Measuring uncertainty and its impact on the economy*

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Abstract

Recent research has focused on measuring economic uncertainty and its impact on the economy. In this paper we introduce a new econometric framework to analyze these issues. Specifically, we build a VAR model for a possibly large set of variables whose volatility is driven by a common unobservable factor, which can be interpreted as the underlying aggregate uncertainty and can also affect the levels of the variables. Hence, contrary to most existing measures, ours reflects changes in both the conditional mean and volatility of the underlying variables, and is estimated taking explicitly into account the existence of aggregate uncertainty. Moreover, our approach allows simultaneous estimation of the uncertainty and its impact on the economy, providing also a coherent measure of the uncertainty around them, while most existing studies rely on a two step approach with one model used to estimate uncertainty and a second one to assess its effects. We introduce a new Bayesian estimation method for the model, which is computationally efficient and allows for estimation even of large models. We then apply the method to estimate uncertainty and its effects using US data, finding that at least medium sized models (about 20 variables) are needed for proper estimation of uncertainty, there is indeed substantial commonality in uncertainty, sizable effects of uncertainty on key macroeconomic variables, but also some uncertainty about uncertainty and its effects. Similar results also hold separately for macroeconomic and financial uncertainty, which can be separately identified in an extended version of our model.

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1 Introduction

In the aftermath of the 2008 financial crisis and the Great Recession the interest of economists and policy makers 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 grown in the last few years. We are particularly interested in econometric studies on measuring uncertainty and its effects on the economy, starting with the seminal paper by Bloom (2009). Other relevant contributions include Bachmann, et al. (2013), Caggiano, Castelnuovo and Groshenny (2014), Basu and Bundick (2015), Jo and Sekkel (2015), Jurado, et al. (2015), Baker, Bloom and Davis (2015), and Gilchrist, Sim and Zakrajek (2014); Bloom (2014) surveys related work.

A common denominator of most of the contributions in the literature is the fact that a measure of uncertainty (either financial or macroeconomic, or both) is estimated in a preliminary step and then used as if it were an 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[1], Basu and Bundick (2015) the VXO[2], Bachmann, et al. (2013) the disagreement in business expectations, Jurado, et al. (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 (2015) an index based on newspapers coverage, 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 VAR model and compute the responses of the macro variables to the uncertainty shock. While such an approach 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 complicates the task of making statistical inference on its effects. In addition, 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 providing results on the impact to just a

[1] According to the CBOE, which created the VIX, it "is based on the S&P 500 Index (SPX), the core index for U.S. equities, and estimates expected volatility by averaging the weighted prices of SPX puts and calls over a wide range of strike prices."

[2] The CBOE's VXO is based on trading of S&P 100 (OEX) options.

few economic indicators.

In this paper we introduce a coherent econometric set-up to construct a measure of aggregate (or macro) uncertainty and to conduct inference on its impact on the macroeconomy. We focus on measures of uncertainty based on the volatility of the forecast errors resulting from optimal predictions based on econometric models, because we believe that this is reasonable from an economic point of view and provides the most convenient set-up for a proper statistical formulation of the problem, as it has been pointed out by Jurado, Ludvigson and Ng (2015); see also Ramey and Ramey (1995) for an early contribution.

The approach we propose for measuring and assessing macroeconomic uncertainty has the following six main features:

A) It permits the use of a possibly large information set. The literature on forecasting with large datasets, see e.g. Stock and Watson (2002) or Banbura, Giannone and Reichlin (2010), 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 (2015b) suggesting that about 20 carefully selected macroeconomic and financial variables could be sufficient.

B) It does not depend on a specific theoretical macroeconomic model. While a theory-based measure could be more efficient, it would be biased if the underlying model is incorrect. Hence, we prefer an econometric based specification, relying on a reduced form model that typically works well for characterizing the dynamic evolution and short term forecasting macroeconomic and financial variables, a (Bayesian) Vector Autoregression (BVAR).

C) It allows for commonality in aggregate uncertainty. The underlying idea in the literature is that aggregate uncertainty is a single unobservable variable that drives the conditional volatility of most or all of the variables under analysis. However, this feature typically is not embedded in the model but rather imposed in a second step, for example, by taking either an average or a principal component of the forecast error volatilities for each of the variables in a large model.

D) It also allows for some idiosyncratic movements in the volatilities of the forecast errors of each variable. This reflects the idea that while there is a single common measure

of aggregate uncertainty, its relevance for individual variables can vary, in particular when working with a large cross-section.[3]

E) Macro uncertainty can also affect the conditional mean of the variables. Actually, this is the key idea in this literature but, strangely enough, often the relationship is only imposed in a separate auxiliary model rather than used at the uncertainty estimation level, so that the estimated measure of uncertainty only reflects the conditional second moments of the variables. In addition, in our specification, because the measure of uncertainty enters the conditional mean of the VAR, the measure of uncertainty reflects information in the levels of the variables.[4]

F) It permits to measure uncertainty around uncertainty. In our set-up, uncertainty is explicitly treated as an unobservable random variable, and our estimation procedure returns its entire posterior distribution, which is readily available for inference.

Our uncertainty measure is based on a BVAR model for a possibly large set of variables, whose stochastic volatilities (SV) are driven by a common unobservable factor. The factor can be interpreted as the underlying aggregate uncertainty and affects not only the variances but also the levels of the macroeconomic variables. To estimate the model (and the volatility factor) we develop a new MCMC algorithm, which is computationally efficient and makes tractable estimation of large models with SV.

Our proposed modeling framework extends the seminal work of Jurado, et al. (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. In the second step, the aggregate uncertainty measure of uncertainty is formed as an average of the individual estimates obtained in the first step. In the third step, the uncertainty estimate is treated as data and inserted into a separate small VAR to compute its effects on the macroeconomy. This approach rules out an assessment of the uncertainty around uncertainty in conducting inference on uncer-

[3] As noted by Jurado, et al. (2015), theoretical models of the business cycle often assume time-varying firm-level uncertainty driven by a common time varying variance of some idiosyncratic shock; see e.g. Bloom (2009), Bloom et al. (2012), and Gilchrist, Sim, and Zakrajsek (2014).

[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) introduce a univariate stochastic volatility-in-mean model, and Jo (2014) and Shin and Zhong (2014) consider multivariate VAR extensions with independent volatility processes. Using stochastic volatilities with a factor structure lets us consider the effects of common uncertainty shocks on the variables in levels, with no movements in the level innovations.

tainty's macroeconomic effects. In our VAR-based framework, our estimate of uncertainty is obtained from a model in which uncertainty affects the conditional mean of each variable in the VAR, and our estimates of the effects of uncertainty reflect the uncertainty around the measure of uncertainty.

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 for 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 (2015a), 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, as emphasized by JLN.

Jo (2014) studies the effects of oil price uncertainty on global real economic activity using a VAR model with stochastic volatility in mean and finding that the effects are sizable. While the model and the results are interesting, the VAR is for a small set of variables and the volatilities for each variable are treated as independent processes.

Shin and Zhong (2014) 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 macro uncertainty as the common factor in volatility.

Our methodology also simplifies the identification of the effects of the uncertainty shocks. In fact, in our model, changes in the (common) volatilities of the VAR's variables provide contemporaneous, identifying information on uncertainty. As a consequence, we are able to allow uncertainty to respond contemporaneously to macroeconomic developments and to contemporaneously affect the macroeconomy, without having to resort to standard VAR

based procedures to identify the uncertainty shock. 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.

We apply our proposed model to monthly US data for the period 1959-2014, finding that at least medium sized models (about 20 variables) are needed for proper estimation of macro uncertainty, and that there is indeed substantial evidence of commonality in volatilities, but idiosyncratic volatilities are not negligible. Interestingly, along one dimension, we find a limited role for the specific forecasting model adopted, with a set of univariate AR-SV models and a single large BVAR-SV model yielding comparable uncertainty estimates, which in turn are similar to the JLN (factor model based) measure. 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. Instead, we find little 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.

Next, in impulse response analysis, we document sizable effects of uncertainty shocks on many macroeconomic and financial variables. As JLN, we find a negative impact on industrial production and employment, but more persistent than in their case: it is significant for about 18 and 36 months, respectively, and there is no rebound afterwards, contrary, e.g., to Bloom (2009). We also detect a significant decrease in capacity utilization, lasting about 18 months, in the orders of durable goods, and in the orders component of the NAPM index, which signal a clear decrease in actual and expected investment. In the labour market, we also find that hours worked generally decrease and unemployment increases, in line with firms trying to avoid hiring adjustment costs, as, e.g., in Nickell (1986) and Bloom (2009). The overall effects on real personal income and real personal consumption expenditures are significantly negative and persistent. In the face of this sizable deterioration in the real economy, the reaction of the federal funds rate is not significant for the first few months. Then, there is a decline for about 18 months, significant in statistical terms but not so much in economic terms. Such a behavior is justified by the nearly muted reaction of inflation to uncertainty shocks. Overall, this picture for inflation is in line with New-Keynesian

model analyses, such as Leduc and Liu (2015), Basu and Bundick (2015), and Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramirez (2015). In terms of financial indicators, we find that both the 10 year and the Baa spreads increase progressively, significantly and persistently, while the S&P500 experiences a major drop on impact and then slowly recovers. The drop in the S&P500 is in line with common wisdom and findings in the finance literature, see, e.g., Bansal and Yaron (2004).

To assess the overall importance of uncertainty shocks, we apply a variance decomposition to our VAR-based model. We find that uncertainty shocks play an important role in the short- and medium-run, with muted effects in the long run. The effects are particularly relevant for the labour market, housing, and financial indicators. Uncertainty shocks are also relevant to explain forecast errors in real personal income and consumption. However, the effects decline rather fast and are no longer significant after one year. Macro uncertainty instead does not seem to drive much variability in inflation.

These empirical findings provide a broad and theory-coherent picture of the effects of macro uncertainty on the economy. A relevant question is whether and to what extent they are driven by the recent financial crisis. To answer this question we have repeated the analysis with a sample ending in 2007, getting qualitatively the same results. The main difference is, naturally, a decrease in the size of the uncertainty shock of about 50% with respect to the most recent period.

Another relevant question is whether it is possible to disentangle macroeconomic and financial uncertainty in our context. For this, we have further extended the model, by allowing the VXO option-based measure, taken as a proxy for financial uncertainty, to enter both the VAR, as a variable, and the specification for the volatilities, which are now all driven by the VXO and by the unobservable factor, in addition to idiosyncratic components. Interestingly, the factor estimated from this extended model is pretty similar to the one emerging from the baseline specification, which confirms its interpretation as a macro uncertainty factor, and it has low correlation with the VXO. Moreover, the responses of the variables to shocks to the factor (macro uncertainty) are also similar to the previous ones, the most notable differences are that including VXO in the model dampens the effects on growth in stock prices and the exchange rate. A shock to macro uncertainty is estimated to have little effect on financial uncertainty, whereas the economic effects of shocks to financial uncertainty are similar to the effects of shocks to macro uncertainty. Overall,

these findings suggest that in our context macro and financial uncertainty can indeed be disentangled, and appear to have similar (negative) effects on the economy.

In conclusion, it is worth emphasizing that, while this paper focuses on measuring uncertainty and its effects on the economy, the estimation methodology we develop is wider in both its scope and its potential applications. In particular, our new MCMC algorithm can be used to estimate any large VAR with stochastic volatility, while current methods only allow estimation of small models, see, e.g., Primiceri (2005).[5] Finally, our model can be also interpreted as a factor model, or a factor augmented VAR (FAVAR), where the factor affects not only the levels but also the conditional volatility of the variables. As such, we also contribute to the vast literature on factor models, see, e.g., Stock and Watson (2015) for an overview.

The paper is structured as follows. Section 2 discusses model specification and estimation. Section 3 presents the data. Section 4 derives our aggregate uncertainty measure. Section 5 studies its effects on the economy. Section 6 disentangles macroeconomic and financial uncertainty. Section 7 summarizes our main findings and concludes.

2 The model

In this section we present the model that we later use to estimate aggregate uncertainty and its effects on the economy. We discuss, in turn, model specification and estimation. We also detail the AR model with stochastic volatility we use in some comparisons.

2.1 Specification

Let y_t denote the $n \times 1$ vector of macroeconomic and financial variables to be used to characterize both aggregate uncertainty and its effects on the economy. Our model, denoted BVAR-GFSV (General Factor Stochastic Volatility), takes the form:

$$y_t = \Pi_0 + \Pi(L)y_{t-1} + \Pi_f(L)\ln f_t + v_t, \tag{1}$$

where p denotes the number of y_t lags in the VAR, Π_0 is an $n \times 1$ vector of intercepts, $\Pi(L) = \Pi_1 - \Pi_2 L - \cdots - \Pi_p L^{p-1}$, with each Π_i an $n \times n$ matrix, $i = 1, ..., p$. The variable

[5] Our earlier work (Carriero, Clark and Marcellino (2015a)) featured a VAR model which also allowed for time varying volatilities in a large cross-section of data, but the estimation of large systems in this earlier paper is limited to a special case in which some restrictive assumptions are necessary (in particular, volatilities have to follow a factor structure with no idiosyncratic components and all the factor loadings must be set equal to 1). Moreover, compared to our previous work, we allow for the uncertainty factor to affect the conditional mean of the variables, a feature that seems particularly relevant when analysing the effects of changing volatilities on macroeconomic variables.

f_t is our measure of (unobservable) aggregate uncertainty, which can affect the levels of the y variables, with $\Pi_f(L) = \Pi_{f,0} - \Pi_{f,1}L - \cdots - \Pi_{f,g}L^g$, with each $\Pi_{f,j}$ an $n \times 1$ vector, $j = 0, ..., g$. Below, we will refer to the coefficient matrix Π that contains $\Pi_0, \Pi_1, ..., \Pi_p$ and $\Pi_{f,0}, \Pi_{f,1}, ..., \Psi_{f,g}$. We will also denote by $\pi^{(i)}$ the vector of coefficients for equation i contained in row i of Π, for the intercept, coefficients on lagged y_t, and coefficients on $\ln f_t$ and its lags for equation i.

Aggregate uncertainty also affects the volatility of the shocks to each y variable. The reduced-form shocks are modeled as follows:

$$v_t = A^{-1}\Lambda_t^{0.5}\epsilon_t, \ \epsilon_t \sim iid \ N(0, I), \tag{2}$$

where A is an $n \times n$ lower triangular matrix with ones on the diagonal, and Λ_t is a diagonal matrix with generic j-th element

$$\lambda_{jt} = f_t^{\beta_j} \cdot h_{j,t}. \tag{3}$$

Hence, the log-volatilities follow a linear factor model:

$$\ln \lambda_{jt} = \beta_j \ln f_t + \ln h_{j,t}, \tag{4}$$

where f_t is the common factor capturing aggregate uncertainty and $h_{j,t}$ is the idiosyncratic volatility component associated with the j-th variable in the VAR. The model is completed by specifying laws of motion for the unobserved states:

$$\ln f_t = \gamma_{n+1,1} \ln f_{t-1} + u_t., \tag{5}$$

$$\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1} + e_{j,t}, \ j = 1, \ldots, n. \tag{6}$$

For identification, we set $\beta_1 = 1$ and assume $\ln f_t$ to have zero unconditional mean. We further assume that the innovations to volatilities, $\nu_t = (e_{1,t}, ..., e_{n,t}, u_t)'$, are jointly distributed as $i.i.d.$ $N(0, \Phi)$ and independent among themselves, so that

$$Var(\nu_t) = \Phi = diag(\phi_1, ..., \phi_n, \phi_{n+1}). \tag{7}$$

The model in (1)-(7) is related to Carriero, Clark and Marcellino (2015a), who impose $\Pi_f(L) = 0$ and consider a small model for computational reasons. As discussed in the introduction, when measuring uncertainty it is instead important to allow n to be large and direct effects of uncertainty on the endogenous macroeconomic and financial variables ($\Pi_f(L) \neq 0$). The model is also related to Cogley and Sargent (2005) and Primiceri (2005),

who also impose $\Pi_f(L) = 0$ and, in addition, assume that there is no factor structure in the 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 (2015a), 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)-(7) 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)-(7) substantially complicates estimation, as we discuss in the next subsection. The reader not interested in technicalities can directly move 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). Following Alessandri and Mumtaz (2014), we set the lag order for the uncertainty factor in the VAR's conditional mean at 1, so that the model includes the current value of uncertainty and one lag.

2.2 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 distribution 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. One of our contributions is to provide an efficient estimation algorithm that allows n to be much larger; in the empirical application we will report results for $n = 23$, but even larger values are feasible (indeed, results for

[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.

$n = 40$ are qualitatively similar to those reported).

To make estimation feasible in a model with a large number of variables and stochastic volatility, we exploit the VAR triangularization of Carriero, Clark and Marcellino (2015c), who consider the case $\Pi_f(L) = 0$ 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 $v_t = A^{-1}\Lambda_t^{0.5}\epsilon_t$:

$$\begin{bmatrix} v_{1,t} \\ v_{2,t} \\ ... \\ v_{n,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & ... & 0 \\ a^*_{2,1} & 1 & & ... \\ ... & & 1 & 0 \\ a^*_{n,1} & ... & a^*_{n,n-1} & 1 \end{bmatrix} \begin{bmatrix} \lambda^{0.5}_{1,t} & 0 & ... & 0 \\ 0 & \lambda^{0.5}_{2,t} & & ... \\ ... & & ... & 0 \\ 0 & ... & 0 & \lambda^{0.5}_{n,t} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ ... \\ \epsilon_{n,t} \end{bmatrix}, \tag{8}$$

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:

$$\begin{aligned}
y_{1,t} &= \pi^{(0)}_1 + \sum_{i=1}^{n}\sum_{l=1}^{p}\pi^{(i)}_{1,l}y_{i,t-l} + \sum_{l=0}^{g}\pi^{(f)}_{l,1}\ln f_{t-l} + \lambda^{0.5}_{1,t}\epsilon_{1,t} \\
y_{2,t} &= \pi^{(0)}_2 + \sum_{i=1}^{n}\sum_{l=1}^{p}\pi^{(i)}_{2,l}y_{i,t-l} + \sum_{l=0}^{g}\pi^{(f)}_{l,2}\ln f_{t-l} + a^*_{2,1}\lambda^{0.5}_{1,t}\epsilon_{1,t} + \lambda^{0.5}_{2,t}\epsilon_{2,t} \\
&... \\
y_{n,t} &= \pi^{(0)}_n + \sum_{i=1}^{n}\sum_{l=1}^{p}\pi^{(i)}_{n,l}y_{i,t-l} + \sum_{l=0}^{g}\pi^{(f)}_{l,N}\ln f_{t-l} + a^*_{n,1}\lambda^{0.5}_{1,t}\epsilon_{1,t} + \cdots + a^*_{n,n-1}\lambda^{0.5}_{n-1,t}\epsilon_{n-1,t} + \lambda^{0.5}_{n,t}\epsilon_{n,t},
\end{aligned}$$

with the generic equation for variable j:

$$y_{j,t} - (a^*_{j,1}\lambda^{0.5}_{1,t}\epsilon_{1,t} + \cdots + a^*_{j,,j-1}\lambda^{0.5}_{j-1,t}\epsilon_{j-1,t}) = \pi^{(0)}_j + \sum_{i=1}^{n}\sum_{l=1}^{p}\pi^{(i)}_{j,l}y_{i,t-l} + \sum_{l=0}^{g}\pi^{(f)}_{l,j}\ln f_{t-l} + \lambda_{j,t}\epsilon_{j,t}. \tag{9}$$

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 (9) 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:

$$y^*_{j,t} = y_{j,t} - (a^*_{j,1}\lambda^{0.5}_{1,t}\epsilon_{1,t} + \cdots + a^*_{j,,j-1}\lambda^{0.5}_{j-1,t}\epsilon_{j-1,t}), \tag{10}$$

and equation (9) becomes a standard generalized linear regression model for the variable in equation (10) with i.i.d. Gaussian disturbances with mean 0 and variance $\lambda_{j,t}$.

