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Measuring Uncertainty and Its Impact on the Economy

Andrea Carriero, Todd E. Clark, and Massimiliano Marcellino

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We propose a new framework for measuring uncertainty and its effects on the economy, based on a large VAR model with errors whose stochastic volatility is driven by two common unobservable factors, representing aggregate macroeconomic and financial uncertainty. The uncertainty measures can also influence the levels of the variables so that, contrary to most existing measures, ours 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. Moreover, identification of the uncertainty shocks is simplified with respect to standard VAR-based analysis, in line with the FAVAR approach and with heteroskedasticity-based identification. Finally, the model, which is also applicable in other contexts, is estimated with a new Bayesian algorithm, which is computationally efficient and allows for jointly modeling many variables, while previous VAR models with stochastic volatility could only handle a handful of variables. Empirically, we apply the method to estimate uncertainty and its effects using US data, finding that there is indeed substantial commonality in uncertainty, sizable effects of uncertainty on key macroeconomic and financial variables with responses in line with economic theory.

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J.E.L. Classification: E44, C11, C13, C33, C55.

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Andrea Carriero is at Queen Mary, University of London (a.carriero@qmul.ac.uk), Todd E. Clark is at the Federal Reserve Bank of Cleveland (todd.clark@clev.frb.org), and Massimiliano Marcellino is at Bocconi University, IGIER and CEPR (massimiliano.marcellino@unibocconi.it). The authors thank Brent Bundick, Josh Chan, Soojin Jo, Gary Koop, Haroon Mumtaz, Rodrigo Sekkel, Minchul Shin, Stephen Terry, Molin Zhong, and seminar participants at the NBER Summer Institute, Federal Reserve Bank of Cleveland, SBIES conference in Philadelphia, John Hopkins University, and the Barcelona summer meeting for several useful comments on an earlier draft. The authors are particularly grateful to Drew Creal for both comments on the paper and his advice on the particle Gibbs sampler. Carriero gratefully acknowledges support for this work from the Economic and Social Research Council [ES/K010611/1], and Marcellino from the Baffi-Carefin center.

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 (2015), Caggiano, Castelnuovo and Groshenny (2014), Gilchrist, Sim and Zakrajsek (2014), Jo and Sekkel (2015), Jurado, Ludvigson, and Ng (2015), and Ludvigson, Ma, and Ng (2016); Bloom (2014) surveys related work.

As noted in Creal and Wu (2016), a common denominator of most of the contributions in the literature is the fact that some measures of uncertainty (either financial, or macroeconomic, 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 (2015) 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 VAR model 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. Therefore the inference heavily relies on the first-step estimates being consistent, which might or might not be the case, depending on whether the size of the cross section is large enough, or whether the model used in the first step is correctly specified.[1] If consistency is not achieved, the second step can potentially suffer from measurement errors in the regressors, which might lead to an endogeneity bias.[2] A related problem is that the uncertainty around the uncertainty estimates can not be 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).

Fourth, most of the structural analyses carried out in the existing work rely on a Cholesky scheme for identification. While such a scheme has some merits, it requires taking a stand on the appropriate ordering of the variables, a choice which is not obvious, since it is unclear whether uncertainty is an impulse or propagation mechanism. Some recent studies making use of financial data develop alternative approaches intended to better address the impulse vs. propagation question. Using a two-step treatment of uncertainty and its effects and a small VAR, Ludvigson, Ma, and Ng (2016) develop an instrumental

[1] One might worry less about this in a large cross-section approach such as that of Jurado, Ludvigson, and Ng (2015). However, the formal analytics underlying the consistency of factor estimates are based on cases in which the dependent variables are data series rather than (stochastic volatility) estimates from a model. Even if one is not concerned with such complications, it is preferable to have an approach which works well in not-large cross sections.

[2] 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.

variables estimator that makes use of synthetic external variables. Berger, Dew-Becker, and Giglio (2016) make use of a distinction between realized stock market volatility and expected future volatility, also with small VARs.

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) 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 avoids problems of misspecification, omitted variable bias, and non-fundamentalness. Finally, the fact that uncertainty is defined as the common component of the time-varying volatilities allows us to uniquely identify uncertainty shocks without having to resort to a Cholesky (or other) identification scheme.

In the discussion so far we have generically referred to uncertainty. More specifically, we consider both macroeconomic and financial uncertainty. Each of these measures of uncertainty 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 variables. Hence, macroeconomic uncertainty can affect financial uncertainty and vice versa, and both can be affected by the business cycle and financial fluctuations. Moreover, the vector of macro and financial uncertainty enters the conditional means of the large VAR equations. As a consequence, macro and financial uncertainty are allowed to contemporaneously affect the macroeconomy and financial conditions.

The model is estimated via a new MCMC algorithm, which is computationally efficient and makes tractable estimation of large models with stochastic volatility (SV). 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.

Our proposed modeling framework extends the seminal work of Jurado, Ludvigson, and Ng (2015) [hereafter, JLN] in several ways. In the JLN approach, individual measures of uncertainty are built for each variable, using an augmented factor model for each variable assuming that uncertainty does not affect the conditional mean, and an aggregate uncertainty measure is formed as an average of these individual estimates. Then, in a second step, the uncertainty estimate is treated as data and inserted into a separate small VAR to compute its effects on the macroeconomy. This approach relies on an identification assumption about structural shocks, and it rules out an assessment of the uncertainty around uncertainty in conducting inference on uncertainty's macroeconomic effects. In our VAR-based framework, the estimate of uncertainty is obtained from a joint model in which uncertainty affects the conditional mean and variances of each variable in the VAR, there is no need to resort to standard VAR based procedures to identify the uncertainty shock, and the estimates of the effects of uncertainty reflect the uncertainty around the measure of uncertainty.

In light of research and practical interest in the interaction of macroeconomic and financial uncertainty, and their effects on the economy, Ludvigson, Ma, and Ng (2016) [hereafter, LMN] develop a model featuring both financial and macroeconomic uncertainty. LMN estimate financial uncertainty using the methodology of JLN, applied to a large set of financial indicators. They then model financial uncertainty, GDP growth and JLN-type macroeconomic uncertainty first in a 3-variable VAR and then in a slightly larger VAR, and study the transmission of financial and macroeconomic uncertainty shocks, using a novel identification procedure that avoids a Cholesky ordering of the variables. Their findings indicate that "higher uncertainty about real economic activity in recessions is fully an endogenous response to business cycle fluctuations, while uncertainty about financial markets is a likely source of them." However, in their approach the uncertainty measures are still both estimated in a preliminary step (using a model that assumes volatilities do not affect the conditional means of variables) and then plugged into a small scale homoskedastic model.

Creal and Wu (2016) develop a model of bond yields and a small set of macroeconomic variables that extends a typical term structure model to allow uncertainty about monetary policy to affect economic activity and bond yields. Their model, like ours, jointly treats uncertainty as a factor in volatility and in conditional means of macroeconomic variables and interest rates. To borrow their wording, the model internalizes the uncertainty. Their estimates show a total of four volatility factors to be important, capturing uncertainty about macroeconomic variables, monetary policy, and the term premium. At a high level, our approach differs in that it permits a relatively large data set, allows uncertainty to affect the levels and volatilities of the variables of interest contemporaneously rather than with a lag, and allows volatility to respond to lagged variables.

Our approach also significantly extends some other, previous econometric work on modeling uncertainty, all using small models. Alessandri and Mumtaz (2014) develop a small nonlinear VAR in four variables that allows volatility to enter the conditional means. However, in order to estimate the common factor they adopt the common volatility specification of Carriero, Clark and Marcellino (2016a), which is more restrictive than the formulation we present here, because there cannot be idiosyncratic volatility and the loadings on the common volatility factor must be all equal across variables. Moreover, their model cannot handle a large dataset, which is instead key for a proper estimation of aggregate uncertainty, a result which was emphasized by JLN and that is also confirmed by the empirical evidence we will provide.

Other contributions in the literature have also proposed the inclusion of volatility in the conditional mean of a VAR, without resorting to a common factor specification for the volatilities. Jo (2014) studies the effects of oil price uncertainty on global real economic activity using a VAR model with stochastic volatility in mean and finds that the effects are sizable. While these results on oil price uncertainty are useful, the VAR is for a small set of variables and the volatilities for each variable are treated as independent processes. Shin and Zhong (2015) introduce a new small VAR model with stochastic volatility, also allowing for volatility-in-mean, in order to study the real effects of uncertainty shocks, which are identified by imposing restrictions on the first and second moment responses of the variables to the uncertainty shock. They provide theoretical methods for estimation and inference for the new model, with the more general structural identification procedure; empirically, they find evidence that an increase in uncertainty leads to a decline in industrial production only if associated with a deterioration in financial conditions. With respect to their specification, we can model a much larger number of variables and allow for a factor structure in the volatilities, permitting us to define uncertainty as the common factor in volatility.

We apply our proposed model to monthly US 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 is mainly due to the use of a large information set, as already pointed out by Giannone, Lenza and Reichlin (2008), and to the monthly frequency of the variables we analyze, as indeed we find somewhat stronger evidence of a moderation in volatility after the mid 1980s when repeating the analysis with quarterly data.

As noted above, we separately identify a macroeconomic uncertainty measure and a financial uncertainty measure. In impulse response analysis, we document sizable effects of uncertainty shocks on many macroeconomic and financial variables. 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, the response of the housing market and consumption expenditures to financial uncertainty is insignificant) as much as a shock to macro uncertainty does. Both types of shocks also cause the credit spread in the model to rise (modestly but significantly). However, for other financial variables, results are more mixed: we find that surprise increases to financial uncertainty reduce measures of aggregate stock prices and returns, whereas the effects of increases in macro uncertainty are not significant.

Therefore, the overall picture emerging from our empirical application is 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, a finding in line with, e.g., LMN.

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.

2 A joint model of uncertainty and business cycle fluctuations

In this section we present the model that we use to estimate aggregate uncertainty and its effects on the economy. We start by summarizing the main features of the model, highlighting the relation and differences with other approaches. Then we discuss, in turn, model specification and estimation. We also detail the univariate autoregressive (AR) model with stochastic volatility we use in some comparisons.

2.1 The model

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.[3] 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. Therefore, our modeling approach allows for uncertainty to contemporaneously affect the macroeconomy, through both first (means) and second order (variances) effects. 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.[4] Finally, it is

[3]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, with studies such as Koop (2013) and Carriero, Clark and Marcellino (2015) suggesting that about 20 carefully selected macroeconomic and financial variables could be sufficient.

[4]Conditional heteroskedasticity in-mean was introduced by French, et al. (1987) with the GARCH-in-mean model. Macroeconomic applications include Elder (2004) and Elder and Serletis (2010) for, respectively, inflation and oil price uncertainty. Koopman and Uspensky (2002) and Chan (2015) introduce univariate stochastic volatility-in-mean models, and Jo (2014) and Shin and Zhong (2015) consider multivariate

worth emphasizing that our model features time variation in the volatilities, and this time variation is driven in part by the uncertainty measures, which means that shocks to the measures of uncertainty are uniquely identified, without resorting to a Cholesky or other identification scheme.

2.2 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 (we discuss below evidence that supports two uncertainty factors). 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 modeled as:

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

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 generic j-th element

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

which implies that the log-volatilities follow a linear factor model:

$$\ln \lambda_{jt} = \begin{cases} \beta_{m,j} \ln m_t + \ln h_{j,t},\ j = 1, \ldots, n_m \\ \beta_{f,j} \ln f_t + \ln h_{j,t},\ j = n_m + 1, \ldots, n \end{cases}. \tag{3}$$

We discuss below the rationale for the block specification of (3), 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 (in the estimates, the AR specification captures serial correlation that is sizable for some variables):

$$\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1} + e_{j,t},\ j = 1, \ldots, n, \tag{4}$$

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.

VAR extensions with independent volatility processes.

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 JLN. A second reason is that two dynamic factors appear sufficient. Carriero, Clark, and Marcellino (2016b) estimate a 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 to account for the vast majority of innovations to volatilities.

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

$$\begin{bmatrix} \ln m_t \\ \ln f_t \end{bmatrix} = D(L) \begin{bmatrix} \ln m_{t-1} \\ \ln f_{t-1} \end{bmatrix} + \begin{bmatrix} \delta'_m \\ \delta'_f \end{bmatrix} y_{t-1} + \begin{bmatrix} u_{m,t} \\ u_{f,t} \end{bmatrix}, \tag{5}$$

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 (5) 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. The inclusion of y_{t-1} in the volatility factor processes can be seen as a version of the leverage effect sometimes included in stochastic volatility models of financial returns. 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. In addition, for identification, we deliberately include the block restrictions of factor loadings in the volatilities specification of (2) in order to allow the comovement between uncertainties captured in the VAR structure and correlated innovations of (5). Conceptually, we believe these block restrictions to be consistent with broad definitions of uncertainty: macro uncertainty is the common factor in the error variances of macro variables, and finance uncertainty is the common factor in the error variances of finance variables. However, these uncertainties are not necessarily independent; they can 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 of interest y_t, contemporaneously and with lags. In particular, y_t is assumed to follow:

$$y_t = \Pi(L)y_{t-1} + \Pi_m(L)\ln m_t + \Pi_f(L)\ln f_t + v_t, \qquad (6)$$

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 each 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. The specification above ensures that business cycle fluctuations respond to movements in uncertainty (macro and financial), 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 $\Pi_f(L)$). The model above differs some in timing with respect to Creal and Wu (2016) and some models of stochastic volatility with leverage in finance (e.g., Omori, et al. 2007). 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 and Shin and Zhong 2015) and the volatility-with-leverage specification of Jacquier, Polson, and Rossi (2004). 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 $t-1$, and in finance applications such as Omori, et al. (2007), volatility is similarly lagged. We find our approach natural for assessing the effects of macro and financial uncertainty, but other approaches are certainly feasible.

The model in (1)-(6) is related to Carriero, Clark and Marcellino (2016a), who impose $\Pi_m(L) = \Pi_f(L) = 0$ and consider a small model for computational reasons. However, as discussed in the introduction, when measuring uncertainty it appears to be important to allow n to be large and to permit direct effects of uncertainty on the endogenous macroeconomic and financial variables ($\Pi_m(L) \neq 0,\ \Pi_f(L) \neq 0$).[5]

The model is also related to Cogley and Sargent (2005) and Primiceri (2005), who also impose $\Pi_m(L) = \Pi_f(L) = 0$ and, in addition, assume that there is no factor structure in the

[5] 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.

volatilities, which amounts to setting $\beta_j = 0$.[6] Finally, the model is related to Alessandri and Mumtaz (2014), who assume that $\beta_j = 1$ for all j, and $\ln h_{j,t} = 0$. 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 suited in this context, as with n large both restrictions are not likely to hold in the data (and indeed Alessandri and Mumtaz (2014) analyze four variables only).

The model in (1)-(6) 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 (2015), who allow for stochastic volatility both in v_t and in the error driving the common factor, u_t.

It is worth mentioning that our model could be applied in a variety of other contexts where volatilities are likely to follow a factor structure and affect the levels of the variables, for example models for stock returns or the term structure of interest rates.

Working with a model as general as (1)-(6) substantially complicates estimation, as we discuss in the next subsection. The reader not interested in technicalities can skip to Section 3. In implementation, we set the VAR lag order at $p = 6$ in monthly data (we use $p = 4$ in some supplemental results with quarterly data). We set the lag order for the uncertainty factors in the VAR's conditional mean (p_m and p_f) at 2, so that, for both uncertainty measures, the model includes the current value and two lags. We also conduct a robustness check with a model in which the current value of uncertainty is zeroed out, so that there are no contemporaneous effects of uncertainty on the conditional means of the VAR. Finally, we set the lag order of the bivariate VAR in the uncertainty factors (d) to 2.

