

MEASURING THE DYNAMIC EFFECTS OF MONETARY POLICY SHOCKS: A BAYESIAN FAVAR APPROACH WITH SIGN RESTRICTION¹

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We estimate the effects of monetary policy shocks in a Bayesian factor-augmented vector autoregression (BFAVAR). We propose a novel identification strategy of imposing sign restrictions directly on the impulse responses of large sets of variables. The key strength of our approach is the additional “bite” due to the differences in factor loadings across sets of time series representing, say, “prices” or “output”. As an important advantage, our procedure does not require a structural interpretation of the factors themselves or adding observables to the list of factors. We impose the conventional wisdom regarding the responses of prices, monetary aggregates, spreads and interest rates. In response to a one-standard deviation monetary policy shock, we find a modest drop in industrial production, reverting within two years, a persistent decline in the CPI, and decreases in yield spreads. By contrast, a standard Cholesky decomposition identification of a monetary policy shock implies a persistent increase in the CPI four years following the shock.

KEYWORDS: Bayesian FAVAR, Dynamic Factor Models, Identification, Sign Restriction, Gibbs Sampling, Monetary Policy Shocks.

1. INTRODUCTION

What are the dynamic effects of monetary policy shocks on the economy? We answer this question by combining two recent advances in empirical macroeconomics: factor-augmented VARs (FAVAR) and identification per sign restrictions. We propose a novel identification strategy of imposing sign restrictions directly on the impulse responses of large sets of variables to shocks in factor VAR. The novel feature and key strength of our approach is the additional “bite” due to the differences in factor loadings across sets of time series representing, say, “prices” or “output”. As an important advantage, our procedure does not require a structural interpretation of the factors themselves or adding observables to the list of factors. We impose the conventional wisdom regarding the responses of prices, monetary aggregates, spreads and interest rates.

Our approach avoids the price puzzle by construction, and remains usable for subsamples as well. We show this per applying our approach to a data set ending in June 2010, thus including the 2008 financial crisis episode and the

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ensuing quantitative easing policies of the Federal Reserve Bank, an episode that generates considerable challenges to any strategy of identifying monetary policy shocks: the results do not change much, even when we restrict the sample to include only the “post-Volcker” years from 1984 to 2010.

Following the lead of Sims [1972,1980,1986], a large literature has developed, analyzing the effects of monetary policy shocks with the aid of vector autoregression (VAR). Most VAR studies consider a small number of variables in order to save degrees of freedom for keeping the model tractable¹. The central bank is likely to take considerably more information into account when choosing its course of actions, however. As pointed out by Bernanke and Boivin [2003], monetary policy takes place in a “data-rich environment”. Bernanke and Boivin [2003], Stock and Watson [2005] and Bernanke, Boivin and Eliasz [2005] therefore introduced factor vector autoregression (FAVAR) models, combining dynamic factor models (DFM) with the VAR analysis.

Identifying assumptions are key. We propose to identify monetary policy shocks with the help of sign restrictions, introduced by Dywer [1997], Faust [1998], Canova and Pina [2005], Canova and De Nicoló [2002] and Uhlig [2005]. A survey and various extensions are in Rubio-Ramirez-Waggoner-Zha(2010). In this approach, the response of key macroeconomic variables such as prices and interest rates to a monetary policy shock is restricted to accord with *a priori* theory, in order to achieve identification. Our key innovation compared to that literature is to use a FAVAR approach. This allows us to impose restrictions on a comparatively large number of observable time series, potentially providing a more exact identification. For example, not one, but many price series can and will be restricted in their response: as each reacts somewhat differently to shocks, the range of potential candidates for monetary policy shocks is reduced. This is important, since sign restrictions offer weak or set identification, as opposed to point identification, see Canova [2007] for a discussion of the latter. Compared to other identification strategies in FAVARs as introduced as well as surveyed by Stock and Watson [2005], our approach avoids a structural interpretation of the factors themselves or adding observables to the list of factors. In fact, our approach can be applied and is appealing more broadly, when a substantial number of observable time series can potentially be restricted in their response to a shock, and thus can also be applied in dynamic factor models.

Sims and Zha [1998] review Bayesian methods for multivariate models and their advantages: our paper is in that tradition. For the estimation we choose a Bayesian likelihood-based estimation based on MCMC methods which is fully parametric. Thus we can explicitly exploit the factor structure of the data and the law of motion of the extracted factors. Our impulse response confidence bands are posterior probability statements rather than confidence sets, an issue raised and analyzed in Moon and Schorfheide [2012] and Granziera, Moon and Schorfheide [2013], and discussed from a Bayesian perspective in Rubio-Ramírez-

¹On the larger side, Leeper, Sims and Zha [1996] employ a Bayesian VAR with 18 variables.

Waggoner-Zha [2010]. We use a set of monthly macroeconomic data from 1960:02 to 2010:06, building and extending a data set provided by Stock and Watson. We check for subsample stability. We compare the results from our approach to the Cholesky identification in FAVARs, as proposed by Bernanke, Boivin and Eliasz [2005]. We choose a benchmark specification in terms of the FAVAR as well as the restrictions imposed, but have studied a number of variations, documented in a technical appendix.

Compared to the VAR sign restriction literature, our confidence bands for the on-impact response is typically considerably more narrow. For the full sample as well as the post-Volcker sample, we find that a monetary policy shock one standard deviation in size raises the Federal Funds Rate by about 15 basis points, before eventually reverting course and an eventual decrease of 10 basis points. In response, we find that industrial production decreases, with a maximum impact of minus 0.2 percent at the median estimate after one year before reverting back. For the subsectors, we find the smallest or even a positive reaction for the industrial production in residential utilities as well as fuels, while industrial production of business equipment as well as durable materials falls somewhat more strongly and more persistently than total industrial production. The effect on real GDP is less pronounced. The posterior confidence bands includes zero or positive reactions, consistent with Uhlig [2005]. We find that the forecast-error revision variance of industrial production due to monetary policy shocks accounts for less than 10 percent at the median estimate, which is consistent with results in Sims and Zha [2006] and Uhlig [2005]. Similar results have been obtained for the period of the US Great Depression in Sims [1999] and Amir Ahmadi and Ritschl [2013]. Employment falls by 0.1 percent within two years, starting from an initial zero response. Total unemployment puzzlingly shows an initial fall of about 0.08 percentage points. The CPI falls by 0.1 percent on impact, and by half a percent eventually within four years, showing a persistent response. Yield spreads initially fall in response, and fall the more strongly, the longer the maturity. The spread between the 3-month TBill and the Federal Funds Rate falls by 5 basis points one month after the shock, whereas the spread between the 10 year Treasury Bond and the Federal Funds Rate falls by 15 basis points. The spread responses are rather tightly estimated.

For the Cholesky identification as proposed by Bernanke, Boivin and Eliasz [2005], we find substantial prize puzzles. For the post-1984 subsample, for example, the CPI response is rather tightly estimated to rise by 0.1 percent within a year. Even within four years, it remains considerably more likely that the CPI response stays positive rather than turning negative. The commodity prices increase on impact. We argue that these results render the Cholesky identification approach considerably less useful for the analysis of monetary policy shocks than ours. The Cholesky decomposition implies a persistent fall in industrial production, whereas our identification shows industrial production to return to a near-zero uncertainty band within two years. This matters in particular for the purpose of political debates regarding monetary policy choices, and provides all

the more reason to adapt our identification rather than a Cholesky identification in a FAVAR.

Since the first draft of this paper, Mumtaz and Surico (2009) too have introduced sign restrictions to FAVARs. There are key differences between their approach and ours, however. These authors use factors as summaries of blocks of data, constructing, for example, a real activity factor. They then apply standard (contemporaneous) sign restriction and conventional identification techniques to the small-scale VAR in these factors. The difference of their paper to the existing literature is thus the application of sign restrictions to these constructed variables, but is conventional otherwise. By contrast, we do not impose a structural interpretation to our factors, and instead impose sign restrictions directly on the responses of the various variables, exploiting the variations in factor loadings across large sets of, say, price responses. It is the latter feature which gives our procedure substantial “bite” and constitutes the major innovation compared to the existing literature. To our knowledge, ours is the first method that allows identification of shocks in dynamic factor models without requiring a structural interpretation of the factors themselves and without requiring adding observables to the list of factors. Our procedure should therefore be appealing and straightforward to use in a variety of applications.

2. THE MODEL

We apply a Bayesian version of the FAVAR model introduced by Bernanke, Boivin and Eliasz [2005]. The idea is to summarize the key dynamics of a large set of time series by a small list, containing some common factors as well as some key variables, and then analyze the dynamic behavior of the latter as well as the responses of the former. We describe the model in state space form. Time is indexed by $t = 1, \dots, T$. The small list of key variables is a $[n_y \times 1]$ vector f_t^y . The remaining time series are a $[n_x \times 1]$ vector x_t . Let f_t denote the $[n_f \times 1]$ vector of unobservable common factors of X_t^c . The $[n_x \times 1]$ vector e_t is a time- t error term. The model is

$$(2.1) \quad X_t^c = \lambda^c f_t^c + \lambda^y f_t^y + e_t$$

$$(2.2) \quad e \sim N(0, R_e)$$

Here λ^c and λ^y denote the matrix of factor loadings of the factors and the perfectly observable variables included as factors with dimension $[n_x \times n_f]$ and $[n_x \times n_y]$ respectively. The covariance matrix R_e is assumed to be diagonal. Hence the error terms of the observable variables are assumed to be mutually uncorrelated. The FAVAR state equation represents the joint dynamics of factors and the key variables $f_t = ((f_t^c)', (f_t^y)')$ following a $VAR(P)$ process.

$$(2.3) \quad \begin{bmatrix} f_t^c \\ f_t^y \end{bmatrix} = \sum_{p=1}^P \phi_p \begin{bmatrix} f_{t-p}^c \\ f_{t-p}^y \end{bmatrix} + u_t$$

$$(2.4) \quad u_t \sim N(0, Q_u)$$

where u_t is the date- t reduced form shock, Q_u is the factor error covariance matrix and ϕ_p are the p -lag coefficient matrices. The dimensions are $[K \times 1]$, $[K \times 1]$ and $[K \times K]$ respectively, where the total number of factors is $K = n_f + n_y$. We assume that Q_u is of full rank.

3. IDENTIFICATION

3.1. Sign Restrictions in FAVARs and DFM

The major objective of this paper is to identify monetary policy shocks in a data-rich environment per imposing sign restrictions as introduced by Uhlig [2005] for the VAR framework. The idea is to achieve identification of structural shocks by imposing sign restrictions on the impulse responses of key macroeconomic variables for a specified horizon.

The structural shocks $\nu_t \in \mathbf{R}^K$ are related to the reduced form shocks u_t of the factor VAR (2.3) per

$$u_t = A\nu_t$$

where the matrix A is an orthogonal invertible matrix of dimension $[K \times K]$, satisfying

$$Q_u = AA'$$

arising from the assumption that the ν_t are uncorrelated and of unit variance,

$$E[\nu_t \nu_t'] = I_K$$

We are only interested in identifying the monetary policy shock. It is therefore sufficient to identify a single column or “impulse vector” a of A , see Uhlig [2005].

Definition 1 The vector $a \in \mathbf{R}^K$ is called an impulse vector, iff there is some matrix A , so that $AA' = Q_u$ and so that a is a column of A

According to the Proposition 1 of Uhlig [2005,pp. 18], any impulse vector can be characterized as follows. Let $\tilde{A}\tilde{A}' = Q_u$ be the Cholesky decomposition. Then a is an impulse vector if and only if there is some K -dimensional vector α of unit length so that

$$a = \tilde{A}\alpha$$

Given the impulse vector, let $r_k(s) \in \mathbf{R}^K$ be the vector response at horizon s to the k -th shock in a Cholesky-decomposition of Q_u . Then the impulse response $r_a(s)$ for a is given by

$$r_a(s) = \sum_{i=1}^K \alpha_i r_i(s).$$

For estimation consider the companion form of (2.1) to (2.4)

$$\begin{aligned} F_t &= \Phi F_{t-p} + u_t \\ X_t &= \Lambda F_t + E_t. \end{aligned}$$

where F_t, X_t, Φ, E_t are defined in the appendix, equations (A.4) in the usual manner. Let $\mathbf{a} = [a', 0_{1, K(P-1)}]'$. Compute

$$r_{a,k}(s) = (\Phi^s \mathbf{a})_k.$$

to obtain the impulse response of the k -th factor in f_t to an impulse in a at horizon s . Note that $r_a(s)$ is the vector of impulse response functions of all factors to an impulse vector a at horizon s . Compute

$$r_a^j(s) = \Lambda_j r_a(s).$$

where Λ_n is the n -th row vector of the factor loading matrix Λ , in order to obtain the impulse response function of variable X_j in X .

We proceed by imposing sign restrictions derived from “conventional wisdom”: after a monetary policy contraction, the federal funds rate should increase, prices should not increase and nonborrowed reserves as well as M1 should decrease. The precise list is stated in section 4.

Assumption 1 A (contractionary) monetary policy impulse vector is an impulse vector \mathbf{a} so that the individual impulse response functions to \mathbf{a} of prices, nonborrowed reserves and M1 are not positive and the impulse responses short term interest rate is positive, for a specified horizons $s=0, \dots, S$.

Note that our strategy can be implemented, even if $n_y = 0$, i.e., even if the model is a dynamic factor model rather than a FAVAR.

3.2. Cholesky Identification in FAVARs

For comparison we also employ the Cholesky Identification following Bernanke, Boivin and Eliasz [2005] who impose a recursive structure. We impose that $f_t^y = [CPI_t, FFR_t]'$, i.e., we use the CPI and the Federal Funds Rate as the key macroeconomic variables in the overall list of factors f_t . Let

$$\begin{aligned} u_t &= \tilde{A}\nu_t \\ \tilde{A}\tilde{A}' &= Q_u \end{aligned}$$

where \tilde{A} is lower triangular Cholesky factor of the covariance matrix Q_u of the reduced form shocks u_t and where the Federal Funds Rate as policy instrument is ordered last in the FAVAR equation. A detailed description and defense of the identification assumptions as well as discussions of alternatives can be found in Bernanke et. al. [2005] and Stock and Watson [2005].

Note that this strategy can only be implemented, when the policy instrument is part of the list of factors, and therefore cannot be implemented in a dynamic factor model as opposed to a FAVAR.

It may be less obvious why it is useful to also include the CPI in the list of factors. It turns out that the FAVAR Cholesky specification can be misspecified, if the monetary authority reacts to the “noise” component in the CPI and the CPI is not included in the list of factors. We provide a more detailed discussion of this point in section B of the appendix. For the same reasons, we include the

CPI as well as the FFR in the specification of our benchmark sign-restricted FAVAR model.