Accordingly, drawing on results detailed in Carriero, Clark and Marcellino (2015c), the posterior distribution of the VAR coefficients can be factorized as (note that $\beta = (\beta_2, ..., \beta_n)$):

$$\begin{aligned} p(\Pi|A, \beta, f_T, h_T, y_T) &= p(\pi^{(n)}|\pi^{(n-1)}, \pi^{(n-2)}, \ldots, \pi^{(1)}, A, \beta, f_T, h_T, y_T) \\ &\quad \times p(\pi^{(n-1)}|\pi^{(n-2)}, \ldots, \pi^{(1)}, A, \beta, f_T, h_T, y_T) \\ &\quad \times p(\pi^{(1)}|A, \beta, f_T, h_T, y_T), \end{aligned}$$

where the vector $\beta = (\beta_2, ..., \beta_n)$ collects the loadings of the uncertainty factor and f_T, $h_T = (h_{1,T}, ..., h_{n,T})$ and y_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 (2015c), 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 factor f_t in the conditional means and variances.

Importantly, as noted in Carriero, Clark and Marcellino (2015c), although the expression (8) 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 posterior of the reduced form coefficients, so changing the order of the variables is inconsequential to the results, even though it is of course convenient to order the variables in a way that is already consistent with the preferred strategy for identification of structural shocks.

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.

2.3 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 denote the vector of coefficients of the idiosyncratic volatility process for variable i as γ_i, and use γ to collect γ_i, $i = 1, \ldots, n+1$. In addition, we group the parameters of the model in (1)-(7), except the vector of factor loadings β, into

$$\Theta = \{\Pi, A, \gamma, \Phi\}. \tag{11}$$

Let s_T denote the time series of the mixture states used in the KSC algorithm to draw h_T.

We use an MCMC algorithm to obtain draws from the joint posterior distribution of model parameters Θ, loadings β, and latent states h_T, f_T, s_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_T):

1. h_T, $\beta \mid \Theta$, s_T, f_T

2. Θ, s_T, $f_T \mid h_T$, β.

The first step relies on a state space system. Defining the rescaled residuals $\tilde{v}_t = Av_t$, taking the log squares of (2), and using (4) yields the observation equations:

$$\ln(\tilde{v}_{j,t}^2 + \bar{c}) = \beta_j \ln f_t + \ln h_{j,t} + \ln \epsilon_{j,t}^2, \ j = 1, \ldots, n. \tag{12}$$

For the idiosyncratic volatility components, the transition and measurement equations of the state-space system are given by (6) and (12), respectively. The system is linear but not Gaussian, due to the error terms $\ln \epsilon_{j,t}^2$. However, $\epsilon_{j,t}$ is a Gaussian process with unit variance; therefore, we can use the mixture of normals approximation of Kim, Shepard and Chib (1998) to obtain an approximate Gaussian system, conditional on the mixture of states s_T. To produce a draw from h_T, $\beta \mid \Theta$, s_T, f_T we then proceed as usual by (a) drawing the time series of the states given the loadings using ($h_T \mid \beta$, Θ, s_T, f_T), following Primiceri's (2005) implementation of the KSC algorithm, and by then (b) drawing the loadings given the states using ($\beta \mid h_T$, Θ, s_T, f_T), using the conditional posterior detailed below in (22). 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:

$$\ln(\tilde{v}_{j,t}^2 + \bar{c}) - \ln h_{j,t} = \beta_j \ln f_t + \ln \epsilon_{j,t}^2, \ j = 1, \ldots, n.$$

With the conditioning on h_T and s_T in the posterior for β, we use this equation, along with the mixture mean and variance associated with the draw of s_T, for sampling the factor loadings with a conditionally normal posterior with mean and variance represented in a GLS form.

The second step conditions on the idiosyncratic volatilities and factor loadings to produce draws of the model coefficients Θ, common uncertainty factor f_T, and the mixture states s_T. Draws from the posterior Θ, s_T, $f_T \mid h_T$, β are obtained in three sub-steps

from, respectively: (a) $\Theta \mid f_T,\ h_T,\ \beta$; (b) $f_T \mid \Theta,\ h_T,\ \beta$; and (c) $s_T \mid \Theta,\ f_T,\ h_T,\ \beta$. More specifically, for $\Theta \mid f_T,\ h_T,\ \beta$ we use the posteriors detailed below, equations (18), (19), (20) and (21). For $f_T \mid \Theta,\ h_T,\ \beta$, we use a modification of the Cogley and Sargent (2005) implementation of the JPR algorithm (single-step Metropolis). The modification is necessitated by the role of the log factor in the conditional mean of the VAR; the residuals that enter the MH calculations need to be recomputed to reflect the proposal and draw of the log factor and its lags in the conditional mean of the VAR. For $s_T \mid \Theta,\ f_T,\ h_T,\ \beta$, we use the 10-state mixture approximation of Omori, et al. (2007) that improves on Kim, Shephard, and Chib's (1998) 7-state approximation.

2.3.1 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 technical Appendix):

$$\begin{aligned}
\text{vec}(\Pi) &\sim N(\text{vec}(\underline{\mu}_\Pi), \underline{\Omega}_\Pi), && (13)\\
a_j &\sim N(\underline{\mu}_{a,j}, \underline{\Omega}_{a,j}),\ j = 2, \ldots, n, && (14)\\
\beta_j &\sim N(\underline{\mu}_\beta, \underline{\Omega}_\beta),\ j = 2, \ldots, n, && (15)\\
\gamma_j &\sim N(\underline{\mu}_\gamma, \underline{\Omega}_\gamma),\ j = 1, \ldots, n+1, && (16)\\
\phi_j &\sim IG(d_\phi \cdot \underline{\phi}, d_\phi),\quad j = 1, \ldots, n+1. && (17)
\end{aligned}$$

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

$$\begin{aligned}
\text{vec}(\Pi)|A, \beta, f_T, h_T, y_T &\sim N(\text{vec}(\bar{\mu}_\Pi), \bar{\Omega}_\Pi), && (18)\\
a_j|\Pi, \beta, f_T, h_T, y_T &\sim N(\bar{\mu}_{a,j}, \bar{\Omega}_{a,j}),\ j = 2, \ldots, n, && (19)\\
\gamma_j|\Pi, A, \beta, \Phi, f_T, h_T, y_T &\sim N(\bar{\mu}_\gamma, \bar{\Omega}_\gamma),\ j = 2, \ldots, n+1, && (20)\\
\phi_j|\Pi, A, \beta, \gamma, f_T, h_T, y_T &\sim IG\left(d_\phi \cdot \underline{\phi} + \sum_{t=1}^{T} \nu_{jt}^2,\ d_\phi + T\right),\ j = 1, \ldots, n+1, && (21)\\
\beta_j|\Pi, A, \gamma, \Phi, f_T, h_T, s_T, y_T &\sim N(\bar{\mu}_\beta, \bar{\Omega}_\beta),\ j = 2, \ldots, n. && (22)
\end{aligned}$$

Expressions for $\bar{\mu}_{a,j}$ 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 $\bar{\mu}_{\beta}$, 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 (2015b). However, as discussed in Carriero, Clark and Marcellino (2015c), with larger models, it is far faster to exploit the triangularization given above and estimate the VAR coefficients on an equation-by-equation basis. Specifically, using the factorization in (11) together with the model in (9) 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:

$$\Pi^{(j)}|\Pi^{(1:j-1)}, A, \beta, f_T, h_T, y_T \sim N(\bar{\mu}_{\Pi^{\{j\}}}, \overline{\Omega}_{\Pi^{\{j\}}}), \tag{23}$$

with

$$\bar{\mu}_{\Pi^{\{j\}}} = \overline{\Omega}_{\Pi^{\{j\}}} \left\{ \sum_{t=1}^{T} X_{j,t} h_{j,t}^{-1} y_{j,t}^{*\prime} + \underline{\Omega}_{\Pi^{\{j\}}}^{-1} (\underline{\mu}_{\Pi^{\{j\}}}) \right\}, \tag{24}$$

$$\overline{\Omega}_{\Pi^{\{j\}}}^{-1} = \underline{\Omega}_{\Pi^{\{j\}}}^{-1} + \sum_{t=1}^{T} X_{j,t} h_{j,t}^{-1} X_{j,t}^{\prime}, \tag{25}$$

where $y_{j,t}^{*}$ is defined in (10) and where $\underline{\Omega}_{\Pi^{\{j\}}}^{-1}$ 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 $\overline{\Omega}_{\Pi}^{-1}$. Note we have implicitly assumed here that the matrix $\underline{\Omega}_{\Pi}^{-1}$ is block diagonal, which means that we are ruling out any prior correlation among the coefficients belonging to different equations. This is a restriction with respect to the more general model; however, we note that the typical priors elicited in the literature for the matrix Ω typically do not involve cross-equation correlations.

2.3.2 Unobservable states

For the unobservable volatility states f_t and $h_{j,t}$, $j = 1, ..., n$, we need to specify priors for the period 0 values, detailed in the technical Appendix. Given the priors and the law of motion for the unobservable states in (5)-(6), draws from the posteriors can be obtained using the algorithm of Kim, Shepard and Chib (1998, KSC) for the idiosyncratic volatilities and the algorithm of Jacquier, Polson, and Rossi (1994, JPR) (as implemented by Cogley and Sargent 2005) for the common factor in volatility. For the common factor in volatility, the dependence of the VAR's conditional mean on the latent volatility process requires the

use of the single-move JPR sampler over the multi-move KSC sampler, with modification of the JPR sampler to take account of the fact that the residuals that enter the MH calculations need to be recomputed to reflect the proposal and draw of the log factor and its lags in the conditional mean of the VAR and, in turn, the VAR's residuals.

2.4 AR-SV model

To facilitate some comparisons to the results of JLN, 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:

$$y_t = \pi_0 + \pi(L)y_{t-1} + \lambda_t^{0.5}\epsilon_t,\ \epsilon_t \sim iid\ N(0,1), \tag{26}$$

$$\ln \lambda_t = \gamma_0 + \gamma_1 \ln \lambda_{t-1} + e_t,\ e_t \sim iid\ N(0,\phi). \tag{27}$$

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 BVAR-GFSV 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

Most of our results are based on 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 Jurado, Ludvigson, and Ng (2015). 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, our 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) to achieve stationarity.[7]

In the results below, we make use of various subsets of the dataset, detailed in Table 1. In some results, we use all of the 129 series to fit AR-SV models and form measures of

[7] The McCracken-Ng transformations are very similar to those of Jurado, Ludvigson, and Ng (2015).

uncertainty with an approach similar to that of Jurado, Ludvigson, and Ng (2015), detailed above. Our primary VAR results are based on a set of 23 variables, which consists of one or two major aggregates or series representing the major categories of the McCracken-Ng dataset. In considering how the size of the dataset affects uncertainty estimates obtained with an approach like that of Jurado, Ludvigson, and Ng (2015), we also report AR-SV-based uncertainty estimate based on 8 or 60 series. We also make some comparisons to the measure of uncertainty estimated by JLN, obtained from the website of Professor Ludvigson. Finally, we also make some use of a financial uncertainty measure we refer to as the VXO. Following Bloom (2009) and Jurado, Ludvigson, and Ng (2015), our VXO series splices a measure of realized volatility (monthly standard deviation of daily returns) for 1960-1985 to 1986-2014 VXO data constructed by the Chicago Board of Options Exchange from the prices of options contracts written on the S&P 100 Index.

4 Measuring Aggregate Uncertainty

4.1 AR-based estimates

A first issue we consider is the role of the forecasting model when computing point estimates of the uncertainty measure. JLN work with a factor-augmented AR model, whose underlying assumption is the existence of few unobservable driving forces common to all the variables, the factors, which are estimated as the first few principal components (PCs) of the variables themselves. As a starting point, we take the opposite view: we model each of our 129 (standardized, as in JLN) variables separately, by means of simple autoregressive (AR) models, with stochastic volatility (SV), detailed above. Hence, we assume no commonality at all among the variables. As mentioned, in a second step, JLN take the average of the forecast error variances for each variable (at different horizons) as their measure of aggregate uncertainty. Similarly, we just use the averages of forecast error variances obtained from the AR-SV models estimated for each variable.

The JLN and AR-SV uncertainty measures are graphed in Figure 1, for h=1, 3, 12-month ahead forecast horizons. The similarity of the two measures is striking: when h=1 the correlation is about 0.99, and it is only slightly lower even for h=12, 0.87. At first sight this result can seem surprising. However, it is well known (see, e.g., Stock and Watson 1999) that AR models produce very good forecasts for a variety of variables, not so different from those resulting from factor models. We have also tried, as JLN, to compute the

first principal component of the volatilities rather than average, in order to estimate an underlying common factor, and the resulting uncertainty measures are very similar to those reported in Figure 1 (see Figure A1 in the supplementary Appendix).

Having established that AR-SV models can be used to approximate very well the JLN uncertainty measure, we next consider the effects of the number (and type) of variables on the point estimate of the uncertainty measure. In Figure 2 we report AR-SV-based uncertainty measures resulting from averaging the SVs of 8, 23, 60 and 129 variables. As mentioned in the previous section, the different subsets of variables mainly differ for the level of considered disaggregation, as detailed in Table 1. The measure for 129 variables is the same as in Figure 1. Those for 60 and 23 variables are extremely similar; they can be hardly distinguished in the figure. However, the measure resulting from the use of just 8 variables is rather different from the other ones. Specifically, it 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. This finding mimics results in the forecasting literature that very large datasets are not necessarily better than medium sized datasets, but the latter are indeed better than smaller datasets; see, e.g., Koop (2013). An implication is that we can focus on 23 variables only and still get reliable point estimates for uncertainty.

4.2 VAR-based estimates

Working with the subset of N=23 variables is quite convenient to compute our proposed measure of aggregate uncertainty. Indeed, while the latter can be computed also for much larger values of N, the required computational time increases substantially. Accordingly, in the following results, we focus on estimates of our proposed BVAR-GFSV model with 23 variables, in monthly data. In the interest of brevity, we do not compare our uncertainty measure 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. (2014) provide such comparisons.

Figure 3 provides the posterior median estimate of uncertainty obtained with the BVAR-GFSV model. For comparability with JLN, we define uncertainty as the square root of the common volatility factor f_t (recall that $\log f_t$ enters the conditional mean of the VAR), such that uncertainty corresponds to a standard deviation. The figure compares our uncertainty estimate to the horizon-specific measures of JLN, for horizons of $h = 1$, 3, and 12 months ahead (by construction, our uncertainty estimate is the same at each horizon, whereas the

JLN estimate changes modestly as the horizon increases).

The results indicate the correlation of our BVAR-GFSV uncertainty estimate with the JLN estimate is quite high, about 0.83 for $h = 1$ and $h = 3$ and about 0.80 for $h = 12$. There are, however, some minor differences. For example, when $h = 1$, 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 BVAR-GFSV.[8]

Figure 3 also reports the 15%-85% credible set bands around our estimated BVAR-GFSV measure of uncertainty, which, as mentioned, is correctly considered a random variable in our approach. The bands are sizable, which suggests that taking uncertainty around uncertainty into account could indeed be important for inference about the significance of changes in uncertainty and effects on the macroeconomy.

From an economic point of view, it is interesting that neither our BVAR-GFSV measure nor the JLN measures of uncertainty 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, with our 23 variable dataset, 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 estimate obtained with quarterly estimates of the BVAR-GFSV model, shown in Figure 4, are similar to those obtained with monthly data, reported in Figure 3. When we instead consider the reduced form volatilities of each variable — defined as the diagonal elements of Σ_t, which reflect both the common uncertainty factor 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 Figure

[8] There are also some differences with respect to the AR-SV based uncertainty measure. These emerge because the volatility estimates from AR-SV and BEBVAR-SV are different for some variables, in particular for the unemployment rate, building permits and NAPM index; see Figure A2 in the supplementary Appendix.

A3) than monthly data (Figure 5). 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.

5 Measuring the impact of uncertainty

5.1 Identification

With our uncertainty measure entering each of the equations of the BVAR-GFSV model (1), 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.

In our specification, a shock to uncertainty affects not only the conditional mean of y_t but also the conditional variance. In analysis such as JLN or Caldara, et al. (2014), it is common to conduct inference on the former while ignoring the latter. To avoid a similar practice, we are able to use our model and generalized impulse response functions (Koop, Pesaran, and Potter 1996), 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.

For computational tractability, we compute the responses using the levels of uncertainty and Σ_t at the end of the sample, in period $t = T$. This is not restrictive, as the shape of the responses does not change over time, only their size changes, depending on the changing variance of the uncertainty shocks. As detailed in the technical Appendix, we compute the generalized impulse response functions (GIRFs) by: for a given draw (j) of the BVAR-GFSV's parameters and volatilities, simulating a baseline path of volatilities and Σ_t, the associated reduced-form shocks to y_t, and y_t, over a period of $t+1$ through $t+h$ observations; constructing a shocked path to uncertainty that reflects the baseline path and a one-standard deviation shock to $\ln f_t$ in period $t = T+1$; computing the associated shocked paths of volatility and y_t; forming the responses as the difference between the baseline and shocked paths of y; repeating these steps 100 times and taking the average to obtain draw (j) of the impulse response. With the J draws of the GIRFs, we compute and report the posterior median and 70 percent credible set.

As this suggests, the specification of the BVAR-GFSV permits us to identify an uncertainty shock and its effects in a way that it is not possible in some of the other approaches in the literature, such as JLN. In our case, changes in the (common) volatilities of the VAR's variables provide contemporaneous, identifying information on uncertainty. As a consequence, we are able to allow uncertainty to respond contemporaneously to macroeconomic developments and to contemporaneously affect the macroeconomy. Put another way, we can allow shocks to uncertainty to have immediate effects on the macroeconomy, at the same time that changes in volatility immediately reflect 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, which is not immune to criticism. In the interest of brevity, we provide in the supplementary Appendix results (in Figure A4) for a constant parameter/constant volatility BVAR in 24 variables — our 23 variables and the 1-step ahead uncertainty estimate (logged, for consistency with our results) of JLN. These results have some similarity to the BVAR-GFSV results discussed below.

5.2 Results

Figure 6 provides the generalized impulse response estimates of a one-standard deviation shock to log uncertainty ($\ln f_t$) in our 23 variable (monthly frequency) BVAR-GFSV specification. Consider first the effects on industrial production and employment, which are both significantly negative, more persistent in the case of 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. Also, and again as in JLN, there is no rebound in employment and industrial production in the long run, contrary, e.g., to Bloom (2009)

In the labour market, we also find that hours worked generally decrease (with peak effect after about one year) and unemployment increases (with peak effect after about 6 months), in line with firms trying to avoid hiring adjustment costs, as, e.g., in Nickell (1986) and Bloom (2009). Interestingly, there are virtually no effects on hourly earnings, 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. Lower consumption is 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 till uncertainty lowers, e.g. Eberly (1994) and Bertola, Guiso and Pistaferri (2005).

In terms of production, we detect a significant decrease in capacity utilization, lasting about 18 months, in the orders of durable goods, and in the orders component of the NAPM index, which signal 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.

In the face of this sizable deterioration in the real economy, the reaction of the federal funds rate is not significant for the first few months. Then, there is a decline for about 18 months, significant in statistical terms but not so much in economic terms (amounting to just 3 basis points or less). Such a behavior is justified by the nearly muted reaction of inflation to uncertainty shocks. Inflation in the PCE price index decreases significantly for only 3-4 months, and the PPI follows a similar pattern (as well as the PPI for commodities), with an even less significant reaction. Overall, this picture 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 as the interest rate does not drop significantly.

In terms of financial indicators, we find that both the 10 year and the Baa spreads over the federal funds rate increase progressively, significantly and persistently, while the S&P500 experiences a major drop on impact and then slowly recovers. The substantial increase in spreads 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). The drop in the S&P500 is in line with common wisdom and findings in the finance literature, see, e.g., Bansal and Yaron (2004).