2.3 Triangularization for estimation

In a Bayesian setting, estimation and inference on the model parameters and unobservable states are based on their posterior distributions. The latter can be obtained by combining the likelihood of the model with prior distributions for the parameters and states. Often, analytical posteriors are not available but draws from them can be obtained by MCMC samplers. However, this is in general so computationally intensive for models with stochastic volatilities that practical implementation of these models has been limited to a handful of variables, with n typically in the range of 3 to 5. To make estimation feasible in a model with

[6] 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.

a large number of variables and stochastic volatility, we exploit the VAR triangularization of Carriero, Clark and Marcellino (2016b), who consider the case $\Pi_m(L) = \Pi_f(L) = 0$ and stochastic volatilities without a common factor structure. With the triangularization, our estimation algorithm will block the conditional posterior distribution of the system of VAR coefficients in n different blocks. In the step of the typical Gibbs sampler that involves drawing the set of VAR coefficients Π, all of the remaining model coefficients are given. Consider again the reduced form residuals $v_t = A^{-1}\Lambda_t^{0.5}\epsilon_t$:

$$\begin{bmatrix} v_{1,t} \\ v_{2,t} \\ ... \\ v_{n,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & ... & 0 \\ a^*_{2,1} & 1 & & ... \\ ... & & 1 & 0 \\ a^*_{n,1} & ... & a^*_{n,n-1} & 1 \end{bmatrix} \begin{bmatrix} \lambda_{1,t}^{0.5} & 0 & ... & 0 \\ 0 & \lambda_{2,t}^{0.5} & & ... \\ ... & & ... & 0 \\ 0 & ... & 0 & \lambda_{n,t}^{0.5} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ ... \\ \epsilon_{n,t} \end{bmatrix}, \tag{7}$$

where $a^*_{j,i}$ denotes the generic element of the matrix A^{-1} which is available under knowledge of A. The VAR can be written as:

$$\begin{aligned} y_{1,t} &= \sum_{i=1}^{n}\sum_{l=1}^{p}\pi_{1,l}^{(i)}y_{i,t-l} + \sum_{l=0}^{p_m}\pi_{l,1}^{(m)}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi_{l,1}^{(f)}\ln f_{t-l} + \lambda_{1,t}^{0.5}\epsilon_{1,t} \\ y_{2,t} &= \sum_{i=1}^{n}\sum_{l=1}^{p}\pi_{2,l}^{(i)}y_{i,t-l} + \sum_{l=0}^{p_m}\pi_{l,2}^{(m)}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi_{l,2}^{(f)}\ln f_{t-l} + a^*_{2,1}\lambda_{1,t}^{0.5}\epsilon_{1,t} + \lambda_{2,t}^{0.5}\epsilon_{2,t} \\ & ... \\ y_{n,t} &= \sum_{i=1}^{n}\sum_{l=1}^{p}\pi_{n,l}^{(i)}y_{i,t-l} + \sum_{l=0}^{p_m}\pi_{l,N}^{(m)}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi_{l,N}^{(f)}\ln f_{t-l} + a^*_{n,1}\lambda_{1,t}^{0.5}\epsilon_{1,t} + \cdots \\ & ... + a^*_{n,n-1}\lambda_{n-1,t}^{0.5}\epsilon_{n-1,t} + \lambda_{n,t}^{0.5}\epsilon_{n,t}, \end{aligned}$$

with the generic equation for variable j:

$$\begin{aligned} & y_{j,t} - (a^*_{j,1}\lambda_{1,t}^{0.5}\epsilon_{1,t} + \cdots + a^*_{j,,j-1}\lambda_{j-1,t}^{0.5}\epsilon_{j-1,t}) \\ = & \sum_{i=1}^{n}\sum_{l=1}^{p}\pi_{j,l}^{(i)}y_{i,t-l} + \sum_{l=0}^{p_m}\pi_{l,j}^{(m)}\ln m_{t-l} + \sum_{l=0}^{p_f}\pi_{l,j}^{(f)}\ln f_{t-l} + \lambda_{j,t}\epsilon_{j,t}. \end{aligned} \tag{8}$$

Consider estimating these equations in order from $j = 1$ to $j = n$. When estimating the generic equation j the term of the left hand side in (8) is known, since it is given by the difference between the dependent variable of that equation and the estimated residuals of all the previous $j - 1$ equations. Therefore we can define:

$$y^*_{j,t} = y_{j,t} - (a^*_{j,1}\lambda_{1,t}^{0.5}\epsilon_{1,t} + \cdots + a^*_{j,,j-1}\lambda_{j-1,t}^{0.5}\epsilon_{j-1,t}), \tag{9}$$

and equation (8) becomes a standard generalized linear regression model for the variable in equation (9) with Gaussian disturbances with mean 0 and variance $\lambda_{j,t}$.

Accordingly, drawing on results detailed in Carriero, Clark and Marcellino (2016b), the posterior distribution of the VAR coefficients can be factorized as:

$$\begin{aligned} p(\Pi|A,\beta,f_{1:T},m_{1:T},h_{1:T},y_{1:T}) &= p(\pi^{(n)}|\pi^{(n-1)},\pi^{(n-2)},\ldots,\pi^{(1)},A,\beta,f_{1:T},m_{1:T},h_{1:T},y_{1:T}) \\ &\quad \times p(\pi^{(n-1)}|\pi^{(n-2)},\ldots,\pi^{(1)},A,\beta,f_{1:T},m_{1:T},h_{1:T},y_{1:T}) \\ &\quad \times p(\pi^{(1)}|A,\beta,f_{1:T},m_{1:T},h_{1:T},y_{1:T}), \end{aligned}$$

where the vector β collects the loadings of the uncertainty factors and $f_{1:T}$, $m_{1:T}$, $h_{1:T} = (h_{1,T},...,h_{n,T})$, and $y_{1:T}$ denote the history of the states and data up to time T. As a result, we are able to estimate the coefficients of the VAR on an equation-by-equation basis. For reasons discussed in Carriero, Clark and Marcellino (2016b), this greatly speeds estimation and permits us to consider much larger systems than we would otherwise be able to consider. Below we provide further details on the estimation algorithm, allowing for the presence of the unobservable uncertainty factors $f_{1:T}$ and $m_{1:T}$ in the conditional means and variances.

Importantly, although the expression (7) and the following triangular system are based on a Cholesky-type decomposition of the variance Σ_t, the decomposition is simply used as an estimation device, not as a way to identify structural shocks. The ordering of the variables in the system does not change the joint (conditional) posterior of the reduced form coefficients, so changing the order of the variables is inconsequential to the results.[7] Moreover, since a shock to uncertainty is uncorrelated with shocks to the conditional mean of the variables, the ordering of the variables in the system has no influence on the shape of impulse responses in our application.

We now discuss in turn the general organization of the MCMC algorithm, estimation of the model coefficients, unobservable states, and the details of the MCMC algorithm used to draw from the joint posterior of coefficients and states. Note that all results in the paper are based on a sample of 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.

[7] This statement refers to drawing from the conditional posterior of the conditional mean parameters, when Σ_t belongs to the conditioning set. One needs also to keep in mind that 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.

2.4 General steps of MCMC algorithm

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 $\gamma = \{\gamma_1, ..., \gamma_n\}$, which collects the coefficients appearing in the conditional means of the transition equations for the states $h_{1:T}$, and $\delta = \{D(L), \delta_m', \delta_f'\}$, which collects the coefficients appearing 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)-(6), except the vector of factor loadings β, into

$$\Theta = \{\Pi, A, \gamma, \delta, \Phi_v, \Phi_u\}. \tag{10}$$

Let $s_{1:T}$ denote the time series of the mixture states used in the Kim, Shephard, and Chib (1998) algorithm (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. $h_{1:T}, \beta \mid \Theta, s_{1:T}, m_{1:T}, f_{1:T}$
2. $\Theta, s_{1:T}, m_{1:T}, f_{1:T} \mid h_{1:T}, \beta$.

The first step relies on a state space system. Defining the rescaled residuals $\tilde{v}_t = Av_t$, taking the log squares of (1), subtracting out the known (in the conditional posterior) contributions of the common factors, and using (3) yields the observation equations ($\bar{c}$ denotes an offset constant used to avoid problems with near-zero values):

$$\begin{cases} \ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{m,j} \ln m_t = \ln h_{j,t} + \ln \epsilon_{j,t}^2, \; j = 1, \ldots, n_m \\ \ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{f,j} \ln f_t = \ln h_{j,t} + \ln \epsilon_{j,t}^2, \; j = n_m + 1, \ldots, n. \end{cases} \tag{11}$$

For the idiosyncratic volatility components, the transition and measurement equations of the state-space system are given by (4) and (11), 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) [hereafter, KSC] 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 ($h_{1:T} \mid \beta$, Θ, $s_{1:T}$, $m_{1:T}$, $f_{1:T}$), following Primiceri's (2005) implementation of the KSC algorithm, and by then (b) drawing the loadings given the states using ($\beta \mid h_{1:T}$, Θ, $s_{1:T}$, $m_{1:T}$, $f_{1:T}$), using the conditional posterior detailed below in (22).[8]

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 Θ, $s_{1:T}$, $f_{1:T} \mid h_{1:T}$, β are obtained in three sub-steps from, respectively: (a) $\Theta \mid m_{1:T}$, $f_{1:T}$, $h_{1:T}$, β; (b) $m_{1:T}$, $f_{1:T} \mid \Theta$, $h_{1:T}$, β; and (c) $s_{1:T} \mid \Theta$, $m_{1:T}$, $f_{1:T}$, $h_{1:T}$, β. More specifically, for $\Theta \mid m_{1:T}$, $f_{1:T}$, $h_{1:T}$, β we use the posteriors detailed below, equations (20), (21), (23), (24), (25), and (26). For $m_{1:T}$, $f_{1:T} \mid \Theta$, $h_{1:T}$, β, we use the particle Gibbs step proposed by Andrieu, Doucet, and Holenstein (2010). For $s_{1:T} \mid \Theta$, $m_{1:T}$, $f_{1:T}$, $h_{1:T}$, β, we use the 10-state mixture approximation of Omori, et al. (2007) that improves on Kim, Shephard, and Chib's (1998) 7-state approximation.

2.4.1 Coefficient priors and posteriors

This subsection details the priors and posteriors we use in the algorithm characterized above. We specify the following (independent) priors for the parameter blocks of the model (parameterization details are given in the appendix):

$$\mathrm{vec}(\Pi) \sim N(\mathrm{vec}(\underline{\mu}_{\Pi}), \underline{\Omega}_{\Pi}), \tag{13}$$

$$a_j \sim N(\underline{\mu}_{a,j}, \underline{\Omega}_{a,j}),\ j = 2, \ldots, n, \tag{14}$$

$$\beta_j \sim N(\underline{\mu}_{\beta}, \underline{\Omega}_{\beta}),\ j = 2, \ldots, n_m, n_{m+2}, ..., n, \tag{15}$$

$$\gamma_j \sim N(\underline{\mu}_{\gamma}, \underline{\Omega}_{\gamma}),\ j = 1, \ldots, n, \tag{16}$$

$$\delta \sim N(\underline{\mu}_{\delta}, \underline{\Omega}_{\delta}), \tag{17}$$

$$\phi_j \sim IG(d_{\phi} \cdot \underline{\phi}, d_{\phi}),\quad j = 1, \ldots, n, \tag{18}$$

$$\Phi_u \sim IW(d_{\Phi_u} \cdot \underline{\Phi_u}, d_{\Phi_u}). \tag{19}$$

[8] In drawing the loadings, we make use of the information in the observable $\ln(\tilde{v}_{j,t}^2)$, with the following transformation of the observation equations:

$$\ln(\tilde{v}_{j,t}^2 + \bar{c}) - \ln h_{j,t} = \begin{cases} \beta_{m,j} \ln m_t + \ln \epsilon_{j,t}^2,\ j = 1, \ldots, n_m \\ \beta_{f,j} \ln f_t + \ln \epsilon_{j,t}^2,\ j = n_m + 1, \ldots, n. \end{cases} \tag{12}$$

With the conditioning on $h_{1:T}$ and $s_{1:T}$ in the posterior for β, we use this equation, along with the mixture mean and variance associated with the draw of $s_{1:T}$, for sampling the factor loadings with a conditionally normal posterior with mean and variance represented in a GLS form.

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

$$\mathrm{vec}(\Pi)|A,\beta,m_{1:T},f_{1:T},h_{1:T},y_{1:T} \sim N(\mathrm{vec}(\bar{\mu}_{\Pi}),\bar{\Omega}_{\Pi}), \tag{20}$$

$$a_j|\Pi,\beta,m_{1:T},f_{1:T},h_{1:T},y_{1:T} \sim N(\bar{\mu}_{a,j},\bar{\Omega}_{a,j}),\ j=2,\ldots,n, \tag{21}$$

$$\beta_j|\Pi,A,\gamma,\Phi,m_{1:T},f_{1:T},h_{1:T},s_{1:T},y_{1:T} \sim N(\bar{\mu}_{\beta},\bar{\Omega}_{\beta}),\quad j=2,\ldots,n_m,n_{m+2},...,n, \tag{22}$$

$$\gamma_j|\Pi,A,\beta,\Phi,m_{1:T},f_{1:T},h_{1:T},y_{1:T} \sim N(\bar{\mu}_{\gamma},\bar{\Omega}_{\gamma}),\ j=1,\ldots,n, \tag{23}$$

$$\delta|\Pi,A,\gamma,\beta,\Phi,m_{1:T},f_{1:T},h_{1:T},y_{1:T} \sim N(\bar{\mu}_{\delta},\bar{\Omega}_{\delta}), \tag{24}$$

$$\phi_j|\Pi,A,\beta,\gamma,m_{1:T},f_{1:T},h_{1:T},y_{1:T} \sim IG\left(d_{\phi}\cdot\underline{\phi}+\sum_{t=1}^{T}\nu_{jt}^2,\ d_{\phi}+T\right),\ j=1,\ldots,n, \tag{25}$$

$$\Phi_u|\Pi,A,\beta,\delta,\gamma,m_{1:T},f_{1:T},h_{1:T},y_{1:T} \sim IW(d_{\Phi_u}\cdot\underline{\Phi_u}+\sum_{t=1}^{T}u_t^2,d_{\Phi_u}+T). \tag{26}$$

Expressions for $\bar{\mu}_{a,j}$, $\bar{\mu}_{\delta}$, and $\bar{\mu}_{\gamma}$ are straightforward to obtain using standard results from the linear regression model. In the interest of brevity, we omit details for these posteriors; the general solutions for these components are readily available in other sources (e.g., Cogley and Sargent (2005) for the treatment of $\bar{\mu}_{a,j}$). 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, as indicated above. In the case of the VAR coefficients $\bar{\mu}_{\Pi}$, with smaller models it is possible to rely on the GLS solution for the posterior mean given in sources such as Carriero, Clark and Marcellino (2015). However, as discussed above, with larger models, it is far faster to exploit the triangularization discussed above and estimate the VAR coefficients on an equation-by-equation basis.[9] Specifically, using the factorization in (10) together with the model in (8) allows us to draw the coefficients of the matrix Π in separate blocks. Again, 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:

$$\pi^{(j)}|\pi^{(1:j-1)},A,\beta,f_{1:T},m_{1:T},h_{1:T},y_{1:T}\sim N(\bar{\mu}_{\pi^{(j)}},\overline{\Omega}_{\pi^{(j)}}), \tag{27}$$

with

$$\bar{\mu}_{\pi^{(j)}} = \overline{\Omega}_{\pi^{(j)}}\left\{\sum_{t=1}^{T}X_{j,t}\lambda_{j,t}^{-1}y_{j,t}^{*\prime}+\underline{\Omega}_{\pi^{(j)}}^{-1}(\underline{\mu}_{\pi^{(j)}})\right\}, \tag{28}$$

$$\overline{\Omega}_{\pi^{(j)}}^{-1} = \underline{\Omega}_{\pi^{(j)}}^{-1}+\sum_{t=1}^{T}X_{j,t}\lambda_{j,t}^{-1}X_{j,t}^{\prime}, \tag{29}$$

[9]Since the triangularization obtains computational gains of order n^2, the cross-sectional dimension of the system can be extremely large, and indeed Carriero, Clark and Marcellino (2016b) present results for a VAR with 125 variables.

where $y^*_{j,t}$ is defined in (9) and where $\underline{\Omega}^{-1}_{\pi(j)}$ and $\underline{\mu}_{\pi(j)}$ denote 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 $\overline{\Omega}^{-1}_{\Pi}$. Note we have implicitly used the fact that the matrix $\underline{\Omega}^{-1}_{\Pi}$ is block diagonal, which is the case in our application, as our prior on the conditional mean coefficients is independent across equations, with a Minnesota-style form.

2.4.2 Unobservable states

For the unobserved volatility states f_t, m_t, and $h_{j,t}$, $j = 1, ..., n$, we need to specify priors for the period 0 values, detailed in the appendix. Given the priors and the law of motion for the unobservable states in (4)-(5), draws from the posteriors can be obtained using the algorithm of Kim, Shepard and Chib (1998, KSC) for the idiosyncratic volatilities and the particle Gibbs step of Andrieu, Doucet, and Holenstein (2010) for the common volatility factors. In the particle Gibbs sampler of the uncertainty factors, we follow Mumtaz and Theodoridis (2016) in using 50 particles. Note also that Chan (2015) provides a sampler designed to jointly sample the log-volatilities when they appear in the conditional means, but his sampler is only viable in the case of independent log-volatilities, which is not the case of this paper.

2.5 AR-SV model

To facilitate some comparisons to the uncertainty estimates of JLN and LMN, we use an AR model with stochastic volatility (AR-SV) to form measures of uncertainty using a methodology similar to theirs. The AR-SV model for a scalar series y_t takes the following form:

$$y_t = \pi_0 + \pi(L) y_{t-1} + \lambda_t^{0.5} \epsilon_t, \ \epsilon_t \sim iid \ N(0,1), \tag{30}$$

$$\ln \lambda_t = \gamma_0 + \gamma_1 \ln \lambda_{t-1} + e_t, \ e_t \sim iid \ N(0, \phi). \tag{31}$$

For each series, we estimate the model using the full sample of data. We follow the approach of JLN in computing, at each moment in time t, the forecast error variance using the error variance λ_t and the estimated AR coefficients, for horizons up to 12 months ahead. We do so for each draw of the posterior distribution (using an MCMC algorithm that is a simplification of that used for our multivariate model) and form the median estimate of uncertainty at each horizon. Finally, we obtain a measure of uncertainty by averaging uncertainty estimates across variables, for cross sections ranging from 8 through 129 series.

3 Data

Our macroeconomic data (and some financial indicators) are taken from the FRED-MD monthly dataset detailed in McCracken and Ng (2015) and available from the Federal Reserve Bank of St. Louis. The FRED-MD dataset is similar to that underlying common factor model analyses, such as Stock and Watson (2005, 2006) and Ludvigson and Ng (2011). Accordingly, the dataset is also similar to the one used by JLN. After dropping out a few series with significant numbers of missing observations and dropping the series non-borrowed reserves because it became extremely volatile with the Great Recession, the total dataset comprises 129 series, over a sample of January 1959 through mid or late 2014, depending on the series. Each series is transformed as in McCracken and Ng (2015) — the McCracken-Ng transformations are very similar to those of JLN — to achieve stationarity.

For financial variables, we use 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 available in datasets constructed by Kenneth French and available on his webpage (LMN take their financial variables from the datasets constructed by Professor French). Specifically, in our baseline results, 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). We obtained similar results when, instead of these 10 variables from Kenneth French, we used more detailed breakdowns of returns (by industry and portfolios sorted on size and book-to-market) available from his datasets.[10]

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 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

[10] 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).

that bear on macroeconomic uncertainty and not directly on financial uncertainty (in LMN, finance uncertainty is based on the volatilities of various measures of stock returns and risk factors, we instead include the credit spread and the S&P 500 index in the set of financial variables.

Our primary VAR results are based on a baseline specification given by 30 macroeconomic and financial variables of interest, which are listed in Table 1 below. Following examples 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.

