will amplify the size of the shock to the variables v_t via the pre-multiplication of the i.i.d. shocks ϵ_t by the matrix $\Lambda_t^{0.5}$, as is clear from (24). Hence, the unconditional distribution of the data can be asymmetric and non-Gaussian, and the conditional distribution features time variation in its variance.

With regards to this aspect it is important to stress that since the impulse response measures the conditional mean response to a shock, any analysis focusing on impulse responses only would

[15]Of course, as we stressed at the beginning of this Section, the absence of the VAR shocks in the factor dynamics can be considered a form of Cholesky ordering in a larger VAR which includes the uncertainty factors among the endogenous variables. Here we are focusing on the ordering within the block of observable variables y_t. However, the joint distribution of the system might be affected by the ordering of the variables in the system due to an entirely different reason: the diagonalization typically used for the error variance Σ_t in stochastic volatility models. Since priors are elicited separately for A and Λ_t, the implied prior of Σ_t will change if one changes the equation ordering, and therefore different orderings would result in different prior specifications and then potentially different joint posteriors. This problem is not a feature of our triangular algorithm, but rather it is inherent to all models using the diagonalization of Σ_t. As noted by Sims and Zha (1998) and Primiceri (2005), this problem will be mitigated in the case (as the one considered in this paper) in which the covariances A do not vary with time, because the likelihood information will soon dominate the prior.

not capture the conditional variance effect. In addition, the interactions noted above complicate the computation of historical decompositions of fluctuations in the data to contributions from the model's various shocks; we describe below an approximate decomposition we use for that purpose. To reflect conditional variance and distributional effects, we use the period of the Great Recession and subsequent recovery to show the impact of uncertainty on the predictive distribution of y_t.[16]

Finally, we stress that our approach takes into account the uncertainty around uncertainty, while earlier studies condition on the point estimates of uncertainty, abstracting from the variance of uncertainty estimates. Our estimates of impulse responses, historical decompositions, and predictive densities account for the variance of the uncertainty measure in the sense that our estimates of the VAR's coefficients reflect that uncertainty is a latent state and not observed data.

5.2 Results

5.2.1 Impulse responses

We compute impulse response functions for each of the 5000 retained draws of the VAR's parameters and latent states and report the posterior medians and 70 percent credible sets of these functions.

While the vector of uncertainty measures $u_t = (u_{m,t}, u_{f,t})'$ is identified for the reasons outlined

[16]Importantly, while the Cholesky ordering of the variables within the VAR does not have an effect on the impulse responses to uncertainty shocks (as discussed above), it does have an impact on the effect of uncertainty shocks on the conditional variances. To see this point consider again our model in (24). Clearly, the conditional variance of y_t is impacted by shocks to the uncertainty factors through the elements of the matrix Λ_t. Since the matrix Λ_t gets pre-multiplied by the matrix A^{-1}, which is a lower triangular matrix whose elements reflect the particular order chosen for the variables in the vector y_t, it follows that the effects on the conditional variance of y_t will be influenced by the specific order in which the variables enter the VAR. We thank a referee for pointing this out. As we discuss in Section 5.2.2, empirically the effects through this channel seem to be small in our application, and we abstract from them.

in the previous Subsection, in order to separately identify the effects of macro and financial uncertainty, an identification assumption is needed for the system in (5). In line with common wisdom that financial variables are "fast" while macroeconomic variables are "slow," we assume a Cholesky identification scheme in which financial uncertainty f_t is ordered last, and hence it contemporaneously responds to both $u_{m,t}$ and $u_{f,t}$, whereas macroeconomic uncertainty responds contemporaneously to $u_{m,t}$ but responds to $u_{f,t}$ with some delay.

Figure 3 provides the impulse response estimates of a one-standard deviation shock to log macro uncertainty ($\ln m_t$). Note that, although the model is estimated with standardized data, for comparability to previous studies the impulse responses are scaled and transformed back to the units typical in the literature. We do so by using the model estimates to: (1) obtain impulse responses in standardized, sometimes (i.e., for some variables) differenced data; (2) multiply the impulse responses for each variable by the standard deviations used in standardizing the data before model estimation; and (3) accumulate the impulse responses of step (2) as appropriate to get back impulse responses in levels or log levels.[17] Accordingly, the units of the reported impulse responses are percentage point changes (based on 100 times log levels for variables in logs or rates for variables not in log terms).[18]

As shown in the penultimate panel of **Figure 3**, the shock to log macro uncertainty produces a

[17]The fact that the model is estimated using some variables differenced for stationarity (e.g., employment and industrial production) implies that, for some of these variables, the long run effects of transitory shocks do not die out. This is in line with what typically happens when analyzing the effects of shocks within a factor model. We have verified in somewhat smaller versions of the model that, without transformation of the variables, we obtain similar results but with effects on activity levels that die out over time.

[18]However, there is one complication to the reading of results on stock prices and returns, relating to the source data: for the S&P 500 variable, we display the response in percentage changes of the price level, but for the CRSP excess return, we display the response of the monthly return, rather than a price level.

rise in uncertainty that gradually dies out, over the course of about one year. As indicated in the last panel of **Figure 3**, financial uncertainty rises in response, also for about a year, although the response of financial uncertainty is estimated less precisely than the response of macro uncertainty.

Now consider the effects of the macro uncertainty shock on industrial production and employment, which are both significantly negative, with a modestly larger response of production than employment. The responses are qualitatively similar to those obtained by JLN, who only focus on these two variables, but in their case the effects are more short-lived, becoming not significant about one year after the shock.

In the labour market, we also find that hours worked generally decrease (with peak effect after about six months) and unemployment increases (with peak effect after about 20 months), in line with firms trying to avoid hiring adjustment costs, as, e.g., in Bloom (2009). Interestingly, in detail provided in the supplementary appendix, there are no significant effects on hourly earnings (average hourly earnings decline, but the estimate is too imprecise to be meaningful), suggesting that wages are rather sticky in the face of uncertainty shocks.