4. EMPIRICAL RESULTS

4.1. Data and Model Specification

We follow the empirical approach of Bernanke, Boivin and Eliasz [2005]. They use the data set of Stock and Watson [1998,1999] which consists of a panel of 120 macroeconomic variables in monthly frequency transformed to induce stationarity. For our analysis we have updated the data set documented in Stock and Watson [2005] with observations from 1960:02-2003:12 to 1960:02-2010:06, slightly changing the set of variables². The data set is listed in Appendix C.1. To check on subsample stability, we also use 1960:02-1979:09 (“Pre-Volcker”) as well 1984:02-2010:06 (“Post-Volcker”). We use a total of $K = 6$ factors f_t . We use $n_y = 2$ key variables, the CPI and the Federal Funds Rate, for reasons described in appendix B, and $n_f = 4$ general factors, which are “extracted” and sampled from the remaining time series in the estimation phase. We used $P = 12$ lags in the factor VAR. The horizon for the sign restriction to hold is set to $H = 6$ which is based on Uhlig (2005). In our baseline specification, the impulse responses of the following variables have been sign-restricted, in order to achieve identification of the monetary policy shock, where numbers refer to table I in appendix C.1:

1. prices: 104 to 111, 113, 114, 116 to 118.
2. monetary aggregates: M1 (69) and nonborrowed reserves (73).
3. interest rates: Federal Funds Rate (82).

We also examined a minimal restriction specification, where we have restricted the following variables:

1. prices: commodity price index (108) and CPI (109).
2. monetary aggregates: M1 (69) and nonborrowed reserves (73).
3. interest rates: Federal Funds Rate (82).

The results are very similar to our benchmark identification, and we thus refrain from reporting the results here: they are available in a technical appendix.

Alternatively, we examine an output-restricted specification where, in addition to the full set of restrictions in our benchmark model, total industrial production (17) as well as real GDP (18) is restricted to fall. This specification is useful for economists, who believe that output surely falls after a monetary contraction, and are interested in the shapes of the impulse responses and their quantitative magnitudes, given these additional identifying assumption. This turns out to result in more tightly estimated responses and (unsurprisingly) rather clearly

²We thank Mark Watson for making his data and computer codes available on his webpage <http://www.princeton.edu/~mwatson/wp.html>. Our updated data set is available on our web pages and in companion material for this paper.

negative responses for output. The results, in form of a comparison to our benchmark specification, is available in a technical appendix to this paper.

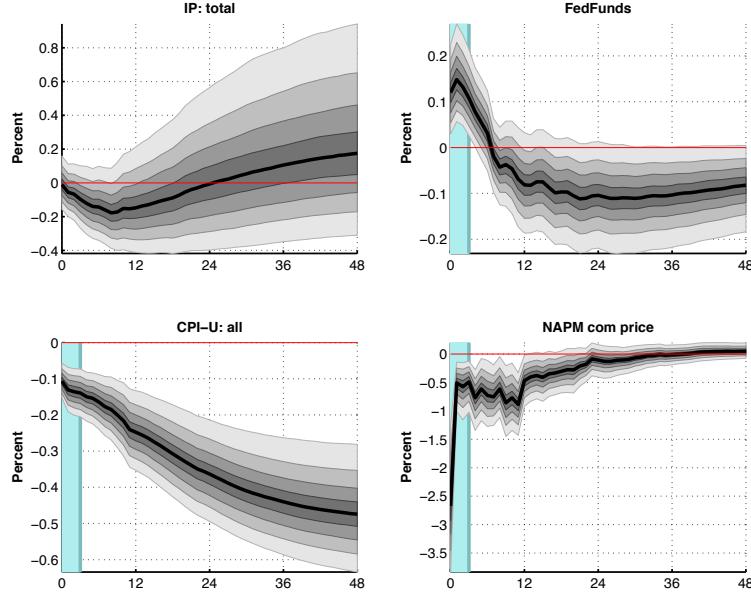
As a robustness check, we employed several variants of our strategy. The details are available as a technical appendix. We considered changing the set of sign-restricted variables as well as the set of key variables f_t^y included as factors. Leaving out the CPI altered the results, which we suspect is due to the misspecification discussed in [B](#). We experimented with changing the number of general factors extracted from the data. We found that little information was added by increasing the dimension of the system, per analyzing the marginal contribution of further factors for the explanation of the variation in the data based on R^2 . We tried several versions with different lag length, but the results compared to the ones reported here do not differ much. We found a tendency that the impact and intensity of the responses of restricted variables increases with the horizon H . For additional subsample checks, we used the data sets 1984:02-2002:12 as well as 1981:09-2002:12, to vary the begin of the “post-Volcker” episode and to exclude the financial crisis of 2008.

4.2. Estimation

For the estimation, we rely on now standard techniques. A detailed survey with several identification schemes in the classical estimation approach can be found in Stock and Watson [2005]. Bernanke, Boivin and Eliasz [2005] present two competing approaches. The second estimation approach described in their paper is the one that we employ in this paper because the likelihood based one-step estimation approach employing MCMC methods explicitly exploits the factor structure. We employ a Bayesian approach. We estimate the model with a multi-move Gibbs sampler for which we have to cast the model into its state space representation. Details matter: they are described in appendix [A](#). All our results are based on 50000 simulation draws of the Gibbs sampler of which the first 40000 were discarded as a burn-in, keeping only the last 10000, in order to avoid an initial transient of the starting values that initiated the simulation. For each of these draws, 100 impulse vectors are drawn and checked for consistency with the sign restrictions: we keep the once that do to calculate the posterior distributions.

In order to assure that the results are based on converged simulations, that represent the respective target distribution completely and e.g. not only some local mode, we apply a number of standard convergence diagnostics for the simulated parameters. We checked the inefficiency factors in figure [\(14\)](#). In figure [\(15\)-\(19\)](#) we plotted the first half of the kept draws against the second to check whether the sampler is still “*moving*” towards the target distribution or whether the whole density of the distribution is represented. Details are reported in a technical appendix.

FIGURE 1.— Selected Impulse Responses for the Baseline Model.



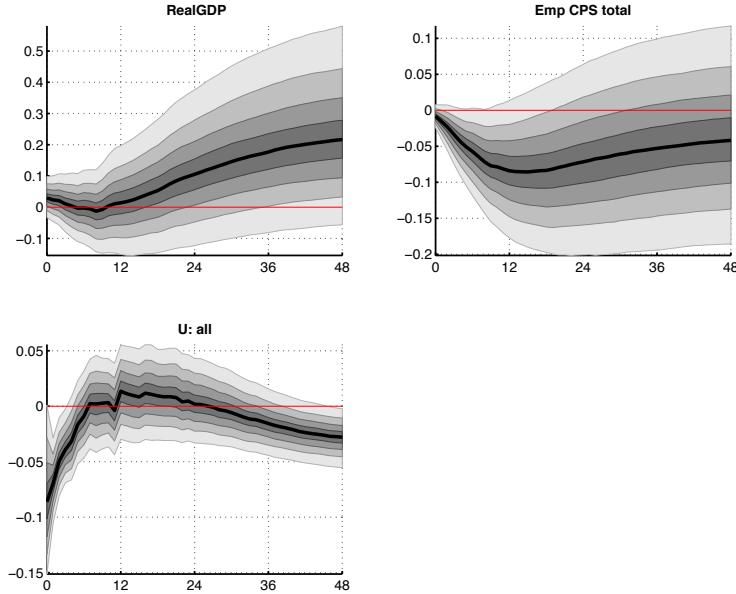
Results identified with sign restriction with the grey shaded area covering the 8 deciles (80% posterior probability bands).

We check the fit of our model. To this end, we estimated the R^2 's from regressing the respective series onto the four factors. Results are listed in table (II) in appendix C.2. These results provide a report to what extend the individual series are driven by common components: those with a low R^2 are driven by idiosyncratic forces rather than the common factors. We find that the model fits well overall. We also estimated the respective marginal contribution of each factor, not reported here, for the explanatory part in the variation of the data. We provide plots of the extracted factors in a technical appendix.

4.3. Impulse Response Analysis

The key statistics suited to answer the question at hand are impulse response functions. Figure (1) shows some of the results for our benchmark specification. A monetary policy shock one standard deviation in size raises the Federal Funds Rate by about 15 basis points, before eventually reverting course and an eventual decrease of 10 basis points. This may reflect either an attempt of the Federal

FIGURE 2.— Selected Impulse Responses for the Baseline Model.

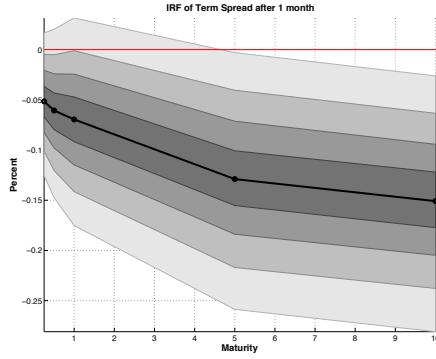


Results identified with sign restriction with the grey shaded area covering the 8 deciles (80% posterior probability bands).

Reserve Bank to reverse an earlier mistake or reflect the increase in the implied real rate, due to the fallen inflation rate. In response, we find that industrial production decreases, with a maximum impact of minus 0.2 percent at the median estimate after one year before reverting back. The 80 percent posterior confidence set two years after the shock ranges from a decline of 0.4 percent to an increase of 0.5 percent. The CPI falls 0.1 percent on impact and nearly half a percent eventually, showing a persistent response. By contrast the commodity price index decreases less strong with a maximum impact after about a year (aside from the initial reaction) before reverting back to the pre shock level a year later. Compared to CPI this may not be surprising as the commodity price index reflects measures traded on the market with presumably more flexible prices.

The rather clearly negative and hump-shaped response of industrial production in (1) may appear to be in contrast to the more neutral finding regarding real GDP reported in Uhlig [2005], when applying sign restrictions in a small-scale VAR. The resolution is partly the distinction between these two variables: as figure (2) shows, the posterior confidence band for the response of real GDP

FIGURE 3.— Impulse Responses after 1 month for the treasury spreads at different maturities vs. the federal funds rate in the baseline model.



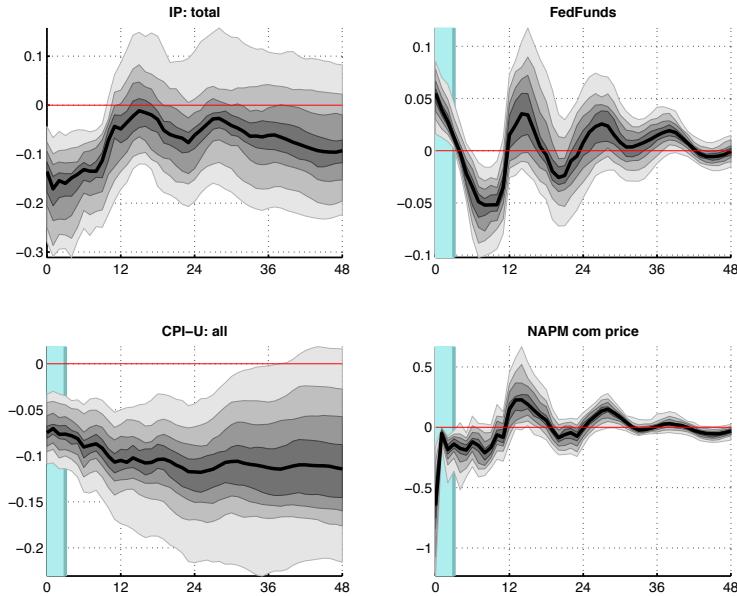
Results identified with sign restriction with the grey shaded area covering the 8 deciles (80% posterior probability bands).

is rather symmetric around zero for the first 12 months following the shock, consistent with Uhlig [2005]. Figure (2) shows that employment falls by 0.1 percent within the first year, starting from an initial zero or modestly negative response. Somewhat puzzlingly, unemployment shows an initial fall of 0.08 percentage points, but rises subsequently from that point during the first two years. We speculate that this is either due to a discouragement effect of fewer displaced workers re-entering the labor force and searching for employment, following a contractionary monetary policy shock, or due to monetary policy misinterpreting a fall in unemployment as a rationale for raising interest rates. For more disaggregated unemployment series, we essentially find only increases, however, see figure (65) in the appendix.

Different sectors are affected differently. Figure (63) in the appendix shows the impulse responses for the industrial production for a variety of sectors. We find the smallest or even a positive reaction for the industrial production in residential utilities as well as fuels, while industrial production of business equipment as well as durable materials falls somewhat more strongly and more persistently than total industrial production. Figure (64) in the appendix shows the reaction of the different price indices. The producer price indices generally fall a bit more than the consumer price indices. Note that we did not restrict the price indices for medical care, or the implicit price deflators. This can serve as a cross-check on our identification: indeed, they all react negatively, except for a very modest price puzzle for the price index for medical services.

Yield spreads initially fall in response. Figure (3) shows the responses of the

FIGURE 4.— Selected Impulse Responses for the pre-Volcker period.

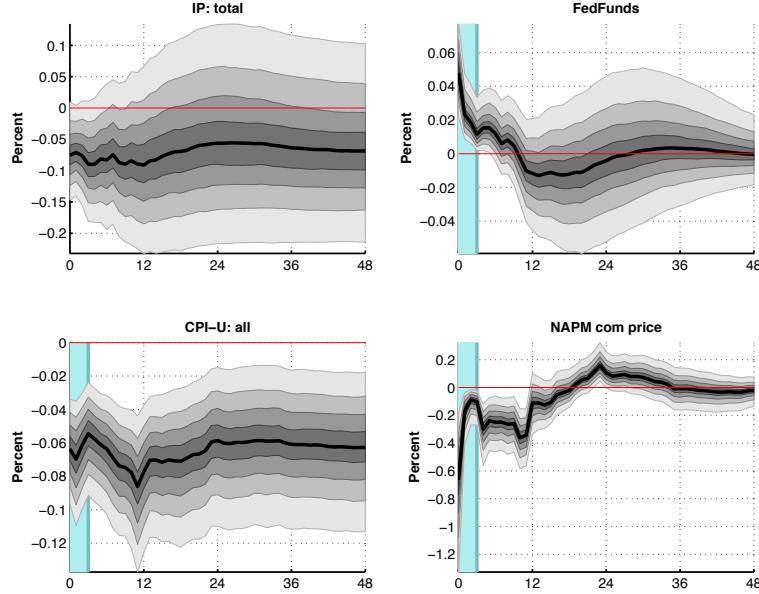


Results identified with sign restriction with the grey shaded area covering the 8 deciles (80% posterior probability bands).

spreads to the Federal Funds Rate one month after the shock, as a function of maturity: the spread response is the larger, the longer the maturity of the bonds. While the 3-mo-FF spread falls by 5 basis points, the 10-year bond falls by 12 basis points, at the median estimate and at the one-month horizon. Figure (68) in the appendix shows the impulse response for each spread: the responses tend to be stronger for longer maturities. These responses are rather tightly estimated.

Figures (4) and (5) show the impulse responses of figure (1), but for the two subsamples 1960:02-1979:09 (“Pre-Volcker”) as well 1984:02-2010:06 (“Post-Volcker”). The results for these variables as well as for most other variables in the VAR remain reasonably robust during the first year or two after the shock, though differences arise. In particular, there appears to be a continuous sequence of reversals in the Federal Funds Rate in the pre-Volcker episode than in the post-Volcker episode. One possible explanation may be that these shocks in the pre-Volcker episode were mistakes that the Federal Reserve subsequently tried to undo, but overshooting a bit in doing so, and so forth. More importantly, the results for the post-Volcker episode look reasonable and plau-

FIGURE 5.— Selected Impulse Responses for the post-Volcker period.