Next, to assess the quantitative relevance of uncertainty shocks for the various variables under analysis, we compute the forecast error variance decomposition, and graph the results (shares of forecast error variance due to the log uncertainty shock) in Figure 7. We find that uncertainty shocks play an important role in explaining short- and medium-horizon errors, with muted effects in the long run. The effects are particularly relevant in the labour market (employment and hours worked, with a peak value of about 25% for employment 6-month ahead), in the real estate market (housing starts and building permits, with a peak value close to 20% for permits 3-month ahead), and in the financial market (SP500 and spreads, with a peak value on impact for the former, about 12%, and delayed for the latter, about 17% for the BAA spread after 18 months ahead). Uncertainty shocks are also relevant to explain forecast errors in real personal income and consumption, with a peak value of about 15% for the former and 20% for the latter. However, the effects decline rather fast and are no longer significant after one year. Macro uncertainty instead does not seem to matter for forecasting price variables, in line with their muted impulse responses to uncertainty shocks.

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 all impulse response functions using estimates of the model with data through just December 2007. From Figure A5 in the supplementary Appendix, the impact effect of the uncertainty shock is qualitatively similar but smaller, and there is an increase in the persistence of all the responses. However, this pattern is mainly due to the size and persistence of the uncertainty shock itself, which are, respectively, smaller and larger. While a smaller shock without the crisis period is intuitive, larger persistence is due to the rather fast decrease in uncertainty after the peak around 2008. Hence, we conclude that the crisis did matter some, but mainly because it changed the size and the persistence of the uncertainty shock; the overall picture is very similar to the full sample analysis.

6 Disentangling macroeconomic and financial uncertainty

The interaction of macroeconomic and financial uncertainty, and their effects on the economy, has attracted considerable attention in the literature. A recent contribution is Ludvig-

son, Ma and Ng (2015), LMN henceforth, to whom we also refer for an extensive literature review.

LMN suggest to derive 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. Their findings indicate that "higher uncertainty about real economic activity in recessions is fully an endogenous response to other shocks that cause business cycle fluctuations, while uncertainty about financial markets is a likely source of the fluctuations. Financial market uncertainty has quantitatively large negative consequences for several measures of real activity including employment, production, and orders."

Interestingly, the results in LMN seem to invalidate those in JLN, as financial uncertainty is omitted in JLN. To understand whether the inclusion of financial uncertainty also affects substantially our results, we proceed as follows. First, in Figure 8 we plot the LMN financial uncertainty measure and the VXO. It turns out that the two measures are quite similar, with a correlation of 0.72. Hence, to measure financial uncertainty directly and simply, we rely on the VXO series (however, we obtain very similar results with the financial uncertainty index estimated by LMN).

In order to disentangle macroeconomic and financial uncertainty in our set-up, we extend the VAR in two dimensions. First, we include the log VXO as an endogenous variable in the VAR model in (1), as the last, or n'th variable, in the ordering. The VXO is in fact a "fast" variable in the terminology of Bernanke et al. (2005), which can react contemporaneously to developments in the economy, while the latter likely react with a delay to changes in the VXO. Second, we modify the specification for the log-volatilities in (4) as follows:

$$\ln \lambda_{jt} = \beta_j \ln f_t + \eta_j \ln VXO_t + \ln h_{j,t}, \;\; j = 1, \ldots, n, \tag{28}$$

where $\eta_n = 0$ and f_t can be now interpreted as the common factor capturing aggregate macroeconomic uncertainty, while the inclusion of the log VXO in (28) captures the effects of financial uncertainty on the volatilities of all variables of the VAR (except log VXO).

Similarly, the inclusion of log VXO in the VAR cleans the effects on the variables of macroeconomic uncertainty from those of financial uncertainty. Note that we do not impose f_t and VXO to be independent, as we believe that they may interact. In fact, in our specification f_t (macro uncertainty) can have an immediate effect on VXO (financial

uncertainty), and financial uncertainty can have an immediate effect on macroeconomic volatility, through the effects captured in (28). This extension of our baseline specification can be estimated with similar techniques as for the basic model.

Interestingly, the estimate of macroeconomic uncertainty resulting from this extended model ($\widehat{f}_t$) is very similar to what we got with the basic specification. In our VXO-augmented model, the correlation of our estimate of macroeconomic uncertainty with the JLN measure of macro uncertainty remains high, at 0.81 for the 1-step horizon; and our estimates from the VXO-augmented model and the baseline model are very similar, with a correlation near 0.9 (see Appendix Figure A6). Moreover, as shown in Figure 9, our estimate of macro uncertainty has only a weak correlation with the VXO, 0.21. Hence. our model seems to disentangle fairly cleanly macro and financial uncertainty. The estimates of the loadings in (28) — omitted in brevity — reflect this separation. For example, the posterior mean of the η coefficient is about 0.25 for employment growth (PAYEMS) and lower for the other economic activity variables of the model, whereas the posterior mean of η is about 0.75 for growth in stock prices (SP500) and between 0.3 and 0.6 for the interest rates and spreads of the model.

The extension of our model to include financial uncertainty also has little effect on our estimates of the effects of shocks to macro uncertainty. The impulse responses for the augmented model provided in Figure 10 are qualitatively very similar to the responses from the baseline model provided in Figure 6. They are generally 50%-75% smaller in size, but this is due to a corresponding reduction in the size of the original uncertainty shock. The most notable differences are that including VXO in the model as we do dampens the effects (and statistical significance) of a macro uncertainty shock on growth in stock prices (SP500) and on the exchange rate (EXUSUK). Consistent with the results described in the previous paragraph, a shock to macro uncertainty is estimated to have little effect on financial uncertainty as captured by the log VXO series included in the augmented VAR.

Finally, we consider the effects of a shock to financial uncertainty using our VXO-augmented model. Broadly, as captured in the impulse responses reported in Figure 11, a shock to financial uncertainty (log VXO) has effects very similar to those of a shock to macro uncertainty (our log f_t). The broad contours of the impulse responses in Figure 11 (shock to log VXO) are very similar to the impulse responses in Figure 10 (shock to log f_t). The scales differ in part because, for comparability to JLN, we scaled up the size of the

shock in Figure 10 to consider a 3-standard deviation shock, whereas we used a 1-standard deviation shock for the log VXO shock in Figure 11.

7 Conclusions

This paper develops a new framework for measuring uncertainty and its effects on the macroeconomy. Specifically, we develop a VAR model for a possibly large set of variables whose volatility is driven by a common unobservable factor, which can be interpreted as the underlying aggregate uncertainty and can also affect the levels of the variables. Hence, contrary to most existing measures, our measure of uncertainty reflects changes in both the conditional mean and volatility of the underlying variables, and it is estimated taking explicitly into account the existence of aggregate uncertainty. Moreover, our approach allows simultaneous estimation of the uncertainty and its impact on the economy, providing also a coherent measure of the uncertainty around them, while most existing studies 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 and in line with the FAVAR approach.

We introduce a new Bayesian estimation method for the model, which 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 then apply the method to estimate uncertainty and its effects using US data, finding that at least medium sized models (about 20 variables) are needed for proper estimation of uncertainty, there is indeed substantial commonality in uncertainty, sizable effects of uncertainty on key macroeconomic variables with responses in line with economic theory, some uncertainty about uncertainty and its effects, and the Great Recession associated with much larger uncertainty shocks but no major changes in their effects on the economy. Finally, similar results also hold separately for macroeconomic and financial uncertainty, which can be separately identified in an extended version of our model.

A Technical Appendix

In this Appendix, we provide the details of the priors we use in the BVAR-GFSV estimation, and we spell out the steps used to compute the generalized 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 as described in the next section, 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 terms and $\log f_t$ terms uninformative and the prior on the lags of y_t take a Minnesota-type form. Specifically, for the intercepts 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 shrinkage $\theta_3 = 1000$. With these settings, we have deliberately made the prior on the uncertainty terms in the VAR uninformative. 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 factor loadings β_j, $j = 2, ..., n$, we use a prior mean of 1 and a standard deviation of 0.4. For the slope coefficient of the log factor process $\gamma_{n+1,1}$ we use a mean of 0.8 and a standard deviation of 0.2. 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 (1.4, 0.4). For the innovations to volatility $\phi_1, ..., \phi_{n+1}$, we use a mean of 0.01 for the common factor and of 0.03 for the idiosyncratic components, with 10 degrees of freedom for each. Finally, for the period 0 values of $\log f_t$ and $\log h_{i,t}$, we set the mean and variance of $\log f_0$ at 0 and 0.5, respectively, and we set the mean and variance of $\log h_{i,0}$ at $\log \sigma_i^2$ and 2.0, respectively.

A.2 GIRF implementation

For computational tractability, we compute the generalized impulse responses using the levels of uncertainty and Σ_t at the end of the sample, in period $t = T$. Specifically, we do the following, for each retained MCMC draw, $j = 1, \ldots, J$, of model parameters and latent states (including Σ_T):

1. Simulate, for $T+1$ through $T+H$ (with $H = 48$), the baseline path of Σ_t by simulating forward both the idiosyncratic components and the common component using their AR processes;

2. For the same time period, simulate a vector of multivariate $N(0, I_n)$ shocks and obtain the vector of reduced form shocks by multiplying by the Choleski decomposition of Σ_{t+h}, for $h = 1, \ldots, H$.

3. Use the autoregressive structure of the VAR and the simulated shocks to obtain the baseline path of y_{t+h}, $h = 1, \ldots, H$.

4. Construct a shocked path to uncertainty that reflects the baseline path and a one-standard deviation shock to $\ln f_t$ in period $t = T + 1$. The size of the one standard deviation shock is the value of $\phi^{0.5}$ in draw j.

5. Construct the shocked path of Σ_t based on the shocked path of $\ln f_t$ and the baseline path of the idiosyncratic components.

6. Obtain the shocked path of reduced form shocks using the multivariate $N(0, I_N)$ shocks obtained in step (2) and the shocked path of Σ_t.

7. Use the autoregressive structure of the VAR and the simulated shocks to obtain the alternative path of y_{t+h}, $h = 1, \ldots, H$.

8. For y_{t+h}, $h = 1, \ldots, H$, and the log factor $\ln f_t$, compute and save the difference between the baseline path and the shocked path.

9. Repeat the above steps 100 times and form the average of the differences obtained in step 8. This average is the j'th draw of the GIRF.

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Table 1: Variable Combinations

variable	mnemonic	included in $N = 60$ set	included in $N = 40$ set	included in $N = 23$ 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 1, continued: Variable Combinations

variable	mnemonic	included in $N = 60$ set	included in $N = 40$ set	included in $N = 23$ 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	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	Y	
5 yr. - FFR spread 5 yr-FF spread	T5YFFM				
10 yr. - FFR spread 10 yr-FF spread	T10YFFM	Y	Y	Y	Y
Aaa - FFR spread Aaa-FF spread	AAAFFM	Y			
Baa - FFR spread Baa-FF spread	BAAFFM	Y	Y	Y	

Table 1, continued: Variable Combinations

variable	mnemonic	included in $N = 60$ set	included in $N = 40$ set	included in $N = 23$ 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	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			

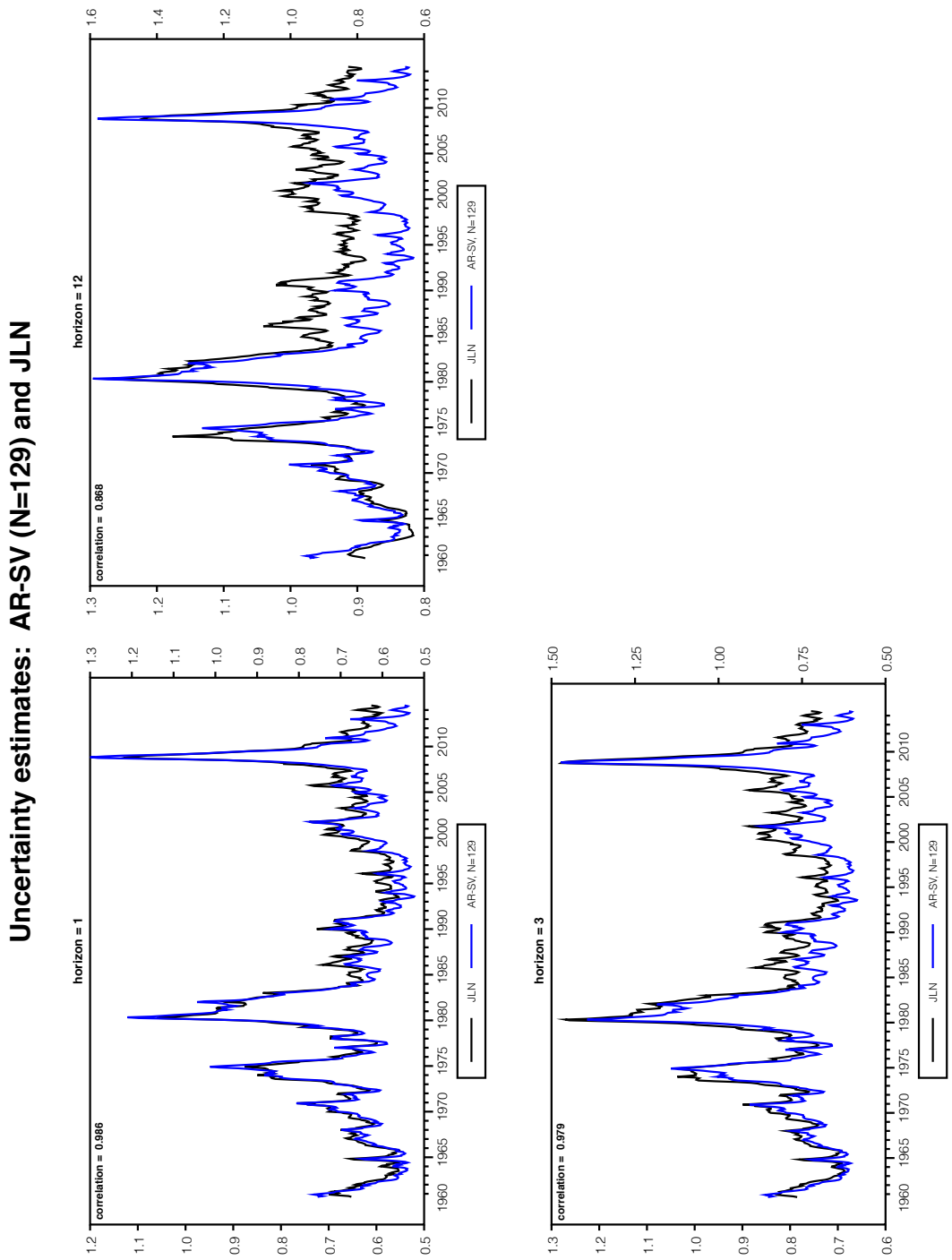


Figure 1: JLN estimate of uncertainty compared to AR-SV estimate obtained with N=129

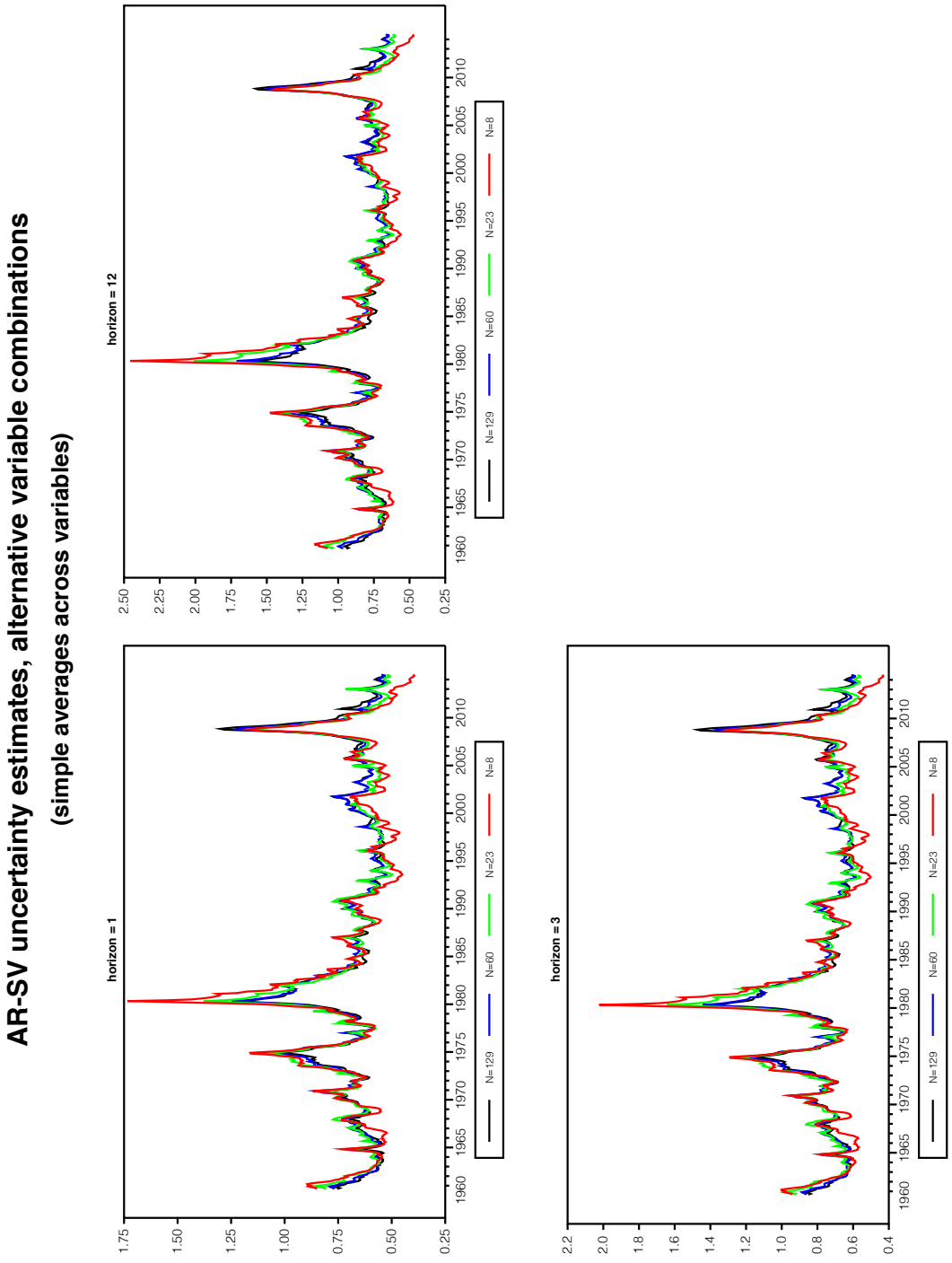
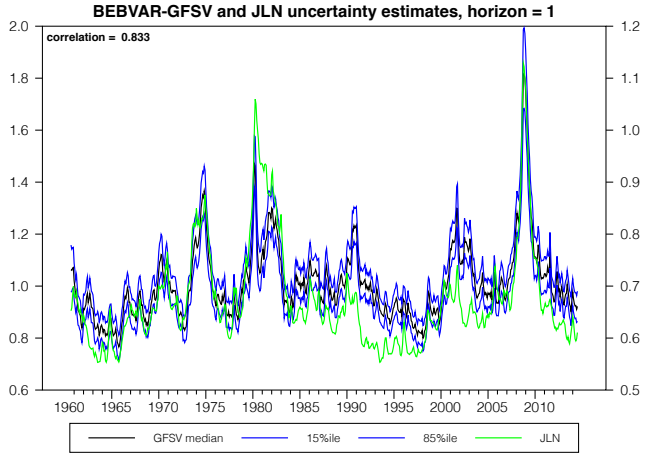
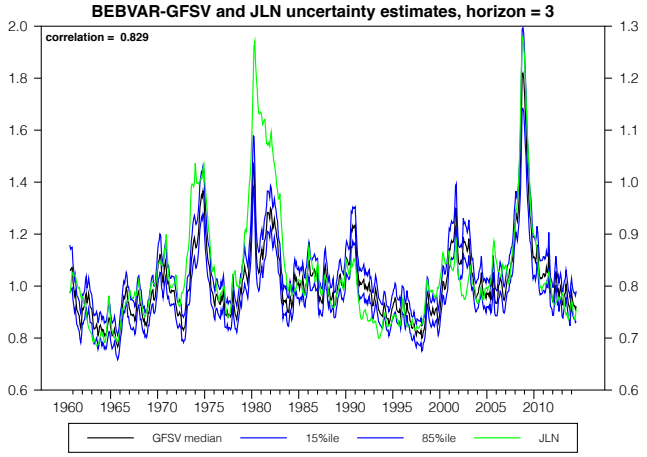