Table 3: variables in the baseline model

Macroeconomic variables	**Financial variables**
All Employees: Total nonfarm	S&P 500
IP Index	Spread, Baa-10y Treasury
Capacity Utilization: Manufacturing	Excess return
Help wanted to unemployed ratio	SMB FF factor
Unemployment rate	HML FF factor
Real personal income	Momentum factor
Weekly hours: goods-producing	R15_R11
Housing starts	Industry 1 return
Housing permits	Industry 2 return
Real consumer spending	Industry 3 return
Real manuf. and trade sales	Industry 4 return
ISM: new orders index	Industry 5 return
Orders for durable goods	
Avg. hourly earnings, goods-prod.	
PPI, finished goods	
PPI, commodities	
PCE price index	
Federal funds rate	

In some additional results, we use all of the 129 macro series to fit AR-SV models and form measures of macro uncertainty with an approach similar to that of JLN. We also consider larger financial data sets that include more disaggregate industry breakdowns (of 43 and 93 sectors) of stock returns, constructed by Kenneth French. In considering how the size of the dataset affects uncertainty estimates obtained with an approach like that of JLN, we also report AR-SV-based macro uncertainty estimates based on 8 or 60 series and AR-SV-based finance uncertainty estimates based on larger sets of series. We also make some comparisons to the measures of uncertainty estimated by JLN and LMN, obtained from the website of Professor Ludvigson.

4 Measuring Aggregate Uncertainty

In the following results, we focus on estimates of our baseline model with 30 variables, in monthly data. We discuss some aspects of robustness in the next section.

Table 2 provides posterior estimates of the factor loadings — the β_m and β_f coefficients of equations (2) and (3). All of the posterior mean estimates are positive and clustered around a value of 1 (as noted above, the loadings on employment and S&P returns are fixed at 1). Some loadings are somewhat below 1 (e.g., orders for durable goods), and others are modestly above 1 (e.g., industrial production). In all cases, the loadings appear to be estimated with reasonable precision. However, the loadings on the finance factor have posterior standard deviations that are noticeably lower than those for the loadings on the macro factor (despite a prior that is the same for the macro and finance factors).

Table 2: Posterior estimates of factor loadings

Variable	**Posterior median (st. dev.)**
Loadings of macro variables on macro factor	
Employment	1.000 (NA)
Ind. prod.	1.255 (0.272)
Capacity utilization	0.685 (0.272)
Help wanted/unemployment	0.737 (0.290)
Unemployment rate	0.851 (0.239)
Real personal income	0.787 (0.306)
Weekly hours, goods	0.815 (0.325)
Housing starts	1.138 (0.246)
Housing permits	1.183 (0.306)
Real consumer spending	1.162 (0.266)
Real manuf. and trade sales	0.619 (0.260)
ISM index, new orders	0.704 (0.236)
Orders for durable goods	0.615 (0.280)
Avg. hourly earnings, goods	1.122 (0.301)
PPI, finished goods	1.172 (0.295)
PPI, commodities	0.734 (0.324)
PCE price index	1.139 (0.263)
Federal funds rate	1.303 (0.321)
Loadings of finance variables on finance factor	
S&P 500	1.000 (NA)
Spread, Baa-10y Treasury	1.119 (0.165)
Excess return	1.002 (0.128)
SMB	0.931 (0.118)
HML	1.021 (0.115)
Momentum	1.521 (0.152)
R15-R11	0.771 (0.141)
Industry 1	0.833 (0.122)
Industry 2	0.781 (0.155)
Industry 3	0.825 (0.120)
Industry 4	0.802 (0.143)
Industry 5	0.903 (0.161)

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 m_t and financial uncertainty as the square root of the common volatility factor f_t, such that macroeconomic and financial uncertainty correspond to a standard deviation. In order to facilitate comparability with other studies, the figure also displays the measures (macro in the top panel and financial in the bottom panel) obtained by JLN (macro) and LMN (financial). 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.

The results indicate the correlation of our uncertainty estimates with the JLN and LMN estimates are quite high, about 0.771 for macro uncertainty and 0.765 for financial uncertainty. There are, however, some differences. One difference is that our estimates are more variable. This variability stems in part from the inclusion of y_{t-1} in the VAR process of the factors. The estimates of the coefficients δ_m and δ_f are generally small but not zero, such that movements in y_{t-1} lead to movements in m_t and f_t. Another difference is that the peak in the JLN measure around the early 1980s recession is quite higher than that around the mid-1970s recession, while the two values are similar for our model. 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 are also somewhat correlated with each other. Using the time series of the posterior median uncertainties (again, defined in this section as standard deviations), the correlation between macro and financial uncertainty is 0.41. The uncertainty estimates of JLN (macro) and LMN (finance) are similarly correlated, with a simple correlation of 0.56 (using their 1-step ahead uncertainty series).

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 SV, as methodology existing before our paper did not make it tractable. Yet their result seems to hold up even once stochastic volatility is allowed in larger models. One possible explanation for weak evidence of a Great Moderation in our uncertainty measure is the use of monthly rather than quarterly data. However, data frequency does not seem to produce a significant difference in low frequency movements in common volatility around the Great Moderation. The broad contours of the uncertainty estimates obtained with quarterly estimates of our model, shown in Figure 2, are similar to those obtained with monthly data. When we instead consider in Figure 3 the reduced form volatilities of each variable — defined as the diagonal elements of Σ_t, which reflect both the common uncertainty factors and idiosyncratic components — Great Moderation effects become evident for some variables. Arguably, for some variables, typically real quantities such as employment (PAYEMS), the Great Moderation effects appear larger in quarterly data (supplementary appendix available upon request) than monthly data (Figure 3). In either case, even in monthly data, the volatility of the federal funds rate (and related term spreads) exhibits a major decrease after the early 1980s, suggesting that a more predictable monetary policy contributed to the stabilization of the other volatilities.

Finally, about the financial uncertainty factor, it is worth noting that it increases during recessions, as the macro uncertainty factor, but also in other periods of financial turmoil. This different temporal pattern may help in disentangling macroeconomic and financial uncertainty.

5 Measuring the impact of uncertainty

5.1 Identification

With our uncertainty measure(s) entering each of the equations of the VAR in y_t, we can easily compute impulse response functions to unexpected aggregate uncertainty shocks. What we do is similar to shock identification in factor augmented VAR models, such as Bernanke, Boivin and Eliasz (2005) or Marcellino and Sivec (2016), but also allowing for (common) stochastic volatility.

Our approach features two important differences with respect to the existing structural analysis exercises on the impact of uncertainty on the macroeconomy.

First, in our specification, a shock to uncertainty affects not only the conditional mean of y_t but also the conditional variance. In analyses such as Bloom (2009), JLN, or Caldara, et al. (2016), it is common to conduct inference on the former while ignoring the latter.

Moreover, our approach takes into account the uncertainty around uncertainty, while these studies condition on the point estimates of uncertainty, thereby abstracting from the variance of uncertainty estimates. To avoid a similar practice, we are able to use our model and impulse response functions to conduct inference on the effects of uncertainty shocks to y_t taking account of their effects on not only the conditional mean but also the conditional variance. Our estimates also account for the variance of the uncertainty measure in the sense that our estimates of the VAR's coefficients reflect the fact that uncertainty is a latent state and not an observed series.

Second, the specification of our model permits us to use the (common) volatilities of the VAR's variables to identify an uncertainty shock and its effects on the VAR's conditional mean, under an assumption of no contemporaneous correlation between factor shocks and VAR shocks. Some other studies in the literature, such as Bloom (2009) and JLN, rely on more restrictive recursive identification schemes.

In our approach, shocks to uncertainty are identified by the very fact that uncertainty is time varying, and appears not only in the conditional means, but also in the conditional variances of an heteroskedastic VAR. To clarify this point consider again the model:

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

where we have explicitly written down the specification of Λ_t. The quadratic term appearing in the likelihood is:

$$\begin{aligned} &\exp[-\frac{1}{2}(y_t - \Pi(L)y_{t-1} + \Pi_m(L)\ln m_t + \Pi_f(L)\ln f_t)' \cdot \\ &\cdot A' \begin{bmatrix} m_t^{\beta_{m,j}} h_{1,t} & & \\ & \ddots & \\ & & f_t^{\beta_{f,j}} h_{n,t} \end{bmatrix}^{-1} A \cdot \underbrace{(y_t - \Pi(L)y_{t-1} + \Pi_m(L)\ln m_t + \Pi_f(L)\ln f_t)}_{v_t}^{\prime}], \end{aligned}$$

which shows that the matrix $A'\Lambda_t^{-1}A$ is uniquely identified. Instead, if the elements of the matrix Λ_t where constant ($\Lambda_t = \Lambda$) and not appearing in the terms v_t, the matrix $A'\Lambda^{-1}A$ would only be identified up to an orthogonal rotation, that is, the error term $A^{-1}\Lambda\epsilon_t$ would be observationally equivalent to any other error term of the form $A^{-1}\Lambda Q\epsilon_t$ with Q an orthogonal matrix. This happens because in the standard setup using a different rotation matrix Q only impacts on the error variance part of the model: different Qs imply different structural errors, but identical reduced form errors, which only appear in the likelihood in the form of their error variance. In our setup instead, the elements of Λ_t are both time varying and related with the conditional mean of the model, so that Λ_t appears in the conditional mean part of the likelihood, and this provides identification.

Note that in our setup the shocks to uncertainty contemporaneously affect y_t and are orthogonal to ϵ_t. The orthogonality between $(u_{m,t},\ u_{f,t})'$ and ϵ_t stems from our modeling strategy that 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, and a component due to the conditionally independent shock ϵ_t, captured in equation (11). 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 $\Lambda_t^{0.5}$. Hence these two components have to be orthogonal to one another in order to be separately identified.[11] However, by including y_{t-1} in the process for the factor m_t (and the factor f_t), our model allows for previous ϵ shocks to affect the factor and, in turn, $\Lambda_t^{0.5}$. In general, our approach exploits the ability to identify the uncertainty factors from observed volatilities and then identify the effects of uncertainty from the first-moment relationship of y_t to the uncertainty factors. In this sense, there is some parallel between our identification and heteroskedasticity-based identification approaches such as Rigobon (2003) and Lanne and Lutkepohl (2008).

As a consequence, we are able to allow uncertainty to contemporaneously affect the macroeconomy and financial markets and contemporaneously respond to macroeconomic and financial developments. The former effect is captured by the inclusion of the uncertainty factors in the VAR's conditional mean given in equation (6). The latter effect is captured in the following way: when a large shock to the innovation v_t of equation (6) occurs, and it reflects a shift in volatility that is common across variables, the uncertainty factors will move higher. That is, large surprises to y_t can yield movements in uncertainty. In contrast, under the more common approach in the literature of obtaining an estimate of uncertainty from elsewhere (e.g., as an average of univariate volatilities as in JLN), and then adding the uncertainty estimate to an otherwise standard VAR, identification requires an additional step in the VAR, which is typically based on the use of a recursive identification scheme,

[11] In this sense, our specification builds on the standard, simpler stochastic volatility common in finance and introduced into macroeconomics by Cogley and Sargent (2005) and Primiceri (2005).

which is not immune to criticism, some of which is represented in studies such as Caldara, et al. (2016) and LMN.[12]

While the vector of uncertainty measures $u_t = (u_{m,t}, u_{f,t})'$ is identified for the reasons outlined above, 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 $u_{f,t}$, while macroeconomic uncertainty responds contemporaneously to $u_{m,t}$ but responds to $u_{f,t}$ with some delay.

We report impulse response functions computed in the usual way (the appendix elaborates on these calculations, showing that the responses are driven by the constant coefficients of the VAR and the log factor processes); we have verified that response functions computed with the generalized approach of Koop, Pesaran, and Potter (1996) as implemented in studies such as Benati (2008) yield the same estimates. The equivalence — and the validity of the simple approach — stem from the independence among the conditional VAR shocks ϵ, the shocks to the volatility factors, and the shocks to the idiosyncratic volatility components. For each of the $j = 1, \ldots, 5000$ retained draws of the VAR's parameters and latent states, we compute impulse response functions. We report the posterior medians and 70 percent credible sets of these functions.

5.2 Results

5.2.1 Impulse responses

Figure 4 provides the impulse response estimates of a one-standard deviation shock to log macro uncertainty ($\ln m_t$) in our 30 variable (monthly frequency) VAR specification. Note that, although the model is estimated with standardized data, 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

[12] In the interest of brevity, we provide in a supplementary appendix available upon request results for a constant parameter/constant volatility BVAR in 31 variables — our 30 variables and the 1-step ahead uncertainty estimate (logged, for consistency with our results) of JLN. These results have some similarity to the baseline model results discussed below.

log levels.[13] 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). As examples, the response of employment is the percentage point response (again, 100 times the log); the response of the unemployment rate is the percentage point change in the unemployment rate; and the response of the federal funds rate is the percentage point change in the annualized federal funds rate. 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 (the response of 100 times the log level of the S&P index), but for the CRSP excess return, we display the response of the return (computed as a monthly return), rather than a price level.

As shown in the penultimate panel of Figure 4, the shock to log macro uncertainty produces a rise in uncertainty that gradually dies out, over the course of about one year. As indicated in the last panel of Figure 4, financial uncertainty rises in response, also for about a year, although the response of finance 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 (as noted above, some of this difference in estimated persistence of effects may be due to our use of differenced data).

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 Nickell (1986) and Bloom (2009). Interestingly, 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, real personal consumption expenditures and real M&T (manufacturing and trade) sales are significantly negative and persistent. The

[13]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.

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 terms of 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, but remains below baseline for the full four year horizon covered in the impulse responses. 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 (contemporaneous) and sizable. Relatively quick and large responses occur for housing starts and permits, the ISM index of new orders, and weekly hours worked (which presumably reflects an intensive margin of adjustment, 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 does decline steadily and by as much as 2 percentage points, although the response is estimated relatively imprecisely. Neither the PPI for commodity prices nor overall consumer prices as captured by the PCE price index (in earlier versions of the model, we obtained the same result for core PCE prices) display a significant change. Overall, this picture of price responses is in line with New-Keynesian models, such as Leduc and Liu (2015), Basu and Bundick (2015), 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), such that lower consumption does not stimulate investment.

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, as noted above, in other specifications with different choices of financial variables, we obtained more notable responses of asset returns to macro uncertainty). The one exception is the credit 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 (2012), 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 findings in the finance literature (e.g., Bansal and Yaron 2004), but the estimated responses are sufficiently imprecise that, in this dataset, they should not be judged meaningful. The responses of the other financial indicators, including the risk factors and industry-level returns, are also overall insignificant, signaling that financial variables are less sensitive to macroeconomic uncertainty than they are to financial uncertainty. This brings us to the next point, to the effects of surprise changes in financial uncertainty.

As we discussed above, in our setup financial uncertainty is estimated in a single step, together with macroeconomic uncertainty, using the identification assumption that it represents the common volatility across a set of financial indicators. The effects of a shock to financial uncertainty are displayed in Figure 5.

As reported in the last panel of Figure 5, the shock to log finance 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 finance uncertainty to finance uncertainty (relatively fast moving) moving in response to a change in macro uncertainty (relatively slow moving).

As to broader effects of finance uncertainty, when compared to a macro uncertainty shock, a finance uncertainty shock has similar, but sometimes smaller and more delayed macroeconomic effects and larger financial effects. More specifically, the effect on industrial production and employment follow a pattern similar to that obtained for the case of macroeconomic uncertainty, with a significantly negative response, more persistent in the case of employment. The effects on the labour market show an increase in unemployment and a decrease in hours worked, 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. Real personal income and real personal consumption expenditures show the same negative response observed for a macro uncertainty shock, but the former is slower and insignificant on impact with respect to the case of a macro uncertainty shock, while the latter is largely insignificant. In perhaps the most notable difference with respect to results for a macro uncertainty shock, a finance uncertainty shock does not have significant effects on the housing sector (starts and permits). Overall, the responses of prices to the finance uncertainty shock are no more significant than the corresponding responses to the macro uncertainty shock.

Turning our attention to the financial variables, on balance they respond more to the finance uncertainty shock than the macro uncertainty shock, although in some cases the responses are imprecisely estimated. The shock to finance 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, with no sign of a rebound after the forecast horizon (4 years). The CRSP excess returns display a negative jump and recover only after 6 months. The industry-level returns included in the model also decline, but the responses are estimated very imprecisely (in some other variable sets, the responses of returns were more precisely estimated). The responses of the risk factors included in the model are also insignificant.

5.2.2 Robustness

In this section we consider some robustness checks of our results.

First, we consider the robustness of our results to the use of a quarterly, rather than monthly, data frequency. Qualitatively, these quarterly results, provided in Figures 6 and 7, are very similar to our baseline estimates with monthly data. There are some differences, such as the more significant response of macro uncertainty to finance uncertainty in the quarterly estimates than the monthly estimates, but our key results from the monthly frequency carry over to the quarterly case.

Second, we consider how estimates of uncertainty depend on the size of the cross section. In this exercise, for simplicity we rely on estimates of SV from the AR-SV model described in section 2, and we consider measures of uncertainty defined as the simple average of the time-varying standard deviations obtained from the SV estimates, for cross-sections of different size. We begin with macroeconomic uncertainty. In the upper panel of Figure 8, we report AR-SV-based uncertainty measures resulting from averaging the SVs of 8, 18, 60 and 129 macroeconomics variables (all monthly data). The different subsets of variables mainly differ for the level of considered disaggregation, as detailed in Table 3. Although not shown directly, the measure of uncertainty obtained by averaging the SV estimates of 129 variables is highly correlated with the series of JLN. As indicated in the top of Figure 8, uncertainty estimates based on 129 and 60 variables are extremely similar; they can be hardly distinguished in the figure. Compared to these estimates, the uncertainty estimates based on 18 or 8 variables differ somewhat. For example, the measure based on just 8 variables presents a substantially higher peak around the recession of the early 1980's and lower values from the early 1990s onwards, particularly so from 2010 onwards. That said, the estimates implied by the two smaller variable sets are still highly correlated (correlations in excess of 0.9) with the estimates based on the two larger variable sets.