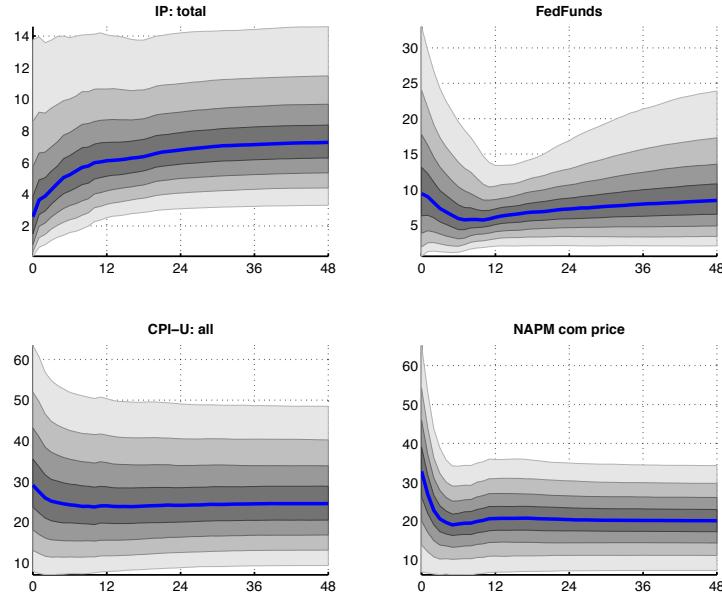


Results identified with sign restriction with the grey shaded area covering the 8 deciles (80% posterior probability bands). The time span for the estimation covers 1984 : 02 – 2006 : 12.

sible, and more consistent with the results for the total sample, including the response for the Federal Funds Rate. We find these results encouraging, as the post-Volcker subsample includes the financial crisis of 2008 and the subsequent quantitative easing episode, generating substantial challenges for any empirical exercise aimed at identifying monetary policy shocks.

Surely, these results should be taken with a grain of salt. It is plausible, that monetary policy has changed both in terms of its reactions to economic news, as well as in its constraints (such as the zero lower bound) and tools. It would be fascinating to extend the methods here to allow for smooth time variation as analyzed e.g. in Primiceri [2005], Cogley-Sargent [2005] and Sargent-Williams-Zha [2006] or for Markov regime shifts as analyzed in Sims-Zha [2006], Sims-Waggoner-Zha [2008] and Auerbach-Gorodnichenko [2012] or to extend the methods to allow for nonlinearities and the peculiarities of the zero lower bound. This is beyond the scope of this paper. We rather wish to emphasize that reasonable progress can already be made with the method at hand, that ours provides an important benchmark before additional extensions, and that extensions of this

FIGURE 6.— Selected FEVD for the Baseline Model.



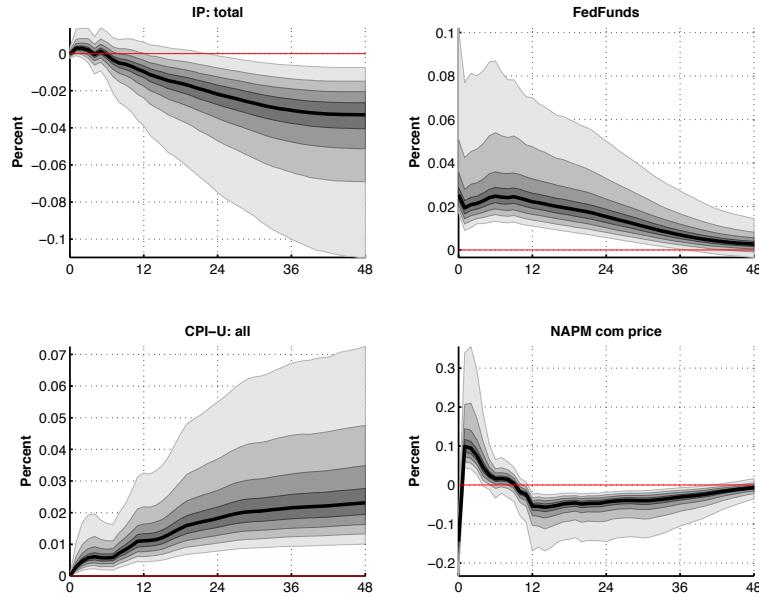
Forecast error variance decomposition for the baseline model identified with sign restriction.
The grey shaded area cover the 9 deciles of the posterior distribution.

method with these additional tools should provide a promising avenue for future research. Some of these issues are, in fact, already taken up in work in progress by Amir-Ahmadi [2009].

Figure (6) shows the forecast error variance decompositions for our four key variables, in the benchmark specification. Monetary policy shocks account for less than 10% of the variation in industrial production and the Federal Funds Rate, consistent with the view that the central bank typically does not role dice, but do explain around 30 percent of the variation in the CPI. These results are amongst others consistent with Sims [1999], Sims and Zha [2006], Uhlig [2005] and Amir-Ahmadi and Ritschl [2008].

Figure (7) shows the impulse response functions for the post-Volcker sample and a FAVAR-Cholesky identification of the monetary policy shock one standard deviation in size as the last shock in the Cholesky decomposition of the factors, where the federal funds rate is ordered last. The results for the entire sample are very similar and available in a technical appendix. The most striking difference is the unreasonable high and long lasting "price puzzle". The CPI response is

FIGURE 7.— Recursive Cholesky identification: post-Volcker Period



Results based on a recursive Cholesky identification with the grey shaded area covering the 8 deciles (80% posterior probability bands). The time span for the estimation covers 1984 : 02 – 2006 : 12.

rather tightly estimated to rise by 0.1 percent within a year. Even within four years, it remains considerably more likely that the CPI response stays positive rather than turning negative. The commodity prices increase on impact. Another anomaly is the increasing reaction (not shown) of nonborrowed reserves which lasts for the whole horizon considered. We argue that these results render the Cholesky identification approach considerably less useful for the analysis of monetary policy shocks than ours. While the Cholesky decomposition implies that industrial production falls by nearly 0.4 percent within a year, and then stays there, our post-Volcker response shown in (5) implies a modest fall by 0.2 percent within a year, with subsequent reversal to an uncertainty band around a zero response within two years. While the difference in the size of the response may entirely be due to the initial difference of the movement in the Federal Reserve Rate (30 basis points for the Cholesky decomposition versus 15 basis points for our identification), the differences in the results regarding the persistence matters in particular for the purpose of political debates regarding monetary policy

choices, and provides all the more reason to adapt our identification rather than a Cholesky identification in a FAVAR.

5. CONCLUSION

In this paper we propose to estimate the effects of monetary policy shocks in a BFAVAR framework identified via sign restriction. We estimate the model from a Bayesian perspective relying on MCMC methods. To infer the effects of a contractionary shock to monetary policy we impose sign restriction on the impulses responses on many prices, monetary aggregates and short term interest rates. FAVAR models as well as dynamic factor models offer the opportunity to impose a larger set of reasonable sign restrictions, leading to sharper identification and results. Sign restrictions in FAVARs offer the advantage of avoiding a structural interpretation of the factors themselves or adding observables to the list of factors. Our approach should therefore prove to be appealing in many applications beyond the one studied here. Our results are reasonable, even with the inclusion of the post-2008 financial-crisis data and remain fairly robust across subsamples, while a more conventional Cholesky identification leads to unreasonably large price puzzles. Compared to the VAR sign restriction literature, our confidence bands for the on-impact response is typically considerably more narrow. We find that after a contractionary monetary policy shock a negative response of output but modest in size. We find that industrial production decreases after a monetary contraction one standard deviation in size, with a maximum impact of minus 0.2 percent at the median estimate after one year, before returning to an uncertainty band around zero within two years. The effect on real GDP is less pronounced and includes zero within the posterior confidence band throughout. Monetary policy shocks account for less than 10 percent of the variation in industrial production and the Federal Funds Rate. The CPI falls by 0.1 percent initially and by half a percent eventually, showing a persistent response. Yield spreads initially fall in response, with the fall ranging from 5 basis points for the 3-month to Federal Funds Rate spread to 25 basis points for ten-year bonds.

APPENDIX A: ESTIMATION AND INFERENCE

For the estimation of FAVAR models Bernanke, Boivin and Eliasz [2005] present two competing approaches. The first one, which they prefer due to their results and the computational simplicity is the two-step estimation based on a dynamic principal component approach. This classical approach goes back to Stock and Watson [2003]. A detailed survey with several identification schemes in the classical estimation approach can be found in Stock and Watson [2005]. The second estimation approach described in their paper is the one that we employ in this paper because the likelihood based one-step estimation approach employing MCMC methods explicitly exploits the factor structure. We pursue the multi-move Gibbs sampler for which we have to cast the model into the state space representation. Let (2.3) be extended by f_t^y which results in

$$(A.1) \quad \begin{bmatrix} X_t^c \\ f_t^y \end{bmatrix} = \begin{bmatrix} \lambda^c & \lambda^y \\ 0 & I_{N_y} \end{bmatrix} \begin{bmatrix} f_t^c \\ f_t^y \end{bmatrix} + \begin{bmatrix} e_t \\ 0 \end{bmatrix}$$

Let $X_t \equiv (X_t^c, f_t^y)'$, $E_t \equiv (e_t', 0_{[N_y \times 1]})'$ and $f_t \equiv (f_t^c, f_t^y)'$, then the model can be rewritten as

$$(A.2) \quad X_t = \lambda f_t + E_t$$

$$(A.3) \quad f_t = \sum_{p=1}^P \phi_p f_{t-p} + u_t$$

where X_t has dimension $[N \times 1]$ with $N = N_c + K_y$. In most empirical applications and also in our specification the lag order P exceeds one hence we have to rewrite the state space in a stacked first order Markov process. This requires the following straight forward definitions for the companion form of the model:

$$(A.4) \quad \lambda \equiv \begin{bmatrix} \lambda^c & \lambda^y \\ 0_{N_y \times K_c} & I_{N_y} \end{bmatrix}$$

$$\phi \equiv [\phi_1, \phi_2, \dots, \phi_P]'$$

$$F_t \equiv (f_t, f_{t-1}, \dots, f_{t-P+1})$$

$$U_t \equiv (u_t, 0, \dots, 0)'$$

The lag polynomial of the FAVAR equation in the first-order representation changes to:

$$\Phi = \begin{bmatrix} \phi_1 & \cdots & \phi_P \\ I_{K(P-1)} & & 0_{K(P-1) \times K} \end{bmatrix}.$$

Now we have to transform the VCV of the FAVAR disturbances with 0's in a straightforward way to adjust the dimensions of the state equation which results in the following matrix:

$$Q = \begin{bmatrix} Q_u & 0 \\ 0 & 0 \end{bmatrix}$$

where Q is of dimension $[PK \times PK]$ extended by zero matrices to match the companion form. We define $\Lambda \equiv [\lambda \ 0 \ \cdots \ 0]$. Then

$$(A.5) \quad F_t = \Phi F_{t-p} + U_t$$

$$(A.6) \quad X_t = \Lambda F_t + E_t$$

$$(A.7) \quad U_t \sim \mathcal{N}(0, Q)$$

$$(A.8) \quad E_t \sim \mathcal{N}(0, R)$$

is the final state-space representation prepared to fit the estimation procedure. Note again that R is diagonal and that e_t and u_t are mutually independent.

A.1. Factor Identification

The factors are only identified up to an invertible rotation. Any rotation of the factors results in the same likelihood for the factors though the models are different. Identifying restrictions have to be set, in order to distinguish the idiosyncratic from the common component. Additionally one can set further identifying assumptions in order to identify the factors and the loadings, separately. We follow the standard identification restrictions either on the factor loading matrix employed by Bernanke, Boivin and Elias [2005] for unique identification against rotational indeterminacy. Since factors are estimated up to a rotation, the normalization should not affect the space spanned by the estimated factors. In the joint estimation case the specified identification against rotation requires that the factors are uniquely identified in the following form

$$(A.9) \quad f_t^* = A f_t^c - B f_t^y$$

where A and B are nonsingular. Restrictions are only imposed on the observation equation. Here we substitute F_t^* into (2.1) due to the fact that restrictions should not be imposed on the VAR dynamics we obtain

$$(A.10) \quad X_t^c = \lambda^c A^{-1} f_t^* + (\lambda^y + \lambda^c A^{-1} B) f_t^y + e_t.$$

For unique identification of the factors and the loadings it is required that $\lambda^c A^{-1} = \lambda^c$ and $\lambda^y + \lambda^c A^{-1} B = \lambda^y$. As discussed in Bernanke, Boivin and Elias [2005] sufficient conditions

are to set the upper $K_c \times K_c$ block of λ^c to identity and the upper $K_c \times N_y$ block of λ^y to a zero matrix³.

A.2. Inference

Bayesian analysis treats the parameters of the model as random variables. We are interested in inference on the parameter space $\theta = (\lambda^f, \lambda^y, R_e, \phi, Q_u)$ and the factors $\{f_t\}_{t=1}^T$. Multi move Gibbs Sampling alternately samples the parameters θ and the factors f_t , given the data. We use the multi move version of the Gibbs sampler because this approach allows us, as a first step, to estimate the unobserved common components, namely the factors via the Kalman filtering technique conditional on the given hyperparameters and data, and as a second step calculate the hyperparameters of the model given the factors and data via the Gibbs sampler in the respective blocking. Let $X^T = (X_t, \dots, X_T)$ and $F^T = (F_1, \dots, F_T)$ define the respective histories. For the estimation of the model we want to derive the posterior densities which requires to empirically approximating the marginal posterior densities of F^T and θ :

$$\begin{aligned} p(F^T) &= \int p(F^T, \theta) d\theta \\ p(\theta) &= \int p(F^T, \theta) dF^T \end{aligned}$$

where

$$p(F^T, \theta)$$

is the joint posterior density and the integrals are taken with respect to the supports of θ and F^T respectively. The procedure applied to obtain the empirical approximation of the posterior distribution is the previously mentioned multi move version of the Gibbs sampling technique by Carter and Kohn [1994] and Frühwirth-Schnatter [1994]⁴.

A.3. Choosing the Starting Values

In general one can start the iteration cycle with any arbitrary randomly drawn set of parameters, as the joint and marginal empirical distributions of the generated parameters will converge at an exponential rate to its joint and marginal target distributions as $S \rightarrow \infty$. This has been shown by Geman and Geman [1984]. Since Gelman and Rubin [1992] have shown that a single chain of the Gibbs sampler might give a "false sense of security", it has become common practice to try out different starting values. We check our results based on four different strategies regarding the set of starting values. One out of many convergence diagnostics involves testing the fragility of the results with respect to the starting values. For the results to be reliable, estimates based on different starting values should not differ. Strictly speaking, the different chains should represent the same target distribution. In order to verify we start our Gibbs sampler with the following summarized starting values respectively.