Figure 2: Uncertainty obtained from AR-SV estimates, different variable sets





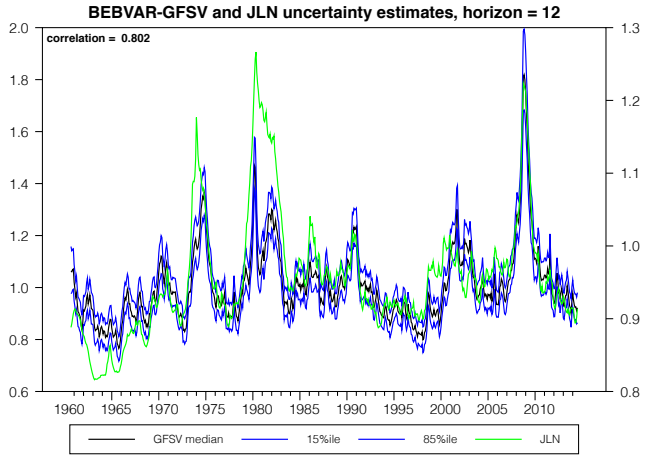


Figure 3: BVAR-GFSV uncertainty estimate, N=23

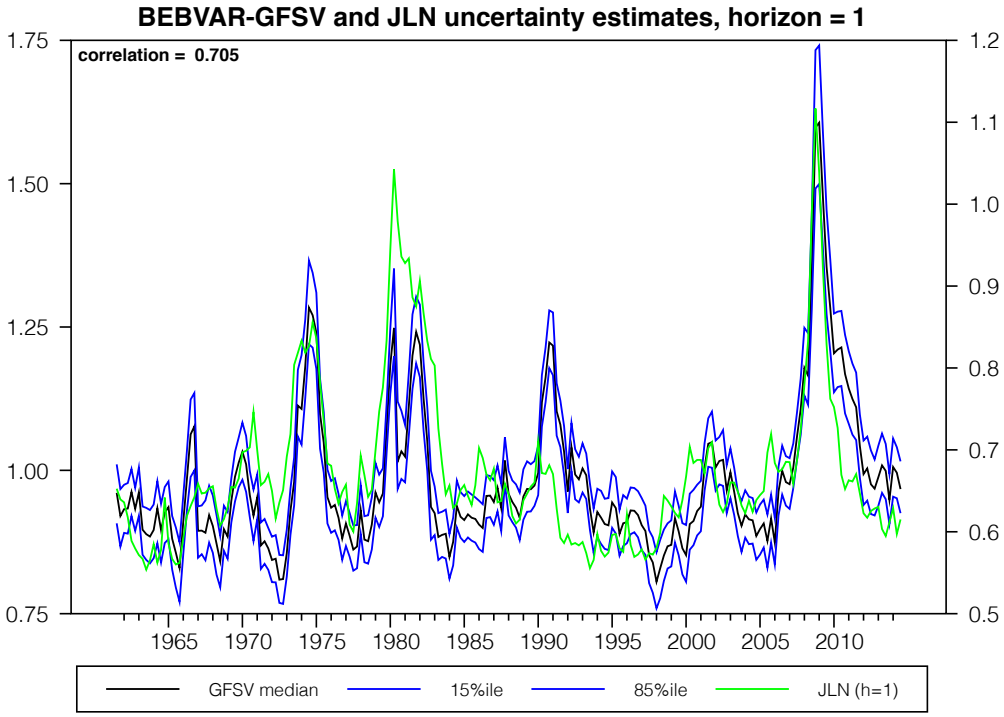


Figure 4: BVAR-GFSV uncertainty estimate (h=1), N=23, quarterly data

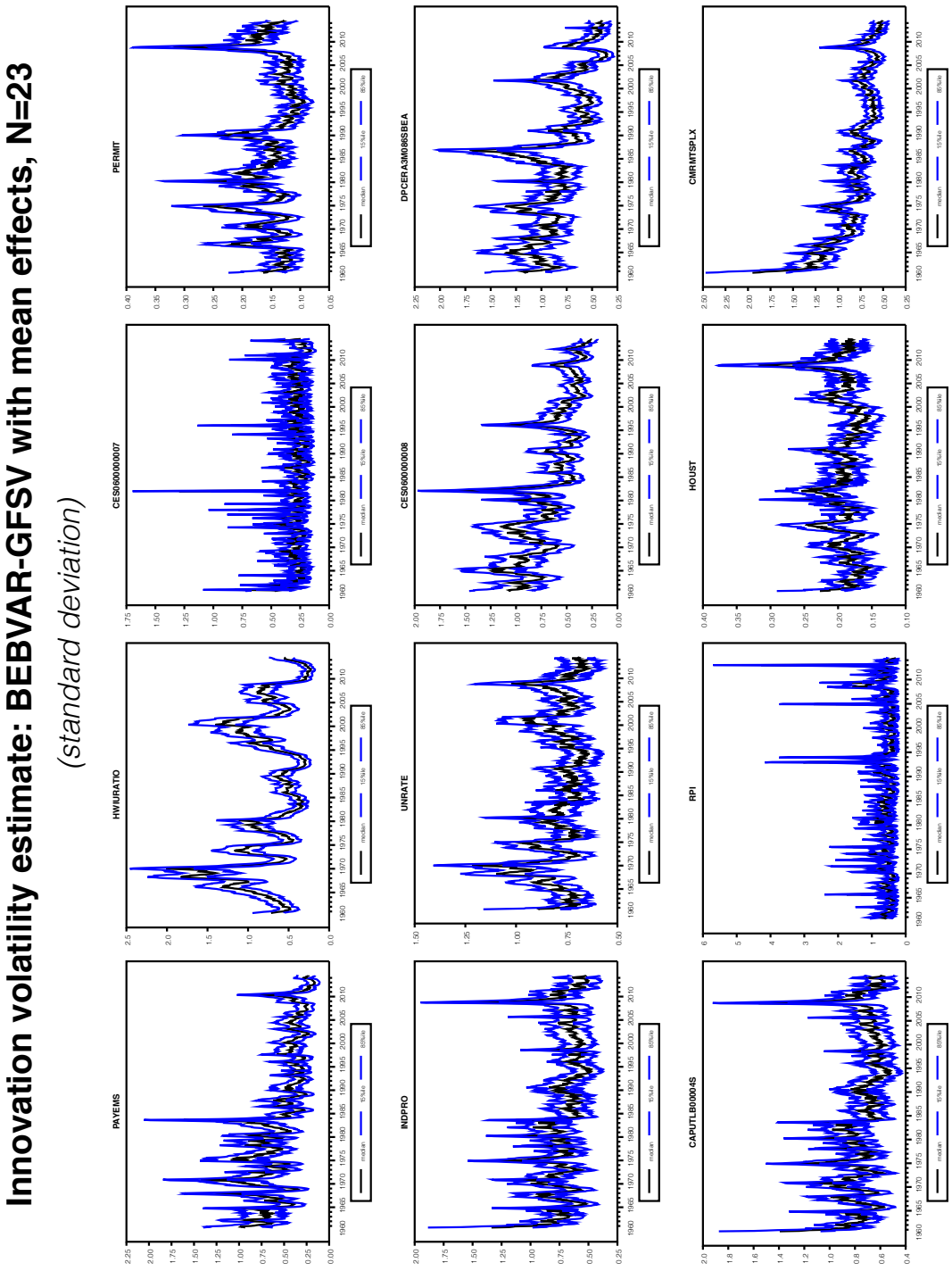


Figure 5: Estimates of reduced-form volatilities, BVAR-GFSV, N=23

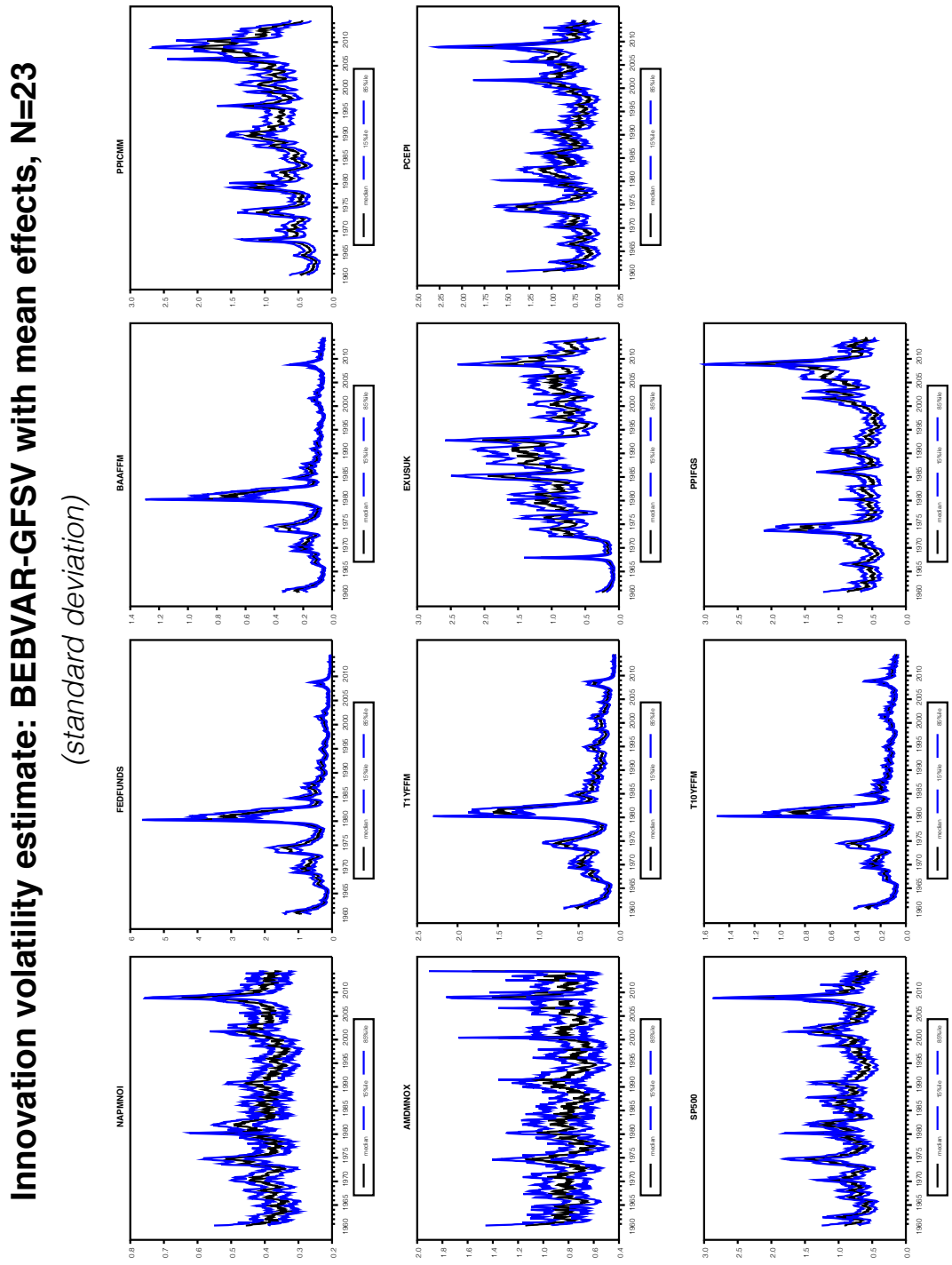


Figure 5: Continued, estimates of reduced-form volatilities, BVAR-GFSV, N=23

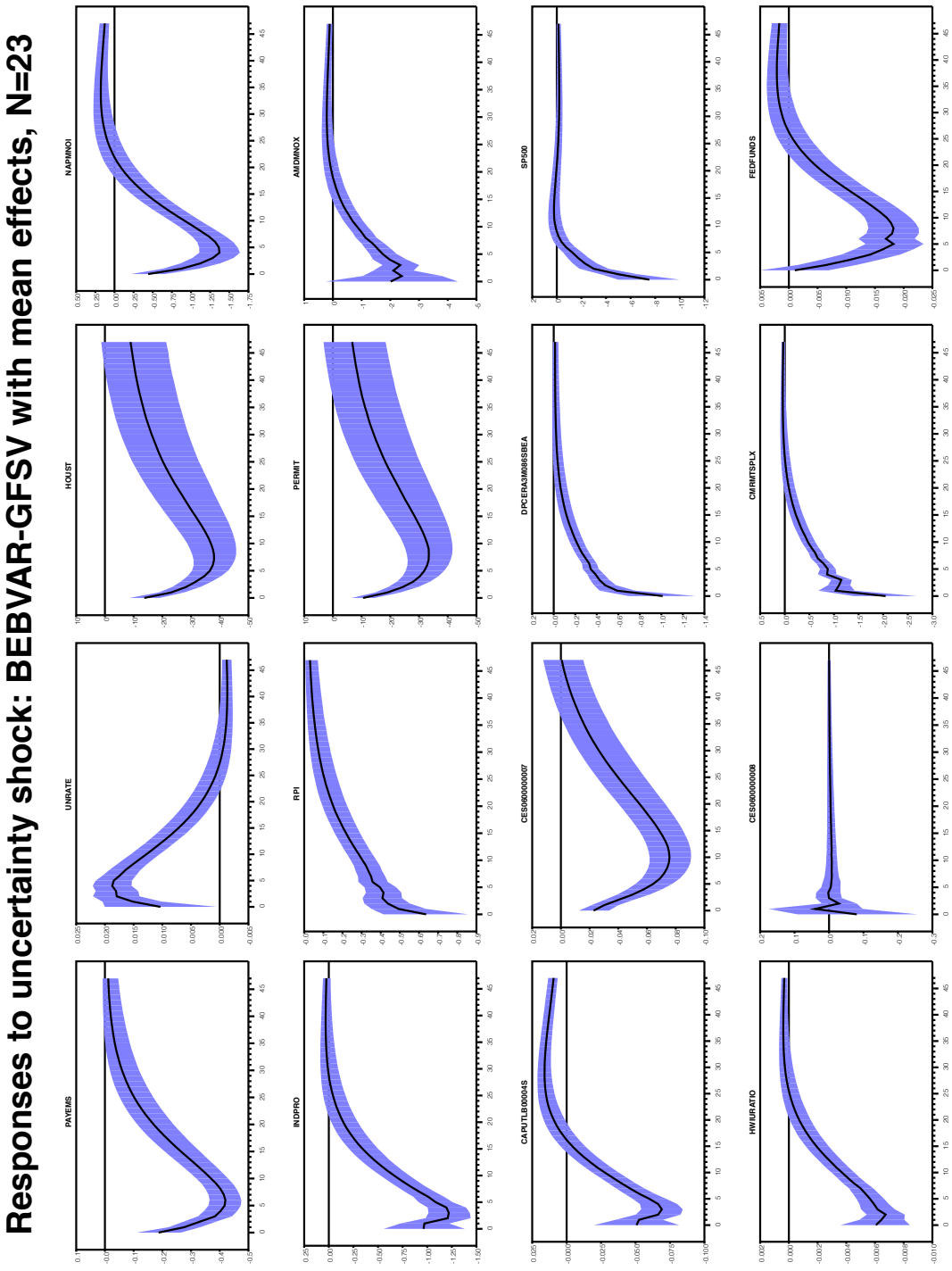


Figure 6: Responses to uncertainty shock, BVAR-GFSV, N=23

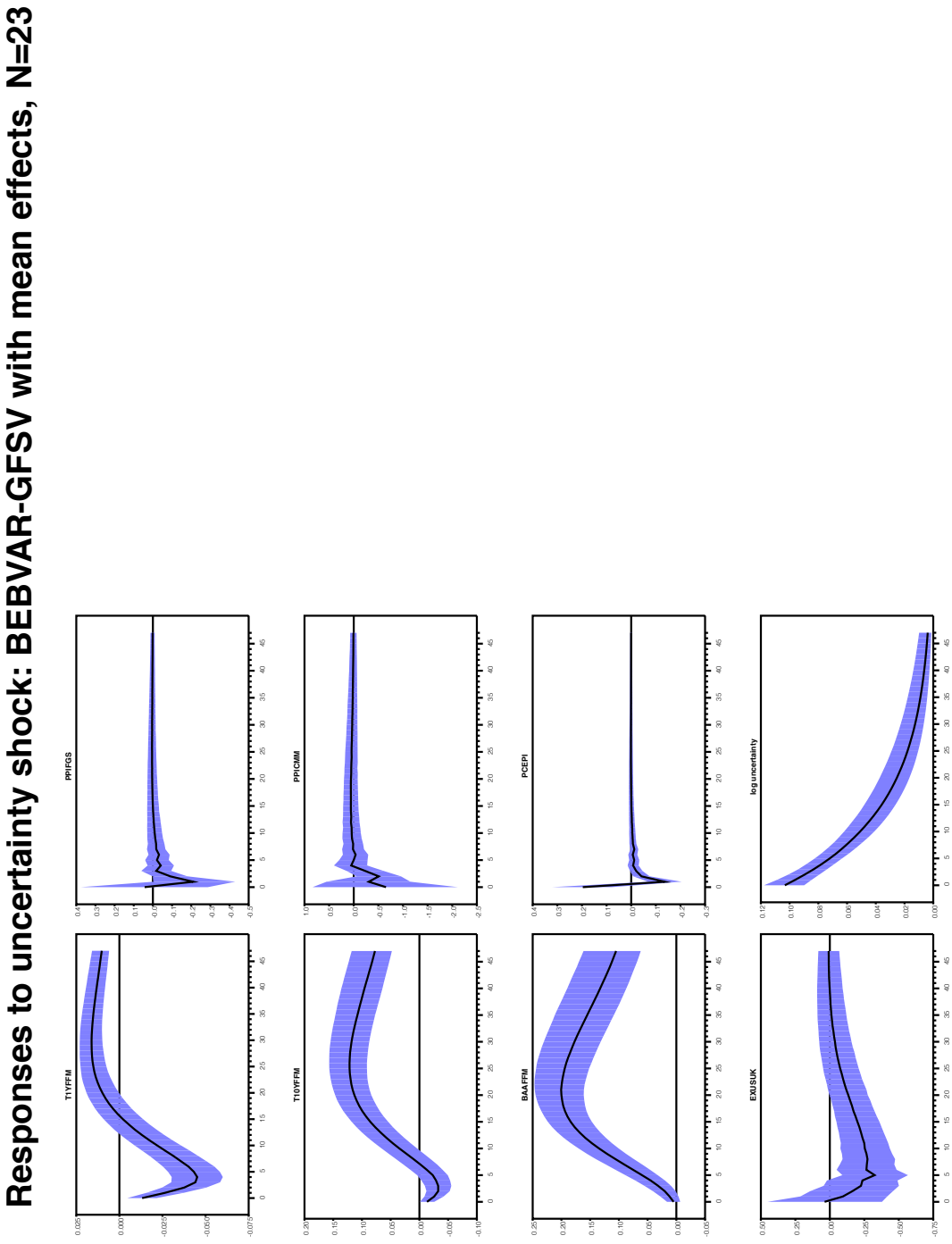


Figure 6: Continued, responses to uncertainty shock, BVAR-GFSV, N=23