Now consider the measures of financial uncertainty obtained by averaging AR-SV estimates, shown in the lower panel of Figure 8. We consider two estimates obtained by averaging volatilities of two different industry-breakdowns of returns from the Kenneth French datasets, one (the most disaggregate) with 93 industries and the other (less disaggregate) with 43 industries. Although not shown directly in the chart, the series based on 93 returns is very highly correlated with the uncertainty estimate of LMN. The series based on a smaller set of 43 returns is extremely similar. Using a smaller set of 12 financial variables — either the set of 12 financial variables included in our baseline model (corresponding to the N=12 set covered in chart) or the alternative set of 12 variables that replaces the five risk factors and 5 industry returns in the baseline set with 10 industry returns — yields modestly different estimates. Again, though, these estimates are highly correlated (correlations in excess of 0.9) with those obtained by using the large datasets. Overall, we view these results as supporting our use of a model that has 18 macro variables and 12 financial variables in order to reasonably capture uncertainty and its effects.

Finally, a relevant question is whether the recent financial crisis had a substantial impact on the results we have obtained. For example, Alessandri and Mumtaz (2014), using a nonlinear VAR model, find that uncertainty has a much stronger (negative) impact on output in periods of financial stress than otherwise. To assess whether this is the case in our baseline results, we recompute the impulse responses using estimates of the model with data through just December 2007. Figures 9 and 10 provide the results. In the shorter sample, it continues to be the case that shocks to both macro uncertainty and financial uncertainty have significant effects on economic activity and some financial variables, with patterns generally similar to those obtained for the full sample of data. However, in the case of the shock to macro uncertainty, the effects are modestly smaller and less precisely estimated than in the baseline case. In the case of the shock to financial uncertainty, the effects for the 1960-2007 sample are quite similar to those for the 1961-2014 period. Overall, we judge that the crisis period has provided useful information for assessing the effects of changes in macro uncertainty but by no means drives it, whereas the crisis period has less effect on the measurement of financial uncertainty and its effects.

6 Conclusions

This paper developed a new framework for measuring uncertainty and its effects on the macroeconomy and financial conditions. Specifically, we developed a VAR model for a possibly large set of variables whose volatility is driven by two common unobservable factors, which can be interpreted as the underlying aggregate macroeconomic and financial uncertainty, respectively. These uncertainty measures reflect common changes in the volatility of the variables under analysis, but can also influence their levels. Hence, contrary to most existing measures, ours reflect changes in both the conditional mean and volatility of the underlying variables, and they are estimated taking explicitly into account the existence of aggregate uncertainty. Creal and Wu (2016) pursue a broadly similar idea of internalizing the treatment of uncertainty, but in a different, much smaller model with a different question.

Moreover, 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. Finally, identification of the uncertainty shock is simplified with respect to standard VAR based analysis, in line with the FAVAR approach and heteroskedasticity-based identification.

We introduced a new Bayesian estimation method for the model, which can be also applied in other contexts, is computationally efficient, and allows for estimation even of large models, while previous VAR models with stochastic volatility could only handle a handful of variables.

We applied the method to estimate uncertainty and its effects using US data, finding that there is indeed 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 provided 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, while financial uncertainty shocks have significant effects on financial variables but also substantially transmit to the macroeconomy.

A Appendix

In this appendix, we provide the details of the priors we use in the multivariate model estimation and explain the computation of impulse responses.

A.1 Priors

For the VAR coefficients contained in Π, we use a Minnesota-type prior. With the variables of interest transformed for stationarity, we set the prior mean of all the VAR coefficients to 0. We make the prior variance-covariance matrix $\underline{\Omega}_{\Pi}$ diagonal. The variances are specified to make the prior on the intercept, $\log m_t$, and $\log f_t$ terms uninformative and the prior on the lags of y_t take a Minnesota-type form. Specifically, for the intercept, $\log m_t$, and $\log f_t$ terms of equation i, the prior variance is $\theta_3^2 \sigma_i^2$. For lag l of variable j in equation i, the prior variance is $\frac{\theta_1^2}{l^2}$ for $i = j$ and $\frac{\theta_1^2 \theta_2^2}{l^2} \frac{\sigma_i^2}{\sigma_j^2}$ otherwise. In line with common settings, we set overall shrinkage $\theta_1 = 0.2$, cross-variable shrinkage $\theta_2 = 0.5$, and intercept/factor shrinkage $\theta_3 = 1000$. With these settings, we have deliberately made the prior on the uncertainty terms in the VAR uninformative (making the prior less uninformative by setting $\theta_3 = 10$ yielded results very similar to the baseline estimates). Finally, consistent with common settings, the scale parameters σ_i^2 take the values of residual variances from AR(p) models from the estimation sample.

As to the volatility-related components of the model, for the rows a_j of the matrix A, we follow Cogley and Sargent (2005) and make the prior fairly uninformative, with prior means of 0 and variances of 10 for all coefficients. For the coefficients ($\gamma_{i,0}$, $\gamma_{i,1}$) (intercept, slope) of the idiosyncratic processes of equation i, $i = 1, \ldots, n$, the prior mean is ($\log \sigma_i^2$, 0.0), where σ_i^2 is the residual variance of an AR(p) model over the estimation sample. The prior standard deviations (assuming 0 covariance) are ($2^{0.5}$, 0.4). For the factor loadings β_j, $j = 2, ..., n$, we use a prior mean of 1 and a standard deviation of 0.4. For the coefficients of the VAR process of the factors, the prior means are zero, except that the first-order lag coefficients of each factor has a mean of 0.8. The prior standard deviations are set to 0.2 for the elements of $D(L)$ and 0.4 for the elements of δ_m and δ_f. For the innovations to the idiosyncratic components of volatility ($\phi_1, ..., \phi_n$), we use a mean of 0.03, with 10 degrees of freedom for each. For the variance-covariance matrix of innovations to the factor processes (Φ_u), we use a mean of 0.01 times an identity matrix, with 10 degrees of freedom. For the period 0 values of $\log m_t$ and $\log f_t$, and $\log h_{i,t}$, we set the mean at 0 and in each draw use the variance implied by the VAR representation of the factors (treating the δ_m and δ_f coefficients as 0) and the draws of the coefficients and error variance matrix. Finally, for the period 0 values of $\log h_{i,t}$, we set the mean and variance at $\log \sigma_i^2$ and 2.0, respectively.

A.2 Impulse response computation

For the purpose of establishing the basis of our impulse response calculations, consider a much simplified model with a single uncertainty factor and lag orders all set at 1:

$$\begin{aligned} y_t &= \Pi y_{t-1} + \Gamma_1 m_t + \Gamma_2 m_{t-1} + \Sigma_t^{0.5} \epsilon_t \\ m_t &= \delta y_{t-1} + \gamma m_{t-1} + u_t, \end{aligned}$$

where $\Sigma_t^{0.5}$ is a short-cut notation for the Choleski decomposition of Σ_t and ϵ_t and u_t are independent normals, with $\epsilon_t \sim N(0, I_n)$ and $u_t \sim N(0, \Phi)$.

To explain how we compute the impulse response, we will use as illustrative examples the responses over periods $t+1$ and $t+2$ to an uncertainty shock in period $t+1$.

By iterative substitution, we can write out expressions for y_{t+1} and y_{t+2} as functions of period t information, shocks in $t+1$ and $t+2$, and Σ_{t+1}, Σ_{t+2}. For simplicity, we can just write things out using the general Σ_{t+1}, Σ_{t+2} and not the decomposition into the time-varying volatility components (factor and idiosyncratic) that drive it, in the general form given in the paper with the richer two-factor model. Specifically, we can express y_{t+1} and y_{t+2} as follows:

$$
\begin{aligned}
y_{t+1} &= (\Pi + \Gamma_1 \delta) y_t + (\gamma \Gamma_1 + \Gamma_2) f_t + \Gamma_1 u_{t+1} + \Sigma_{t+1}^{0.5} \epsilon_{t+1} \\
y_{t+2} &= (\Pi + \Gamma_1 \delta) y_{t+1} + (\gamma \Gamma_1 + \Gamma_2)(\gamma f_t + \delta y_t) + \Sigma_{t+2}^{0.5} \epsilon_{t+2} + \Gamma_1 u_{t+2} + (\gamma \Gamma_1 + \Gamma_2) u_{t+1}.
\end{aligned}
$$

For space, the expression for y_{t+2} takes the shortcut of including directly y_{t+1} rather than replacing it with the expression for y_{t+1} from the first equation.

Now consider the impulse responses — specifically, the changes in y_{t+1} and y_{t+2} induced by an uncertainty shock u_{t+1}. Following textbook sources such as Hamilton (1994), we treat the impulse response as the change in the forecast of y induced by the shock to uncertainty, taking the shock to uncertainty as known. In general, the shock to uncertainty affects future y through both the conditional mean terms $\Gamma_1 m_t + \Gamma_2 m_{t-1}$ and the error variance $\Sigma_t^{0.5}$. However, the changes in Σ_{t+1} and Σ_{t+2} induced by the shock u_{t+1} are independent of ϵ_{t+1} and ϵ_{t+2}. As a result, the point forecasts of y_{t+1} and y_{t+2} change due to the conditional mean effects but not due to changes in the error variance matrix. So we compute the impulse responses as follows, for a given value of the uncertainty shock u_{t+1}:

$$
\begin{aligned}
IR_{t+1} &= \Gamma_1 u_{t+1} \\
IR_{t+2} &= (\Pi + \Gamma_1 \delta) \Gamma_1 u_{t+1} + (\gamma \Gamma_1 + \Gamma_2) u_{t+1}.
\end{aligned}
$$

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Table 3: Variable Combinations

variable	mnemonic	included in $N = 60$ set	included in $N = 40$ set	included in $N = 18$ set	included in $N = 8$ set
Real Personal Income	RPI	Y	Y	Y	
RPI ex. Transfers	W875RX1				
Real PCE	DPCERA3M086SBEA	Y	Y	Y	Y
Real M&T Sales	CMRMTSPLx	Y	Y	Y	
Retail and Food Services Sales	RETAILx	Y			
IP Index	INDPRO	Y	Y	Y	Y
IP: Final Products and Supplies	IPFPNSS				
IP: Final Products	IPFINAL				
IP: Consumer Goods	IPCONGD				
IP: Durable Consumer Goods	IPDCONGD	Y	Y		
IP: Nondurable Consumer Goods	IPNCONGD	Y	Y		
IP: Business Equipment	IPBUSEQ	Y			
IP: Materials	IPMAT				
IP: Durable Materials	IPDMAT	Y			
IP: Nondurable Materials	IPNMAT	Y			
IP: Manufacturing	IPMANSICS	Y	Y		
IP: Residential Utilities	IPB51222S				
IP: Fuels	IPFUELS				
ISM Manufacturing: Production	NAPMPI	Y			
Capacity Utilization: Manufacturing	CAPUTLB00004S	Y	Y	Y	
Help-Wanted Index for US Help wanted indx	HWI				
Help Wanted to Unemployed ratio	HWIURATIO	Y	Y	Y	
Civilian Labor Force	CLF16OV				
Civilian Employment	CE16OV	Y	Y		
Civilian Unemployment Rate	UNRATE	Y	Y	Y	Y
Average Duration of Unemployment	UEMPMEAN	Y	Y		
Civilians Unemployed <5 Weeks	UEMPLT5				
Civilians Unemployed 5-14 Weeks	UEMP5TO14				
Civilians Unemployed >15 Weeks	UEMP15OV				
Civilians Unemployed 15-26 Weeks	UEMP15T26				
Civilians Unemployed >27 Weeks	UEMP27OV	Y			
Initial Claims	CLAIMSx	Y	Y		
All Employees: Total nonfarm	PAYEMS	Y	Y	Y	Y
All Employees: Goods-Producing	USGOOD				
All Employees: Mining and Logging	CES1021000001				
All Employees: Construction	USCONS				
All Employees: Manufacturing	MANEMP				
All Employees: Durable goods	DMANEMP	Y			
All Employees: Nondurable goods	NDMANEMP	Y			
All Employees: Service Industries	SRVPRD	Y			
All Employees: TT&U	USTPU				
All Employees: Wholesale Trade	USWTRADE				
All Employees: Retail Trade	USTRADE				
All Employees: Financial Activities	USFIRE				
All Employees: Government	USGOVT				
Hours: Goods-Producing	CES0600000007	Y	Y	Y	
Overtime Hours: Manufacturing	AWOTMAN	Y	Y		
Hours: Manufacturing	AWHMAN				
ISM Manufacturing: Employment	NAPMEI	Y			

Table 3, continued: Variable Combinations

variable	mnemonic	included in $N = 60$ set	included in $N = 40$ set	included in $N = 18$ set	included in $N = 8$ set
Starts: Total	HOUST	Y	Y	Y	
Starts: Northeast	HOUSTNE				
Starts: Midwest	HOUSTMW				
Starts: South	HOUSTS				
Starts: West	HOUSTW				
New Private Housing Permits (SAAR)	PERMIT	Y	Y	Y	
New Private Housing Permits, Northeast (SAAR)	PERMITNE				
New Private Housing Permits, Midwest (SAAR)	PERMITMW				
New Private Housing Permits, South (SAAR)	PERMITS				
New Private Housing Permits, West (SAAR)	PERMITW				
ISM: PMI Composite Index	NAPM				
ISM: New Orders Index	NAPMNOI	Y	Y	Y	
ISM: Supplier Deliveries Index	NAPMSDI	Y	Y		
ISM: Inventories Index	NAPMII				
Orders: Durable Goods	AMDMNOx	Y	Y	Y	
Unfilled Orders: Durable Goods	AMDMUOx	Y			
Total Business Inventories	BUSINVx				
Inventories to Sales Ratio	ISRATIOx	Y	Y		
Money Stock	M1SL				
Money Stock	M2SL	Y	Y		
Real M2 Money Stock	M2REAL				
St. Louis Adjusted Monetary Base	AMBSL				
Total Reserves	TOTRESNS				
Commercial and Industrial Loans	BUSLOANS	Y	Y		
Real Estate Loans	REALLN				
Total Nonrevolving Credit	NONREVSL				
Credit to PI ratio	CONSPI	Y			
S&P: Composite	S&P 500	Y	Y		
S&P: Industrials	S&P: indust				
S&P: Dividend Yield	S&P div yield	Y	Y		
S&P: Price-Earnings Ratio	S&P PE ratio				
Effective Federal Funds Rate	FEDFUNDS	Y	Y	Y	Y
Month AA Comm. Paper Rate CPF3M Comm paper	CP3M				
3-Month T-bill	TB3MS				
6-Month T-bill	TB6MS				
1-year T-bond	GS1	Y	Y		
5-year T-bond	GS5				
10-year T-bond	GS10	Y	Y		
Corporate Bond Yield Aaa bond	AAA	Y			
Corporate Bond Yield Baa bond	BAA	Y	Y		
CP - FFR spread CP-FF spread	COMPAPFF				
3 Mo. - FFR spread 3 mo-FF spread	TB3SMFFM				
6 Mo. - FFR spread 6 mo-FF spread	TB6SMFFM				
1 yr. - FFR spread 1 yr-FF spread	T1YFFM	Y	Y		
5 yr. - FFR spread 5 yr-FF spread	T5YFFM				
10 yr. - FFR spread 10 yr-FF spread	T10YFFM	Y	Y		Y
Aaa - FFR spread Aaa-FF spread	AAAFFM	Y			
Baa - FFR spread Baa-FF spread	BAAFFM	Y	Y		

Table 3, continued: Variable Combinations

variable	mnemonic	included in $N = 60$ set	included in $N = 40$ set	included in $N = 18$ set	included in $N = 8$ set
Switzerland / U.S. FX Rate	EXSZUS	Y			
Japan / U.S. FX Rate	EXJPUS				
U.S. / U.K. FX Rate	EXUSUK	Y	Y		
Canada / U.S. FX Rate	EXCAUS				
PPI: Finished Goods	PPIFGS	Y	Y	Y	
PPI: Finished Consumer Goods	PPIFCG				
PPI: Intermediate Materials	PPIITM	Y			
PPI: Crude Materials	PPICRM	Y			
Crude Oil Prices: WTI	oilprice				
PPI: Commodities	PPICMM	Y	Y	Y	Y
ISM Manufacturing: Prices	NAPMPRI	Y			
CPI: All Items	CPIAUCSL	Y			
CPI: Apparel	CPIAPPSL				
CPI: Transportation	CPITRNSL				
CPI: Medical Care	CPIMEDSL				
CPI: Commodities	CUSR0000SAC				
CPI: Durables	CUUR0000SAD				
CPI: Services	CUSR0000SAS				
CPI: All Items Less Food	CPIULFSL				
CPI: All items less shelter	CUUR0000SA0L2				
CPI: All items less medical care	CUSR0000SA0L5				
PCE: Chain-type Price Index	PCEPI	Y	Y	Y	Y
PCE: Durable goods	DDURRG3M086SBEA	Y	Y		
PCE: Nondurable goods	DNDGRG3M086SBEA				
PCE: Services	DSERRG3M086SBEA	Y	Y		
Ave. Hourly Earnings: Goods	CES0600000008	Y	Y	Y	
Ave. Hourly Earnings: Construction	CES2000000008				
Ave. Hourly Earnings: Manufacturing	CES3000000008				
MZM Money Stock	MZMSL				
Consumer Motor Vehicle Loans	DTCOLNVHFNM				
Total Consumer Loans and Leases	DTCTHFNM				
Securities in Bank Credit	INVEST	Y			