The overall effects on real personal income (reported in the appendix), consumption expenditures and real M&T (manufacturing and trade) sales are significantly negative and persistent. The fall in consumption is likely due to lower current and future expected income but also, likely, to the need to increase precautionary savings (e.g., Bansal and Yaron 2004) and the preference to postpone buying durable goods until uncertainty declines (e.g., Eberly 1994 and Bertola, Guiso and Pistaferri 2005).

In other indicators of production, we detect a significant, persistent decrease in capacity utilization. Utilization bottoms out after about 15 months (with a peak response of about 30 basis points) and then slowly rises. Orders of durable goods and the new orders component of the ISM index also fall significantly, signaling a clear decrease in actual and expected investment. This is in line with the presence of sizable investment adjustment costs, e.g. Ramey and Shapiro (2001) and Cooper and Haltiwanger (2006), that firms try to avoid in the presence of higher uncertainty. An even more significant effect emerges in the building sector, where adjustment costs can be expected

to be even higher, with prolonged decreases in housing starts and building permits.

One other notable result in the responses of economic activity to the shock in macro uncertainty concerns timing: for some, but not all indicators, the response to the shock is immediate and sizable. Relatively quick, large responses occur for housing starts and permits, the ISM index of new orders, and weekly hours worked (which presumably reflects an intensive margin, rather than the extensive margin captured by employment). Slower, although eventually large and significant, responses occur for variables such as employment, unemployment, and industrial production.

Despite the significant decline of economic activity in response to the macro uncertainty shock, there doesn't appear to be evidence of a broad decline in prices. The PPI for finished goods declines steadily and by as much as 2 percentage points, although the response is estimated relatively imprecisely. But overall consumer prices as captured by the PCE price index fail to display a significant change. Overall, this picture of price responses is in line with New-Keynesian models, such as Leduc and Liu (2016), Basu and Bundick (2016), and Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramirez (2015), which predict a small effect of uncertainty on inflation due to sticky prices (and possibly wages).

In the face of this sizable deterioration in the real economy and absence of much movement in prices, the federal funds rate gradually falls. The reaction of the federal funds rate is minimal for the first few months. Then, there is a steady, statistically significant decline for about 20-22 months. The response of the funds rate reaches about -20 basis points, not quite as large as the movement in employment but almost double the peak response of the unemployment rate. Such a response appears to be about in line with the parameterization of the Taylor (1999) rule, if one replaces the rule's output gap with an unemployment gap and assumes that Okun's law justifies roughly doubling Taylor's coefficient of 1 on the output gap.

The responses of financial indicators to the shock to macro uncertainty are — collectively speaking — muted and imprecisely estimated (however, in some specifications with different choices of financial variables, we obtained more notable responses of asset returns to macro uncertainty). The one exception is the spread between the Baa and 10 year Treasury yields, which displays a

modest, but persistent and significant, rise, with a hump-shape pattern. The substantial increase in the credit spread likely increases borrowing costs for firms, further reducing their investment, as in studies looking at the effects of uncertainty in models with financial constraints, such as Arellano, Bai, and Kehoe (2016), Christiano, Motto, and Rostagno (2014), and Gilchrist, Sim, and Zakrasjek (2014). Aggregate stock prices and returns as captured by the S&P 500 price index and the excess CRSP return decline, in line with common wisdom and the finance literature (e.g., Bansal and Yaron 2004), but the estimated responses are imprecise. The responses of other financial indicators, including the risk factors and industry-level returns, are also overall insignificant.

The effects of a shock to financial uncertainty are displayed in **Figure 4**. As reported in the last panel, the shock to log financial uncertainty produces a rise in uncertainty that only gradually dies out, over the course of almost two years. In response, macro uncertainty changes very little, by an amount that is not significant. Based on this and the corresponding result for a shock to macro uncertainty, our estimates and identification attribute the comovement between macro and financial uncertainty to financial uncertainty (relatively fast moving) moving in response to a change in macro uncertainty (relatively slow moving).

As to broader effects of financial uncertainty, when compared to a macro uncertainty shock, a financial uncertainty shock has similar, but sometimes smaller and more delayed, macroeconomic effects and larger financial effects. More specifically, the effects on industrial production and employment follow patterns similar to those obtained for a shock to macroeconomic uncertainty, with a significantly negative response. The unemployment rate rises and hours worked fall, but the reaction of the latter is smaller on impact and in general slower than what happens in the case of the macroeconomic uncertainty shock. In perhaps the most notable difference with respect to results for a macro uncertainty shock, a financial uncertainty shock does not have significant effects on the housing sector (starts and permits).

Turning our attention to the financial variables, on balance they respond more to the financial uncertainty shock than the macro uncertainty shock, although in some cases the responses are imprecisely estimated. The shock to financial uncertainty produces a persistent and significant rise

in the credit spread, with a hump-shape pattern. It also produces a sizable falloff in aggregate stock prices and returns. The response of the S&P500 price level is negative and significant. The CRSP excess returns display a negative jump and recover only after six months. However, the responses of the risk factors included in the model are insignificant.

5.2.2 Historical decompositions

To assess the broader importance of uncertainty shocks to the macroeconomy and financial markets, we estimate historical decompositions. In a standard linear model, an historical decomposition of the total s-step ahead prediction error variance of y_{t+s} can be easily obtained by constructing a baseline path (forecast) without shocks, and then constructing the contribution of shocks. With linearity, the sums of the shock contributions and the baseline path equal the data. In our case, the usual decomposition cannot be directly applied because of interactions between Λ_{t+s} and ϵ_{t+s}: shocks to log uncertainty affect the forecast errors through $\Lambda_{t+s}\epsilon_{t+s}$, and, over time, shocks ϵ_{t+s} affect Λ_{t+s} through the response of uncertainty to lagged y. However, it is possible to decompose the total contribution of the shocks into three parts: (i) the direct contributions of the uncertainty shocks u_{t+s} to the evolution of y; (ii) the direct contributions of the VAR "structural" shocks ϵ_{t+s} to the path of y taking account of movements in Σ_{t+s} that arise as uncertainty responds to y but abstracting from movements in Σ_{t+s} due to uncertainty shocks; and (iii) the interaction between shocks to uncertainty and the structural shocks ϵ_{t+s}.