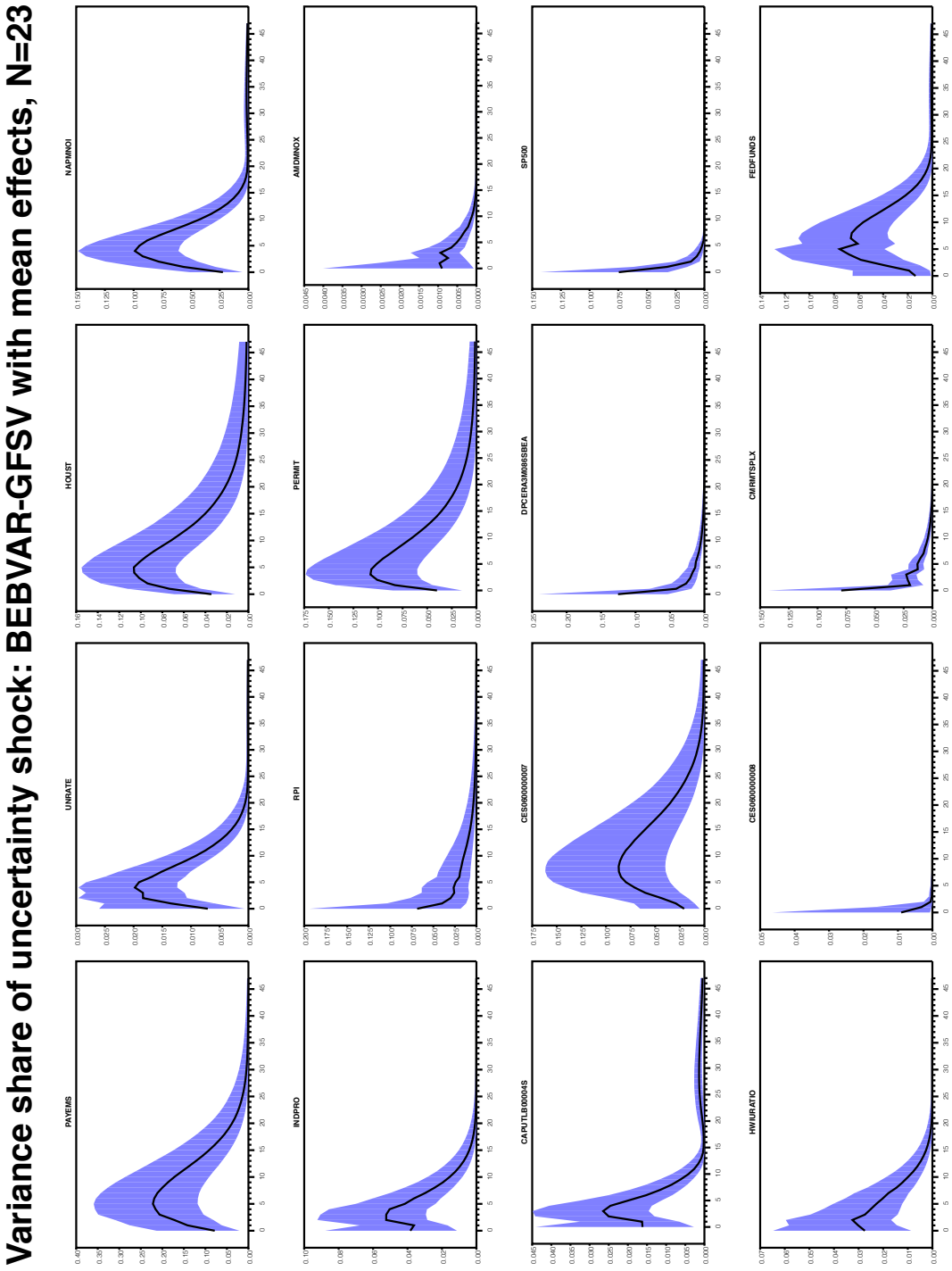


Figure 7: Variance shares of uncertainty shock, BVAR-GFSV, N=23

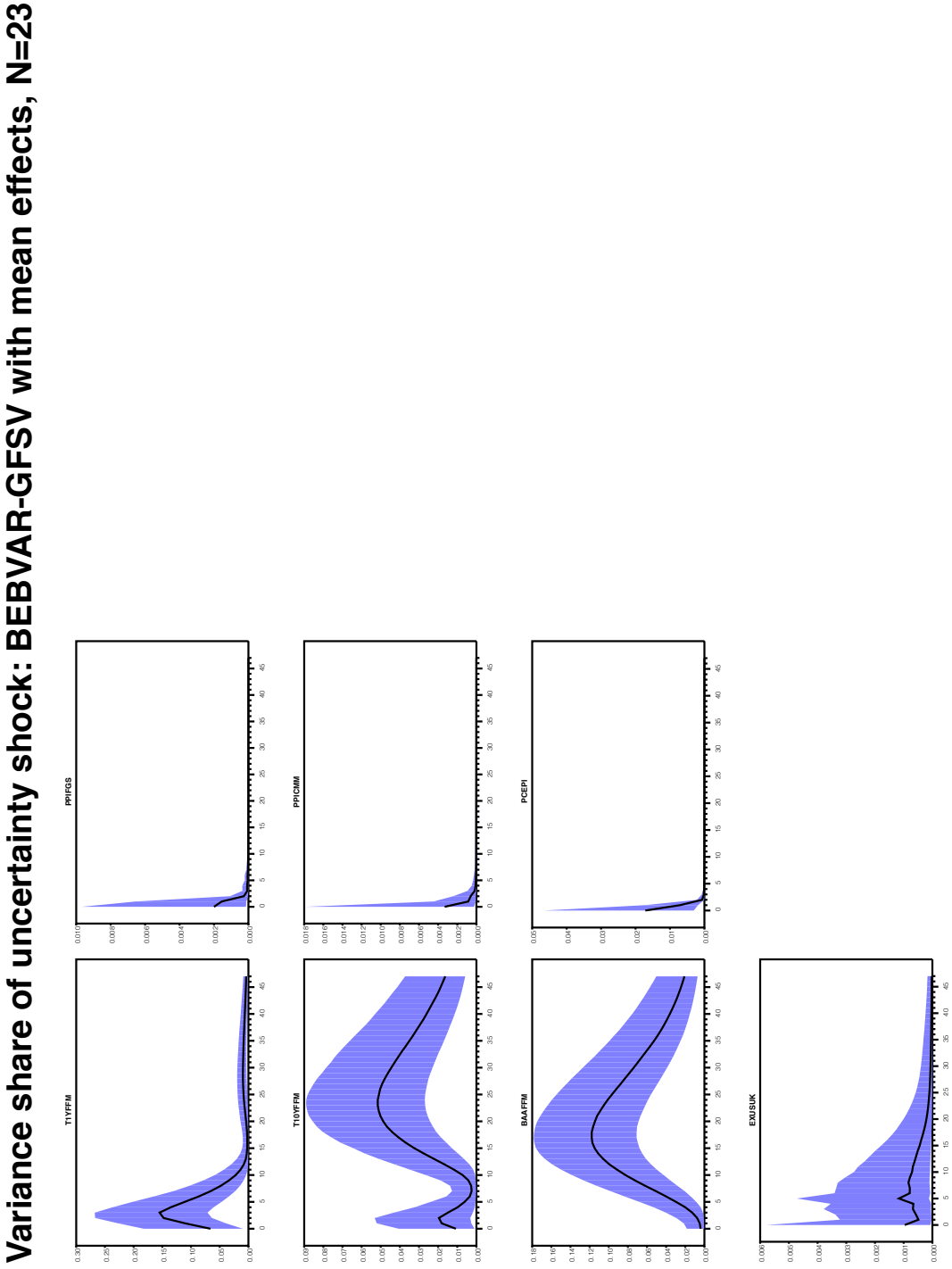


Figure 7: Continued, variance shares of uncertainty shock, BVAR-GFSV, N=23

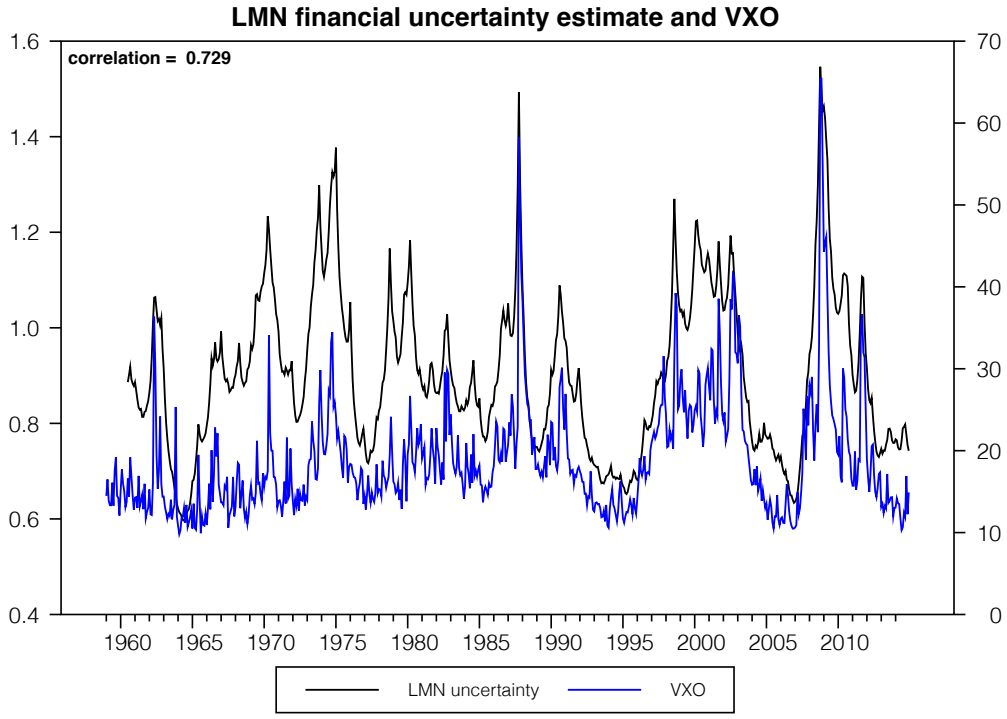


Figure 8: Financial uncertainty estimate of LMN compared to VXO

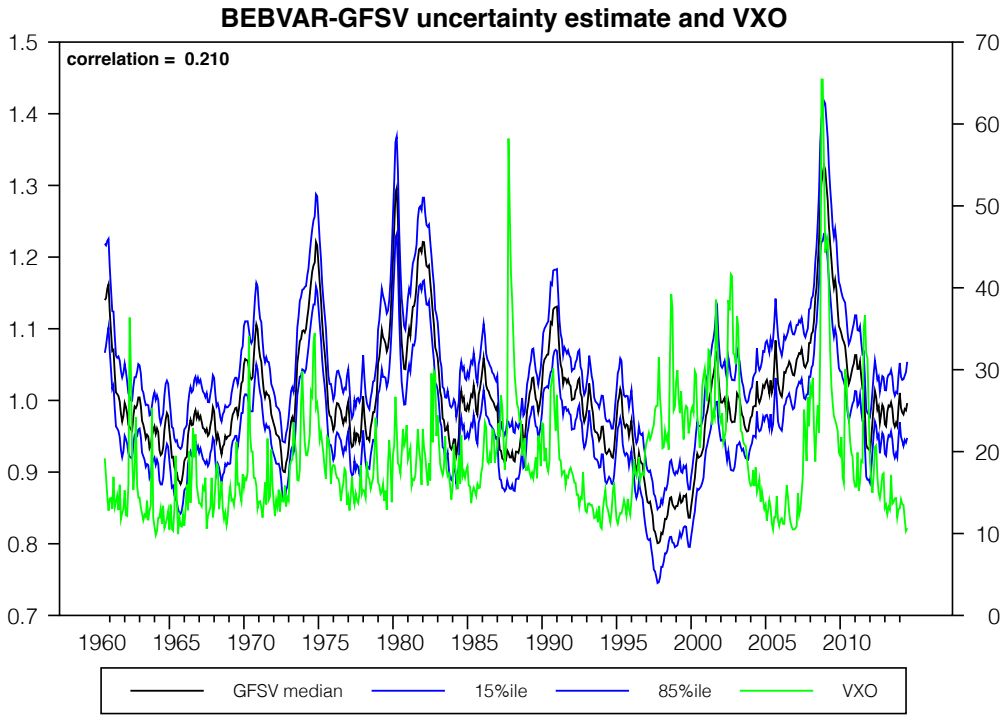


Figure 9: BVAR-GFSV macro uncertainty estimate (h=1) compared to VXO, model with VXO, N=24, monthly data

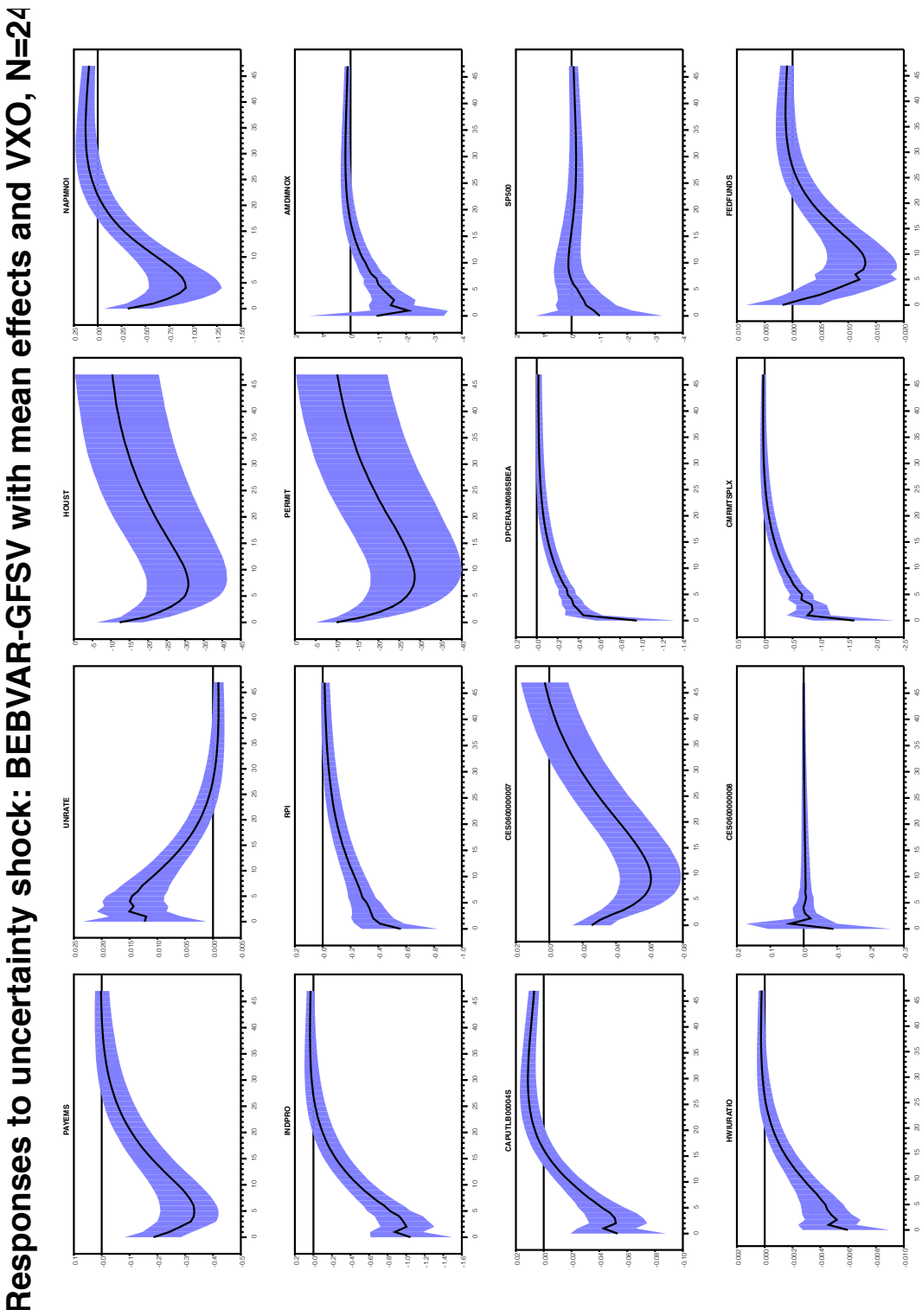


Figure 10: Responses to macro uncertainty shock, BVAR-GFSV with financial uncertainty, N=24

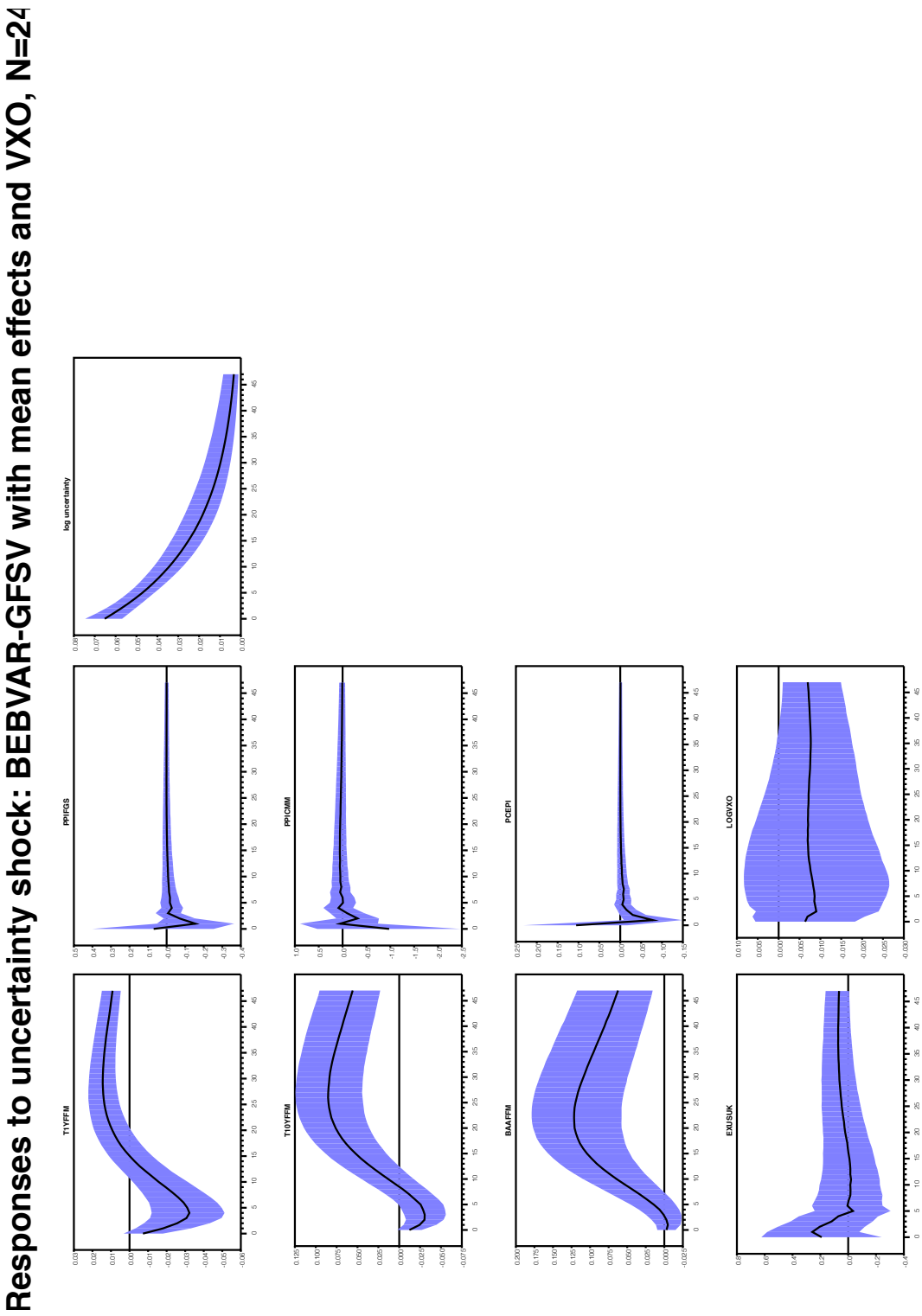


Figure 10: Continued, responses to macro uncertainty shock, BVAR-GFSV with financial uncertainty, N=24