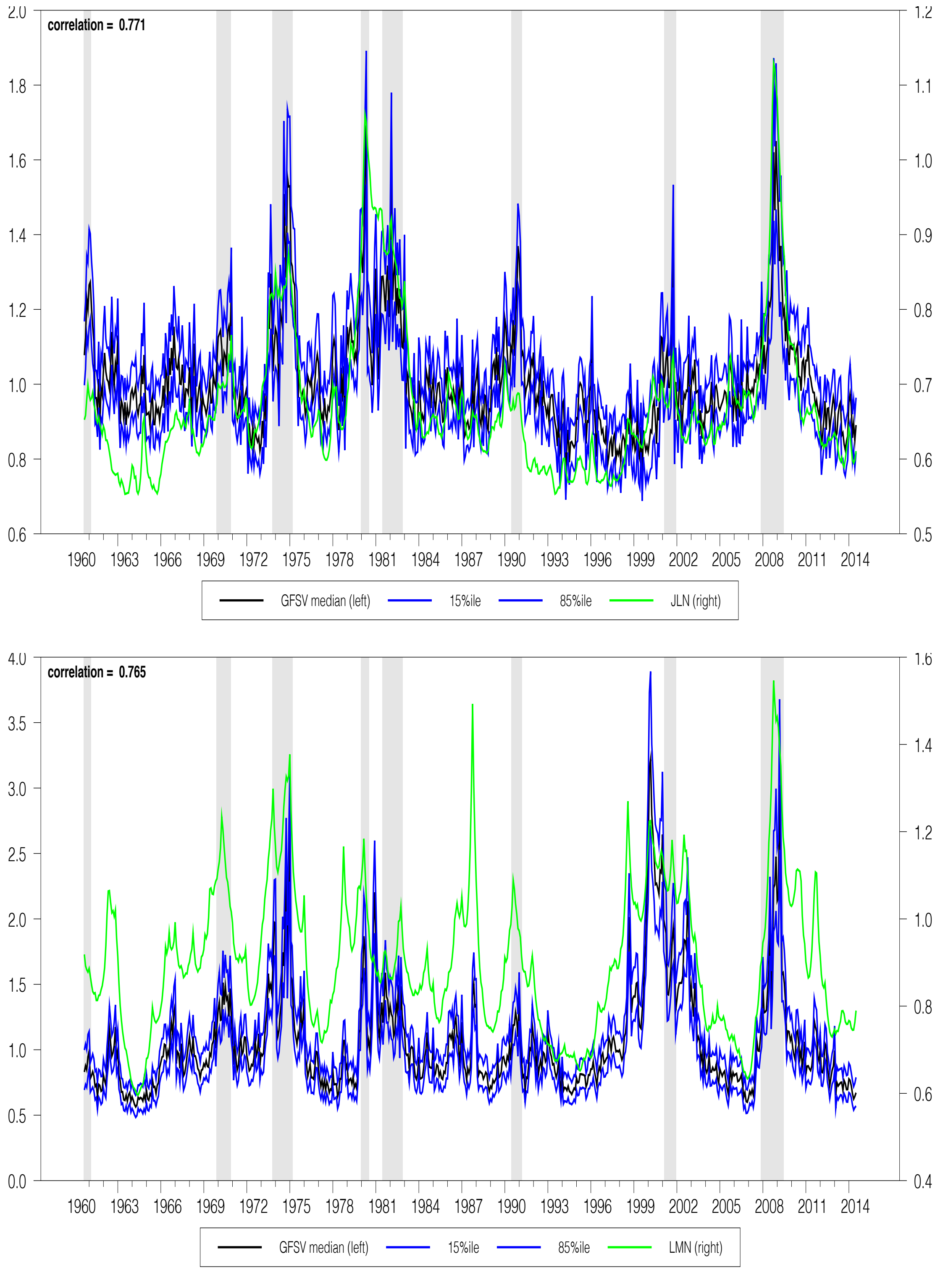


Figure 1: Uncertainty estimates, monthly data: posterior median (black line) and 15%/70% quantiles (blue lines), with macro uncertainty in the top panel and financial uncertainty in the bottom panel. The green line represents the corresponding estimates from JLN (top) and LMN (bottom). The gray bars indicate NBER recessions.

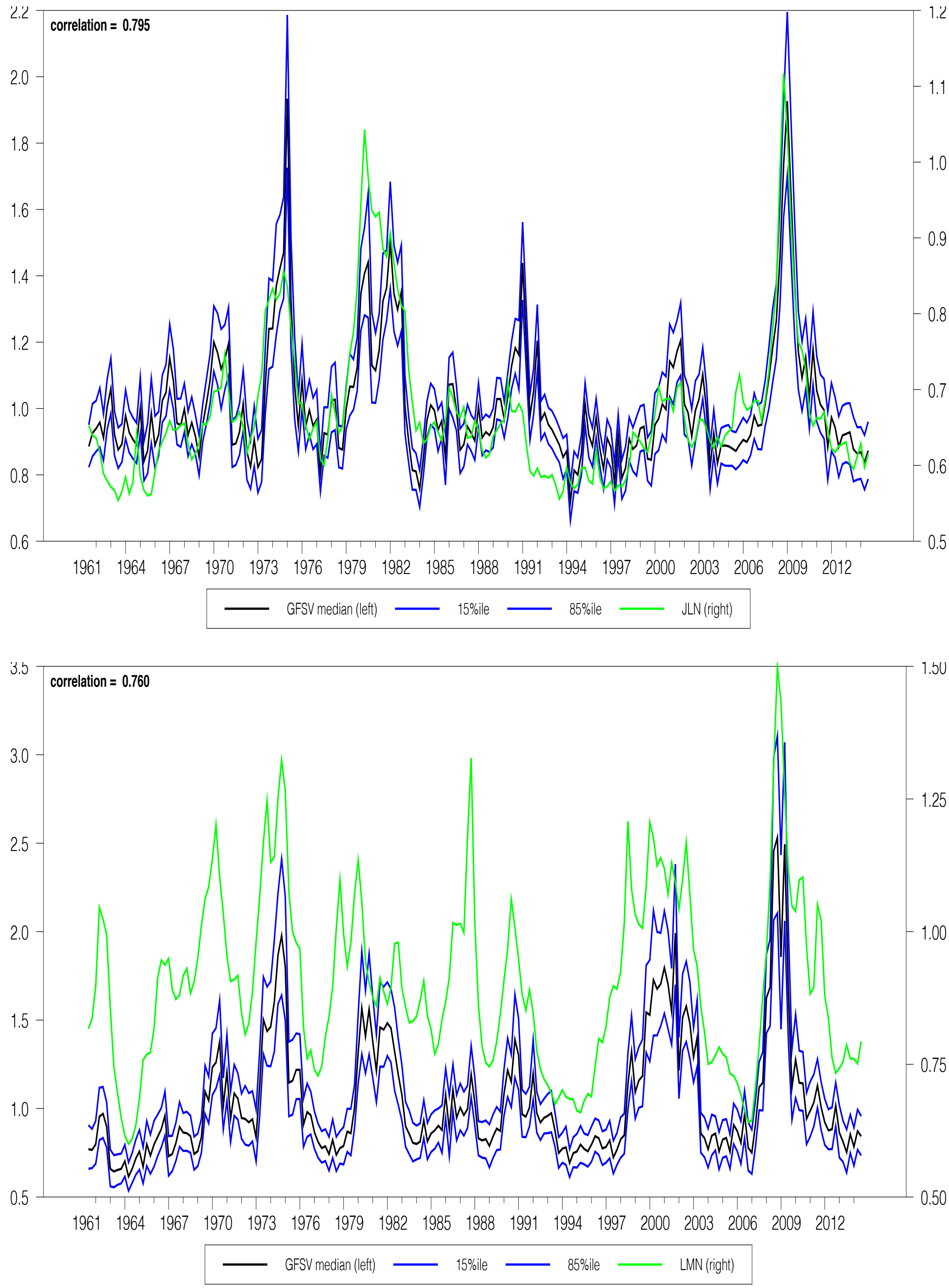


Figure 2: Uncertainty estimates, quarterly data: posterior median (black line) and 15%/70% quantiles (blue lines), with macro uncertainty in the top panel and financial uncertainty in the bottom panel. The green line represents the corresponding estimates from JLN (top) and LMN (bottom).

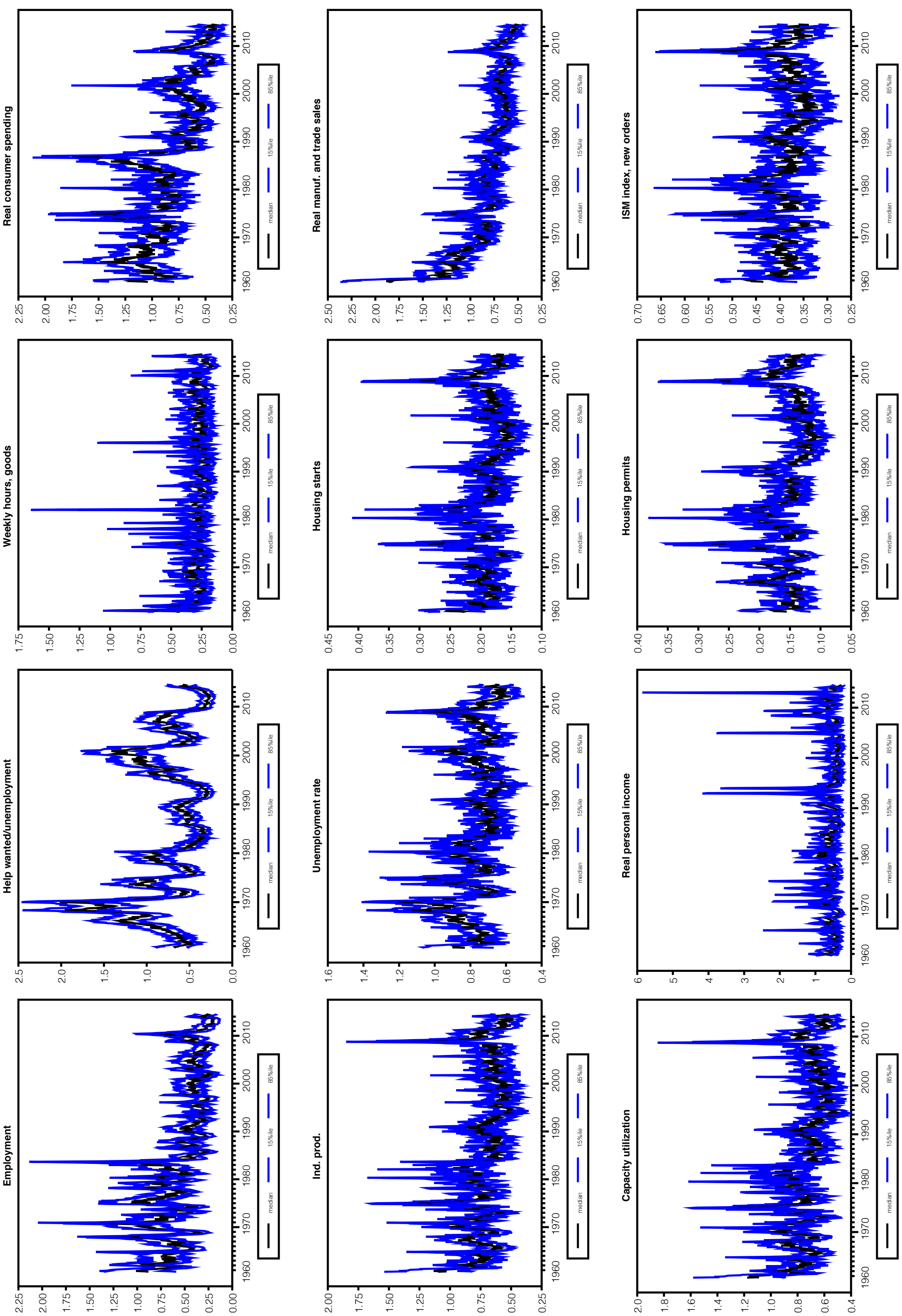


Figure 3: Reduced-form volatilities, 30-variable model, monthly data: posterior median (black line) and 15%/70% quantiles (blue lines)

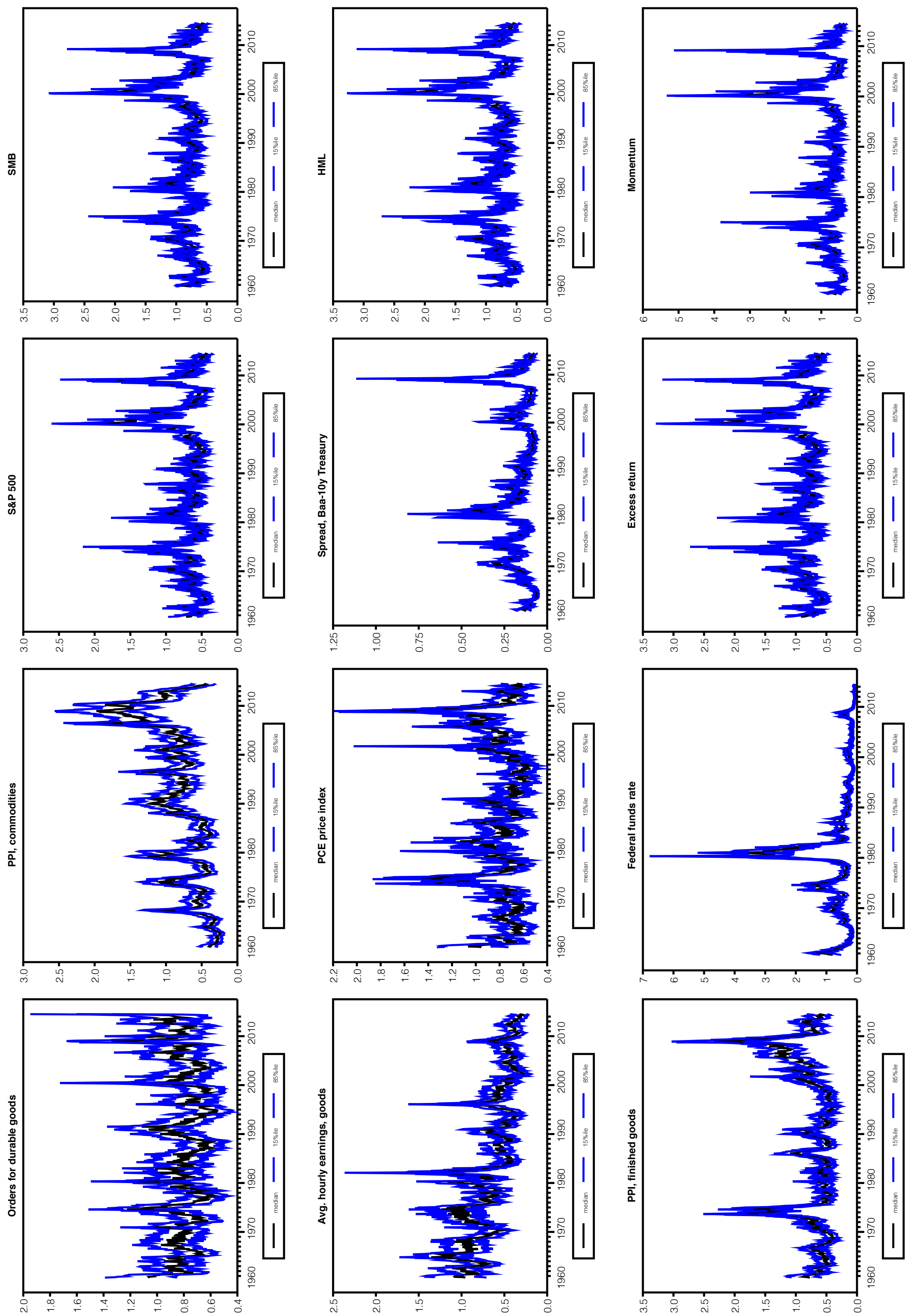


Figure 3: Continued, reduced-form volatilities, 30-variable model, monthly data: posterior median (black line) and 15%/70% quantiles (blue lines)

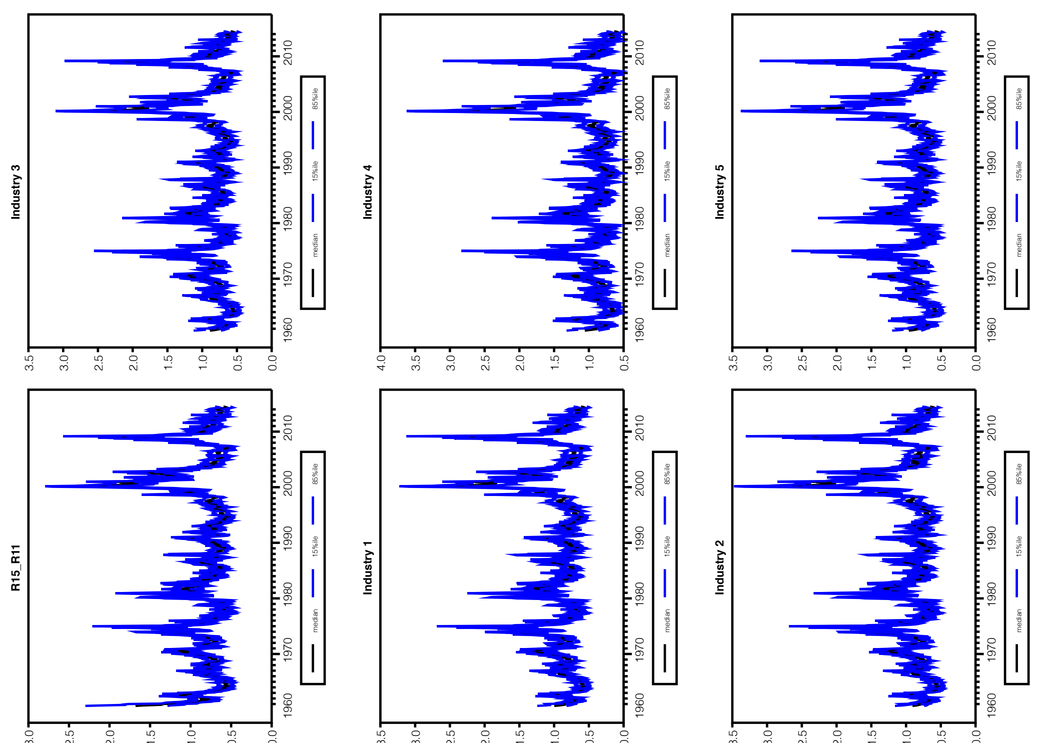


Figure 3: Continued, reduced-form volatilities, 30-variable model, monthly data: posterior median (black line) and 15%/70% quantiles (blue lines)