To be more specific, consider a simple one-factor model with lag orders of 1:

$$\begin{cases} y_t = \Pi y_{t-1} + \Gamma_1 m_t + \Gamma_2 m_{t-1} + v_t \\ m_t = \delta y_{t-1} + \gamma m_{t-1} + u_t \end{cases}, \tag{25}$$

where v_t and u_t are independent, with variances Σ_t and Φ_u, respectively. So we can replace v_t above with $\Sigma_t^{0.5}\epsilon_t$, where $\Sigma_t^{0.5}$ is a short-cut notation for the Cholesky decomposition of Σ_t and ϵ_t is $N(0, I_n)$. The one step ahead forecast errors are $y_{t+1} - E_t y_{t+1} = \Sigma_{t+1}^{0.5}\epsilon_{t+1} + \Gamma_1 u_{t+1}$. Now let $\hat{\Sigma}_{t+s|t}$ denote the future error variance matrix that would prevail in the absence of future shocks

to uncertainty. This would be constructed from forecasts of future uncertainty accounting for movements in y driven by ϵ shocks and the path of idiosyncratic volatility terms (incorporating shocks to these terms). The following decomposition can be obtained by adding and subtracting $\hat{\Sigma}_{t+1|t}$ terms in the forecast error:

$$y_{t+1} - E_t y_{t+1} = \Gamma_1 u_{t+1} + \hat{\Sigma}^{0.5}_{t+1|t}\epsilon_{t+1} + (\Sigma^{0.5}_{t+1} - \hat{\Sigma}^{0.5}_{t+1|t})\epsilon_{t+1}. \tag{26}$$

In this decomposition, the first term gives the direct contribution of the uncertainty shock, the second term gives the direct contribution of the structural shocks to the VAR, and the third term gives the interaction component. The third term can be simply measured as a residual contribution, as the data less the direct contributions from the uncertainty shock and the structural shocks to the VAR. We apply this basic decomposition to our more general model to obtain historical decompositions.

One potential complication with this approach is that, in the interaction components, there is not a good way to separate the roles of aggregate uncertainty and idiosyncratic volatility, because Σ_t is the product of such terms containing innovations to aggregate uncertainty and innovations to idiosyncratic components. Since the terms are multiplicative and not additive, there isn't a clear way to isolate the role of aggregate uncertainty from the role of idiosyncratic components. Moreover, any attempt to do so would be dependent on the ordering of the variables within the VAR, because as we discussed in Section 5.1, the effect of uncertainty on the conditional variance of y_t is influenced by the matrix A^{-1} and hence the ordering of the variables within the VAR matters. Because of these complications, and because the interaction effects are empirically much less pronounced than the direct effects, we chose to leave the interaction component as is, without attempting to separate the roles of aggregate uncertainty and idiosyncratic volatility in the interaction component.

Partly out of concern for chart readability, and light of general interest in the contributions of uncertainty to the Great Recession and the ensuring recovery, we provide results for the period from 2003 through 2014. (The appendix provides results for a sample 1985 to 2002, which includes periods of economic expansion and two relatively mild recessions. These results are qualitatively

similar. It also provides a color version of the chart for 2003 through 2014.) The charts show the standardized data series, a baseline path corresponding to the unconditional forecast, the direct contributions of shocks to (separately) macroeconomic and financial uncertainty, and the direct contributions of the VAR's shocks. The reported estimates are posterior medians of decompositions computed for each draw from the posterior. Finally, in light of space constraints, the charts below provide results for a subset of selected variables; results for the full set of variables are available in the supplemental appendix.

As indicated in Figure 5, the decomposition estimates indicate that around the Great Recession, shocks to uncertainty contribute materially to fluctuations in economic activity, the federal funds rate, the credit spread, and uncertainty itself, but not much to inflation or stock prices (or other financial indicators). However, for the macroeconomic and financial variables of the model, the effects of uncertainty shocks are generally dominated by the contributions of the VAR's shocks. Benati (2016) obtains a broadly similar result, with a different approach.

5.2.3 Predictive densities

To assess the distributional effects described in section 5.1, we estimate predictive densities for all of the variables in the system under two scenarios — a baseline scenario and an alternative scenario with additional shocks to uncertainty, in line with those estimated from our model. The densities cover a period spanning the Great Recession and much of subsequent recovery, from December 2007 (the NBER peak) through December 2012.

To obtain a baseline predictive density, for each retained posterior draw, we simulate draws of the time series of fundamental shocks to i) log idiosyncratic volatility ($e_{j,t}$), ii) log uncertainty (u_t), and iii) the VAR's variables (ϵ_t). Using these draws, we compute the baseline path of idiosyncratic volatility, uncertainty (Σ_t follows from the value of idiosyncratic volatility and uncertainty), and y_t.

To create the alternative path, we augment the baseline draws of shocks with additional shocks to uncertainty. In particular, we use additional shocks for the period of the NBER-dated recession, from December 2007 through June 2009, that are equal to the estimated shocks (posterior medians)

to uncertainty from our model. With the baseline paths of $e_{j,t}$ and ϵ_t and the alternative paths of u_t that add our estimated shocks to the baseline paths, we compute forward the alternative paths of uncertainty (Σ_t follows from the value of idiosyncratic volatility and uncertainty) and y_t; the path of idiosyncratic volatility is exactly the same as in the baseline.

Figure 6 shows the effects of uncertainty shocks on the predictive distributions of selected variables (results for the full set of variables are available in the supplemental appendix). The solid black line and gray shading report the predictive density of a baseline path for the variables. The alternative path denoted by the dotted (median) and dashed lines (15 and 85 percent quantiles) instead shows the predictive density with additional uncertainty shocks (for December 2007 through June 2009) corresponding to those obtained with our estimated model. Note that, as in the impulse responses, the estimated predictive distributions have been scaled and transformed back to the units typical in the literature, as described in the section on impulse responses.