- (i) Randomly draw θ_0 from (over)dispersed distribution
- (ii) Set θ_0 to rather "agnostic values" which involves setting 0's for coefficients and 1's for variances⁵
- (iii) Set θ_0 to results from principal component analysis.⁶ In such a way the number of draws required for convergence can be reduced considerably.

³Note that this identification strategy is over-identified. However, for comparison purposes we follow closely the approach of Bernanke, Boivin and Eliasz [2005].

⁴For a survey and more details see Kim and Nelson [1999], Eliasz [2005] and Bernanke, Boivin and Eliasz [2005]

⁵This strategy has been applied by Belviso and Milani [2007].

⁶This strategy is particularly suited for large models as the ones studied here and has been proposed by Eliasz [2005].

(iv) Set θ_0 to parameters of the last iteration of the previous run.

Despite the strategies above convergence is never guaranteed, particularly in large models. Hence it is recommended to restart a chain many times applying the strategy 4.

A.4. Conditional density of the factors F^T given X^T and θ

In this subsection we want to sample from $p(F^T | X^T, \theta)$ assuming that the data and the hyperparameters of the parameter space θ are given, hence we describe Bayesian inference on the dynamic evolution of the factors f_t conditional on X_t^c for $t = 1, \dots, T$ and conditional on θ . The transformations that are required to draw the factors have been done in the previous section. The conditional distribution, from which the state vector is generated, can be expressed as the product of conditional distributions by exploiting the Markov property of state space models in the following way

$$p(F^T | X^T, \theta) = p(F_T | X^T, \theta) \prod_{t=1}^{T-1} p(F_t | F_{t+1}, X^T, \theta)$$

The state space model is linear and Gaussian, hence we have:

$$(A.11) \quad F_T | X^T, \theta \sim N(F_{T|T}, P_{T|T})$$

$$(A.12) \quad F_{t|T} | F_{t+1|T}, X^T, \theta \sim N(F_{t|t, F_{t+1|T}}, P_{t|t, F_{t+1|T}})$$

with

$$(A.13) \quad F_{T|T} = E(F_T | X^T, \theta)$$

$$(A.14) \quad P_{T|T} = Cov(f_T | X^T, \theta)$$

$$(A.15) \quad F_{t|t, F_{t+1|T}} = E(F_t | F_{t|t}, F_{t+1}, \theta)$$

$$(A.16) \quad P_{t|t, F_{t+1|T}} = Cov(F_t | F_{t|t}, F_{t+1}, \theta).$$

We first run the Kalman filter generating $F_{t|t}$ and $P_{t|t}$ for $t = 1, \dots, T$. For the initialization we set $F_{1|0} = 0_{KP \times 1}$ and $P_{1|0} = I_{KP}$ and iterate through the Kalman filter according to

$$(A.17) \quad F_{t|t} = F_{t|t-1} + P_{t|t-1} \Lambda' H^{-1} \eta_{t|t-1}$$

$$(A.18) \quad P_{t|t} = P_{t|t-1} - P_{t|t-1} \Lambda' H^{-1} \Lambda P_{t|t-1}$$

where $\eta_{t|t-1} = (X_t - \Lambda F_{t|t-1})$ is the conditional forecast error and its covariance is denoted by $H_{t|t-1} = (\Lambda P_{t|t-1} \Lambda' + R_e)$. Furthermore let

$$(A.19) \quad F_{t|t-1} = \Phi F_{t-1|t-1}$$

$$(A.20) \quad P_{t|t-1} = \Phi P_{t-1|t-1} \Phi' + Q_u.$$

The last iteration of the Kalman filter yields $F_{T|T}$ and $P_{T|T}$ required for (A.11) to draw the last observation and start the Kalman smoother according to (A.12) going backwards through the sample for F_t , $t = T-2, T-3, \dots, 1$ updating the filtered estimates with the sampled factors one period up subject to

$$(A.21) \quad F_{t|t, F_{t+1|T}}^* = F_{t|t} + P_{t|t} \Phi^{*\prime} J_{t+1|t}^{-1} \xi_{t+1|t}$$

$$(A.22) \quad P_{t|t, F_{t+1|T}}^* = P_{t|t} - P_{t|t} \Phi^{*\prime} J_{t+1|t}^{-1} \Phi^* P_{t|t}.$$

where $\xi_{t+1|t} = F_{t+1|T}^* - \Phi^* F_{t|t}$ and $J_{t+1|t} = \Phi^* P_{t|t} \Phi^* + Q^*$. Note that Q^* refers to the upper $K \times K$ block of Q and Φ^* and F_t^* denote the first K rows of Φ and F_t respectively. This is required when Q is singular which is the case for the companion form when there is more than one lag in (A.3). Here we closely follow Kim and Nelson [1999] where a detailed explanation and derivation can be found.

A.5. Conditional density of the parameters θ given X^T and F^T

Sampling from the conditional distribution of the parameters $p(\theta | X^T, F^T)$ requires the blocking of the parameters into the two parts that refer to the observation equation and to the state equation respectively. The blocks can be sampled independently from each other conditional on the extracted factors and the data.

A.5.1. Conditional density of Λ and R_e

This part refers to observation equation of the state space model which, conditional on the estimated factors and the data, specifies the distribution of Λ and R_e . The errors of the observation equation are mutually orthogonal with diagonal R_e . Hence we can apply equation by equation OLS in order to obtain the ols estimates $\hat{\Lambda}_n$ and \hat{e}^c as the observation equation amounts to a set of independent regressions. Note that the subscript n refers to the n -th equation and all hat variables refer to the respective ols estimates. We assume conjugate priors

$$\begin{aligned} p(R_{nn}) &= \mathcal{IG}(\delta_0/2, \eta_0/2) \\ p(\Lambda_n | R_{nn}) &= \mathcal{N}(\Lambda_{n0}, R_{nn} M_{n0}^{-1}) \end{aligned}$$

which according to Bayesian results⁷ conform to the following conditional posterior distribution

$$\begin{aligned} p(R_{nn} | \tilde{X}_T, \tilde{F}_T) &= \mathcal{IG}(\delta_i/2, \eta_i/2) \\ p(\bar{\Lambda}_{nn} | \tilde{X}_T, \tilde{F}_T, R_{nn}) &= \mathcal{N}(\bar{\Lambda}_n, R_{nn} M_n^{-1}). \end{aligned}$$

with

$$\begin{aligned} \eta_n &= \eta_0 + T \\ \delta_n &= \delta_0 + (\hat{e}_n^c)'(\hat{e}_n^c) + (\hat{\Lambda}_n - \Lambda_{n0})' [M_{n0}^{-1} + (F_T^n)' F_T^n]^{-1} (\hat{\Lambda}_n - \Lambda_{n0}) \\ \bar{M}_n &= M_{n0} + (F_T^n)' F_T^n \\ \Lambda_n &= \bar{M}_n (M_{n0}^{-1} \Lambda_{n0} + (F_T^n)' F_T^n) \hat{\Lambda}_n \end{aligned}$$

where we set the same prior specification ($\delta_0 = 6, \eta_0 = 10^{-3}, M_{n0} = I_{K_c}, \Lambda_{n0} = 0_{K_c \times 1}$) as in Bernanke, Boivin and Eliasz [2005] in order to allow an adequate comparison. M_0 denotes the matrix in the prior on the coefficients of the n -th equation of Λ_n . The factor normalization discussed earlier requires to set $M_0 = I$. The regressors of the n -th equation are represented by F_T^n and the fitted errors of the n -th equation are represented by \hat{e}_{tn}^c .

A.5.2. Conditional density of $\text{vec}(\phi)$ and Q_u

The next Gibbs block requires to draw $\text{vec}(\phi)$ and Q_u conditional on the most current draws of the factors and the data. We employ the Normal-Inverse Wishart prior according to Uhlig [1994]

$$\begin{aligned} p(Q_u) &= \mathcal{IW}(S_0, \nu_0) \\ p(\text{vec}(\phi) | Q_u) &= \mathcal{N}(\bar{\phi}_0, Q_u \otimes N_0^{-1}) \end{aligned}$$

which results in the following posterior:

$$\begin{aligned} p(Q_u | X^T, F^T) &= \mathcal{IW}(S_T, \nu_T) \\ P(\text{vec}(\phi) | X^T, F^T, Q_u) &= \mathcal{N}(\text{vec}(\bar{\phi}_T), Q_u \otimes N_T^{-1}) \end{aligned}$$

with

$$\begin{aligned} \nu_T &= T + \nu_0 \\ N_T &= N_0 + (F_{T-1}' F_{T-1}) \\ \bar{\phi}_T &= N_T^{-1} (N_0 \bar{\phi}_0 + F_{T-1}' F_{T-1} \hat{\phi}) \\ S_T &= \frac{\nu_0}{\nu_T} S_0 + \frac{T}{\nu_T} \hat{Q}_u + \frac{1}{\nu_T} (\hat{\phi} - \bar{\phi}_0)' N_0 (N_T)^{-1} (F_{T-1}' F_{T-1}) (\hat{\phi} - \bar{\phi}_0) \end{aligned}$$

This prior and has the following specification

$$\nu_0 = 0$$

$$N_0 = 0_{K \times K}$$

where the choice of S_0 and $\bar{\phi}_0$ are arbitrary as they cancel out in the posterior. We alternatively also implemented the Normal-Wishart prior for according to Kadiyala and Karlsson [1997] where the diagonal elements of Q_0 are set to the corresponding p -lag univariate autoregressions, σ_i^2 . The diagonal elements of Ω_0 are constructed such that the prior variances of the parameter of the k lagged j 'th variable in the i 'th equation equals $\sigma_i^2/k\sigma_j^2$. Hence $S_0 = Q_0$ and $\bar{\phi}_0 = \mathbf{0}$.

⁷For a derivation see Gelman, Carlin, Stern and Rubin [1995],

Results were virtually the same. To ensure stationarity, we truncate the draws by discarding the draws of ϕ with the largest eigenvalue greater than 1 in absolute value.

APPENDIX B: A NOTE ON THE FAVAR SPECIFICATION

Bernanke, Boivin and Eliasz add the Federal Funds Rate as the key policy variable to a list of factors. The following considerations show, that one ought to also include those variables, for which the “noise” component in the factor representation is relevant for the monetary authority, when choosing its monetary policy instrument. Without it, the model is misspecified, and the identification of the monetary policy shock is incorrect.

While this may sound reasonably obvious in this rather general form, these considerations may also show, why prices might respond positively to a monetary policy shock identified in a FAVAR, when prices are not included in the core VAR. This insight may help to understand the puzzling results for the CPI index in figures IV and V of Bernanke, Boivin and Eliasz [2005].

To provide a simple example, suppose that a price index component p_t and an interest rate component r_t follow the data generating process

$$(B.1) \quad p_t = -\alpha r_{t-1} + \gamma p_{t-1} + \epsilon_{p,t}$$

$$(B.2) \quad r_t = \phi p_t + \epsilon_{m,t}$$

where α, γ, ϕ are positive coefficients, where $\epsilon_{p,t}$ and where $\epsilon_{m,t}$ are shocks to the price level and to monetary policy respectively, assumed to be independent with each other and across time as well as normally distributed with variances $\sigma_{\epsilon,p}^2$ and $\sigma_{\epsilon,m}^2$.

It is best to think about the components p_t and r_t as the noise components in a factor structure. The model above thus makes the extreme assumption, that the monetary policy shock is entirely contained in the “noise” component of the interest rates. There are also more general versions. For example, the structure above is relevant if the monetary policy shock does not affect the price level via the other factors, but solely through the direct effect of interest rates on the “noise component” of the price level. It is also relevant, if part of the monetary policy shock component in a FAVAR without the price level included in the core VAR can actually be explained by movements in the price level, and it is the part of interest rates driven by that component, which affects the price level.

Note that the model implies

$$(B.3) \quad p_t = (\gamma - \alpha\phi)p_{t-1} + \epsilon_{p,t} - \alpha\epsilon_{m,t-1}$$

Assume that $0 \leq \gamma - \alpha\phi < 1$, and one can see that a positive monetary policy shock $\epsilon_{m,t}$ will affect the price level negatively with a one period delay, and with the price level gradually climbing back up to zero.

The empirical issue is now to correctly identify the monetary policy shock $\epsilon_{m,t}$. The approach in Bernanke-Boivin-Eliasz recommends to add the federal funds rate to the available factors. Since there are no factors in the model above (or since they have already been subtracted out), this amounts to estimating the model

$$(B.4) \quad r_t = \beta r_{t-1} + u_t$$

$$(B.5) \quad p_t = \lambda r_t + \nu_t$$

where the first equation represents the factor model (with zero factors aside from the interest rate), the second equation is the factor representation of the price level with a factor loading λ on the interest rate component as the only available factor. Usually, u_t would be interpreted as the monetary policy shock. Given the assumptions above, the coefficients can easily be calculated.

PROPOSITION 1 Assume $0 \leq \gamma - \alpha\phi < 1$.

1. The variance of the price component is given by

$$E[pp] = \frac{\sigma_{\epsilon,p}^2 + \alpha^2 \sigma_{\epsilon,m}^2}{1 - (\gamma - \alpha\phi)^2}$$

The variance of the interest rate component is given by

$$E[rr] = \phi^2 E[pp] + \sigma_m^2$$

2. For large samples, the estimates for β and λ converge to

$$(B.6) \quad \beta \rightarrow \gamma - \alpha\phi - \gamma \frac{\sigma_m^2}{E[rr]}$$

$$(B.7) \quad \lambda \rightarrow \frac{1}{\phi} \left(1 - \frac{\sigma_m^2}{E[rr]} \right)$$

3. If $\phi > 0$, then $\lambda > 0$. If $\phi = 0$, then $\beta = 0$ and $\lambda = 0$.

PROOF: These results follow from straightforward calculations:

1. The equation for $E[pp]$ follows directly from (B.3). For $E[rr]$, use (B.2) to write $E[rr] = E[(\phi p + \epsilon_m)(\phi p + \epsilon_m)]$ and exploit $E[p\epsilon_m] = 0$.
2. For the covariance $E[r_t p_t]$ of r_t with p_t or the autocovariance $E[r_t r_{t-1}]$, note $E[r_t p_t] = E[(\phi p_t + \epsilon_{m,t})p_t] = \phi E[pp]$ as well as

$$E[r_t r_{t-1}] = E[\phi(-\alpha\phi r_{t-1} + \gamma p_{t-1} + \epsilon_{p,t})r_{t-1}] = -\alpha\phi E[rr] + \gamma\phi E[r_t p_t]$$

Now, calculate $\beta \rightarrow E[r_t r_{t-1}]/E[rr]$ and $\lambda \rightarrow E[r_t p_t]/E[rr]$.

3. Direct.

Q.E.D.