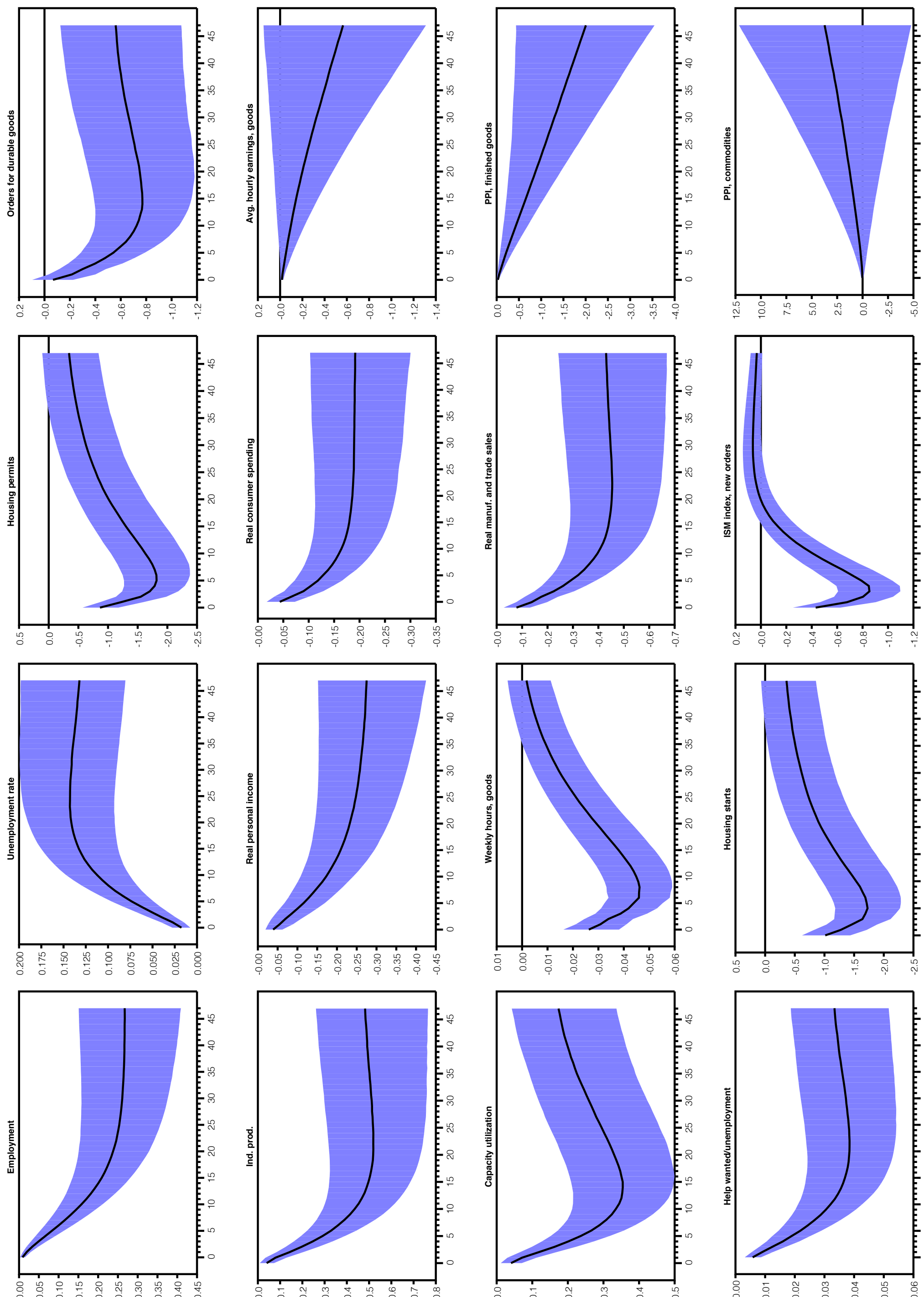


Figure 4: Impulse responses, one st. dev. shock to macro uncertainty, 30-variable model, monthly data: posterior median (black line) and 15%/70% quantiles (blue shading)

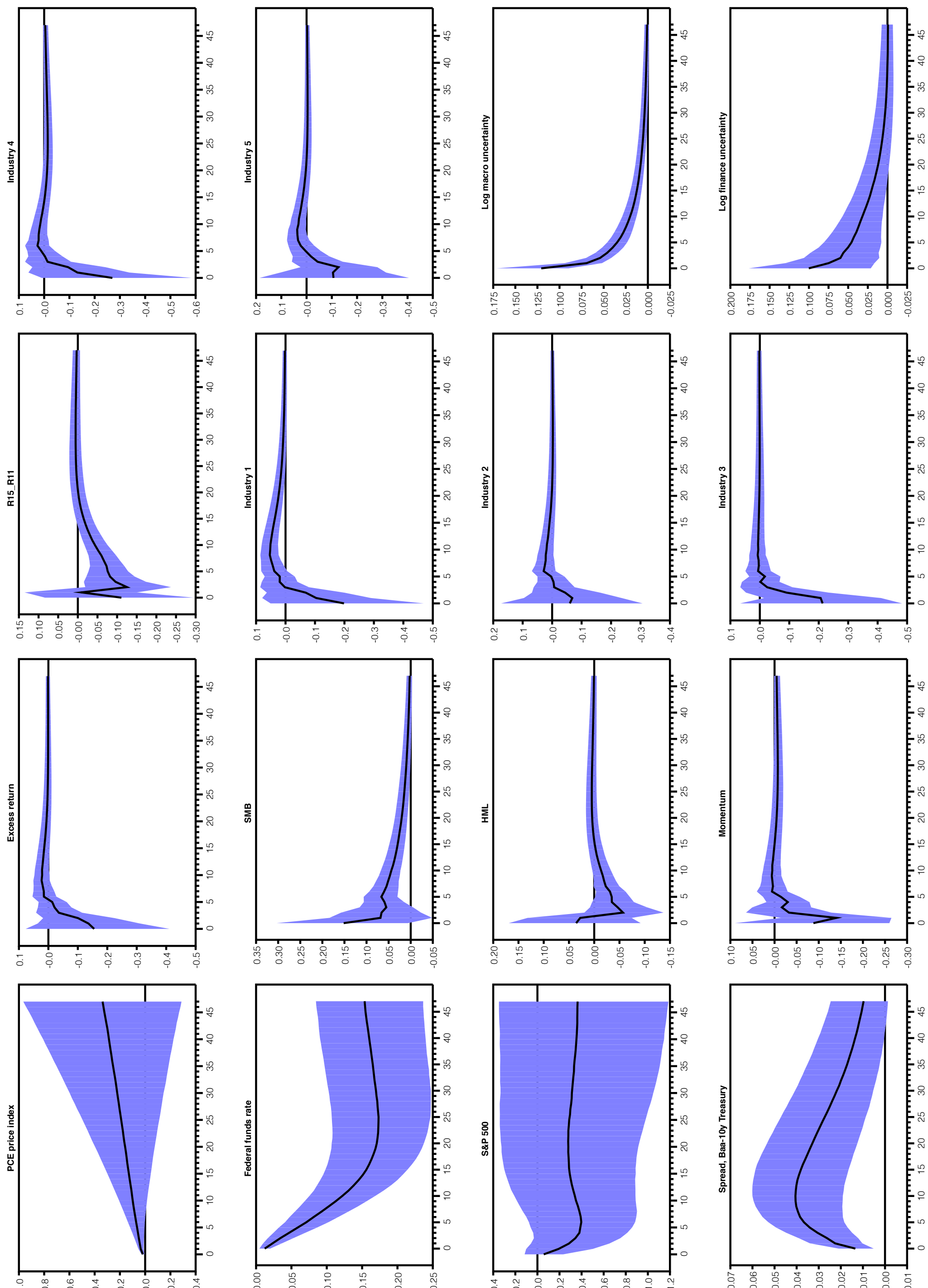


Figure 4: Continued, impulse responses, one st. dev. shock to macro uncertainty, 30-variable model, monthly data: posterior median (black line) and 15%/70% quantiles (blue shading)

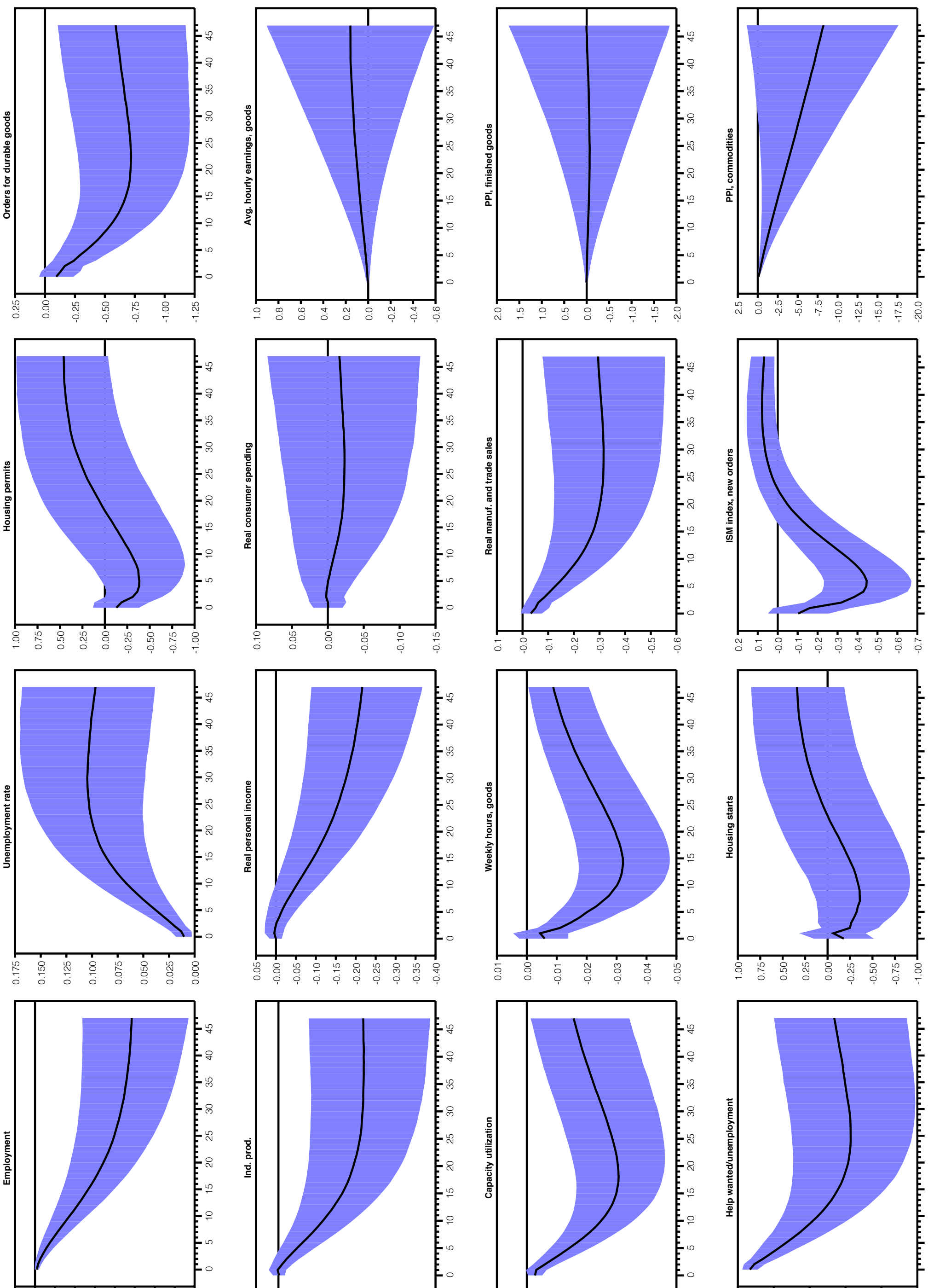


Figure 5: Impulse responses, one st. dev. shock to financial uncertainty, 30-variable model, monthly data: posterior median (black line) and 15%/70% quantiles (blue shading)

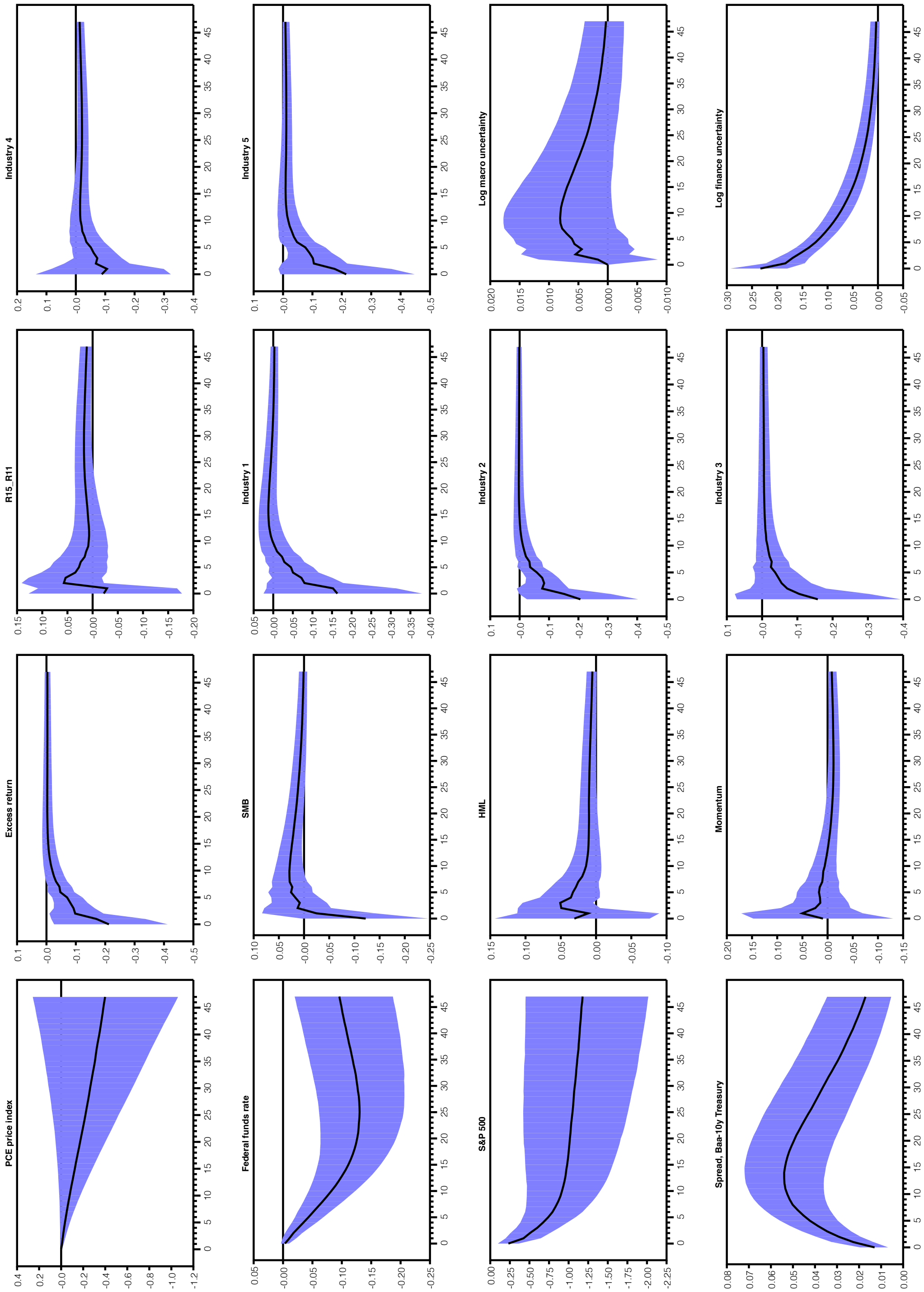


Figure 5: Continued, impulse responses, one st. dev. shock to financial uncertainty, 30-variable model, monthly data: posterior median (black line) and 15%/70% quantiles (blue shading)