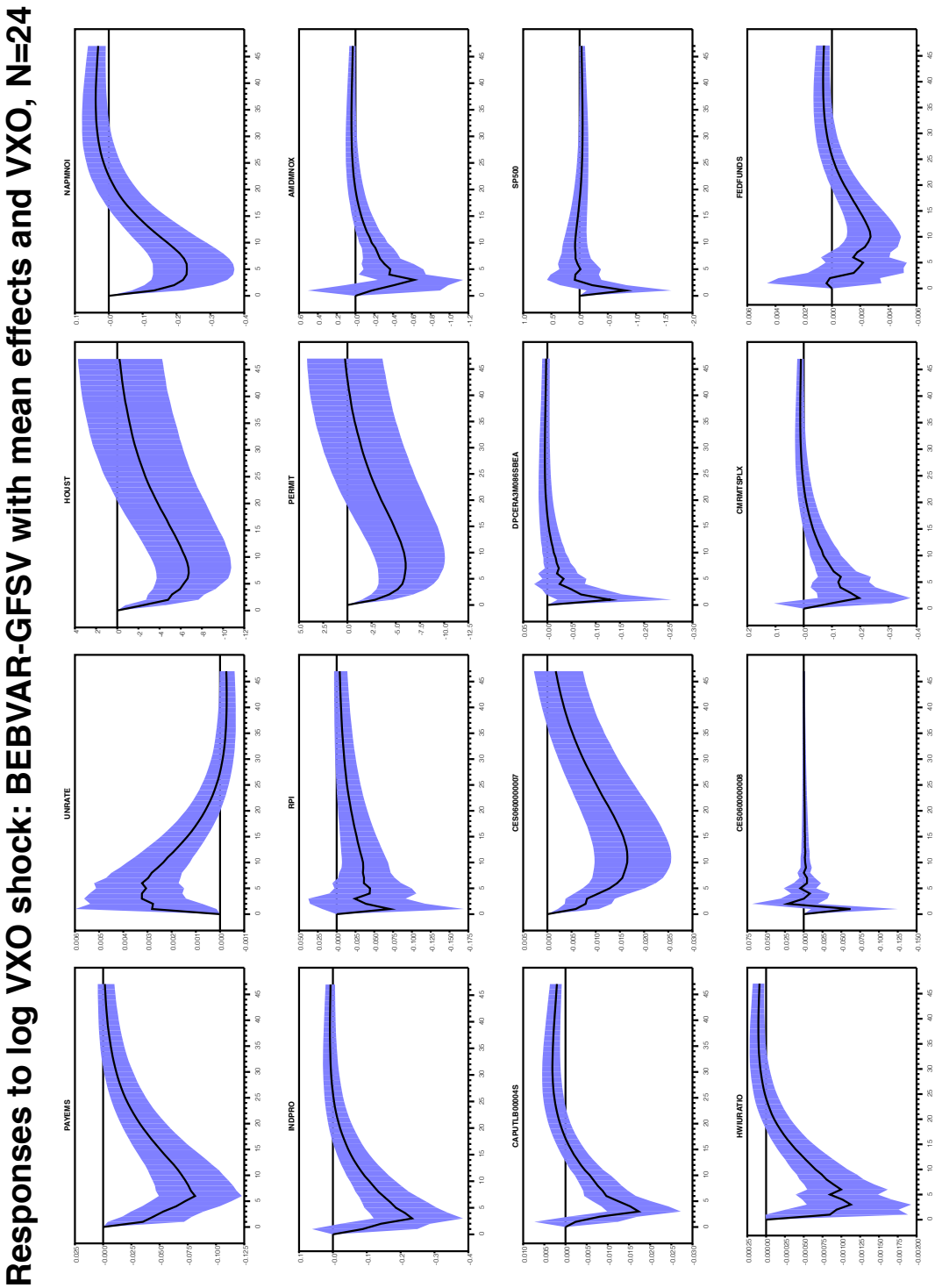


Figure 11: Responses to financial uncertainty shock, BVAR-GFSV with financial uncertainty, N=24

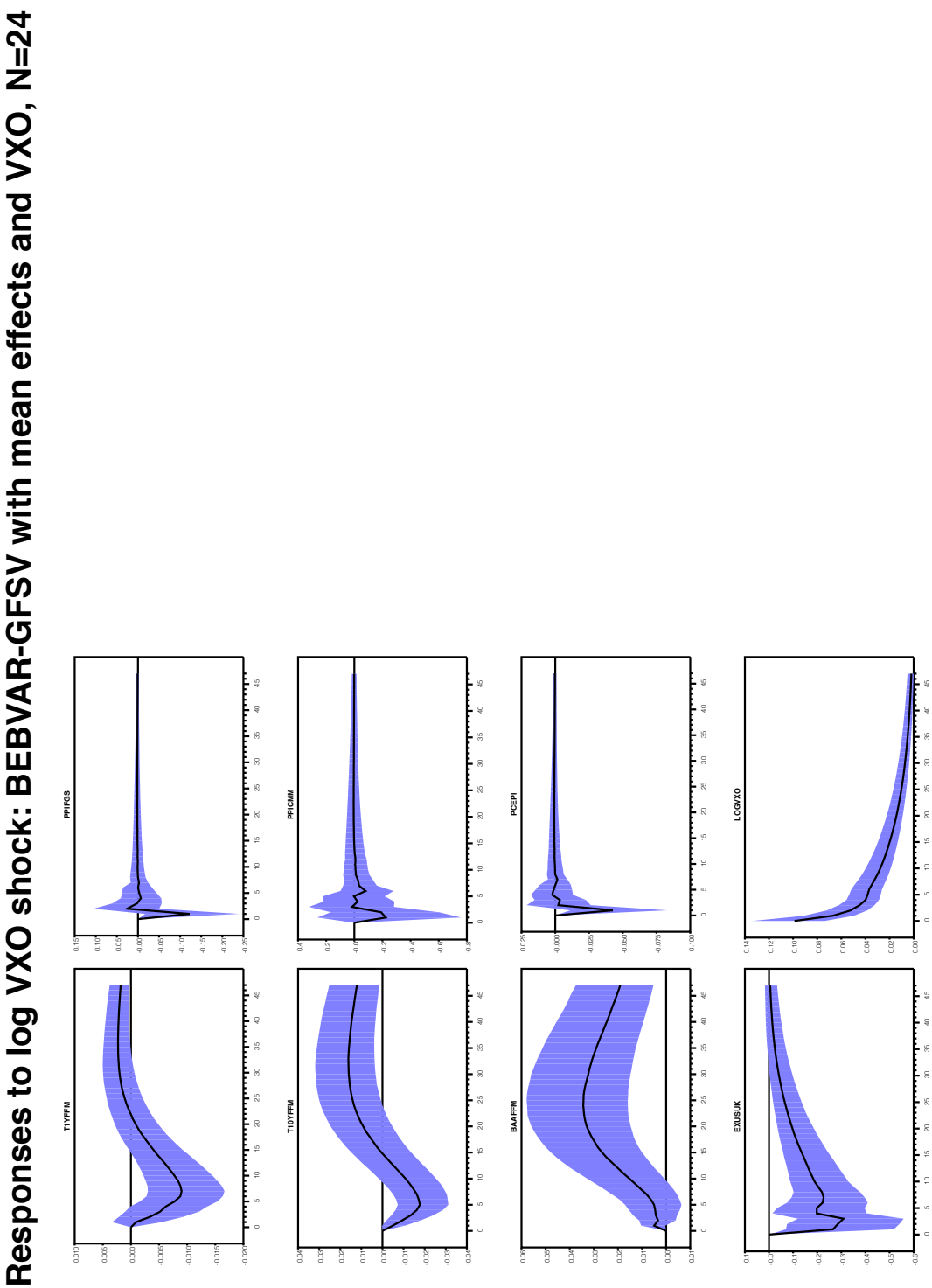


Figure 11: Continued, responses to financial uncertainty shock, BVAR-GFSV with financial uncertainty, N=24

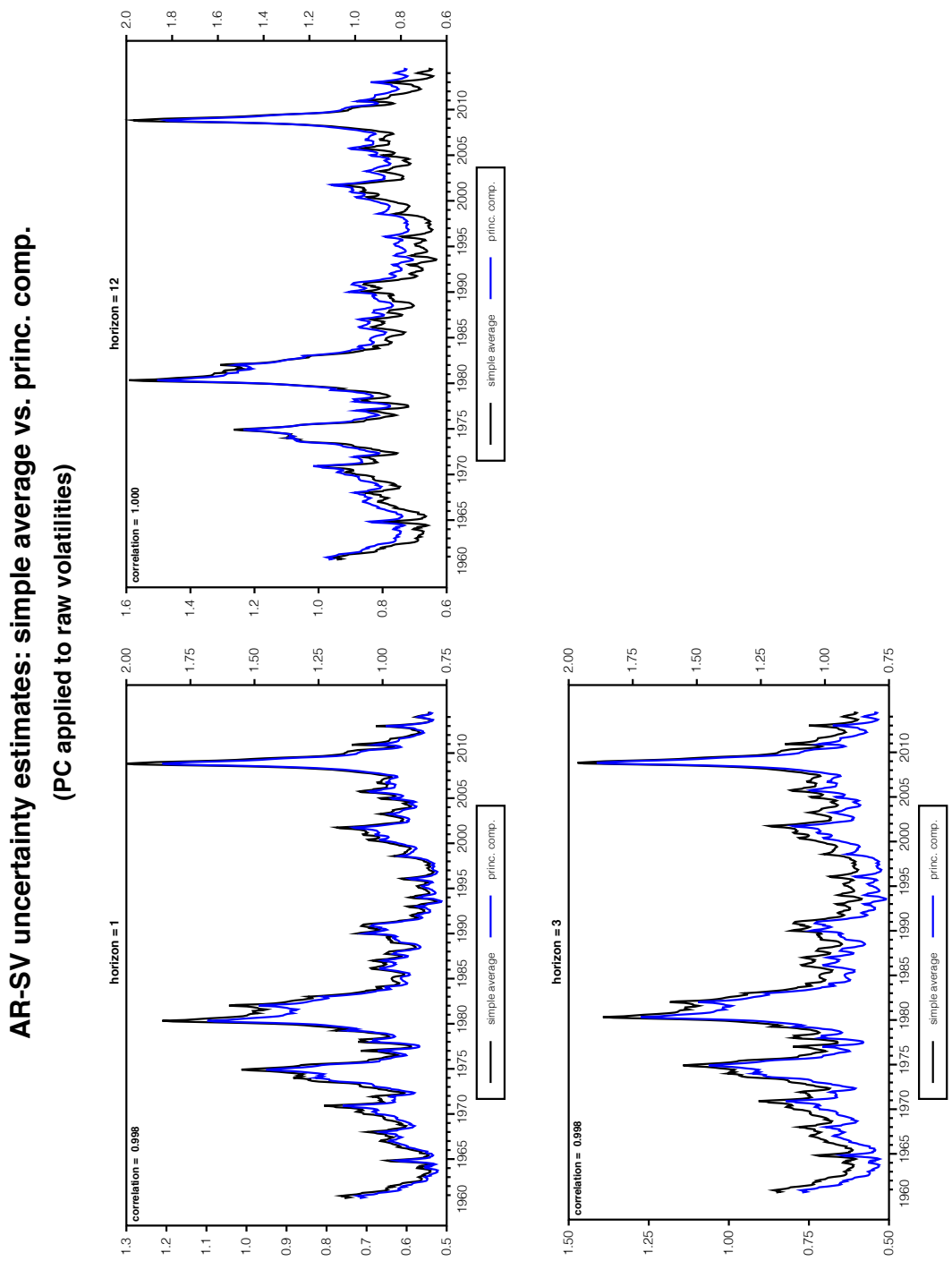


Figure A1: Uncertainty estimates using AR-SV volatilities, N=129: simple average and principal component obtained from raw volatilities

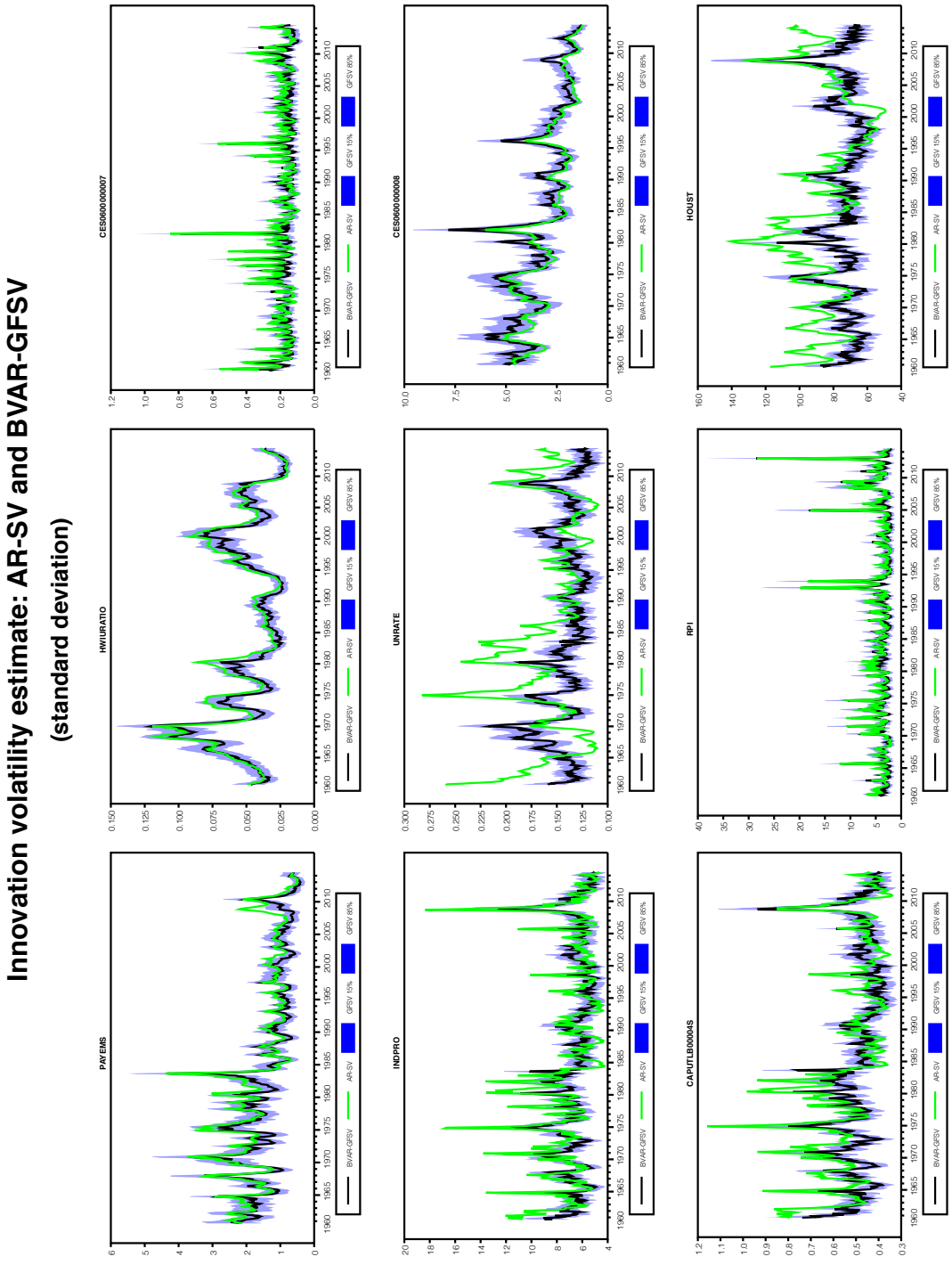


Figure A2: Estimates of reduced-form volatilities, AR-SV and BVAR-GFSV, N=23

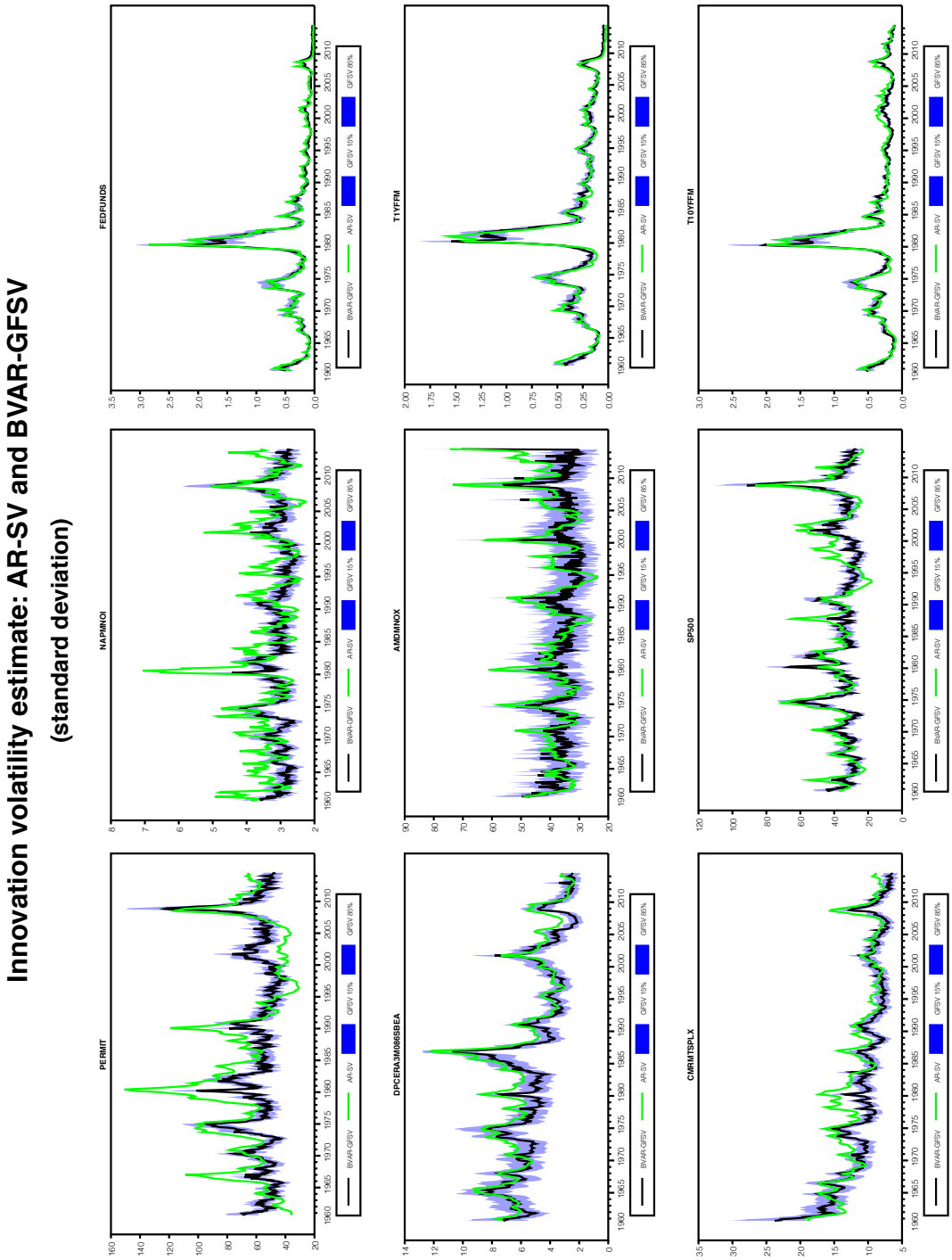


Figure A2: Continued, estimates of reduced-form volatilities, AR-SV and BVAR-GFSV, N=23

