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# Corrigendum to: Measuring Uncertainty and Its Impact on the Economy*

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**Abstract**

Carriero, Clark, and Marcellino (2018, CCM2018) used a large BVAR model with a factor structure to stochastic volatility to produce an estimate of time-varying macroeconomic and financial uncertainty and assess uncertainty's effects on the economy. The results in CCM2018 were based on an estimation algorithm that has recently been shown to be incorrect by Bognanni (2021) and fixed by Carriero, et al. (2021). In this note we use the algorithm correction of Carriero, et al. (2021) to correct the estimates of CCM2018. Although the correction has some impact on the original results, the changes are small and the key findings of CCM2018 are upheld.

*Keywords: Triangular algorithm, Bayesian VARs, stochastic volatility, large datasets*

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

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*Corresponding author: Todd E. Clark, todd.clark@researchfed.org. The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Cleveland or the Federal Reserve System. We are grateful to Mark Bognanni for identifying a problem in the triangular estimation algorithm of Carriero, Clark, and Marcellino (2019), later corrected in Carriero, et al. (2021).

# 1 Introduction

To make tractable the estimation of the large model of Carriero, Clark, and Marcellino (2018, hereafter denoted CCM2018), we used an equation-by-equation approach to the vector autoregression (VAR) based on a triangularization of the conditional posterior distribution of the coefficient vector developed in Carriero, Clark, and Marcellino (2019, hereafter CCM2019). However, Bognanni (2021) recently identified a conceptual problem with the triangular algorithm of CCM2019; the triangularization does not deliver the intended posterior of the VAR's coefficients. The same problem afflicts the estimation algorithm used in CCM2018.

In response, Carriero, et al. (2021) have developed a corrected triangular algorithm for Bayesian VARs that does yield the intended posterior. This new algorithm permits an equation-by-equation approach to the VAR and offers the same basic computational advantages of the original triangular algorithm. In addition, the new algorithm can be used to properly estimate the uncertainty model of CCM2018.

In this note, we provide corrected versions of the published results of CCM2018. Drawing from Carriero, et al. (2021), Section 2 briefly explains the problem with the original triangular algorithm and the correction. Section 3 presents corrected versions of the results of CCM2018. Although the correction has some impact on results, these impacts are small, and the key findings of CCM2018 are upheld.

# 2 Original algorithm and correction

For convenience, we briefly detail the model used in CCM2018. Let $y_t$ denote the $n \times 1$ vector of variables of interest, split into $n_m$ macroeconomic and $n_f = n - n_m$ financial variables. Let $v_t$ be the corresponding $n \times 1$ vector of reduced-form shocks to these variables, also split into two groups of $n_m$ and $n_f$ components. The reduced-form shocks are:

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

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

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

The variables $h_{j,t}$ — which do not enter the conditional mean of the VAR, specified below — capture idiosyncratic volatility components associated with the $j$-th variable in the VAR, and are assumed to follow (in logs) an autoregressive process:

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

with $\nu_t = (e_{1,t}, ..., e_{n,t})'$ jointly distributed as $i.i.d.\ N(0, \Phi_\nu)$ and independent among themselves, so that $\Phi_\nu = diag(\phi_1, ..., \phi_n)$. These shocks are also independent from the conditional errors $\epsilon_t$. The reduced-form error covariance matrix is $\Sigma_t = A^{-1} \Lambda_t A^{-1\prime}$.

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

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

where $D(L)$ is a lag-matrix polynomial of order $d$. The shocks to the uncertainty factors $u_{m,t}$ and $u_{f,t}$ are independent from the shocks to the idiosyncratic volatilities $e_{j,t}$ and the conditional errors $\epsilon_t$, and they are jointly normal with mean 0 and variance $\text{var}(u_t) = \text{var}((u_{m,t}, u_{f,t})') = \Phi_u$.

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

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

where $p$ denotes the number of $y_t$ lags in the VAR, $\Pi(L) = \Pi_1 - \Pi_2 L - \cdots - \Pi_p L^{p-1}$, with $\Pi_i$ 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 $p_f$. In explaining estimation, it will be helpful to collect the coefficients of $\Pi(L)$, $\Pi_m(L)$, and $\Pi_f(L)$ in a $k \times n$ matrix $\Pi$ and the regressors of each equation in the $k \times 1$ vector $x_t$, and write the VAR system as

$$y_t = \Pi' x_t + v_t. \tag{6}$$

Estimating the model with a Gibbs sampler requires the conditional posterior for the matrix of VAR coefficients $\Pi$. With smaller models, it is common to rely on a GLS solution for the posterior mean of the coefficient vector of the system of equations. However, such a system-of-equations approach slows considerably with larger models. In CCM2018, we instead estimated the VAR coefficients on an equation-by-equation basis, following a factorization of the posterior developed in CCM2019. Specifically, let $\pi^{(j)}$ denote the $j$-th column of the matrix $\Pi$, and let $\pi^{(1:j-1)}$ denote all of the previous columns. For each equation $j$, we drew $\pi^{(j)}$ from a multivariate Gaussian distribution with mean and variance as follows:

$$\begin{aligned} \bar{\mu}_{\pi^{(j)}} &= \overline{\Omega}_{\pi^{(j)}} \left\{ \Sigma_{t=1}^{T} x_t \lambda_{j,t}^{-1} y_{j,t}^{*\prime} + \underline{\Omega}_{\pi^{(j)}}^{-1} (\underline{\mu}_{\pi^{(j)}}) \right\}, \\ \overline{\Omega}_{\pi^{(j)}}^{-1} &= \underline{\Omega}_{\pi^{(j)}}^{-1} + \Sigma_{t=1}^{T} x_t \lambda_{j,t}^{-1} x_t', \end{aligned}$$