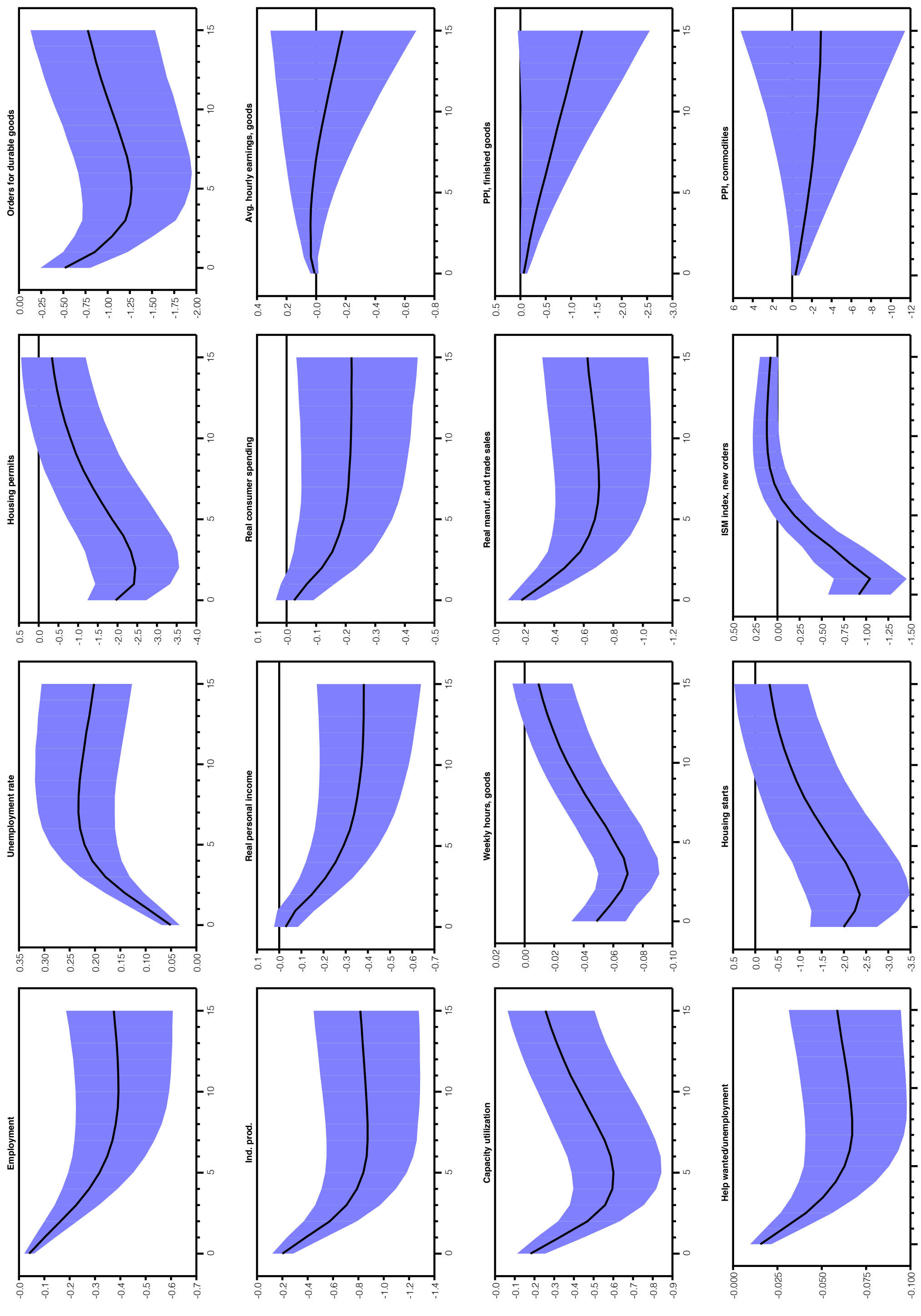


Figure 6: Impulse responses, one st. dev. shock to macro uncertainty, 30-variable model, quarterly data: posterior median (black line) and 15%/70% quantiles (blue shading)

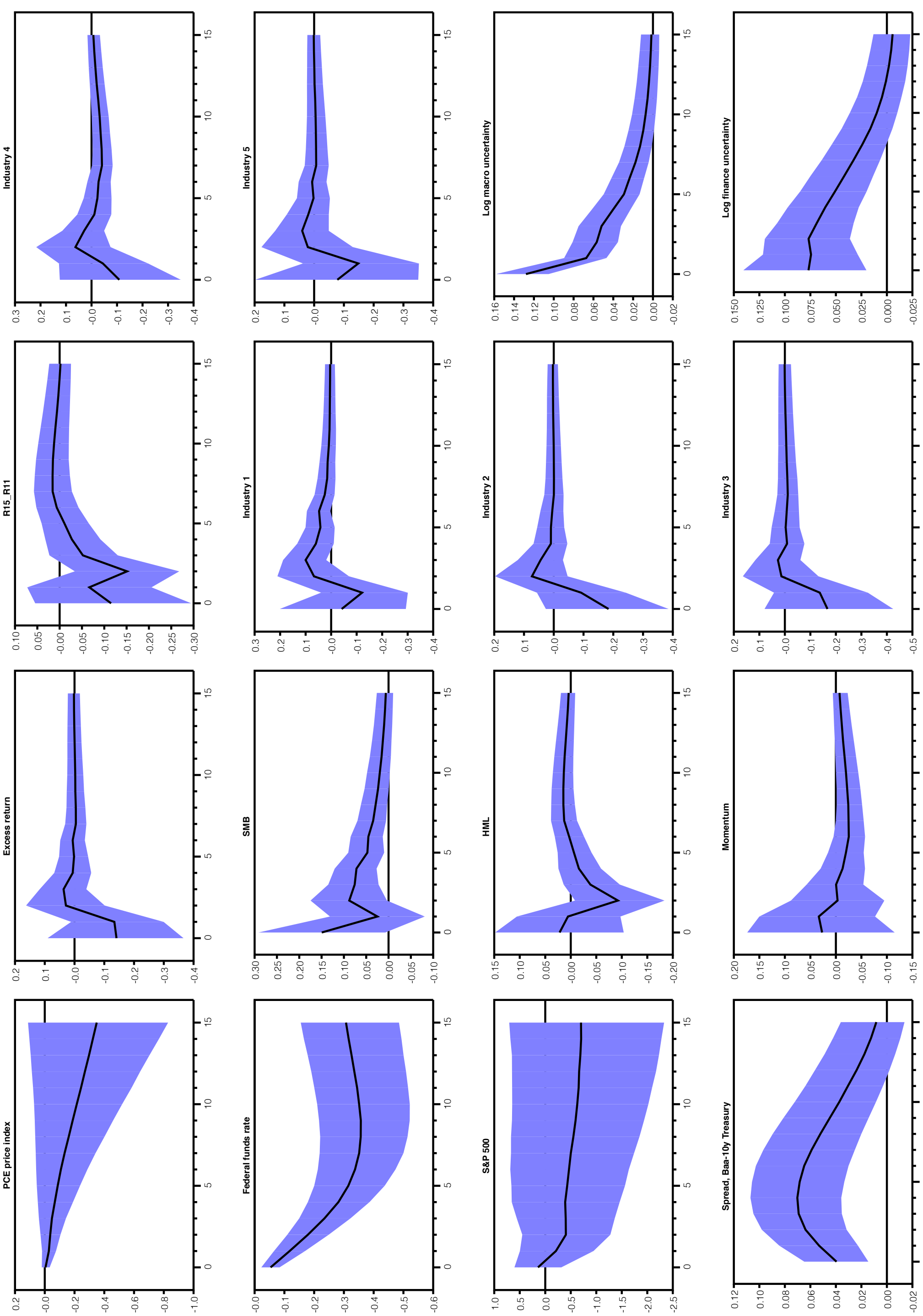


Figure 6: Continued, impulse responses, one st. dev. shock to macro uncertainty, 30-variable model, quarterly data: posterior median (black line) and 15%/70% quantiles (blue shading)

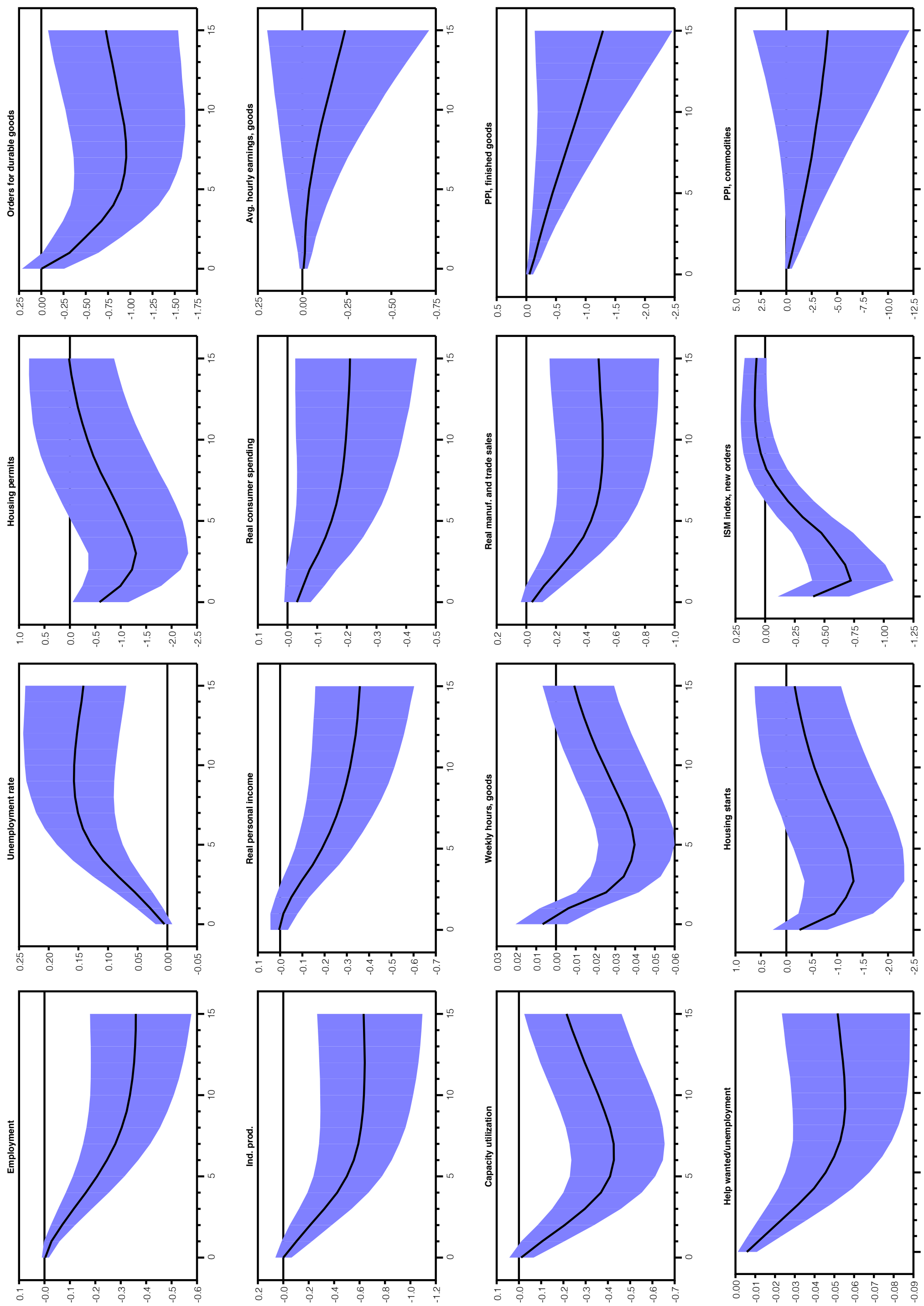


Figure 7: Impulse responses, one st. dev. shock to financial uncertainty, 30-variable model, quarterly data: posterior median (black line) and 15%/70% quantiles (blue shading)

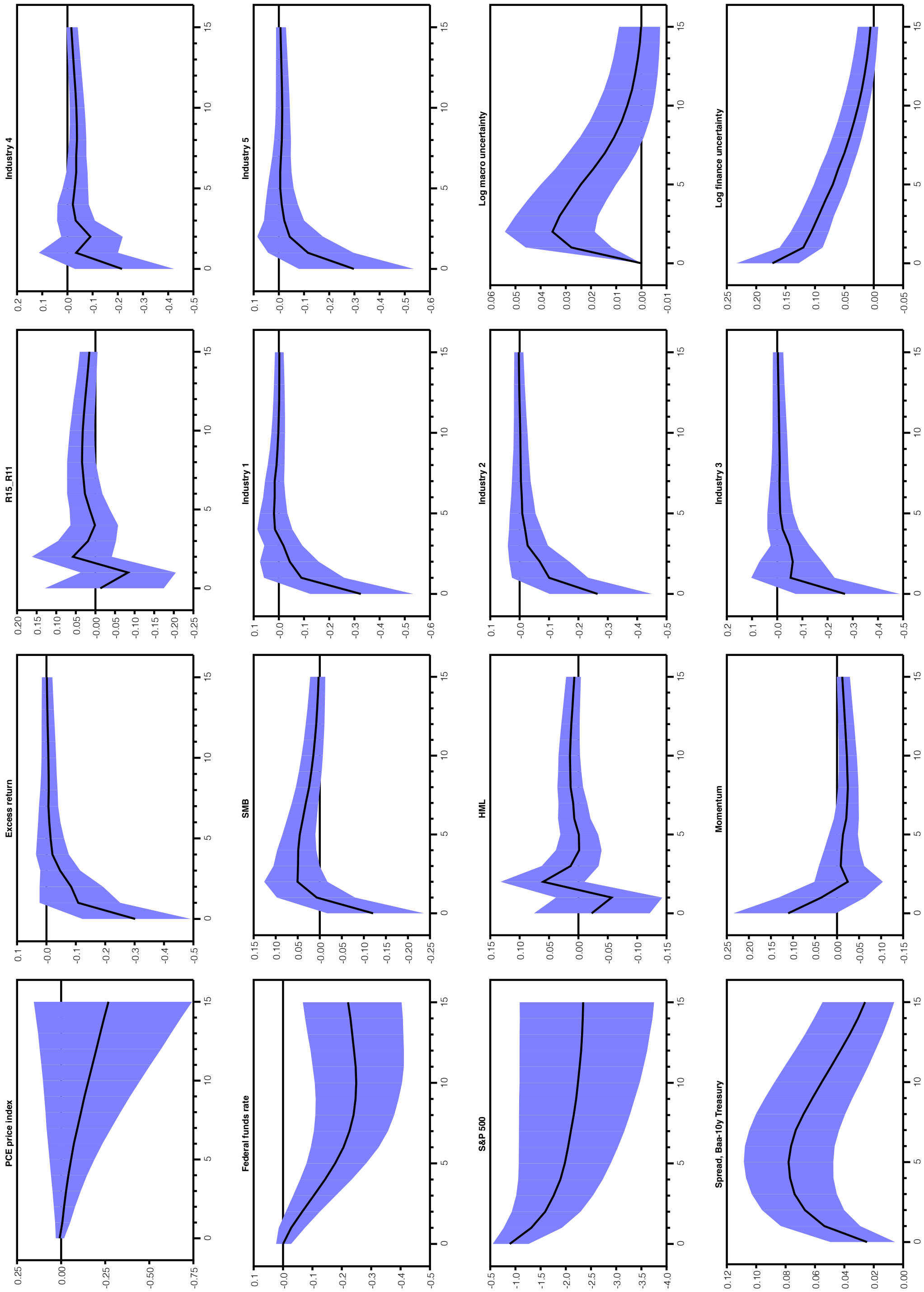
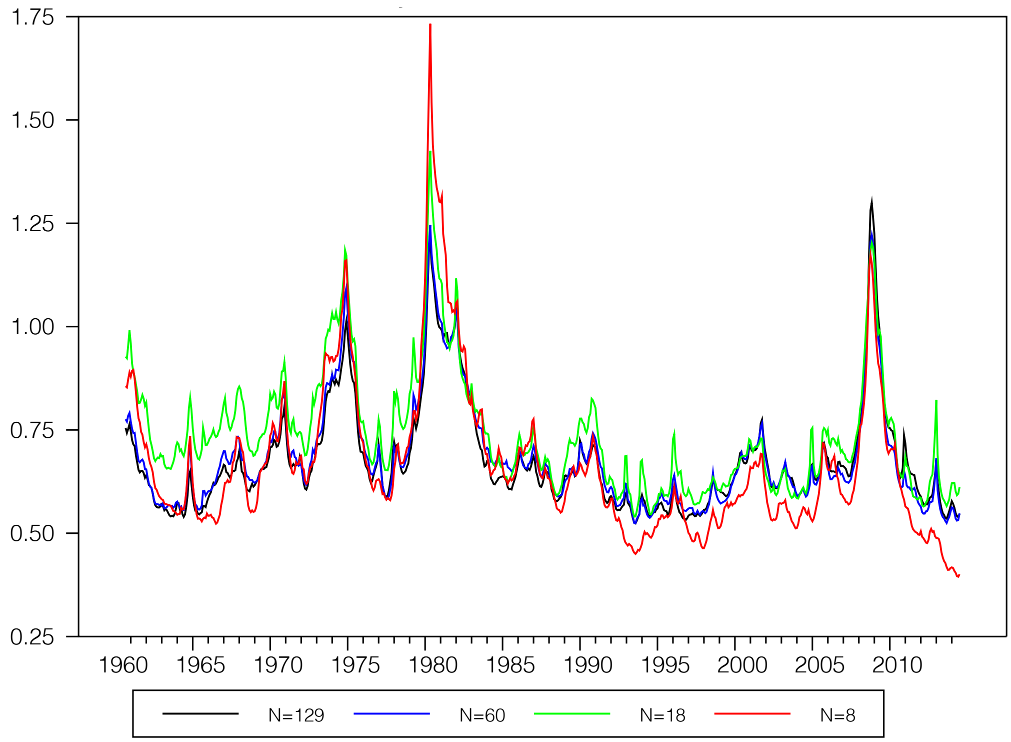


Figure 7: Continued, impulse responses, one st. dev. shock to financial uncertainty, 30-variable model, quarterly data: posterior median (black line) and 15%/70% quantiles (blue shading)



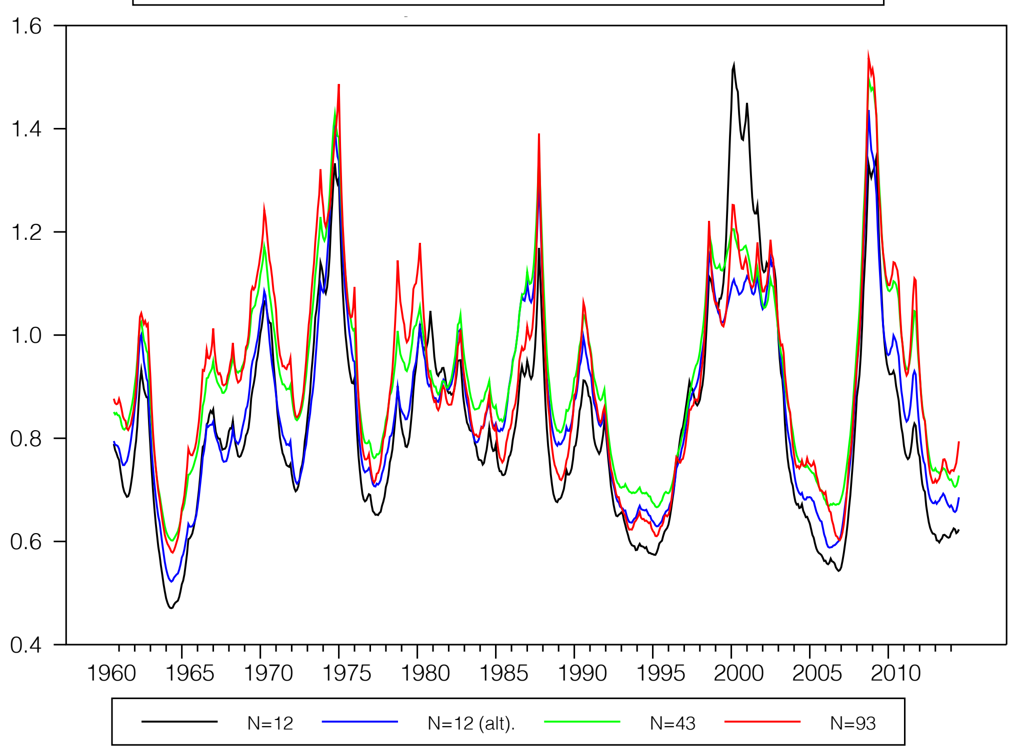


Figure 8: Uncertainty obtained from AR-SV estimates, different variable sets. The top panel of macro measures includes averages across different variable sets indicated in Table 3. The variable set N=18 corresponds to the set of macroeconomic variables included in the baseline model. The bottom panel of financial measures includes averages across the N=12 financial variables included in the baseline model, an alternative set of 12 variables that drop the Fama-French factors and use a 10-industry breakdown, a set of 43 industry-level portfolio returns, and a set of 93 industry-level portfolio returns.