Note now, that the impulse response of the price component to u_t , the “identified” monetary policy shock, is simply λ times the impulse response of r_t to a monetary policy shock. Since $\lambda > 0$ for $\phi > 0$, there will be a price puzzle on impact. If furthermore $\beta > 0$, a condition which is easily met, the price component appears to react positively to a monetary policy shock throughout. Put differently, if the “noise” price component matters to monetary policy in setting interest rates, and if the researcher fails to include prices in the “core” VAR, one easily obtains a price puzzle.

On the other hand, note the shocks could be correctly identified from a VAR in (r_t, p_t) with one lag and a Cholesky-decomposition. Thus adding both, the interest rate as well as the CPI index, to the factor specification, would resolve this problem and result in correct identification of the monetary policy shock.

APPENDIX C: TABLES AND FIGURES

C.1. Data

Table (I) contains our set of monthly macroeconomic data from 1960 : 02 to 2010 : 06, building and extending a data set provided by Stock and Watson [2005] and lists the short name of each series, its mnemonic (the series label used in the source database) and a brief data description.

Pos	Shortname	Mnemonics	Description
1	PI	a0m052	Personal income (AR, bil. chain 2005 \$)
2	PI less transfers	A0M051	Personal income less transfer payments (AR, bil. chain 2005 \$)

Pos	Shortname	Mnemonics	Description
3	M&T sales	A0M057	Manufacturing and trade sales (mil. Chain 1996 \$)
4	Retail sales	A0M059	Sales of retail stores (mil. Chain 2000 \$)
5	IP: products	IPS11	INDUSTRIAL PRODUCTION INDEX - PRODUCTS, TOTAL
6	IP: final prod	IPS299	INDUSTRIAL PRODUCTION INDEX - FINAL PRODUCTS
7	IP: cons gds	IPS12	INDUSTRIAL PRODUCTION INDEX - CONSUMER GOODS
8	IP: cons dble	IPS13	INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS
9	iIP:cons nondurable	IPS18	INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS
10	IP:bus eqpt	IPS25	INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT
11	IP: matls	IPS32	INDUSTRIAL PRODUCTION INDEX - MATERIALS
12	IP: dble mats	IPS34	INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS
13	IP:nondble mats	IPS38	INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS
14	IP: mfg	IPS43	INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)
15	IP: res util	IPS307	INDUSTRIAL PRODUCTION INDEX - RESIDENTIAL UTILITIES
16	IP: fuels	IPS306	INDUSTRIAL PRODUCTION INDEX - FUELS
17	IP: total	IPS10	INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX
18	RealGDP	RealGDP	RealGDP
19	PCE Def	PCEPI	Personal Consumption Expenditures: Chain-type Price Index (Keep used as defator in progam)
20	PCED lfe	PCEPILFE	Personal Consumption Expenditures: Chain-Type Price Index Less Food and Energy (Keep used as defator in progam)
21	NAPM prodn	PMP	NAPM PRODUCTION INDEX (PERCENT)
22	Cap util	A0m082	Capacity Utilization (Mfg)
23	Emp CPS total	LHEM	CIVILIAN LABOR FORCE: EMPLOYED, TOTAL (THOUS.,SA)
24	Emp CPS	LHNAG	CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES (THOUS.,SA)
25	nonag	LHUR	UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%.SA)
26	U: mean duration	LHU680	UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)
27	U < 5 wks	LHU5	UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)
28	U 5-14 wks	LHU14	UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)
29	U 15+ wks	LHU15	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)
30	U 15-26 wks	LHU26	UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)
31	U 27+ wks	LHU27	UNEMPLOY.BY DURATION: PERSONS UNEMPL.27 WKS + (THOUS.,SA)
32	UI claims	A0M005	Average weekly initial claims, unemploy. insurance (thous.)
33	Emp: total	CES002	EMPLOYEES ON NONFARM PAYROLLS - TOTAL PRIVATE
34	Emp: gds prod	CES003	EMPLOYEES ON NONFARM PAYROLLS - GOODS-PRODUCING
35	Emp: mining	CES006	EMPLOYEES ON NONFARM PAYROLLS - MINING
36	Emp: const	CES011	EMPLOYEES ON NONFARM PAYROLLS - CONSTRUCTION
37	Emp: mfg	CES015	EMPLOYEES ON NONFARM PAYROLLS - MANUFACTURING
38	Emp: dble gds	CES017	EMPLOYEES ON NONFARM PAYROLLS - DURABLE GOODS
39	Emp: nondbles	CES033	EMPLOYEES ON NONFARM PAYROLLS - NONDURABLE GOODS
40	Emp: services	CES046	EMPLOYEES ON NONFARM PAYROLLS - SERVICE-PROVIDING
41	Emp: TTU	CES048	EMPLOYEES ON NONFARM PAYROLLS - TRADE, TRANSPORTATION, AND UTILITIES
42	Emp: wholesale	CES049	EMPLOYEES ON NONFARM PAYROLLS - WHOLESALE TRADE
43	Emp: retail	CES053	EMPLOYEES ON NONFARM PAYROLLS - RETAIL TRADE
44	Emp: FIRE	CES088	EMPLOYEES ON NONFARM PAYROLLS - FINANCIAL ACTIVITIES
45	Emp: Govt	CES140	EMPLOYEES ON NONFARM PAYROLLS - GOVERNMENT
46	Avg hrs	CES151	AVERAGE WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFAR
47	Overtime: mfg	CES155	AVERAGE WEEKLY HOURS OF PRODUCTION OR NONSUPERVISORY WORKERS ON PRIVATE NONFAR
48	Avg hrs: mfg	aom001	Average weekly hours, mfg. (hours)
49	NAPM empl	PMEMP	NAPM EMPLOYMENT INDEX (PERCENT)
50	HStarts: Total	HSFR	HOUSING STARTS:NONFARM(1947-58);TOTAL FARM&NONFARM(1959-)(THOUS.,SA)
51	HStarts: NE	HSNE	HOUSING STARTS:NORTHEAST (THOUS.U.)SA.
52	HStarts: MW	HSMW	HOUSING STARTS:MIDWEST(THOUS.U.)SA.
53	HStarts: South	HSSOU	HOUSING STARTS:SOUTH (THOUS.U.)SA.
54	HStarts: West	HSWST	HOUSING STARTS:WEST (THOUS.U.)SA.
55	BP: total	HSBR	HOUSING AUTHORIZED: TOTAL NEW PRIV HOUSING UNITS (THOUS.,SAAR)
56	BP: NE	HSBNE	HOUSES AUTHORIZED BY BUILD. PERMITS:NORTH(THOU.U.)SA.
57	BP: MW	HSBMW	HOUSES AUTHORIZED BY BUILD. PERMITS:MIDWEST(THOU.U.)SA.
58	BP: South	HSBSOU	HOUSES AUTHORIZED BY BUILD. PERMITS:SOUTH(THOU.U.)SA.
59	BP: West	HSBWST	HOUSES AUTHORIZED BY BUILD. PERMITS:WEST(THOU.U.)SA.
60	PMI	PMI	PURCHASING MANAGERS' INDEX (SA)
61	NAPM new orders	PMNO	NAPM NEW ORDERS INDEX (PERCENT)
62	NAPM vendor del	PMDEL	NAPM VENDOR DELIVERIES INDEX (PERCENT)
63	NAPM Inventories	PMNV	NAPM INVENTORIES INDEX (PERCENT)

Pos	Shortname	Mnemonics	Description
64	Orders: cons gds	A0M008	Mfrs' new orders, consumer goods and materials (bil. chain 1982 \$)
65	Orders: dble gds	A0M007	Mfrs' new orders, durable goods industries (bil. chain 2000 \$)
66	Orders: cap gds	A0M027	Mfrs' new orders, nondefense capital goods (mil. chain 1982 \$)
67	Unf orders: dble	A1M092	Mfrs' unfilled orders, durable goods indus. (bil. chain 2000 \$)
68	M&T invent M1	A0M070 FM1	Manufacturing and trade inventories (bil. Chain 2005 \$) MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL\$,SA)
70	M2	FM2	MONEY STOCK:M2(M1+O'NITE RPS,EURO\$,G/P&B/D MMMF&SAV&SM TIME DEP(BIL\$, MONETARY BASE, ADJ FOR RESERVE REQUIREMENT CHANGES(BIL\$,SA))
71	MB	FMFBA	DEPOSITORY INST RESERVES:TOTAL,ADJ FOR RESERVE REQ CHGS(BIL\$,SA)
72	Reserves tot	FMRRA	DEPOSITORY INST RESERVES:NONBORROWED,ADJ RES REQ CHGS(BIL\$,SA)
73	Reserves non-bor	FMRNBA	Real Estate Loans at All Commercial Banks
74	LoansRealEst C&I loans	LoansRealEst FCLNQ	Commercial and Industrial Loans at All Commercial Banks (BUS-LOANS), bil \$(SA)
75	Cons credit Inst cred/PI	CCINRV A0M095	CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19) Ratio, consumer installment credit to personal income (pct.)
77	S&P 500	FSPCOM	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)
78	DJIA	FSDJ	COMMON STOCK PRICES: DOW JONES INDUSTRIAL AVERAGE
79	S&P div yield	FSDXP	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)
80	S&P PE ratio	FSPXE	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%Cyclically Adjusted)
82	FedFunds	FYFF	INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)
83	Commpaper	CP90	Commercial Paper Rate (AC)
84	3 mo T-bill	FYGM3	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)
85	6 mo T-bill	FYGM6	INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)
86	1 yr T-bond	FYGT1	INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)
87	5 yr T-bond	FYGT5	INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)
88	10 yr T-bond	FYGT10	INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)
89	Aaabond	FYAAAC	BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM)
90	Baa bond	FYBAAC	BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)
91	CP-FF spread	scp90	cp90-fyff
92	3 mo-FF spread	sfygm3	fygm3-fyff
93	6 mo-FF spread	sFYGM6	fygm6-fyff
94	1 yr-FF spread	sFYGT1	fygt1-fyff
95	5 yr-FFspread	sFYGT5	fygt5-fyff
96	10yr-FF spread	sFYGT10	fygt10-fyff
97	Aaa-FF spread	sFYAAC	fyaac-fyff
98	Baa-FF spread	sFYBAAC	fybaac-fyff
99	Ex rate: major	Ex rate: major	FRB Nominal Major Currencies Dollar Index (Linked to EXRUS in 1973:1)
100	Ex rate: Switz	EXRSW	FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.\$)
101	Ex rate: Japan	EXRJAN	FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.\$)
102	Ex rate: UK	EXRUK	FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)
103	EX rate: Canada	EXRCAN	FOREIGN EXCHANGE RATE: CANADA (CANADIAN \$ PER U.S.\$)
104	PPI: fin gds	PWFSA	PRODUCER PRICE INDEX: FINISHED GOODS (82=100,SA)
105	PPI: cons gds	PWFCSA	PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS (82=100,SA)
106	PPI: int matls	PWIMSA	PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS(82=100,SA)
107	PPI: crude matls	PWCMSA	PRODUCER PRICE INDEX:CRUDE MATERIALS (82=100,SA)
108	NAPM com price	PMCP	NAPM COMMODITY PRICES INDEX (PERCENT)
109	CPI-U: all	PUNEW	CPI-U: ALL ITEMS (82-84=100,SA)
110	CPI-U: apparel	PU83	CPI-U: APPAREL & UPKEEP (82-84=100,SA)
111	CPI-U: transp	PU84	CPI-U: TRANSPORTATION (82-84=100,SA)
112	CPI-U: medical	PU85	CPI-U: MEDICAL CARE (82-84=100,SA)
113	CPI-U: comm.	PUC	CPI-U: COMMODITIES (82-84=100,SA)
114	CPI-U: dbles	PUCD	CPI-U: DURABLES (82-84=100,SA)
115	CPI-U: services	PUS	CPI-U: SERVICES (82-84=100,SA)
116	CPI-U: ex food	PUXF	CPI-U: ALL ITEMS LESS FOOD (82-84=100,SA)
117	CPI-U: ex shelter	PUXHS	CPI-U: ALL ITEMS LESS SHELTER (82-84=100,SA)
118	CPI-U: ex med	PUXM	CPI-U: ALL ITEMS LESS MEDICAL CARE (82-84=100,SA)

Pos	Shortname	Mnemonics	Description
119	PCE defl	GMDC	PCE,IMPL PR DEFL:PCE (2005=100)
120	PCE defl: dibes	GMDCD	PCE,IMPL PR DEFL:PCE; DURABLES (2005=100)
121	PCE defl: nondble	GMDCN	PCE,IMPL PR DEFL:PCE; NONDURABLES (2005=100)
122	PCE defl: ser- vices	GMDCS	PCE,IMPL PR DEFL:PCE; SERVICES (2005=100)
123	AHE: goods	CES275	AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPER- VISORY WORKERS ON PRIVATE NO
124	AHE: const	CES277	AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPER- VISORY WORKERS ON PRIVATE NO
125	AHE: mfg	CES278	AVERAGE HOURLY EARNINGS OF PRODUCTION OR NONSUPER- VISORY WORKERS ON PRIVATE NO
126	Consumer ex- pect	HHSNTN	U. OF MICH. INDEX OF CONSUMER EXPECTATIONS(BCD-83)

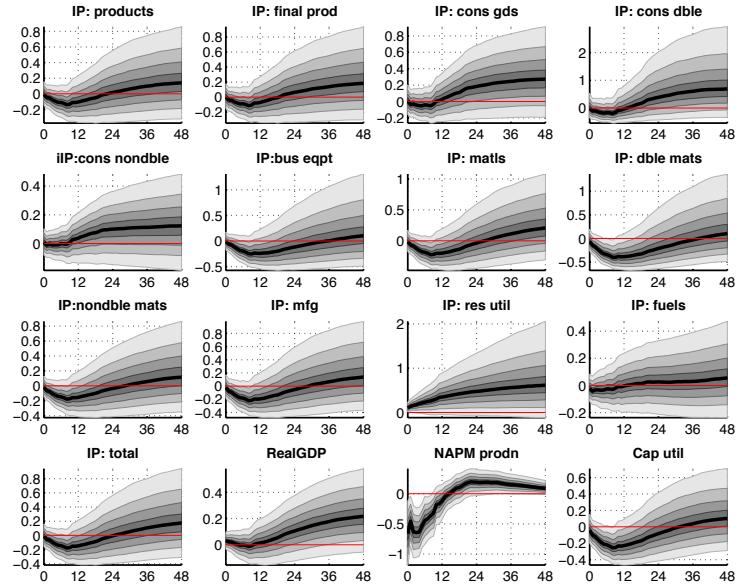
C.2. *Tables*

TABLE II
Share of Variance Explained by Common Factors.