where $y_{j,t}^{*} = y_{j,t} - (a_{j,1}^{*} \lambda_{1,t}^{0.5} \epsilon_{1,t} + \cdots + a_{j,,j-1}^{*} \lambda_{j-1,t}^{0.5} \epsilon_{j-1,t})$, with $a_{j,i}^{*}$ denoting the generic element of the matrix $A^{-1}$ and $\underline{\Omega}_{\pi^{(j)}}^{-1}$ and $\underline{\mu}_{\pi^{(j)}}$ denoting the prior moments of the $j$-th equation, given by the $j$-th column of $\underline{\mu}_{\Pi}$ and the $j$-th block on the diagonal of $\underline{\Omega}_{\Pi}^{-1}$. Based on CCM2019, we intended for this approach to yield draws from the (correct) conditional posterior

$$\pi^{(j)} | \pi^{(1:j-1)}, A, \beta, f_{1:T}, m_{1:T}, h_{1:T}, y_{1:T} \sim \mathcal{N}(\bar{\mu}_{\pi^{(j)}}, \overline{\Omega}_{\pi^{(j)}}). \tag{7}$$

However, as follows from the results in Bognanni (2021), drawing the VAR's coefficients in this way does not deliver the intended posterior distribution of the coefficient matrix. That is, drawing the coefficients as was done in CCM2018 does not actually sample from the density (7). As explained in more detail in Carriero, et al. (2021), the actual density associated with the original algorithm is missing a term, involving the information about $\pi^{(j)}$ contained in the most recent observations of the dependent variables of equations $j + 1, ..., n$.

To correctly use the information in question in an algorithm for sampling from the conditional posterior for the VAR's coefficients, Carriero, et al. (2021) propose using a sequence of Gibbs sampler draws. Specifically, in the model setting of CCM2018, one can correctly sample from the joint distribution $\Pi | A, \beta, f_{1:T}, m_{1:T}, h_{1:T}, y_{1:T}$ by cycling through the full conditional distributions

$$\pi^{(j)} \mid \pi^{(-j)}, A, \beta, f_{1:T}, m_{1:T}, h_{1:T}, y_{1:T} \tag{8}$$

for $j = 1, \ldots, n$, where $\pi^{(j)}$ is the $j$-th column of the $k \times n$ matrix $\Pi$ — that is, the vector of coefficients appearing in equation $j$ — and $\pi^{(-j)} = (\pi^{(1)\prime}, \ldots, \pi^{(j-1)\prime}, \pi^{(j+1)\prime}, \ldots, \pi^{(n)\prime})'$ collects all the coefficients in the remaining equations.

To establish this corrected approach, consider the triangular representation of the system:

$$\tilde{y}_t = Ay_t = A\Pi' x_t + \Lambda_t^{0.5}\epsilon_t = A(x_t'\Pi)' + \Lambda_t^{0.5}\epsilon_t, \tag{9}$$

which can be expressed as the following system of equations:

$$\begin{aligned}
\tilde{y}_{1,t} &= x_t'\pi^{(1)} + \lambda_{1,t}^{0.5}\epsilon_{1,t} \\
\tilde{y}_{2,t} &= a_{2,1}x_t'\pi^{(1)} + x_t'\pi^{(2)} + \lambda_{2,t}^{0.5}\epsilon_{2,t} \\
\tilde{y}_{3,t} &= a_{3,1}x_t'\pi^{(1)} + a_{3,2}x_t'\pi^{(2)} + x_t'\pi^{(3)} + \lambda_{3,t}^{0.5}\epsilon_{3,t} \\
&\vdots \\
\tilde{y}_{n,t} &= a_{n,1}x_t'\pi^{(1)} + \cdots + a_{n,n-1}x_t'\pi^{(n-1)} + x_t'\pi^{(n)} + \lambda_{n,t}^{0.5}\epsilon_{n,t},
\end{aligned} \tag{10}$$

with $\tilde{y}_t = Ay_t$ a vector with generic $j$-th element $\tilde{y}_{j,t} = y_{j,t} + a_{j,1}y_{1,t} + \cdots + a_{j,j-1}y_{j-1,t}$.

With this recursive system (10), it is evident that the coefficients $\pi^{(j)}$ of equation $j$ influence not only equation $j$, but also the following equations $j+1,...,n$, which is yet another way of seeing that these equations have some extra information about $\pi^{(j)}$ that the old algorithm missed. Importantly though, it remains true that the previous equations $1,...,j-1$ have no information about the coefficients of equation $j$. With coefficient priors $\pi^{(j)} \sim N(\underline{\mu}_{\pi^{(j)}}, \underline{\Omega}_{\pi^{(j)}})$, $j = 1, ...n$, that are independent across equations (as is the case in all common VAR implementations), the first $j-1$ elements in the quadratic term above do not contain $\pi^{(j)}$. It follows that the conditional distribution $p(\pi^{(j)} \mid \pi^{(-j)}, A, \beta, f_{1:T}, m_{1:T}, h_{1:T}, y_{1:T})$ can be obtained using the subsystem composed of the last $n-j+1$ equations of (10).

In implementation, for drawing the coefficients of equation $j$, we use only equations $j$ and higher to sample $p(\pi^{(j)} \mid \pi^{(-j)}, A, \beta, f_{1:T}, m_{1:T}, h_{1:T}, y_{1:T})$:

$$
\begin{aligned}
z_{j,t} &= x_t' \pi^{(j)} + \lambda_{j,t}^{0.5} \epsilon_{j,t} \\
z_{j+1,t} &= a_{j+1,j}' x_t' \pi^{(j)} + \lambda_{j+1,t}^{0.5} \epsilon_{j+1,t} \\
&\vdots \\
z_{n,t} &= a_{n,j} x_t' \pi^{(j)} + \lambda_{n,t}^{0.5} \epsilon_{n,t},
\end{aligned}
$$

where $z_{j+l,t} = \tilde{y}_{j+l,t} - \sum_{i \neq j, i=1}^{j+l} a_{j+l,i} x_t' \pi^{(i)}$, for $l = 0, ..., n-j$, and $a_{i,i} = 1$.