Consistent with the simple impulse responses, the shocks to uncertainty cause the path of economic activity to shift down. For many but not all variables, the shocks also have a distributional effect beyond just moving the center of the distribution: they also cause the distribution to rotate downward. The 15th percentile of the 70 percent credible set appears to fall more than does the 85th percentile. These effects are most evident for those variables for which an uncertainty shock affects the median of the distribution, particularly for measures of economic activity (employment, industrial production, etc.), the federal funds rate, and the credit spread. For variables for which the median responses are smaller (e.g., for the PCE price index), there are no obvious distributional effects. Overall, these estimates show effects on predictive distributions that conventional approaches of inserting an uncertainty measure in a linear, homoskedastic VAR are not able to capture.

5.3 Robustness

We have examined the robustness of our results along a wide variety of dimensions and found our main results to be robust. The supplementary appendix details these checks and their results. In the interest of space, in this section we briefly describe a few of these checks, as follows.

- Using quarterly data yields results qualitatively very similar to those for monthly data.
- Using a sample ending before the Great Recession shows that our results are not driven by the volatility of that period.
- Restricting the model to make the idiosyncratic volatility components constants and not time-varying has little effect on financial uncertainty. However, the restriction makes the estimate of macroeconomic uncertainty far more variable and reduces its effects on the economy. Our baseline estimates indicate that idiosyncratic components are sizable, and we believe them to be important in many settings, including a model in monthly data such as ours.
- To assess the potential importance of restricting the matrix A to be constant, we considered (out of computational considerations) smaller, one-factor models in which A is time-varying as in Primiceri (2005). In these settings, allowing A to be time-varying yields results similar to those with a constant A. These results suggest this particular restriction is unlikely to have a material effect on our results.
- Alternative settings on the volatility-related priors yield results very similar to those reported.

6 Conclusions

This paper develops a new framework for measuring uncertainty and its effects on the macroeconomy and financial conditions. Specifically, we develop a VAR model for a possibly large set of variables whose volatility is driven by two common unobservable factors, corresponding to aggregate macroeconomic and financial uncertainty. These uncertainty measures reflect common changes in the volatility of the variables under analysis, but can also influence their levels.

Our approach allows simultaneous estimation of the uncertainty measures and their impact on the economy, providing also a coherent measure of the uncertainty around them, while most existing studies (with the notable exception of Creal and Wu 2016) rely on a two-step approach with one model used to estimate uncertainty and a second one to assess its effects.

In estimates of the model with U.S. data, we find substantial commonality in uncertainty, sizable effects of uncertainty on key macroeconomic and financial variables with responses in line with economic theory, and some uncertainty about uncertainty and its effects. We provide results separately for macroeconomic and financial uncertainty, showing that macro uncertainty shocks have a major impact on macroeconomic variables but their effects do not transmit substantially to financial variables, whereas financial uncertainty shocks have significant effects on financial variables but also substantially transmit to the macroeconomy. However, looking at the historical contribution of realized uncertainty shocks to macroeconomic fluctuations, the general picture is that while shocks to uncertainty contribute to the Great Recession and subsequent recovery, they are dominated by the VAR's shocks, and as a general matter they play a modest role in macroeconomic and financial fluctuations. Finally, in an assessment of predictive distributions over recent years, we find that shocks (increases) to uncertainty affect not only the centers of the distributions but also the shapes of the distributions, causing the distributions to rotate downward.

7 References

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Table 1: Variables in the baseline model

Macroeconomic variables	*Financial variables*
All employees: total nonfarm ($\Delta \ln$)	S&P 500 ($\Delta \ln$)
Industrial production index ($\Delta \ln$)	Spread, Baa-10y Treasury
Capacity utilization: manufacturing (Δ)	Excess return
Help wanted to unemployed ratio (Δ)	SMB FF factor
Unemployment rate (Δ)	HML FF factor
Real personal income ($\Delta \ln$)	Momentum factor
Weekly hours: goods-producing	R15_R11
Housing starts (ln)	Industry 1 return
Housing permits (ln)	Industry 2 return
Real consumer spending ($\Delta \ln$)	Industry 3 return
Real manuf. and trade sales ($\Delta \ln$)	Industry 4 return
ISM: new orders index	Industry 5 return
Orders for durable goods ($\Delta \ln$)	
Avg. hourly earnings, goods-producing ($\Delta^2 \ln$)	
PPI, finished goods ($\Delta^2 \ln$)	
PPI, commodities ($\Delta^2 \ln$)	
PCE price index ($\Delta^2 \ln$)	
Federal funds rate (Δ)	

Note: For those variables transformed for use in the model, the table indicates the transformation in parentheses following the variable description.

Table 2: Correlations of uncertainty shocks with other shocks

known shock	macro uncertainty shock	financial uncertainty shock
Productivity: Fernald TFP	0.057	0.120
(1960:Q4-2014:Q2)	(0.425)	(0.137)
Oil supply: Hamilton (2003)	0.059	0.052
(1960:Q4-2014:Q2)	(0.333)	(0.388)
Oil supply: Kilian (2008)	-0.115	-0.025
(1971:Q1-2004:Q3)	(0.241)	(0.827)
Monetary policy: Guykaynak, et al. (2005)	-0.009	0.128
(1990:Q1-2004:Q4)	(0.928)	(0.136)
Monetary policy: Coibion, et al. (2016)	-0.097	0.001
(1969:Q1-2008:Q4)	(0.451)	(0.995)
Fiscal policy: Ramey (2011)	0.044	0.087
(1960:Q4-2008:Q4)	(0.681)	(0.118)
Fiscal policy: Mertens and Ravn (2012)	-0.031	-0.027
(1960:Q4-2006:Q4)	(0.692)	(0.592)

Notes: The table provides the correlations of the orthogonalized shocks to uncertainty (measured as the posterior medians of $C_{\Phi}^{-1}u_t$, where C_{Φ} denotes the Choleski decomposition of Φ) with selected macroeconomic shocks. The monthly shocks from the model are averaged to the quarterly frequency. Entries in parentheses provide the sample period of the correlation estimate (column 1) and the p-values of t-statistics of the coefficient obtained by regressing the uncertainty shock on the macroeconomic shock (and a constant). The variances underlying the t-statistics are computed with the pre-whitened quadratic spectral estimator of Andrews and Monaghan (1992).