Variable	R^2	Variable	R^2	Variable	R^2
FedFunds	1	Emp: mfg	0.76	S&P PE ratio	0.39
CPI-U: all	1	PCE defl: nondble	0.74	IP:nondble mats	0.39
1 yr T-bond	1	Emp: gds prod	0.74	Unf orders: dble	0.38
6 mo T-bill	1	IP: dble mats	0.73	Avg hrs: mfg	0.37
Aaabond	1	IP: matls	0.72	PCE defl: dlbcs	0.34
5 yr T-bond	0.99	CP-FF spread	0.71	Emp: retail	0.32
3 mo T-bill	0.99	Emp: dble gds	0.7	M&T sales	0.31
10 yr T-bond	0.99	Emp: total	0.69	Avg hrs	0.3
Aaa-FF spread	0.99	NAPM Inventories	0.67	Orders: cons gds	0.3
Commpaper	0.99	IP: cons gds	0.66	U 15+ wks	0.28
Baa bond	0.99	IP: cons dble	0.62	Emp: FIRE	0.28
10yr-FF spread	0.99	NAPM vendor del	0.6	Emp CPS nonag	0.24
Baa-FF spread	0.98	Emp: wholesale	0.6	PI less transfers	0.23
1 yr-FF spread	0.98	CPI-U: transp	0.59	iIP:cons nondble	0.23
6 mo-FF spread	0.98	IP:bus eqpt	0.58	UI claims	0.22
5 yr-FFspread	0.98	U: all	0.57	Emp: const	0.22
IP: mfg	0.97	PCED_lfe	0.57	Emp CPS total	0.21
Cap util	0.96	S&P div yield	0.56	PPI: crude matls	0.2
PMI	0.94	CPI-U: services	0.56	U 27+ wks	0.2
IP: total	0.93	NAPM com price	0.55	CPI-U: apparel	0.17
CPI-U: ex med	0.92	PPI: int matls	0.55	Overtime: mfg	0.17
3 mo-FF spread	0.92	PCE defl: services	0.54	Cons credit	0.16
NAPM empl	0.89	PPI: fin gds	0.53	PI	0.16
IP: products	0.86	Emp: nondbles	0.5	LoansRealEst	0.16
NAPM prodn	0.85	Emp: TTU	0.5	AHE: goods	0.16
CPI-U: ex shelter	0.85	PPI: cons gds	0.49	AHE: mfg	0.15
NAPM new ordrs	0.83	Consumer expect	0.49	Orders: dble gds	0.14
CPI-U: ex food	0.83	Emp: services	0.45	MB	0.13
PCE Def	0.82	M&T invent	0.41	BP: total	0.13
PCE defl	0.82	C&I loans	0.4	U 15-26 wks	0.12
CPI-U: comm.	0.81	CPI-U: dbles	0.39	Reserves tot	0.11
IP: final prod	0.8	CPI-U: medical	0.39	U: mean duration	0.1
BP: South	0.1	HStarts: South	0.05	IP: fuels	0.03
RealGDP	0.1	Emp: mining	0.05	DJIA	0.03
U 5-14 wks	0.09	BP: MW	0.05	U 5 wks	0.03
M1	0.09	Ex rate: Japan	0.05	HStarts: West	0.02
Emp: Govt	0.09	BP: West	0.05	Orders: cap gds	0.02
Retail sales	0.08	M2	0.04	Reserves nonbor	0.02
AHE: const	0.08	Ex rate: UK	0.04	S&P 500	0.02
Inst cred/PI	0.08	BP: NE	0.04	HStarts: MW	0.02
HStarts: Total	0.06	EX rate: Canada	0.03	HStarts: NE	0.02
Ex rate: major	0.05	Ex rate: Switz	0.03	IP: res util	0.01

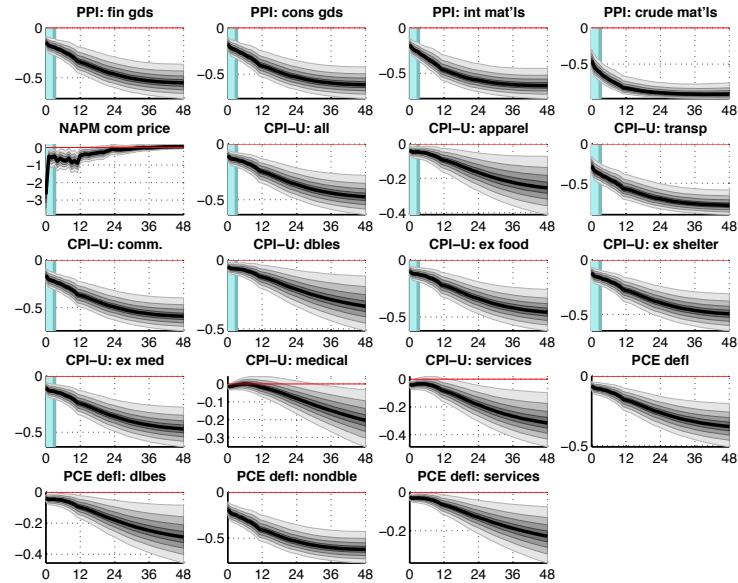
C.3. *Figures: Benchmark Model*

FIGURE 8.— Output Responses: Benchmark Model



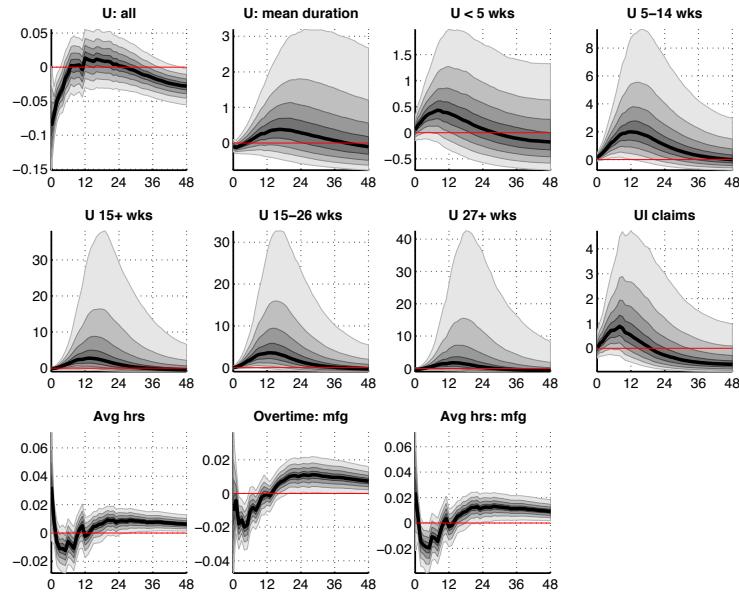
This figure provides plots of posterior IRFs for a selection of many output indicators for the benchmark model.

FIGURE 9.— Price Responses: Benchmark Model



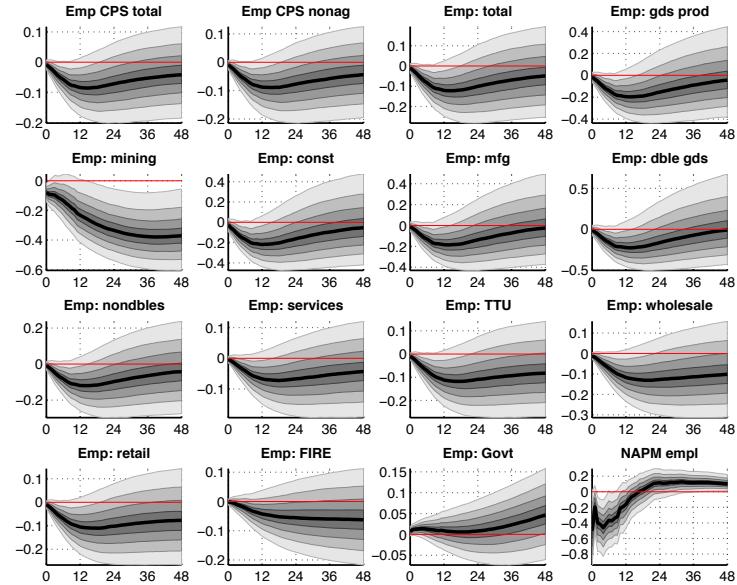
This figure provides plots of posterior IRFs for a selection of many price indicators for the benchmark model.

FIGURE 10.— **Unemployment Responses: Benchmark Model**
for the benchmark model.



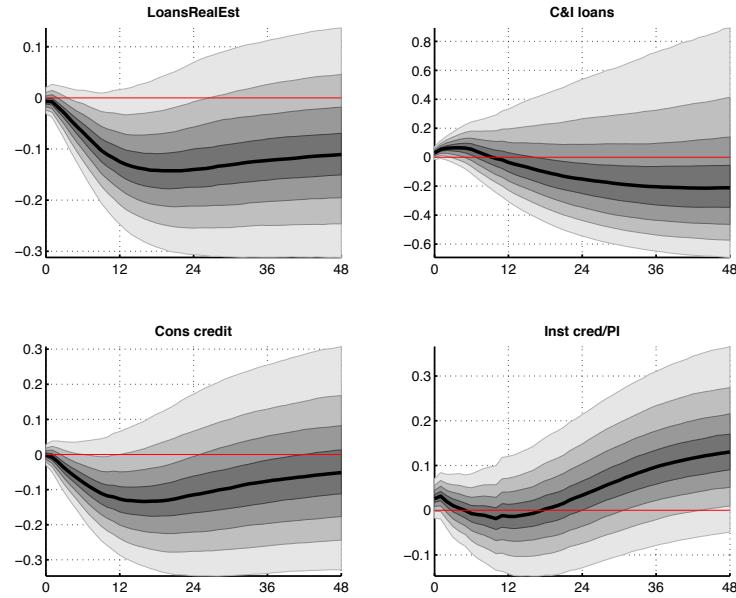
This figure provides plots of posterior IRFs for a selection of many unemployment indicators

FIGURE 11.— Employment Responses: Benchmark Model



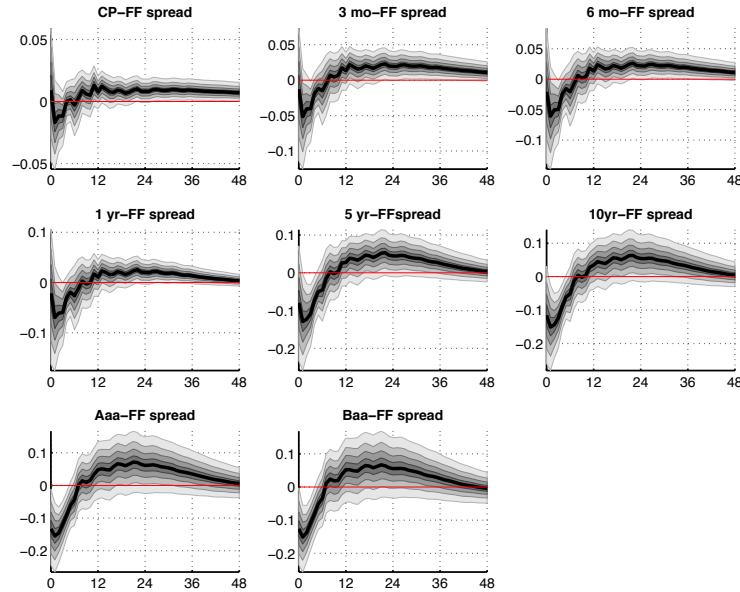
This figure provides plots of posterior IRFs for a selection of many employment indicators for the benchmark model.

FIGURE 12.— Loan Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many loan indicators for the benchmark model.

FIGURE 13.— Spread Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many spread indicators for the benchmark model.

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TECHNICAL APPENDIX — NOT FOR PUBLICATION

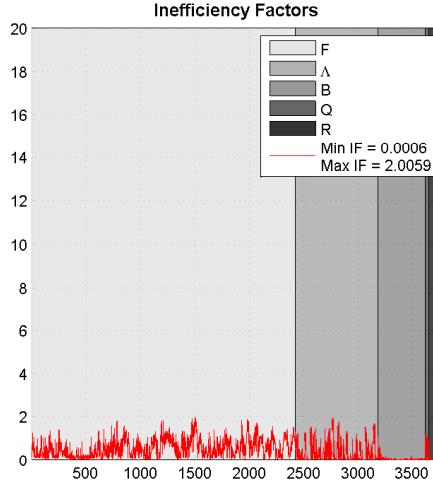
A.4. Figures: Convergence Diagnostics

Following Primiceri(2005), we assess the convergence of the Markov chain by inspecting the autocorrelation properties of the ergodic distributions draws. Specifically, in what follows, we consider the draws inefficiency factors (henceforth, IFs), defined as the inverse of the relative numerical efficiency measure of Geweke (1992),

$$(A.1) \quad RNE = (2\pi)^{-1} \frac{1}{S(0)} \int_{-\pi}^{\pi} S(\omega) d\omega$$

is the spectral density of the sequence of draws from the Gibbs sampler for the quantity of interest at the frequency ω . We estimate the spectral densities by smoothing the periodograms in the frequency domain by means of a Bartlett spectral window. Following Berkowitz and Diebold (1998), we select the bandwidth parameter automatically via the procedure introduced by Beltrao and Bloomfield (1987). Figures (XXX) show, the draws IFs for the models hyperparameters i.e. the free elements of the matrices B, Q, Λ, R, F . As the figures show, the autocorrelation of the draws is uniformly very low, being in the vast majority of cases around or below 2, thus suggesting that the Markov chains have indeed converged⁸.

FIGURE 14.— Inefficiency Factors for all parameters



This figure reports the inefficiency factors (IFs) for the posterior estimates of the parameters. The IF is the inverse of the relative numerical efficiency measure of Gewekes (1992), i.e. the IF is an estimate of $(1 + 2 \sum_{k=1}^{\infty} \rho_k)$, where ρ_k is the k-th autocorrelation of the chain. Following Primiceri (2005) our estimates estimate are performed using a 4 percent tapered window for the estimation of the spectral density at frequency zero. Values of the IFs below or around twenty are regarded as satisfactory. All parameters are clearly below with the highest IF of 2.

⁸As stressed by Primiceri (2005, Appendix B), values of the IFs below or around twenty are generally regarded as satisfactory.