Then, using the above triangular representation, the full conditional distribution $(\pi^{(j)} \mid \pi^{(-j)}, A, \beta, f_{1:T}, m_{1:T}, h_{1:T}, y_{1:T})$ is

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

where

$$
\overline{\Omega}_{\pi^{(j)}}^{-1} = \underline{\Omega}_{\pi^{(j)}}^{-1} + \sum_{i=j}^{n} a_{i,j}^2 \sum_{t=1}^{T} \frac{1}{\lambda_{i,t}} x_t x_t', \tag{11}
$$

$$
\overline{\mu}_{\pi^{(j)}} = \overline{\Omega}_{\pi^{(j)}} \left( \underline{\Omega}_{\pi^{(j)}}^{-1} \underline{\mu}_{\pi^{(j)}} + \sum_{i=j}^{n} a_{i,j} \sum_{t=1}^{T} \frac{1}{\lambda_{i,t}} x_t z_{i,t} \right). \tag{12}
$$

As documented in Carriero, et al. (2021), this approach preserves the gains in computational complexity described in CCM2019. Although the use of additional information (data) for all but the $n$-th equation makes this algorithm empirically slower than that originally used in the paper, in application the computational time is comparable. Accordingly, in this note, we use this approach to sampling the VAR's coefficients to correct and update the results of CCM2018.[1]

# 3 Corrected results

In general, the correction of the estimation algorithm has proven to make it somewhat more difficult to disentangle measures of macroeconomic and financial uncertainty. Abstracting from algorithm considerations, some challenges are to be expected, given the comovement of forecast error variances across the variables of the model, the counter-cyclicality of uncertainty, the non-linear features of the model, and the large size of the model. The algorithm correction seems to have made these challenges steeper, for reasons not easy to pinpoint. For example, with some of the loose prior settings of CCM2018, estimates with the new algorithm showed more issues with mixing and convergence of the MCMC chain.

Accordingly, to be able to reliably estimate the model with the corrected algorithm, we have made two changes relative to the settings of CCM2018. First, we have tightened a few prior settings. We lowered the hyperparameter $\theta_3$ governing shrinkage of the factor coefficients in the VAR's conditional mean from the paper's uninformative setting of 1000 to a more modestly informative setting of 1. We also lowered the prior variance on the elements of the $A$ matrix from the paper's largely uninformative setting of 10 to a more modestly informative setting of 1. Second, we have shortened the estimation sample, so that it starts in January 1985 instead of July 1960 as in the paper. With the shorter sample, there are fewer concerns with potential sample instabilities

[1]See Carriero, et al. (2021) for an implementation of computations that makes use of a data-matrix type of notation that is easy to implement and computationally efficient in programming languages such as Matlab.

owing to various structural shifts in the economy, monetary policy in particular. Some other work in the uncertainty literature (e.g., Baker et al. (2016) and Basu and Bundick (2017)) also focuses on samples starting in the mid-1980s. Since some other studies on uncertainty, such as Alessandri and Mumtaz (2019) and Shin and Zhong (2020), started estimation in the 1970s, we have repeated our analysis with a sample starting in 1975, finding results qualitatively very similar to those reported below.

In the remainder of this note, we provide results for the 1985-2014 sample corresponding to those in CCM2018, but using the corrected algorithm for VAR estimation described above. In general, the corrected results are qualitatively the same as those provided in CCM2018.

**Figure 1** displays the posterior distribution of the updated measures of macro (top panel) and financial uncertainty (bottom panel). The updated estimates are very similar to those of the paper, with correlations (paper with corrected algorithm) of about 0.9 for the macro factor and 0.98 for the financial factor. It continues to be the case that the macro and financial factors are modestly correlated, with a correlation of about 0.3 for the 1985-2014 period in both the original and updated estimates. Relative to the paper, the main difference in the uncertainty estimates is that the new macro factor is a little more variable than the paper's estimate. But in general, the new estimates display the same features as did the original estimates. For example, the financial uncertainty factor increases not only during recessions, as does the macro uncertainty factor, but also in other periods of financial turmoil. As indicated in Figure 1, our estimates of uncertainty show significant increases around some of the political and economic events that Bloom (2009) highlights as periods of uncertainty, as in the case of financial uncertainty around the Black Monday event of 1987.

**Figure 2** reports the updated estimates of the reduced-form volatilities of the variables in our model, i.e., the diagonal elements of $\Sigma_t^{0.5}$, which reflect both the common uncertainty factors and idiosyncratic components, along with the estimated idiosyncratic volatilities (reported in the chart as $h_{i,t}^{0.5}$). In broad terms, these results are comparable to the paper's original estimates. For example, the volatility of the funds rate declines sharply in the 1980s. As another, for some variables (e.g, industrial production), most variability appears to be driven by the common factors, whereas for a few others (e.g., real consumer spending, the PPI for finished goods, and the federal funds rate) the idiosyncratic variation is preponderant, explaining most of the overall variation in the volatility.

**Table 2** (preserving the numbering of the paper for ease of reference) provides correlations of our updated estimates of macroeconomic and financial uncertainty shocks with some well-known macro shocks. In most cases, the uncertainty shocks continue to show little correlation with "known" macroeconomic shocks. For example, the correlations of uncertainty shocks with productivity shocks are small and insignificant in these updated estimates, as they were in the paper's reported results. However, with the shorter sample and updates, there are a few instances of small, significant correlations of the uncertainty shocks with "known" macroeconomic shocks. For example, the monetary policy shocks have a small, statistically significant correlation with the shock to financial uncertainty. Some of the shift in these results seems to be due just to the shortening of the sample; in a few cases, with the sample starting in 1985, the uncertainty shocks of the paper's original estimates show similarly significant correlations with "known" macroeconomic shocks.