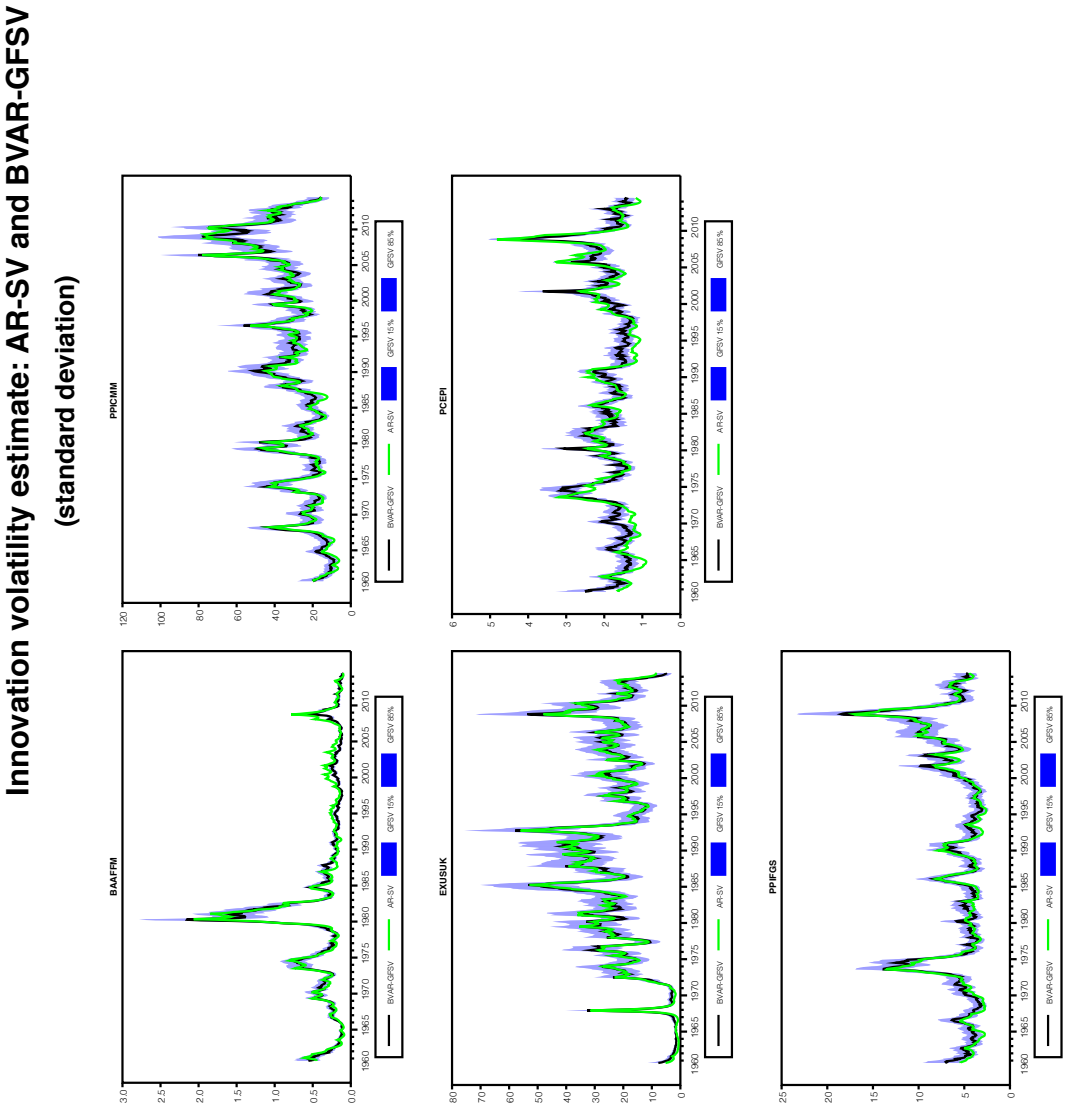


Figure A2: Continued, estimates of reduced-form volatilities, AR-SV and BVAR-GFSV, N=23

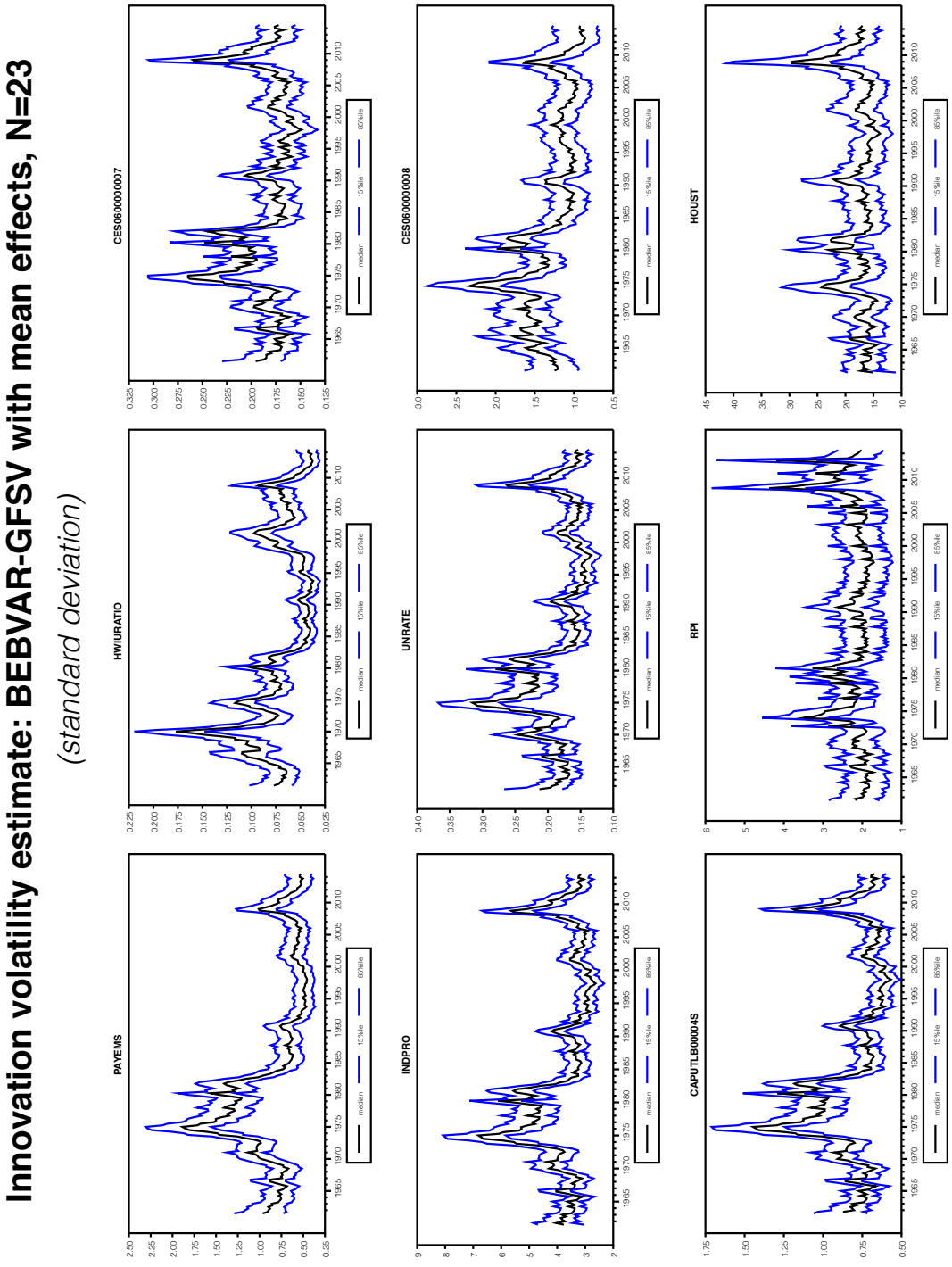


Figure A3: Estimates of reduced-form volatilities, BVAR-GFSV, N=23, quarterly data

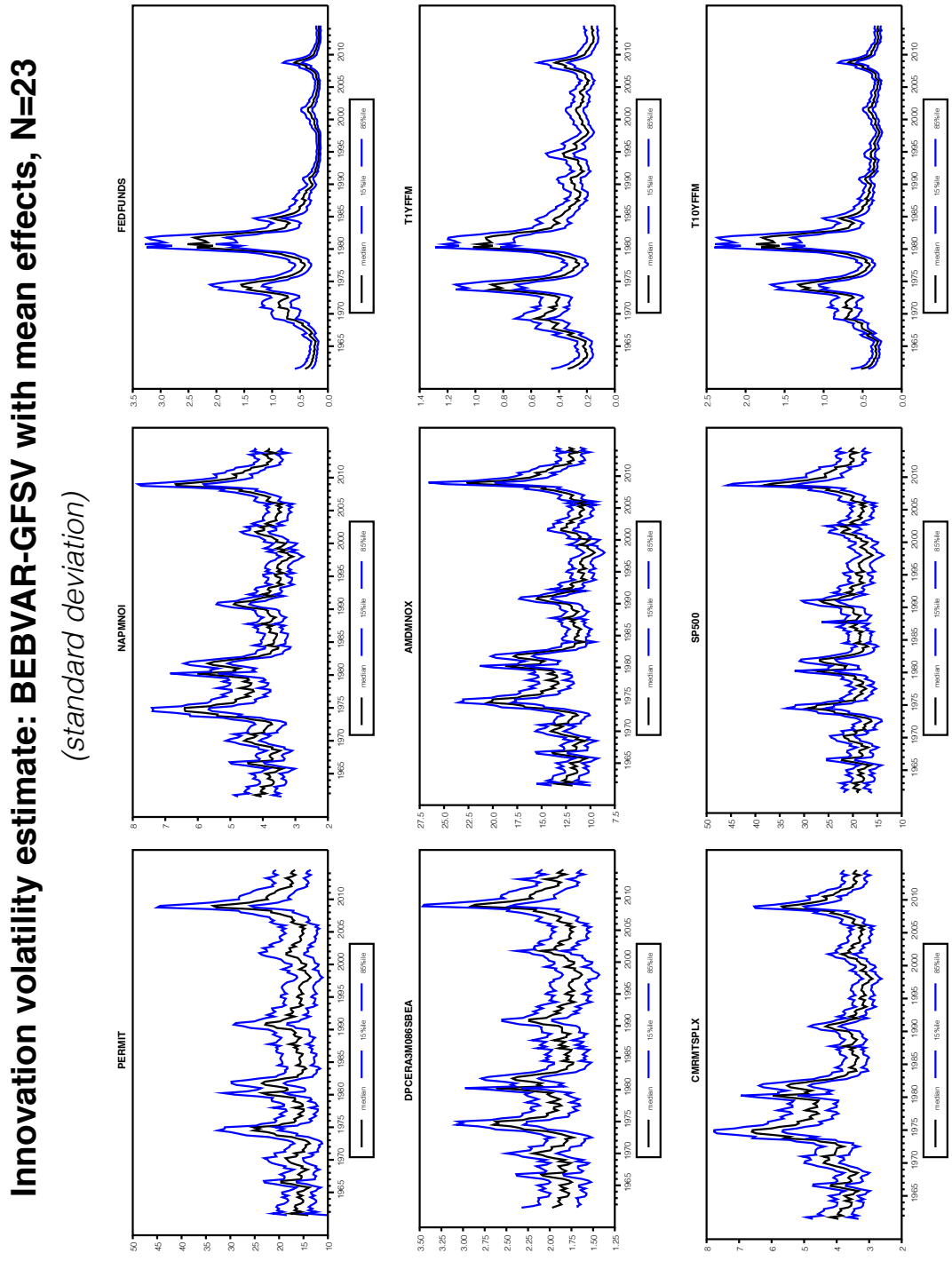


Figure A3: Continued, Estimates of reduced-form volatilities, BVAR-GFSV, N=23, quarterly data

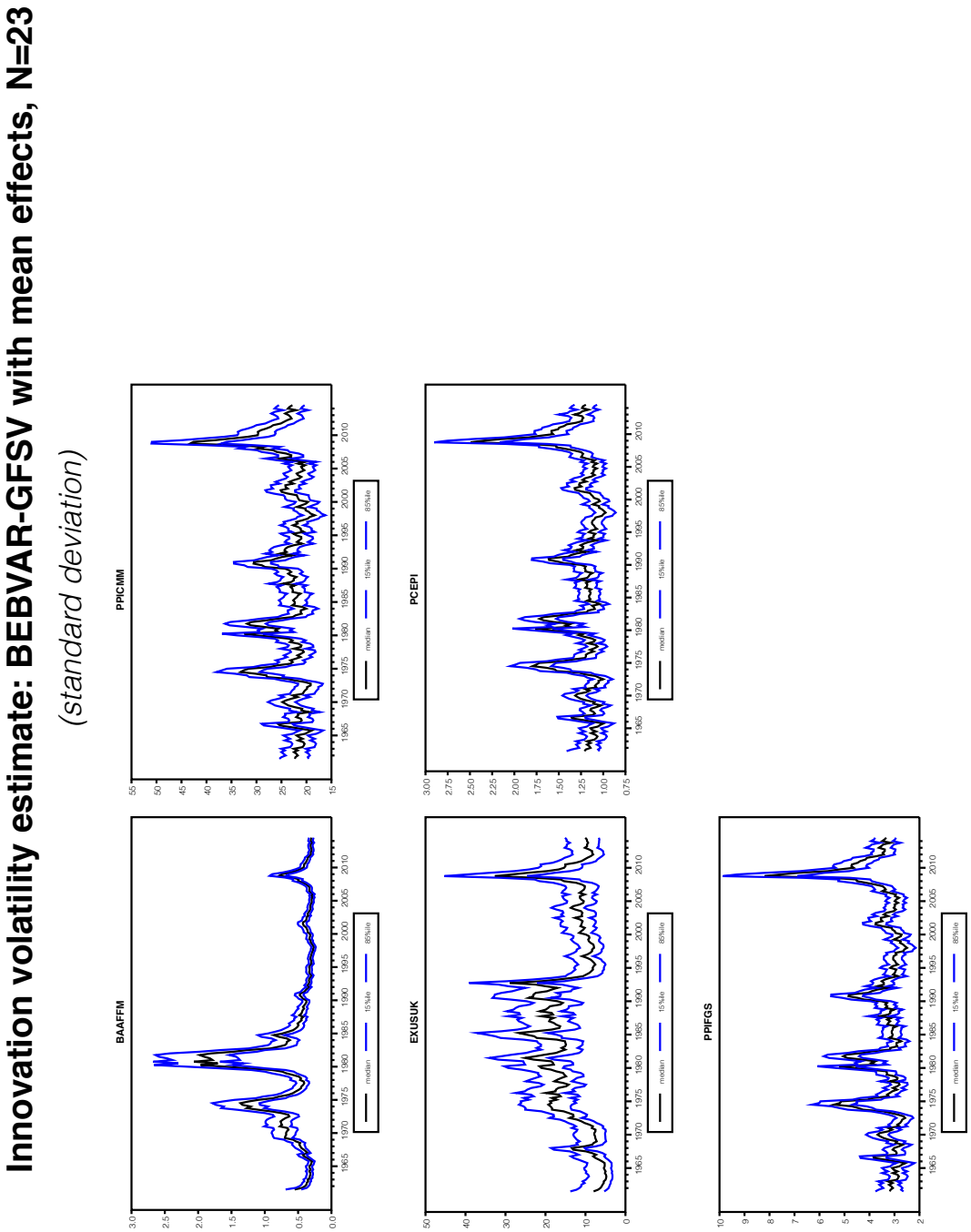


Figure A3: Continued, Estimates of reduced-form volatilities, BVAR-GFSV, N=23, quarterly data

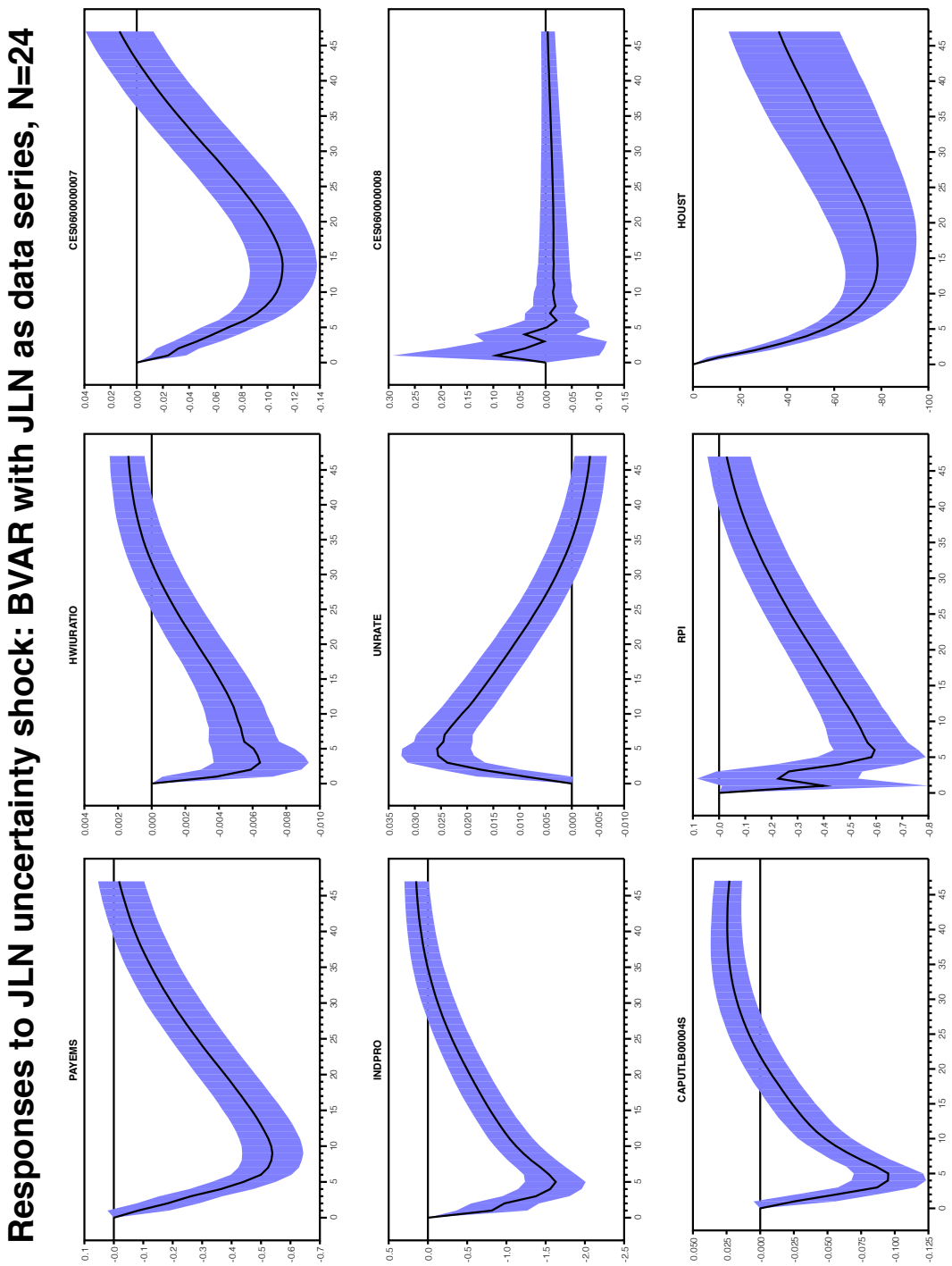


Figure A4: Responses to uncertainty shock, BVAR with JLN uncertainty as endogenous variable, N=24