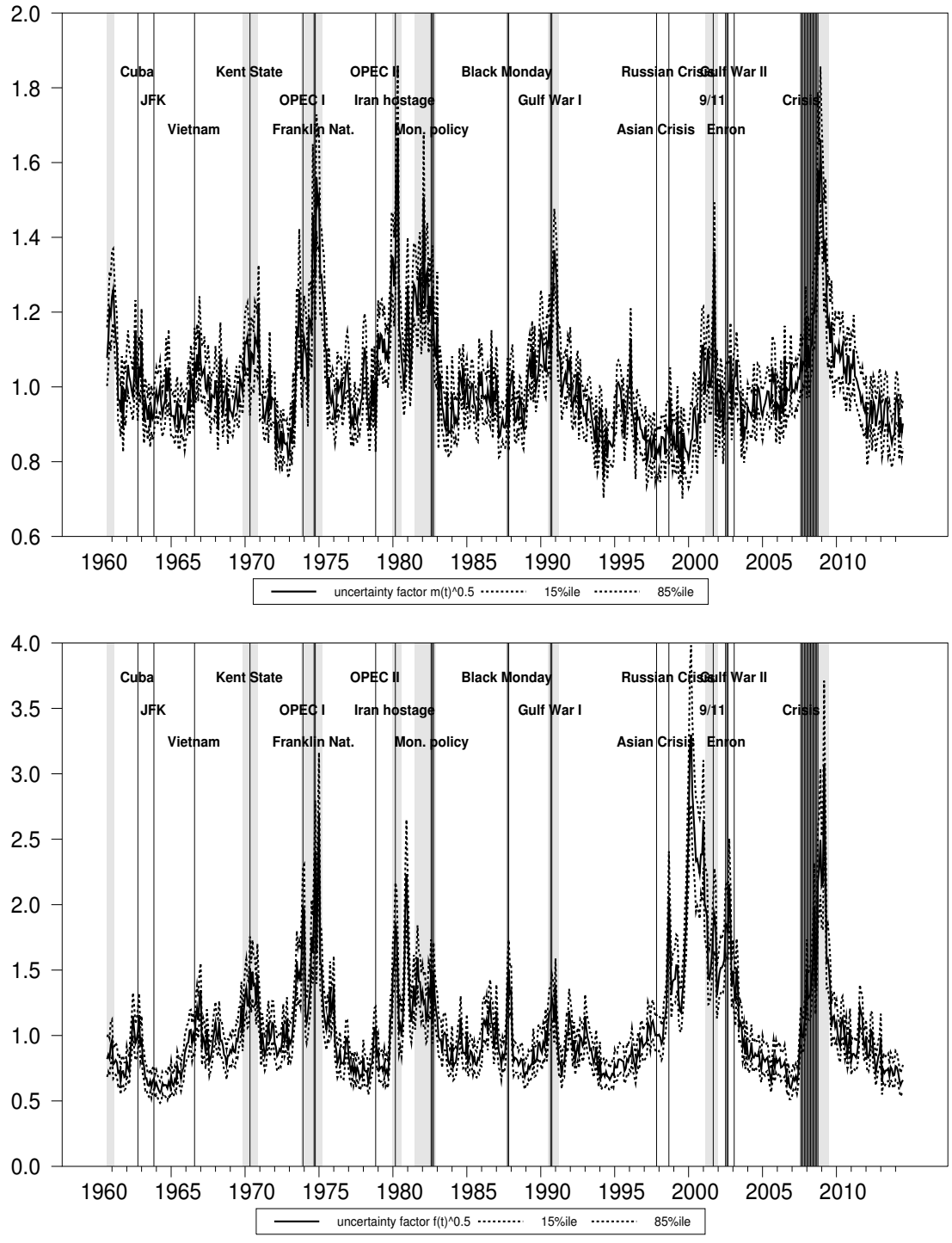

Figure 1: Uncertainty estimates: posterior median (solid black line) and 15%/85% quantiles (dotted lines), with macro uncertainty ($m_t^{0.5}$) in the top panel and financial uncertainty ($f_t^{0.5}$) in the bottom panel. The gray shading indicates periods of NBER recessions. The periods indicated by black vertical lines or regions correspond to the uncertainty events highlighted in Bloom (2009). Labels for these events are indicated in text horizontally centered on the event's start date.