**Figure 3** provides the impulse response estimates of a one-standard-deviation shock to log macro uncertainty ($\ln m_t$). These estimates are qualitatively the same as those reported in the paper. The shock to log macro uncertainty produces a rise in uncertainty that gradually dies out, over the course of about one year. Financial uncertainty rises in response, also for about a year, although the response of financial uncertainty is estimated less precisely than the response of macro uncertainty. Activity measures including consumption, real M&T (manufacturing and trade) sales, industrial production, and capacity utilization decline significantly. The labor market also deteriorates, with employment and hours falling and the unemployment rate rising. 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. Although the PPI for finished goods declines steadily (with an imprecise estimate), overall consumer prices as captured by the PCE price index fail to display a significant change. In the face of this sizable deterioration in the real economy and in the absence of much movement in prices, the federal funds rate gradually falls. The responses of financial indicators to the shock to macro uncertainty are somewhat mixed, often muted, and sometimes imprecisely estimated. However, in these corrected estimates as compared to the paper's original results, the shock to uncertainty produces a larger and more precisely estimated falloff in the S&P 500 and excess return.

**Figure 4** provides the impulse response estimates of a one-standard-deviation shock to log financial uncertainty ($\ln f_t$). These updated estimates are also comparable to those reported in the published paper, although in this case of a financial uncertainty shock, the corrected responses tend to be a little smaller than those reported in CCM2018. The shock to log financial uncertainty produces a rise in uncertainty that only gradually dies out, over the course of almost two years. In response, macro uncertainty slightly declines (whereas in the paper's estimates it slightly rose), although by an amount that would not be significant at confidence levels modestly greater than 70 percent (as they are barely significant at 70 percent). As to broader effects of financial uncertainty, when compared to a macro uncertainty shock, a financial uncertainty shock has similar macroeconomic effects, but often modestly smaller or sometimes less precisely estimated. However, in these estimates, as in the paper's results, a financial uncertainty shock does not have significant effects on the housing sector (starts and permits). In addition, as in the paper's results, the shock to financial uncertainty produces a persistent and significant rise in the credit spread, with a hump-shaped pattern. It also produces a sizable falloff in aggregate stock prices and returns, but the responses of the risk factors included in the model are insignificant.

**Figure 5** provides corrected historical decomposition results for the period from 2003 through 2014. The charts show the standardized data series, a baseline path corresponding to the unconditional forecast, the direct contributions of shocks to (separately) macroeconomic and financial uncertainty, and the direct contributions of the VAR's shocks. The reported estimates are posterior medians of decompositions computed for each draw from the posterior. These updated results are also qualitatively similar to those provided in the paper. Around the Great Recession, shocks to uncertainty contribute to fluctuations in economic activity, the federal funds rate, the credit spread, and uncertainty itself, but not much to inflation or stock prices (or other financial indicators). However, for the macroeconomic and financial variables of the model, the effects of uncertainty shocks are generally dominated by the contributions of the VAR's shocks. One qualitative difference with the corrected results compared to the estimates originally reported is that the contribution of shocks to financial uncertainty is smaller in the new estimates.

**Figure 6** shows the effects of uncertainty shocks on the predictive distributions of selected variables. The solid black line and gray shading report the predictive density of a baseline path for the variables. The alternative path denoted by the dotted (median) and dashed lines (15 and 85 percent quantiles) instead shows the predictive density with additional uncertainty shocks (for December 2007 through June 2009) corresponding to those obtained with our estimated model. These corrected results are very similar to the original estimates provided in CCM2018. Consistent with the simple impulse responses, the shocks to uncertainty cause the path of economic activity to shift down. For many but not all variables, the shocks also have a distributional effect beyond just moving the center of the distribution: they also cause the distribution to rotate downward. The 15th percentile of the 70 percent credible set appears to fall more than does the 85th percentile. These effects are most evident for those variables for which an uncertainty shock affects the median of the distribution, particularly for measures of economic activity (employment, industrial production, etc.), the federal funds rate, and the credit spread. For variables for which the median responses are smaller (e.g., for the PCE price index), there are no obvious distributional effects.

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Table 2: Correlations of uncertainty shocks with other shocks

| known shock | macro uncertainty shock | financial uncertainty shock |
|---|---|---|
| Productivity: Fernald TFP | -0.065 | 0.137 |
| (1985:Q1-2014:Q2) | (0.406) | (0.164) |
| Oil supply: Hamilton (2003) | 0.144 | 0.150 |
| (1985:Q1-2014:Q2) | (0.039) | (0.009) |
| Oil supply: Kilian (2008) | -0.123 | 0.064 |
| (1985:Q1-2004:Q3) | (0.236) | (0.651) |
| Monetary policy: Guykaynak, et al. (2005) | -0.054 | 0.159 |
| (1990:Q1-2004:Q4) | (0.570) | (0.029) |
| Monetary policy: Coibion, et al. (2016) | -0.143 | -0.332 |
| (1985:Q1-2008:Q4) | (0.173) | (0.000) |
| Fiscal policy: Ramey (2011) | 0.076 | 0.093 |
| (1985:Q1-2008:Q4) | (0.343) | (0.036) |
| Fiscal policy: Mertens and Ravn (2012) | 0.079 | -0.033 |
| (1985:Q1-2006:Q4) | (0.101) | (0.248) |