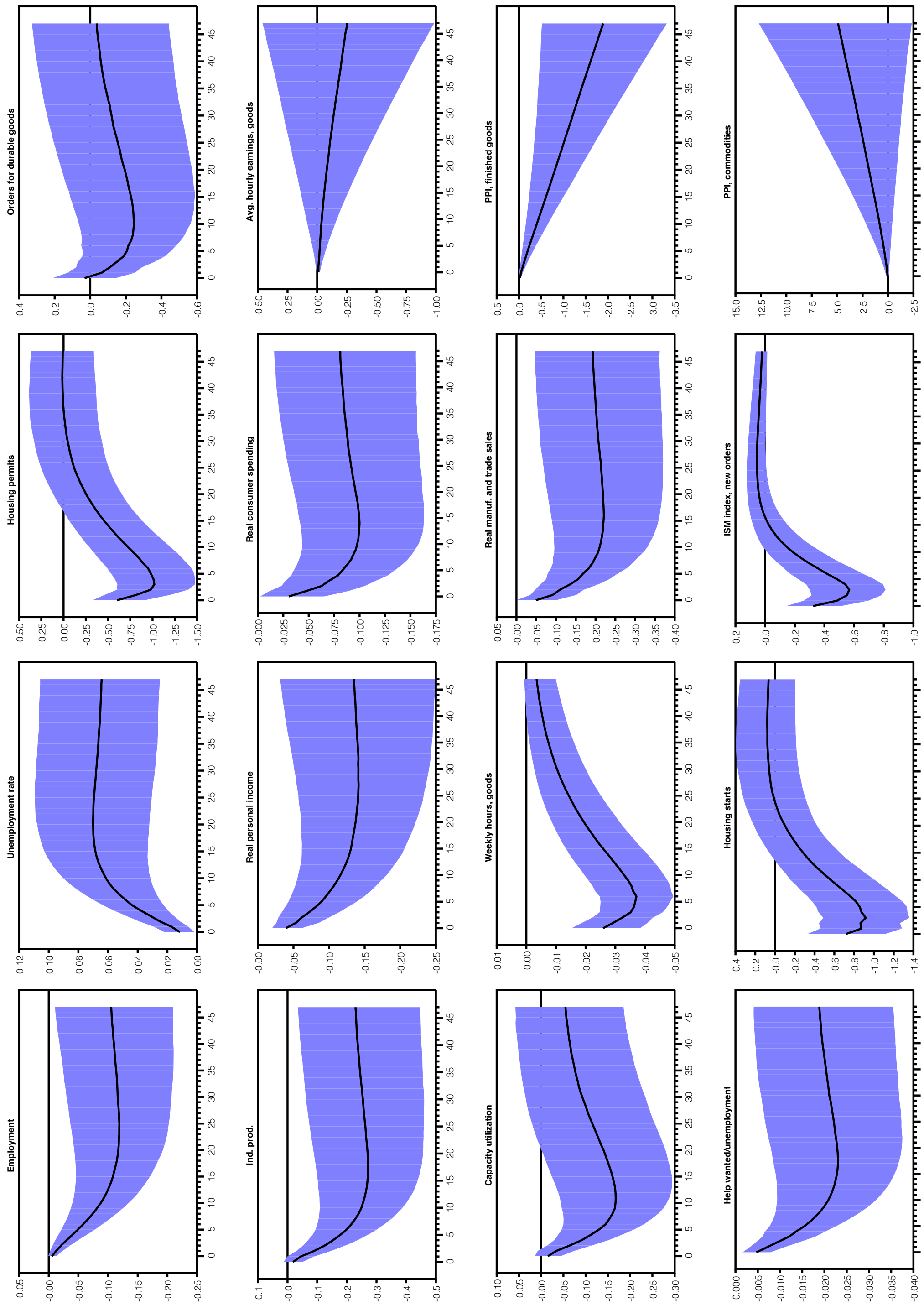


Figure 9: Impulse responses, one st. dev. shock to macro uncertainty, 30-variable model, monthly data ending in Dec. 2007: posterior median (black line) and 15%/70% quantiles (blue shading)

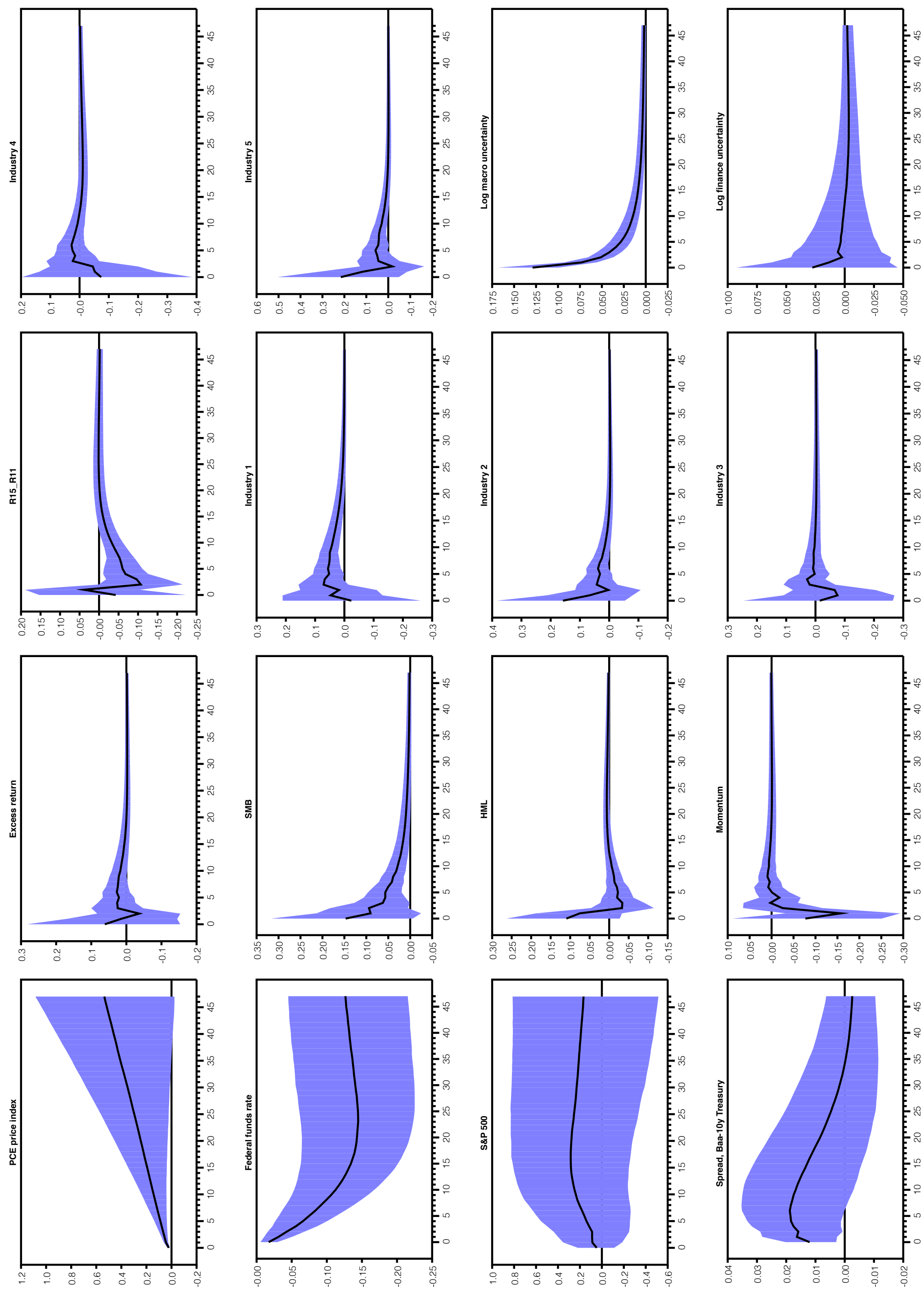


Figure 9: Continued, impulse responses, one st. dev. shock to macro uncertainty, 30-variable model, monthly data ending in Dec. 2007: posterior median (black line) and 15%/70% quantiles (blue shading)

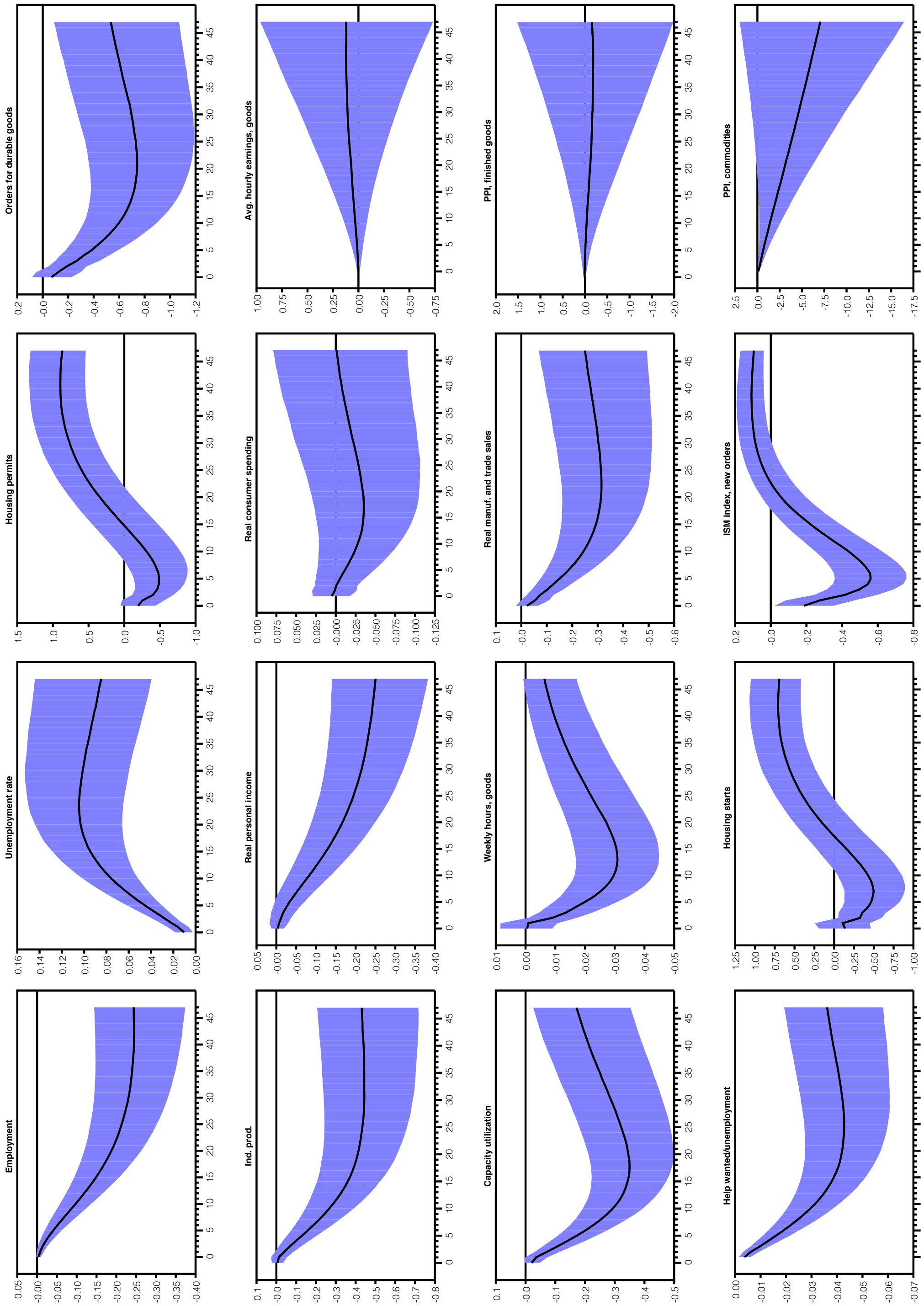


Figure 10: Impulse responses, one st. dev. shock to financial uncertainty, 30-variable model, monthly data ending in Dec. 2007: posterior median (black line) and 15%/70% quantiles (blue shading)

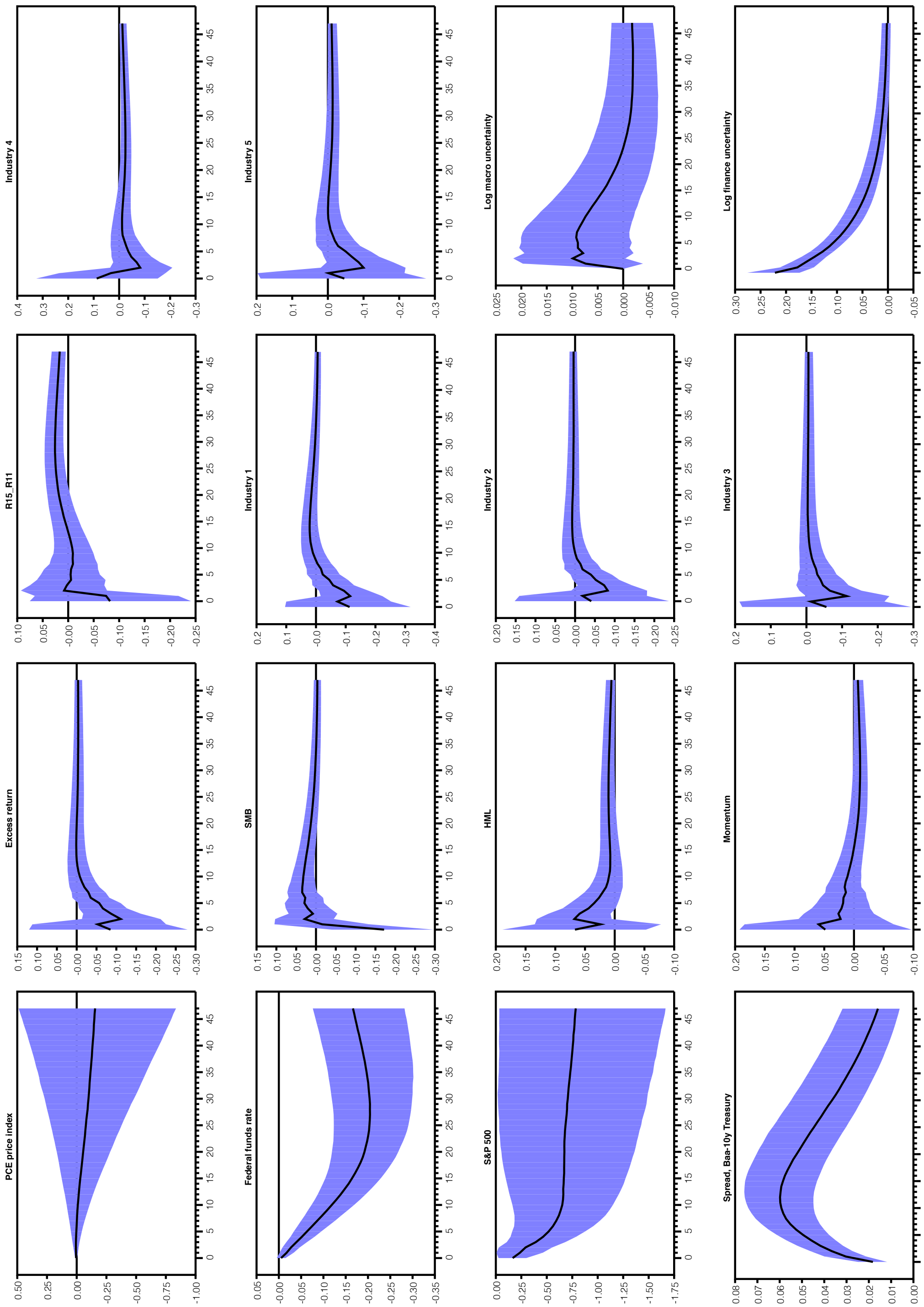


Figure 10: Continued, impulse responses, one st. dev. shock to financial uncertainty, 30-variable model, monthly data ending in Dec. 2007: posterior median (black line) and 15%/70% quantiles (blue shading)