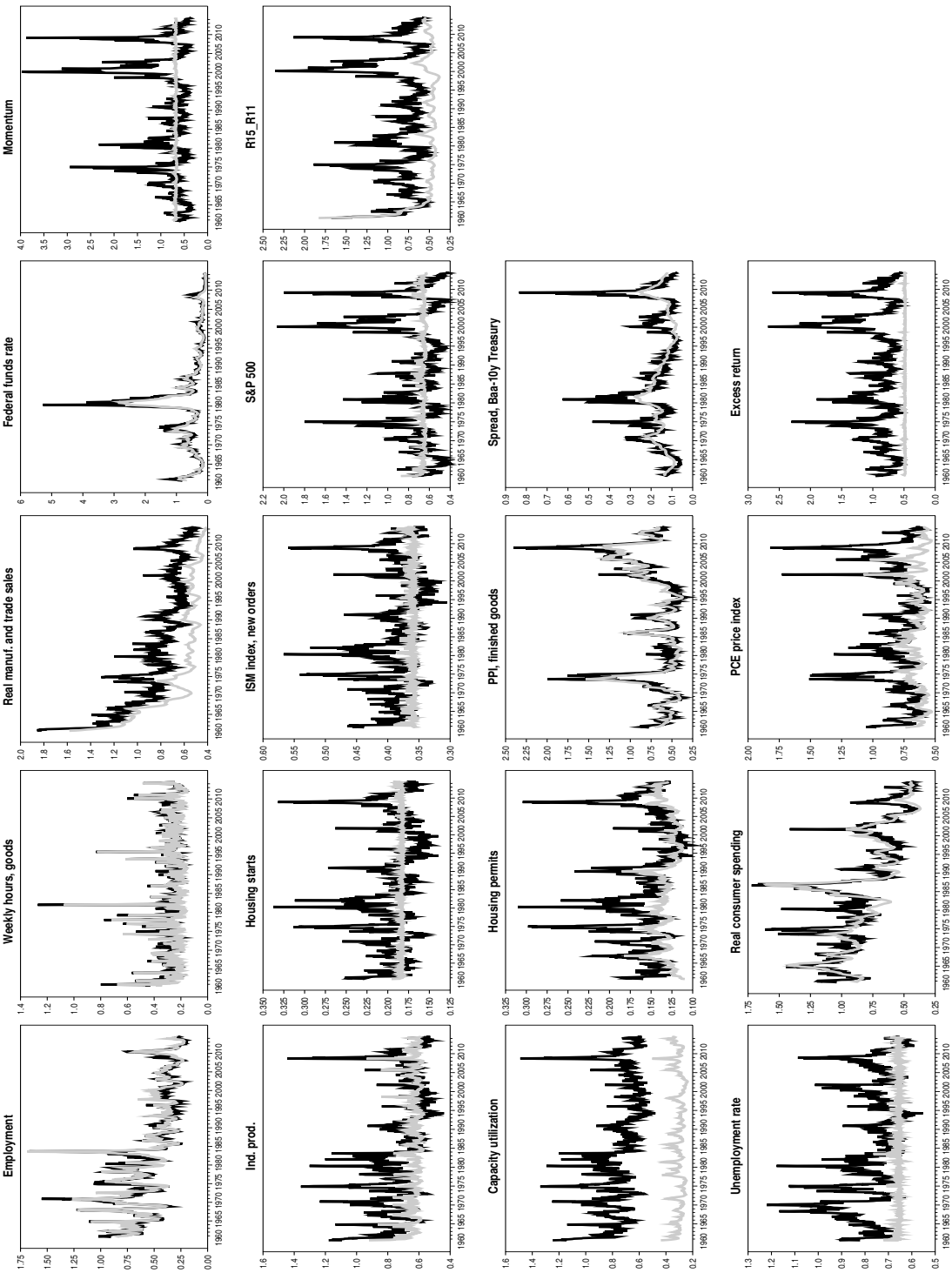

Figure 2: Reduced-form (black line) and idiosyncratic volatilities ($h_{i,t}^{0.5}$, gray line), selected variables, posterior medians

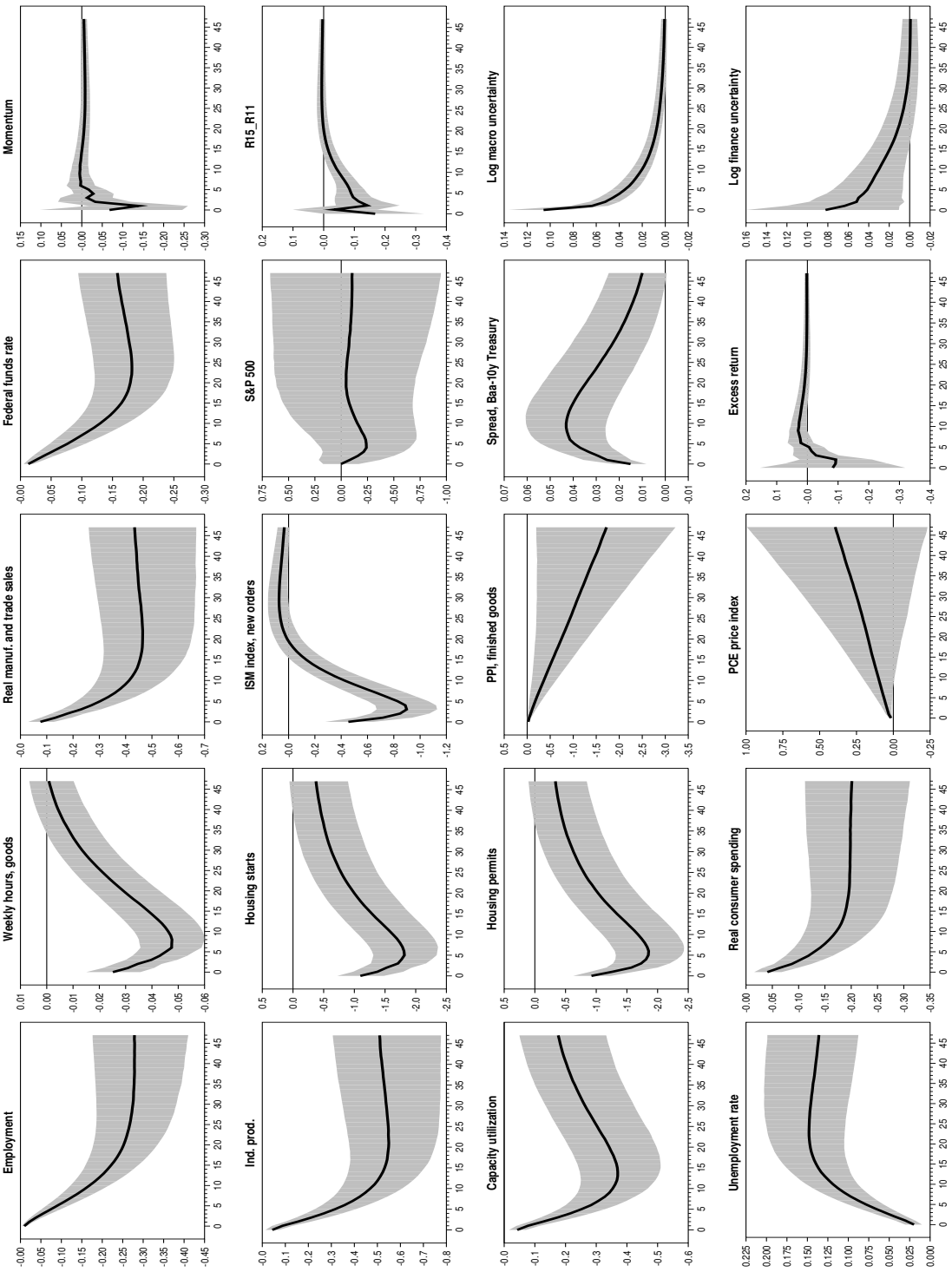

Figure 3: Impulse responses for one standard deviation shock to macro uncertainty, selected variables, posterior median (black line) and 15%/85% quantiles (gray shading)