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

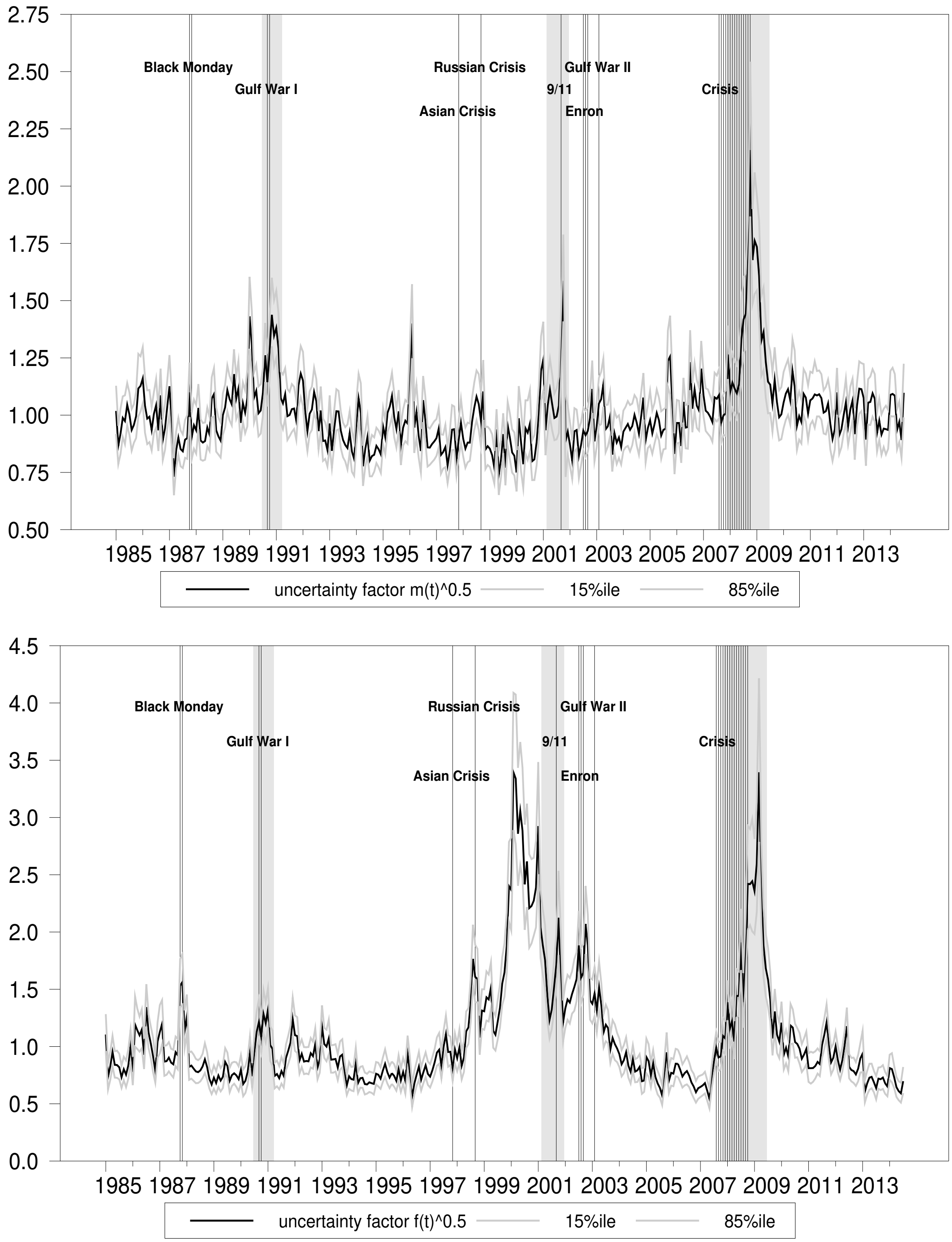


Figure 1: Uncertainty estimates: posterior median (solid black line) and 15%/85% quantiles (dotted lines), with macro uncertainty ($m_t^{0.5}$) in the top panel and financial uncertainty ($f_t^{0.5}$) in the bottom panel. The gray shading indicates periods of NBER recessions. The periods indicated by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