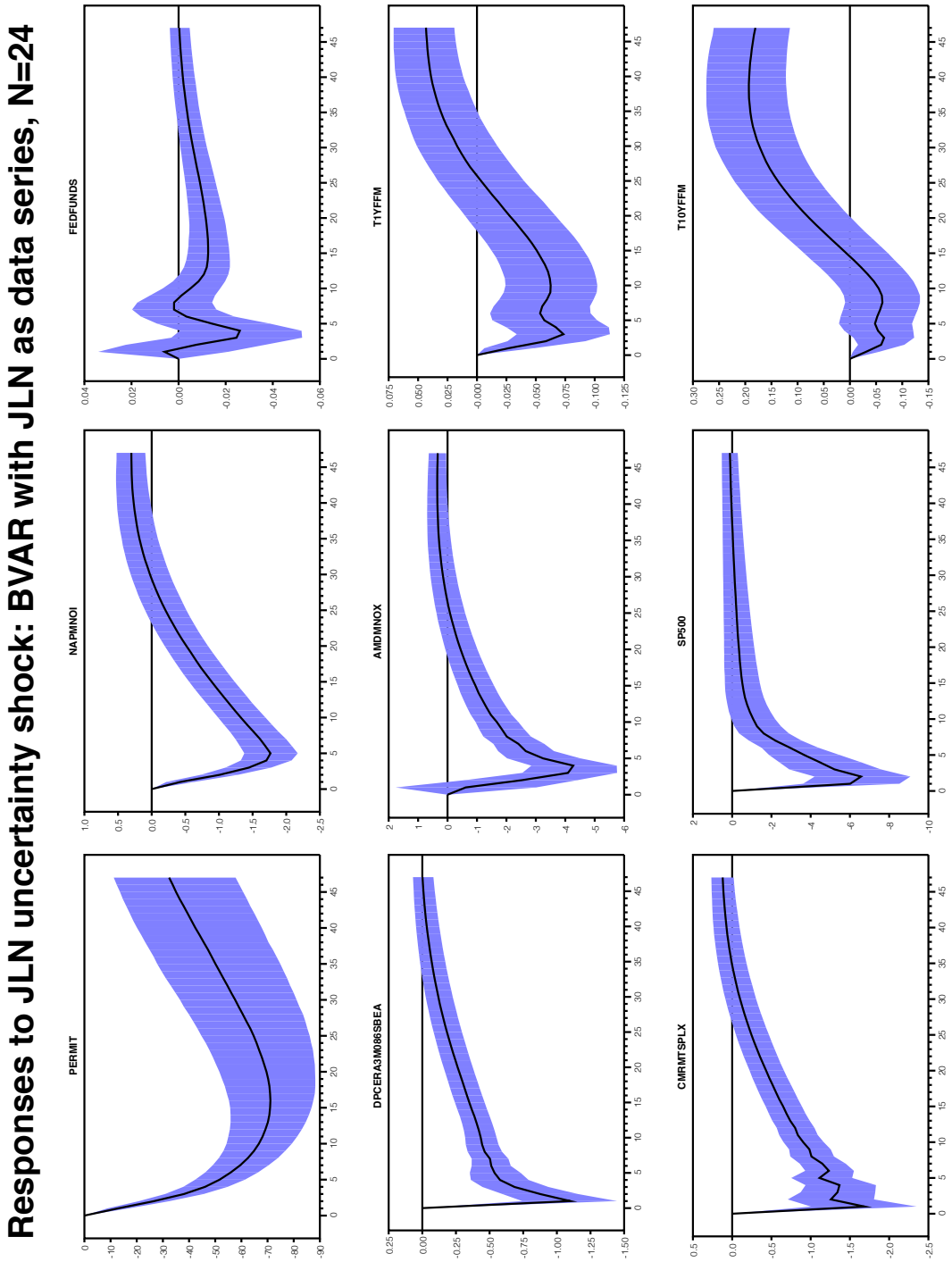


Figure A4: Continued, responses to uncertainty shock, BVAR with JLN uncertainty as endogenous variable, N=24

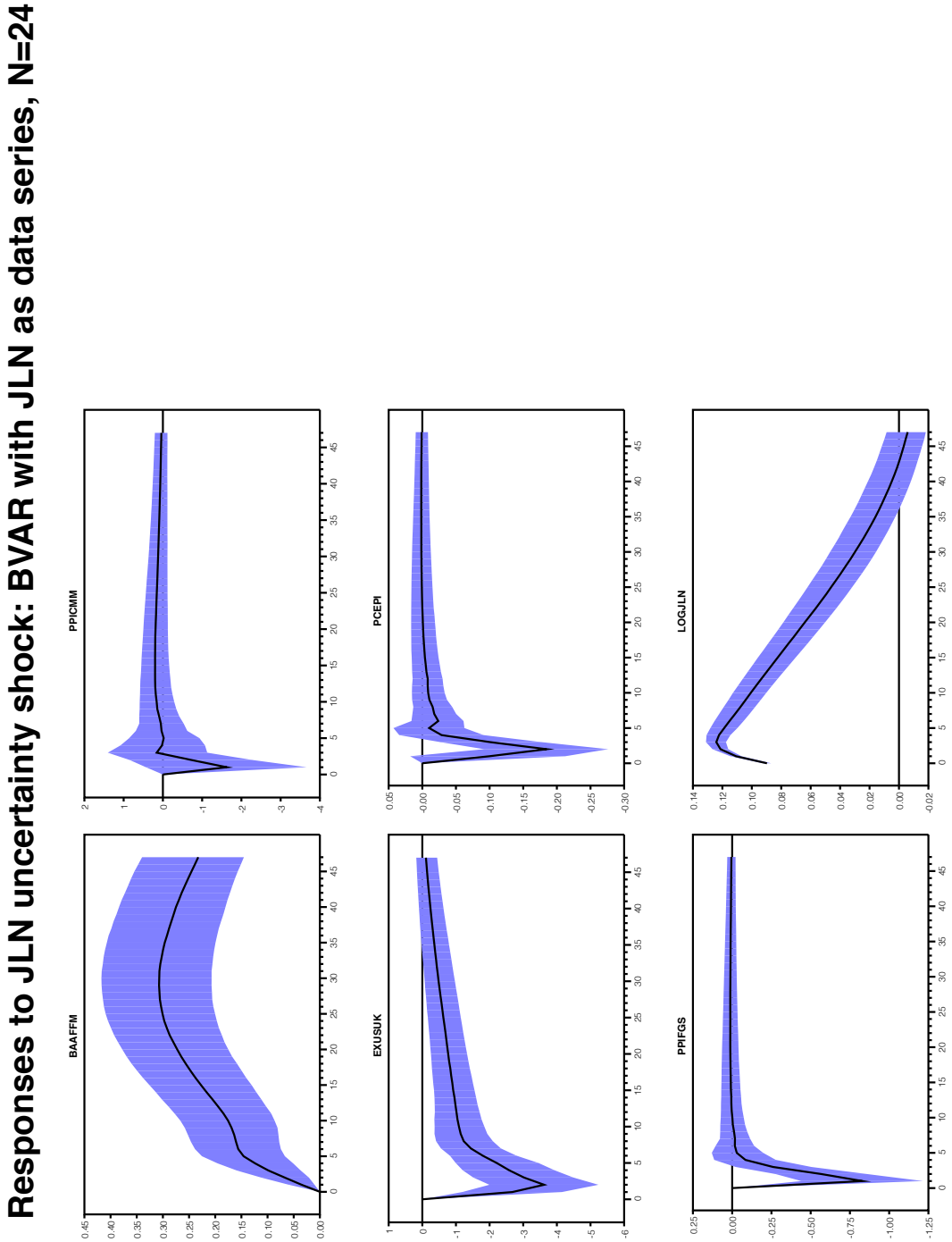


Figure A4: Continued, responses to uncertainty shock, BVAR with JLN uncertainty as endogenous variable, N=24

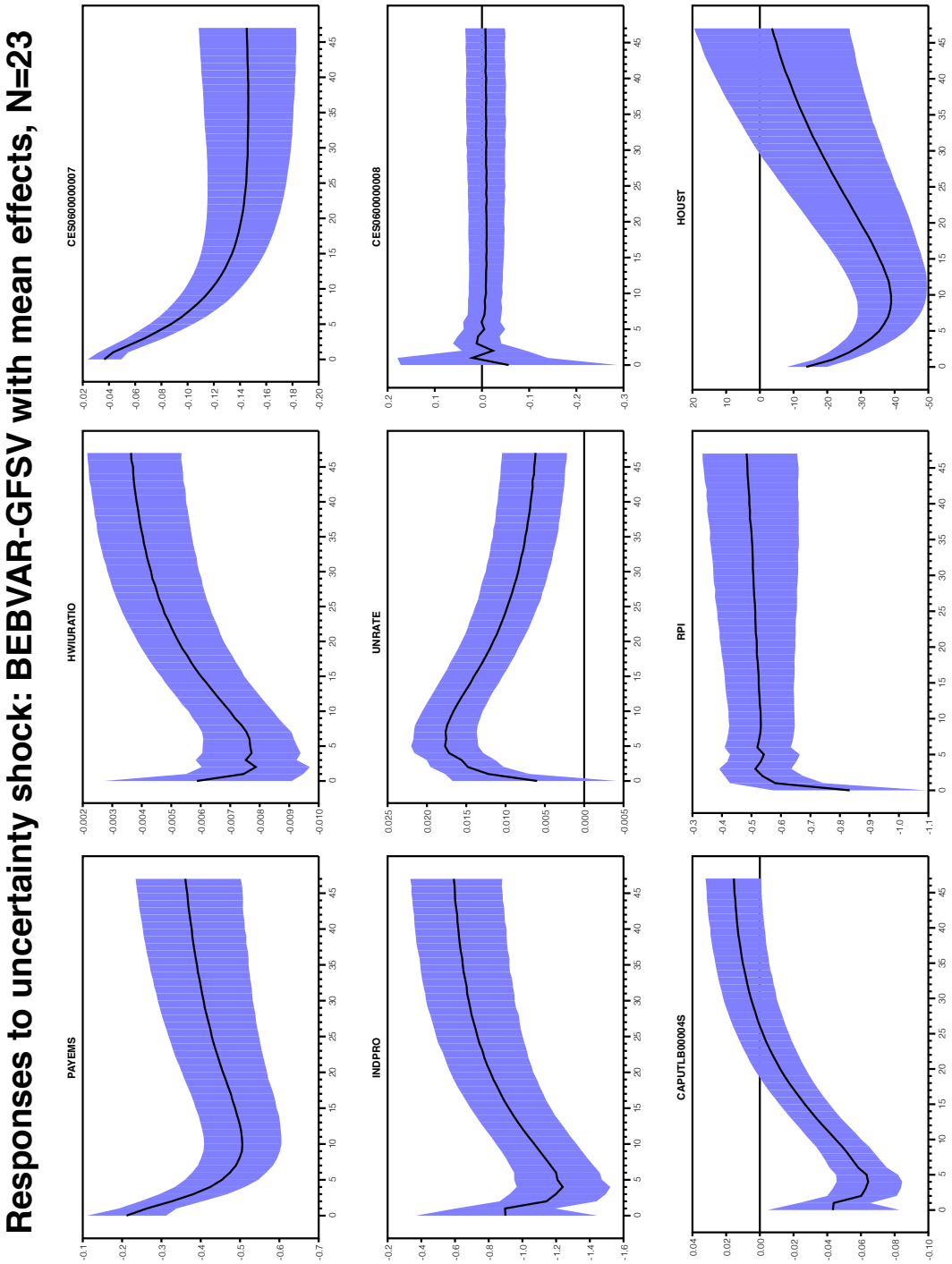


Figure A5: Responses to uncertainty shock, BVAR-GFSV, N=23, sample ending in 2007

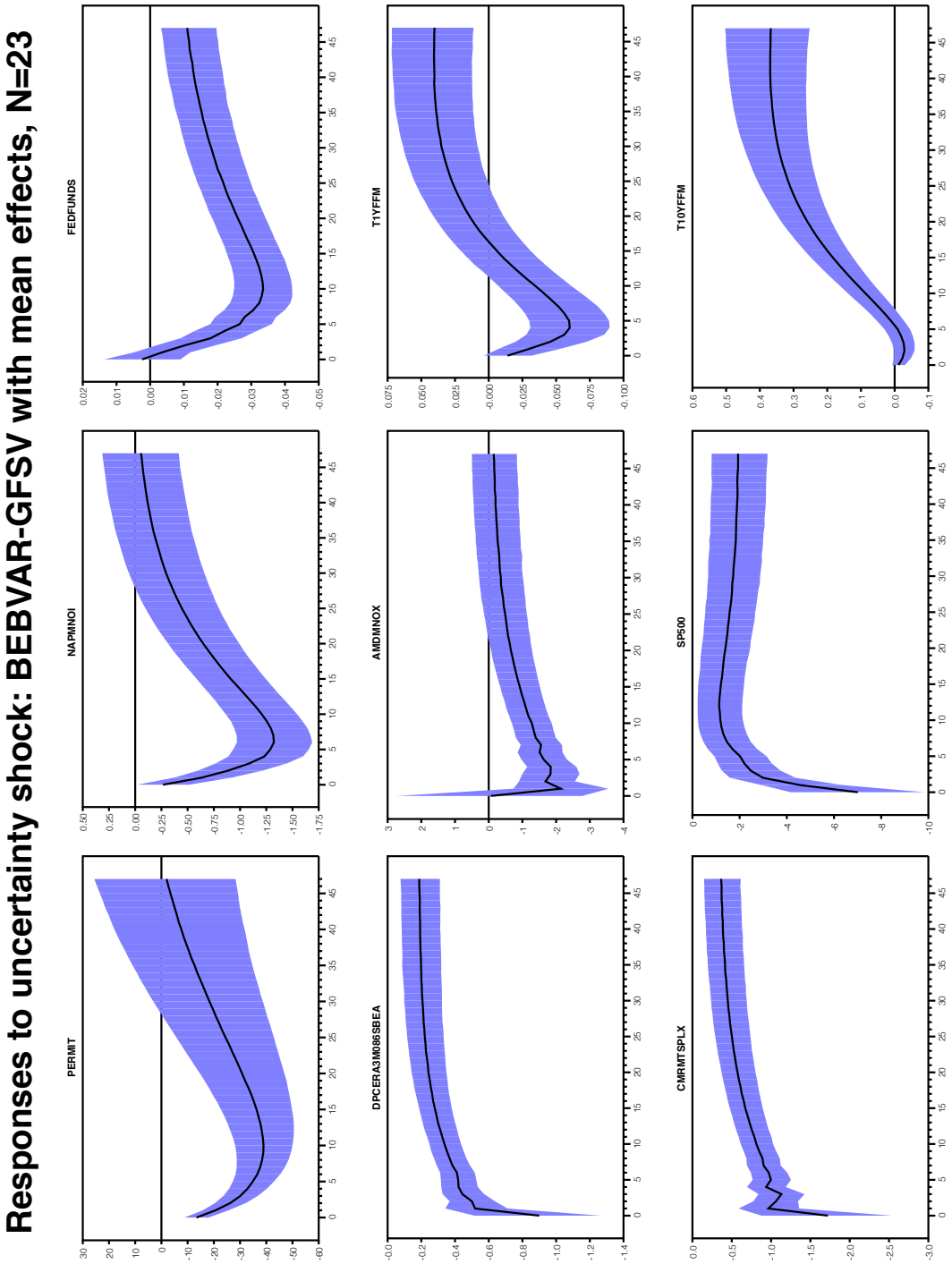


Figure A5: Continued, Responses to uncertainty shock, BVAR-GFSV, N=23, sample ending in 2007

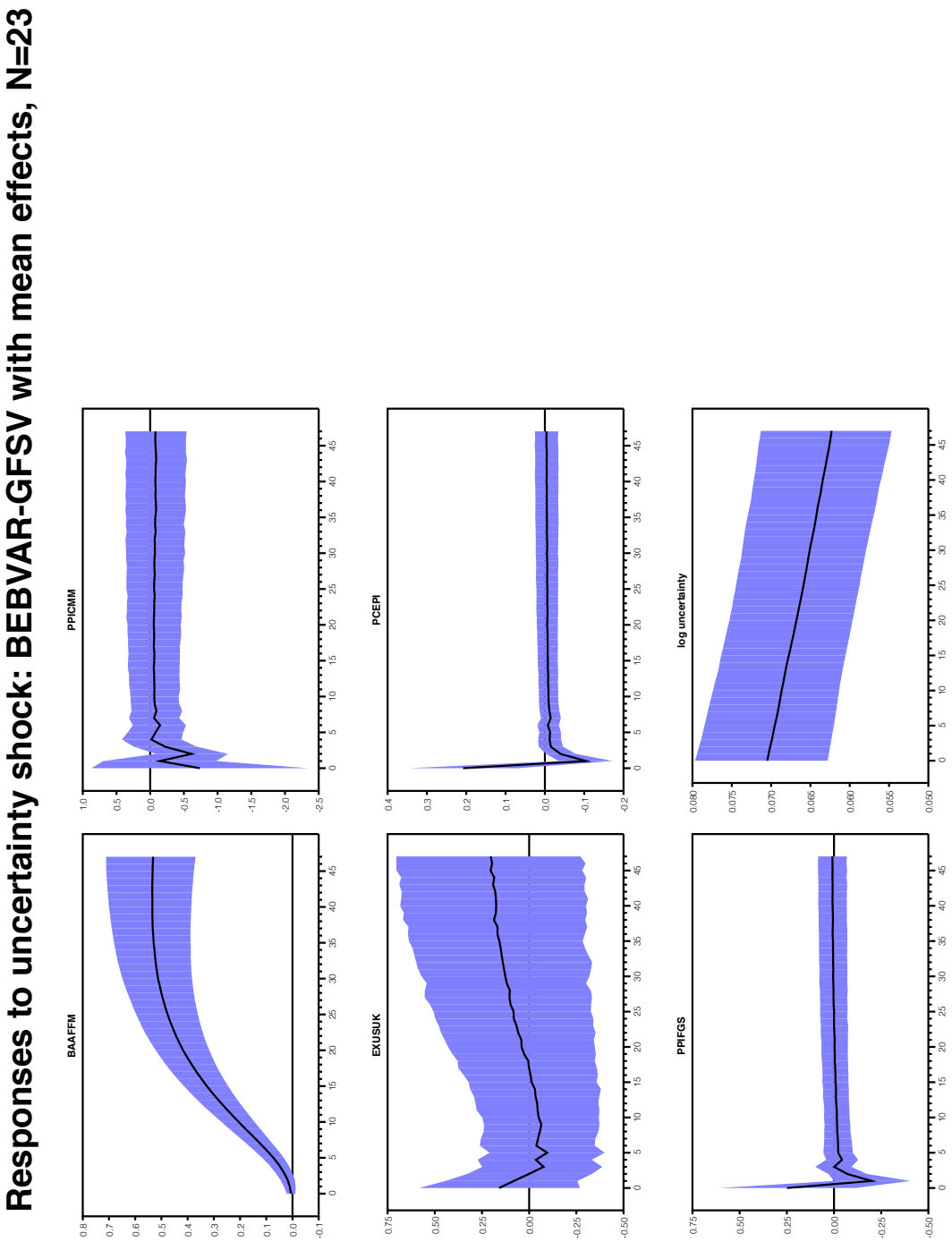


Figure A5: Continued, Responses to uncertainty shock, BVAR-GFSV, N=23, sample ending in 2007

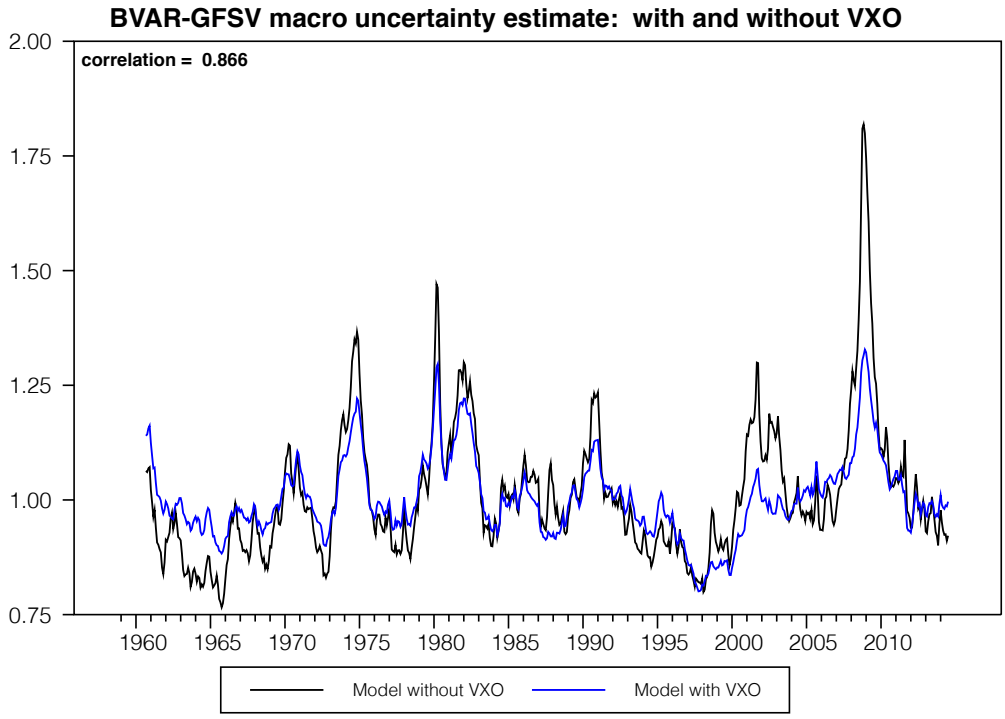


Figure A6: BVAR-GFSV macro uncertainty estimate (h=1), baseline model (N=23) and model augmented with with VXO (N=24)