FIGURE 15.— Convergence of Factors

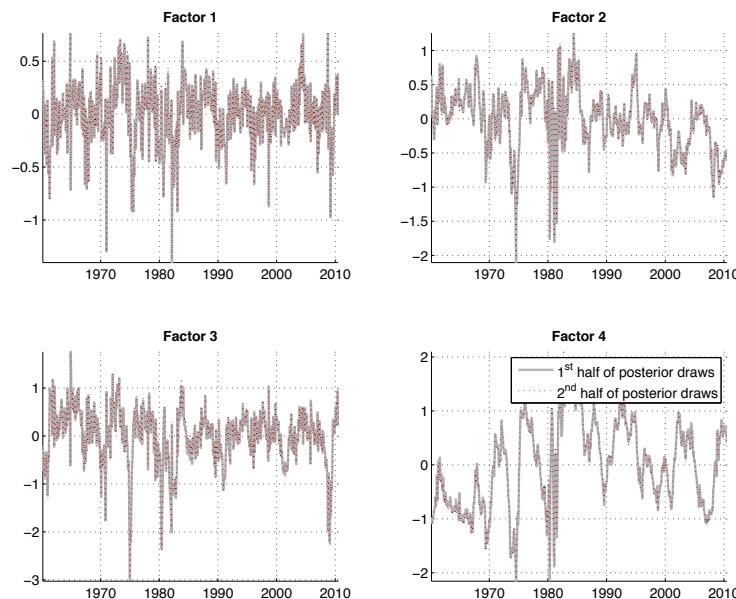


FIGURE 16.— Convergence of Coefficients

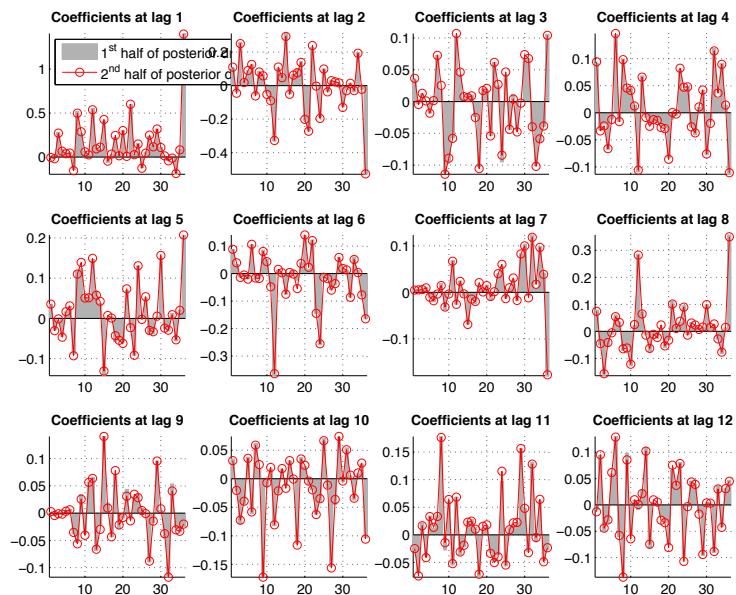


FIGURE 17.— Convergence of state error covariance matrix

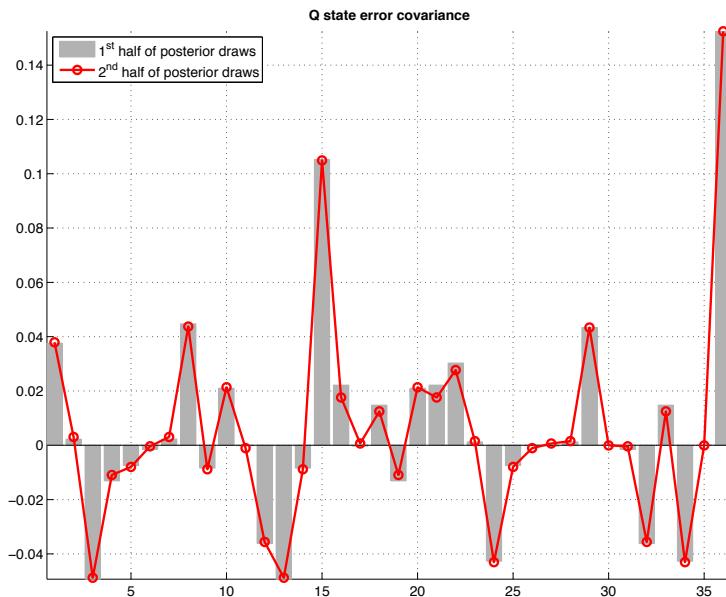


FIGURE 18.— Convergence of idiosyncratic covariance matrix

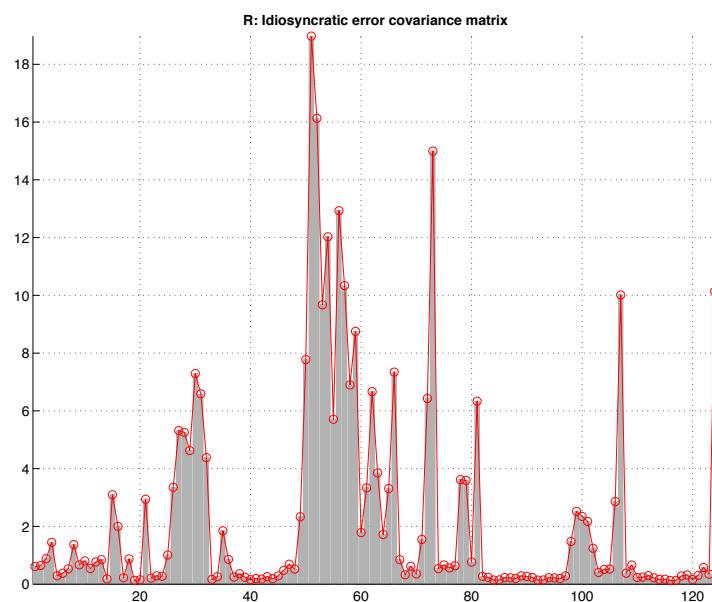
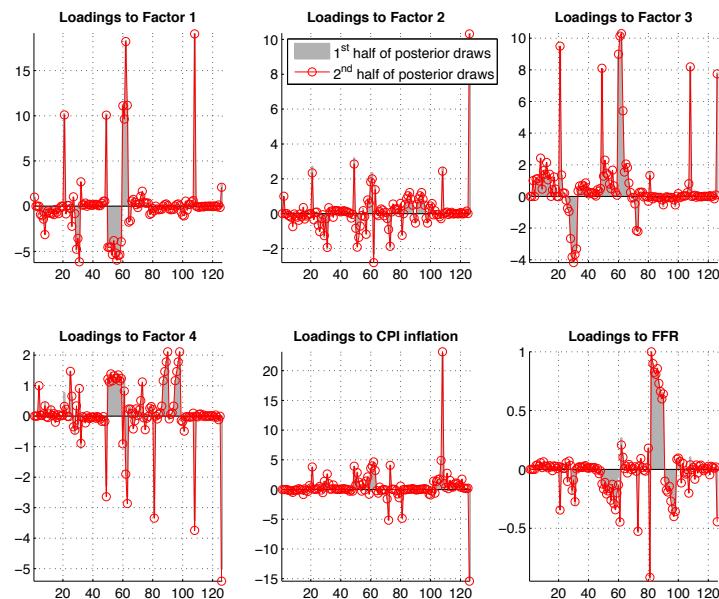


FIGURE 19.— Convergence of factor loadings



A.5. Figures: Comparisons

FIGURE 20.— Recursive Cholesky identification: full sample

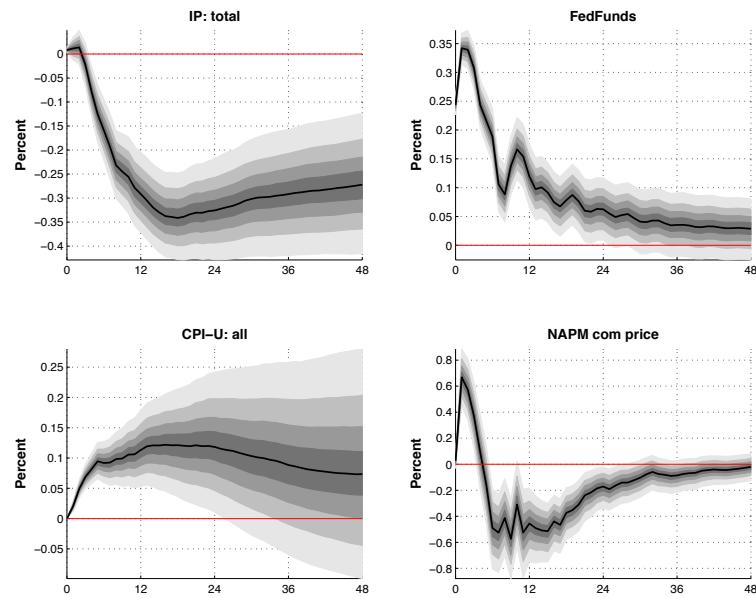
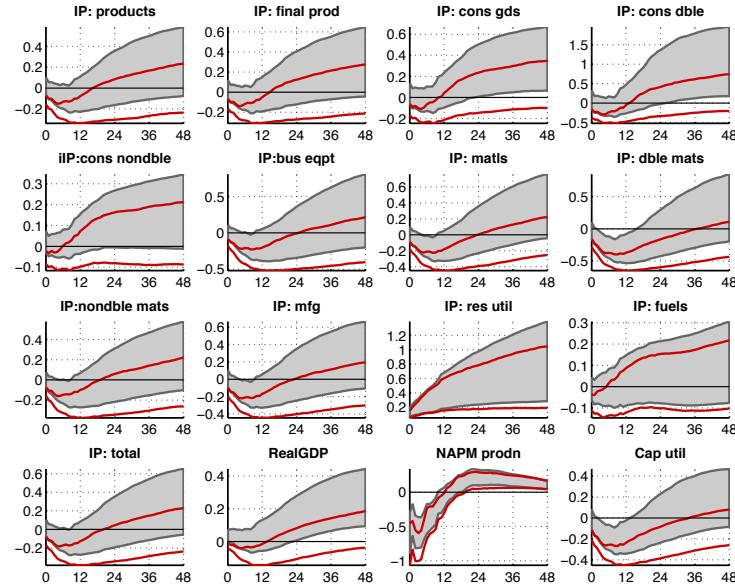


FIGURE 21.— Selected output IRFs comparing two different sets of sign restrictions: baseline restrictions (grey) and the additional output restriction (red) for the full sample model.



In Figure (??) **COMMENT: CHANGE THE FIGURES, FOCUS ON COMPARISON BETWEEN OUTPUT-RESTRICTED AND BENCHMARK!** we compare the results for the output-restricted specification to the results from the benchmark specification. While it may not be surprising that we find a more pronounced decline in industrial production as a result, we also find considerably tighter confidence bands, indicating that this particular identification restriction has considerable “bite”. We do not recommend imposing it, however, unless one already “believes” in the continuous, contractionary impact of a monetary policy shock, and wishes to examine its quantitative consequences, given this additional assumption.

FIGURE 22.— Selected price IRFs comparing two different sets of sign restrictions: baseline restrictions (grey) and the additional output restriction (red) for the full sample model.

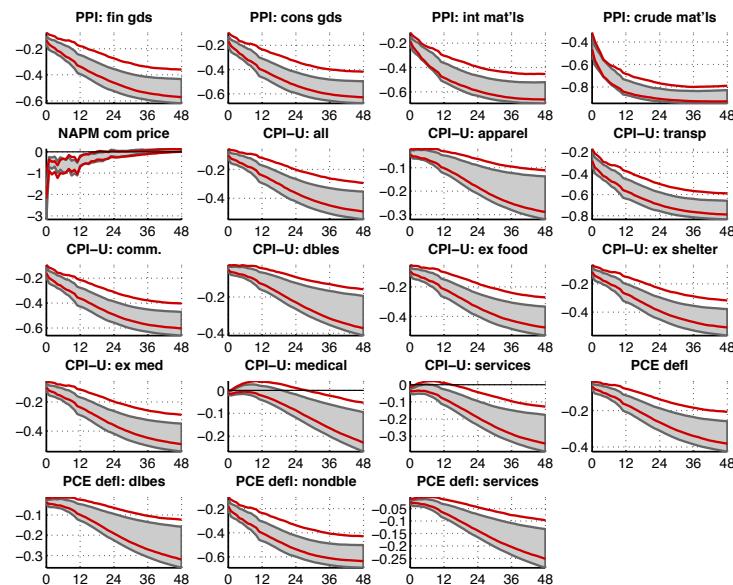


FIGURE 23.— Selected unemployment IRFs comparing two different sets of sign restrictions: baseline restrictions (grey) and the additional output restriction (red) for the full sample model.

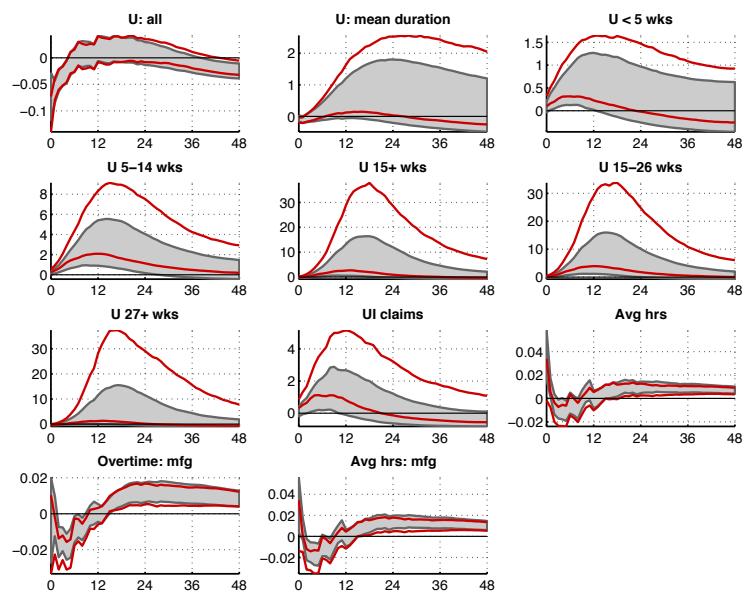


FIGURE 24.— Selected employment IRFs comparing two different sets of sign restrictions: baseline restrictions (grey) and the additional output restriction (red) for the full sample model.

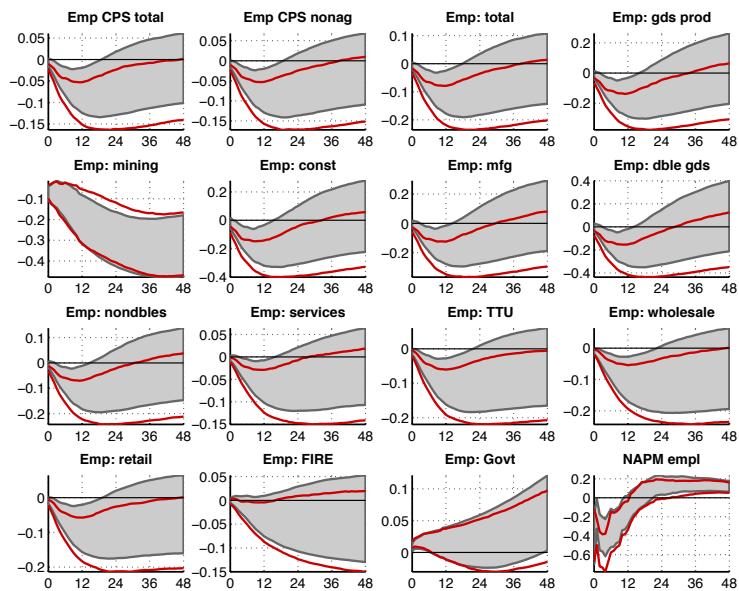


FIGURE 25.— Selected spread IRFs comparing two different sets of sign restrictions: baseline restrictions (grey) and the additional output restriction (red) for the full sample model.