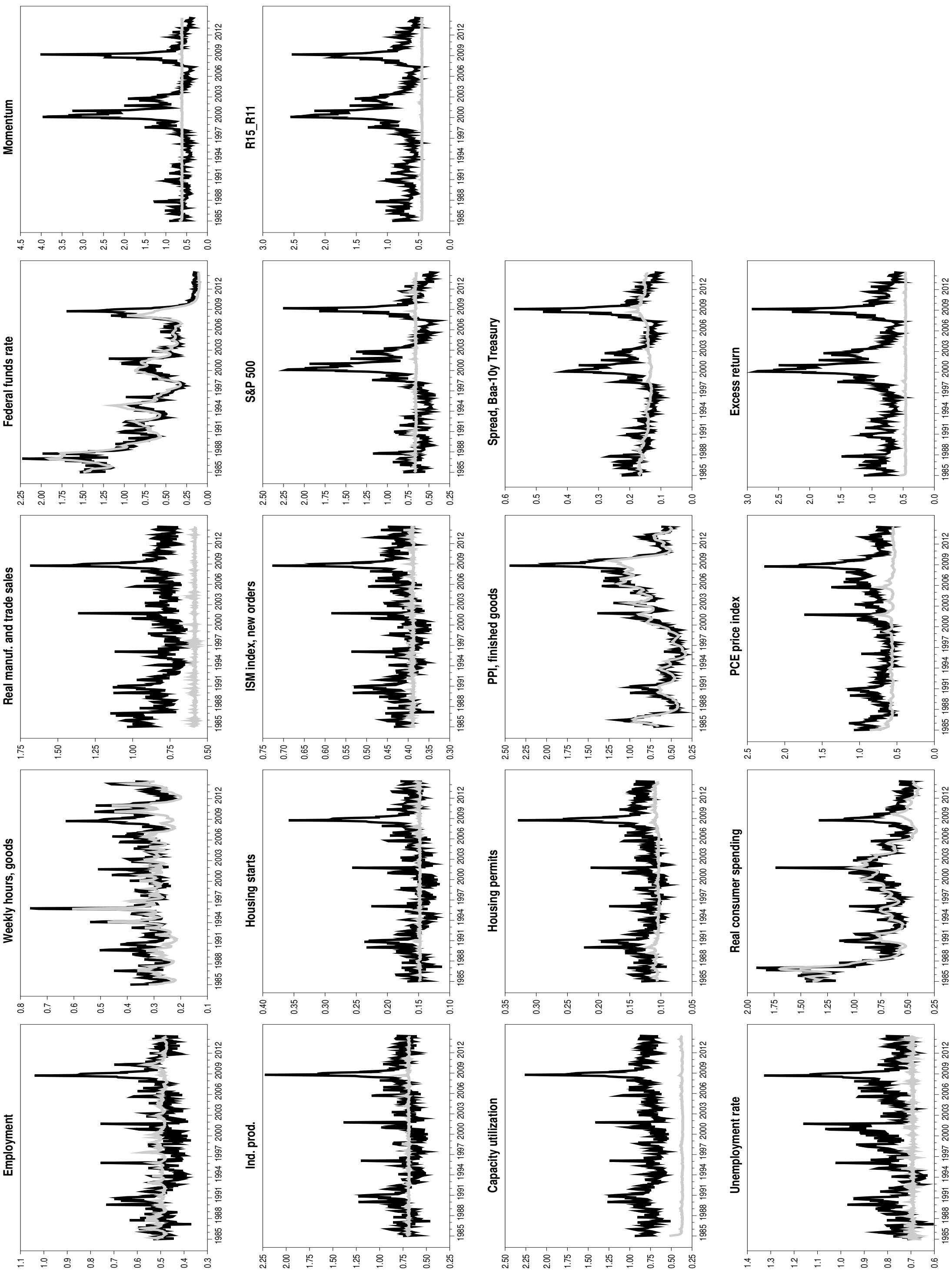


Figure 2: Reduced-form (black line) and idiosyncratic volatilities ($h_{i,t}^{0.5}$, gray line), selected variables, posterior medians

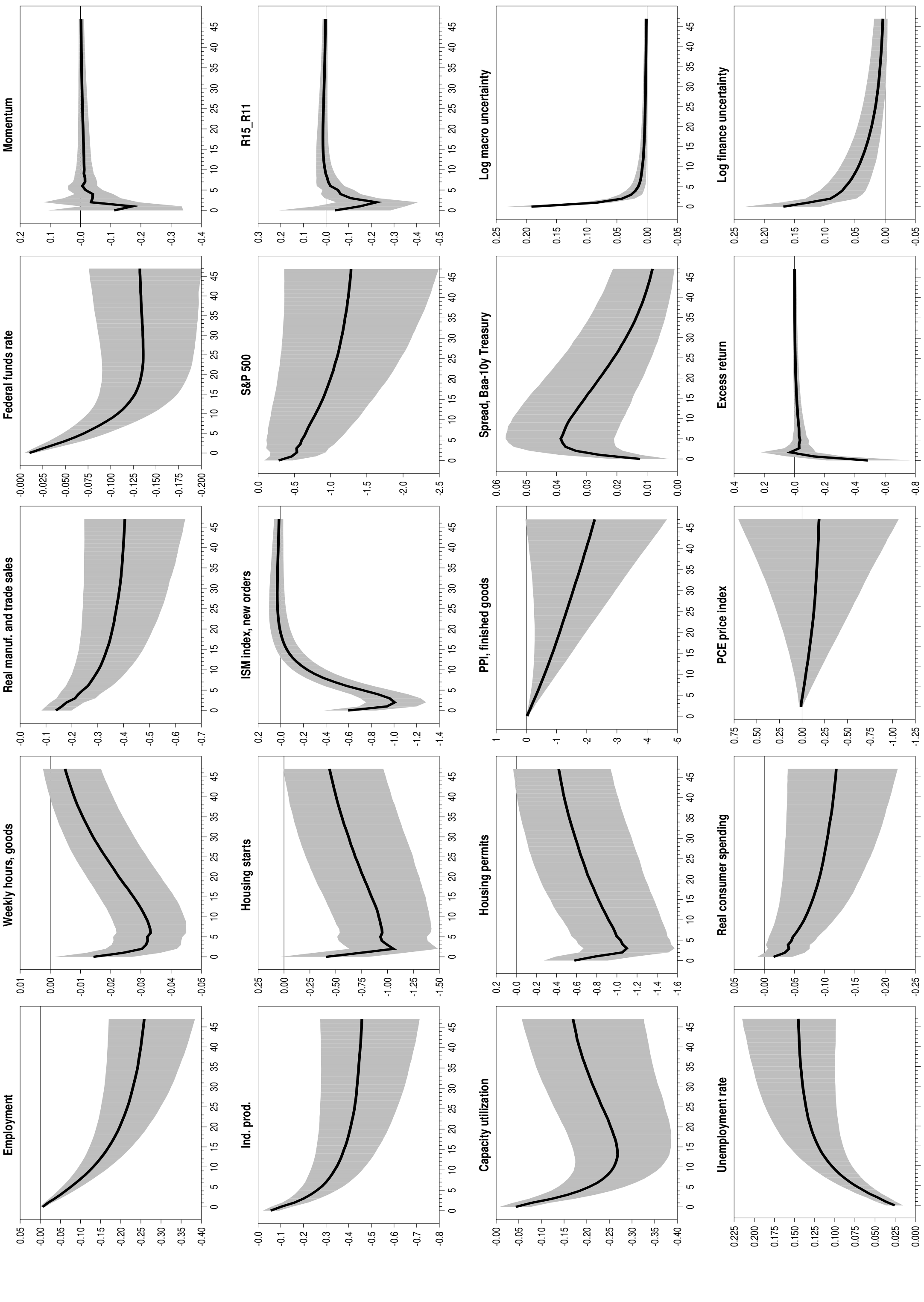


Figure 3: Impulse responses for one-standard-deviation shock to macro uncertainty, selected variables, posterior median (black line) and 15%/85% quantiles (gray shading)