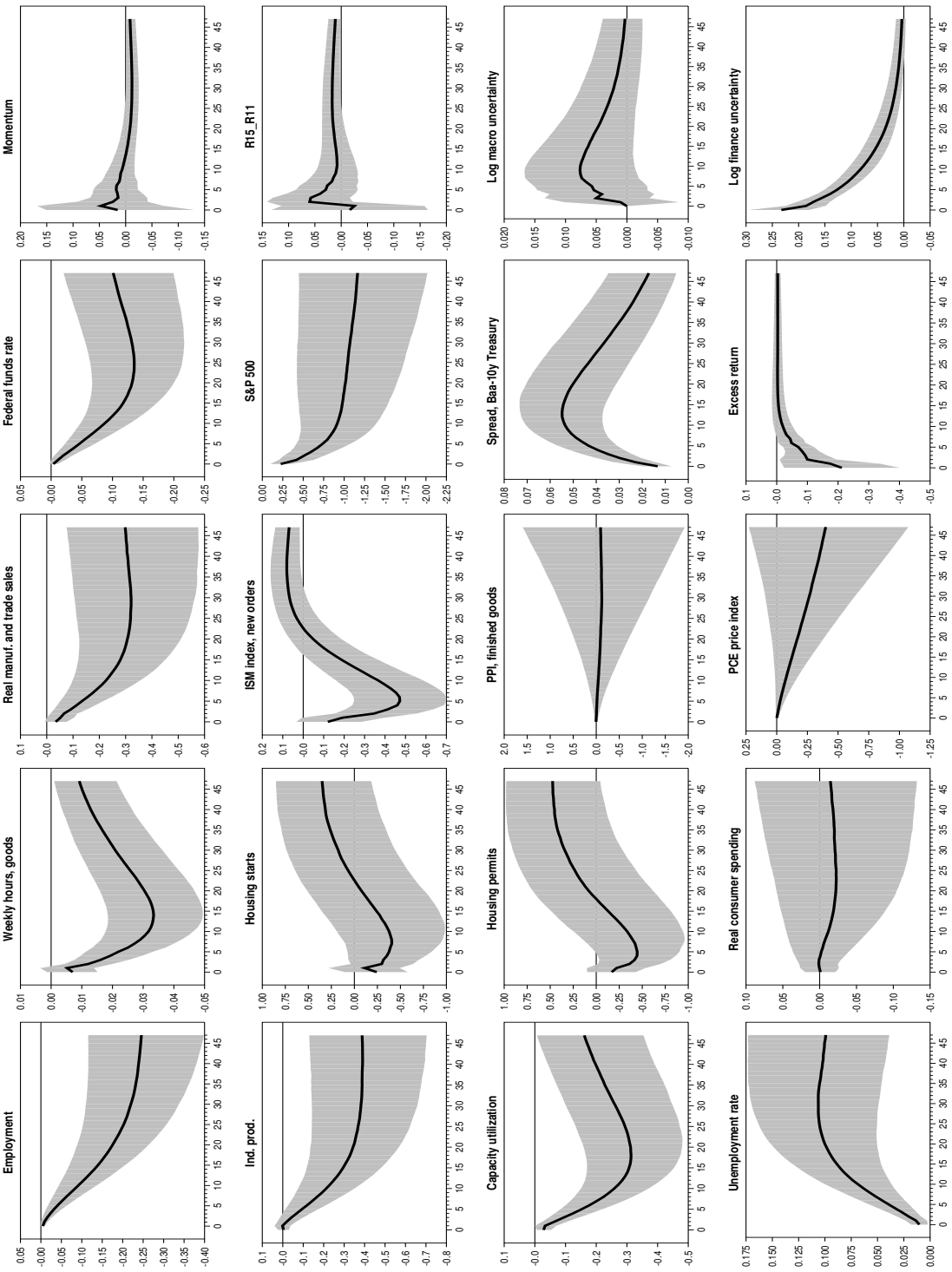

Figure 4: Impulse responses for one standard deviation shock to financial uncertainty, selected variables, posterior median (black line) and 15%/85% quantiles (gray shading)