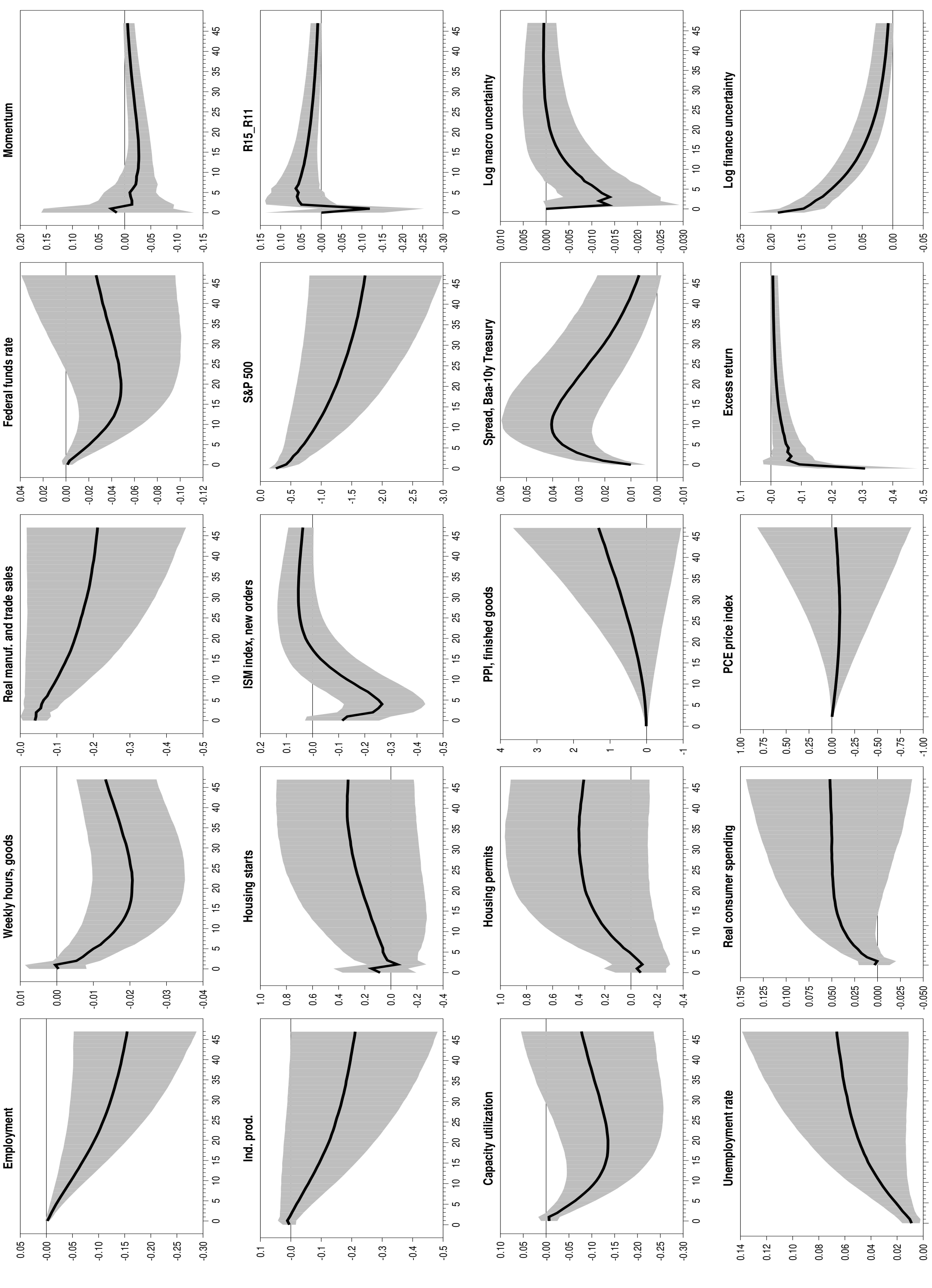


Figure 4: Impulse responses for one-standard-deviation shock to financial uncertainty, selected variables, posterior median (black line) and 15%/85% quantiles (gray shading)

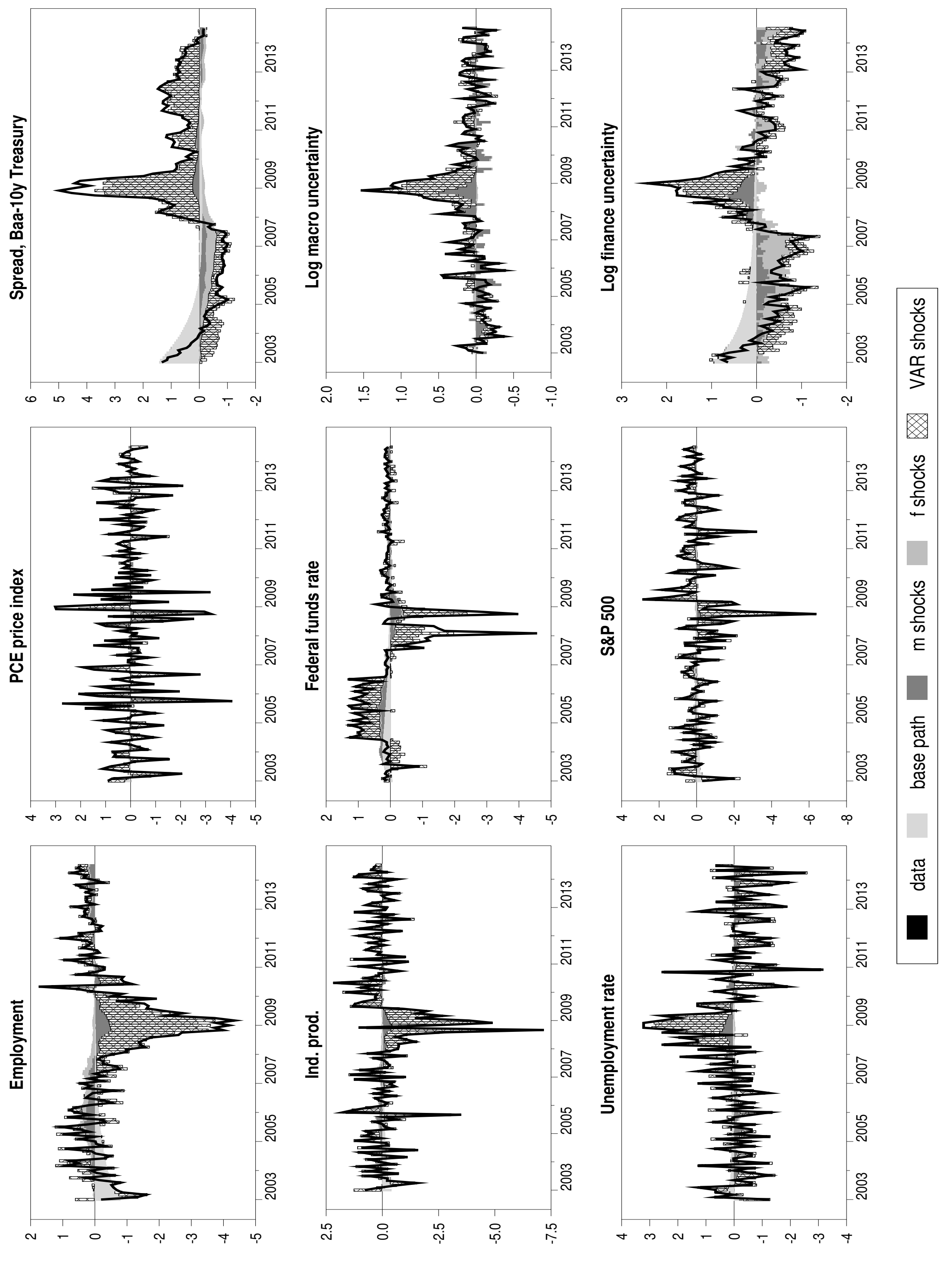


Figure 5: Historical decomposition for 2003-2014, selected variables, posterior medians, with actual data series in solid black line

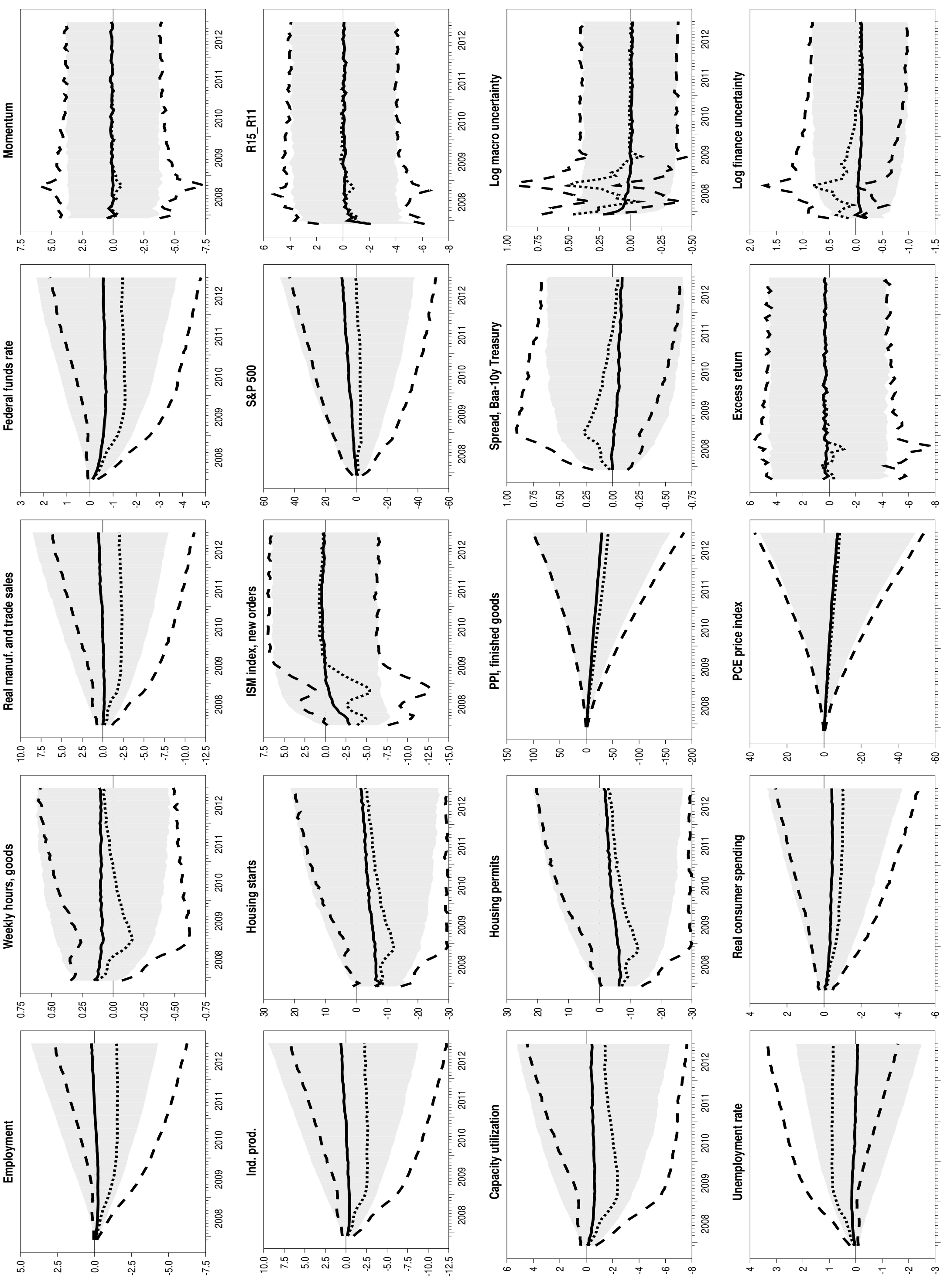


Figure 6: Effects of uncertainty shocks on predictive distributions, December 2007 through December 2012, selected variables. The baseline path is reported as the solid black line (median) with gray shading (15%/85% quantiles). The path with the effects of the estimated uncertainty shocks over the period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