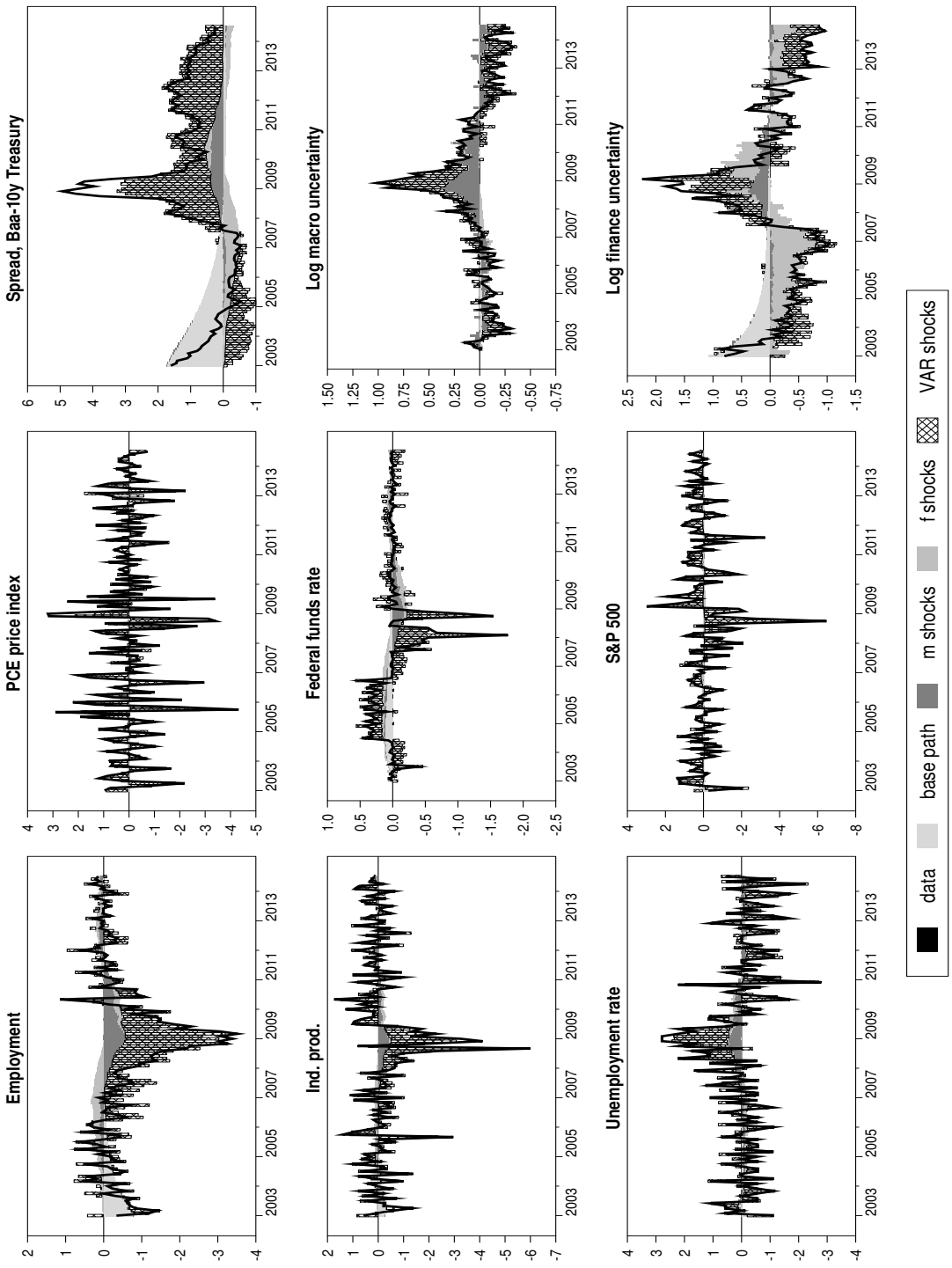

Figure 5: Historical decomposition for 2003-2014, selected variables, posterior medians, with actual data series in solid black line

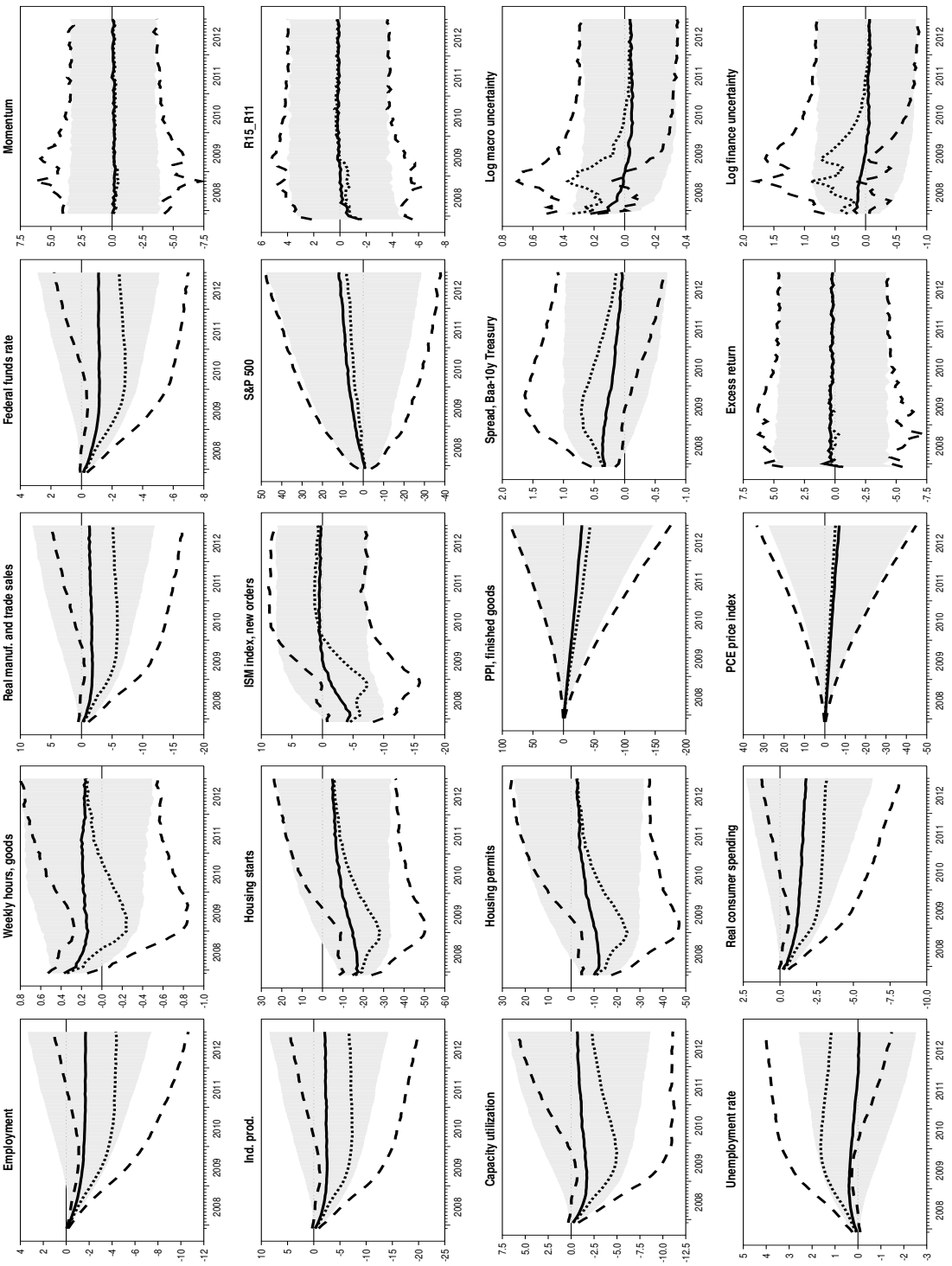

Figure 6: Effects of uncertainty shocks on predictive distributions, December 2007 through December 2012, selected variables. The baseline path is reported as the solid black line (median) with gray shading (15%/85% quantiles). The path with the effects of the estimated uncertainty shocks over the period is reported as the dotted line (median) with dashed lines (15%/85% quantiles).