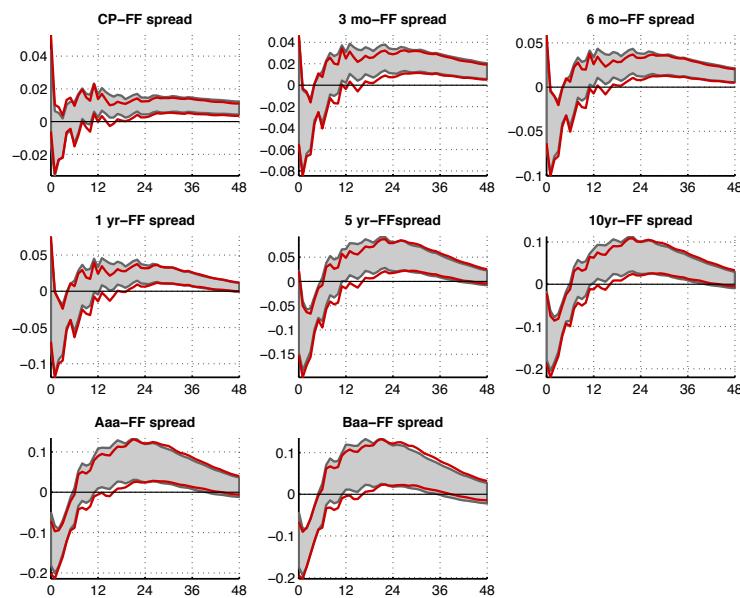


FIGURE 26.— Selected loan IRFs comparing two different sets of sign restrictions: baseline restrictions (grey) and the additional output restriction (red) for the full sample model.

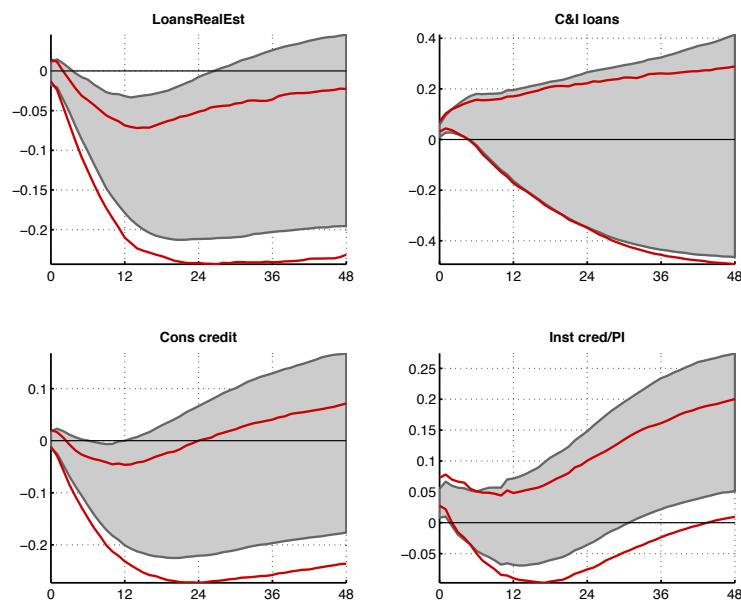


FIGURE 27.— Selected output IRFs comparing all three different sets of sign restrictions: baseline restrictions (grey), the additional output restriction (red) and the minimal set (blue) of sign restrictions for the full sample model.

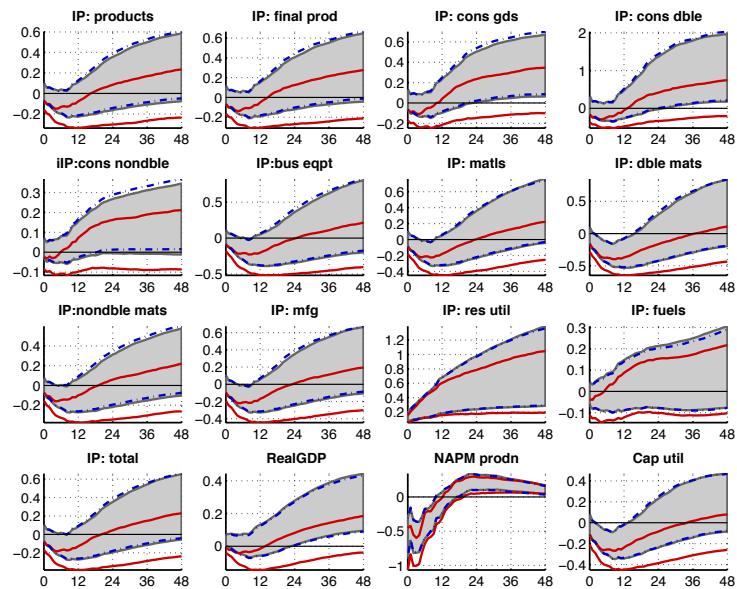


FIGURE 28.— Selected price IRFs comparing all three different sets of sign restrictions: baseline restrictions (grey), the additional output restriction (red) and the minimal set (blue) of sign restrictions for the full sample model.

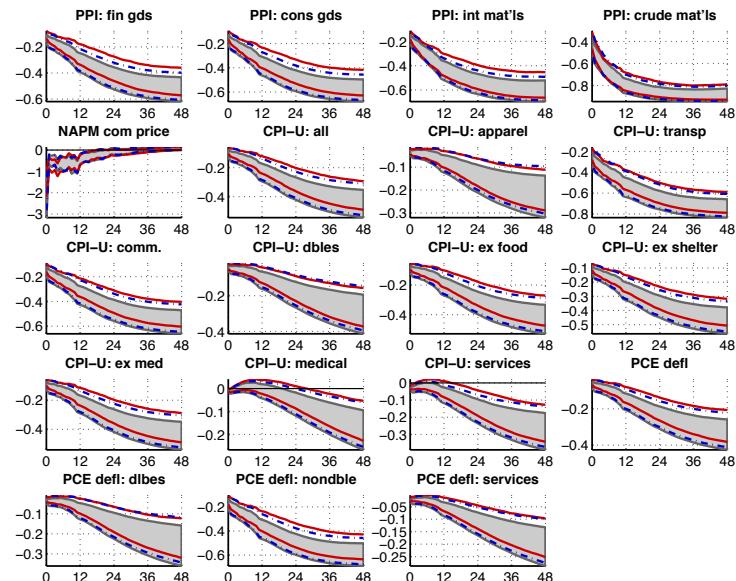


FIGURE 29.— Selected unemployment IRFs comparing all three different sets of sign restrictions: baseline restrictions (grey), the additional output restriction (red) and the minimal set (blue) of sign restrictions for the full sample model.

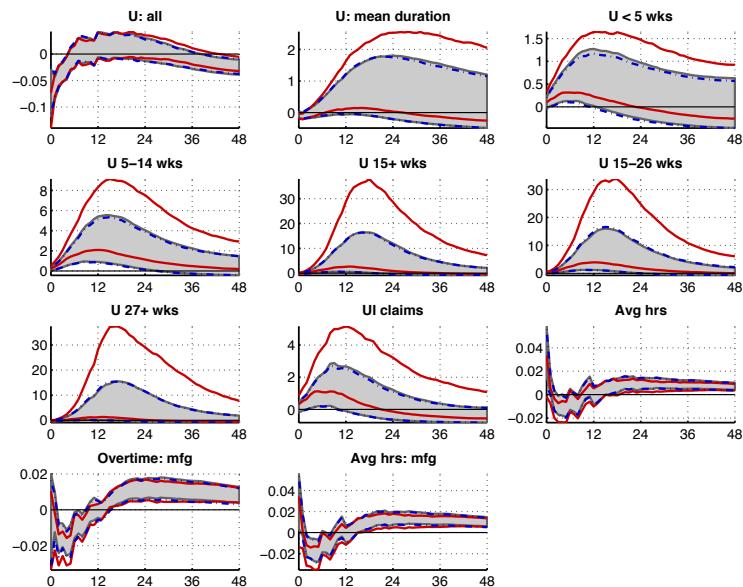


FIGURE 30.— Selected employment IRFs comparing all three different sets of sign restrictions: baseline restrictions (grey), the additional output restriction (red) and the minimal set (blue) of sign restrictions for the full sample model.

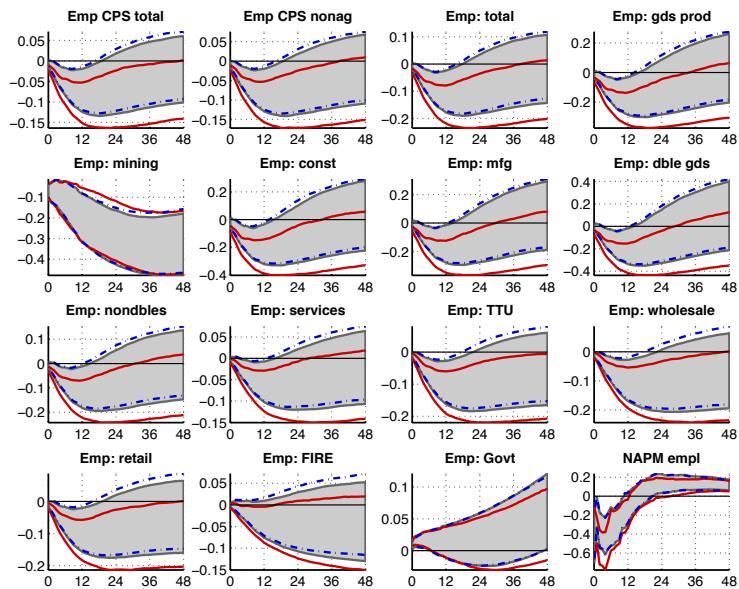


FIGURE 31.— Selected spread IRFs comparing all three different sets of sign restrictions: baseline restrictions (grey), the additional output restriction (red) and the minimal set (blue) of sign restrictions for the full sample model.

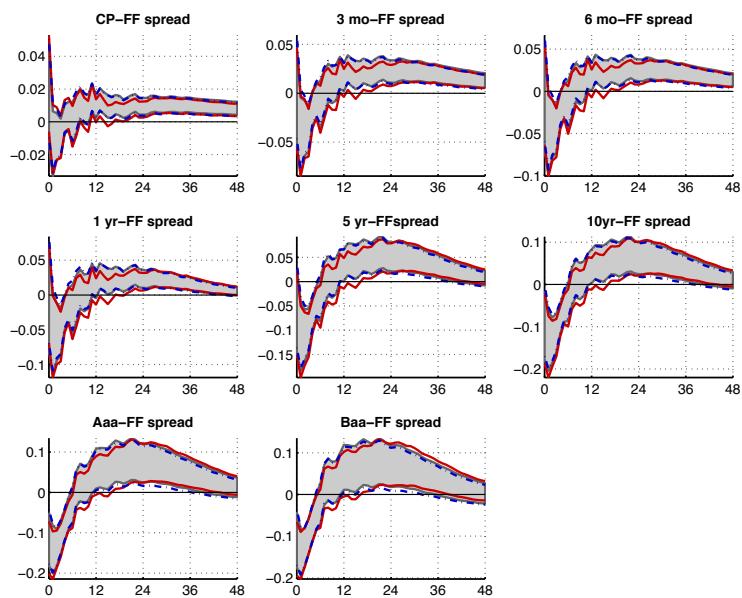
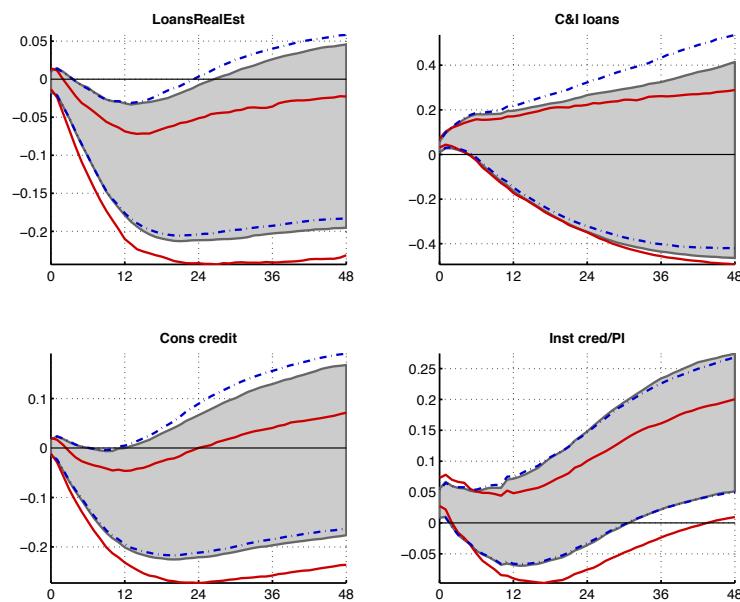


FIGURE 32.— Selected loan IRFs comparing all three different sets of sign restrictions: baseline restrictions (grey), the additional output restriction (red) and the minimal set (blue) of sign restrictions for the full sample model.



APPENDIX B: VARIATIONS

In this section, we explore and document variations on our model specification and subsamples to cover potential model and parameter instabilities. The table below summarizes all variations we considered in the paper.

TABLE III
MODEL VARIATION.

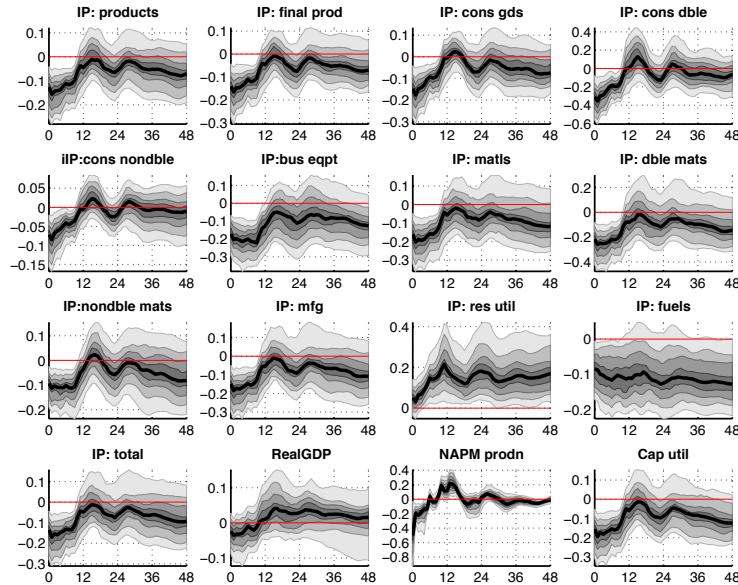
Model Version	Core VAR (f_t^y)	Time Span
Baseline Model	[CPI, FFR]	1960 : 02 – 2010 : 06
Variation 1	[FFR]	1960 : 02 – 2010 : 06
Variation 2	[CPI, FFR]	1960 : 02 – 1979 : 09
Variation 3	[FFR]	1960 : 02 – 1979 : 09
Variation 4	[CPI, FFR]	1984 : 02 – 2010 : 06
Variation 5	[FFR]	1984 : 02 – 2010 : 06
Variation 6	[CPI, FFR]	1984 : 02 – 2007 : 01
Variation 7	[FFR]	1984 : 02 – 2003 : 12
Variation 8	[FFR]	1981 : 09 – 2010 : 06

B.1. *Figures: Variation 1*

In this subsection we analyze the data for the full sample covering 1960 : 02 – 2010 : 06 including only the federal funds rate in the core VAR for the FAVAR model.

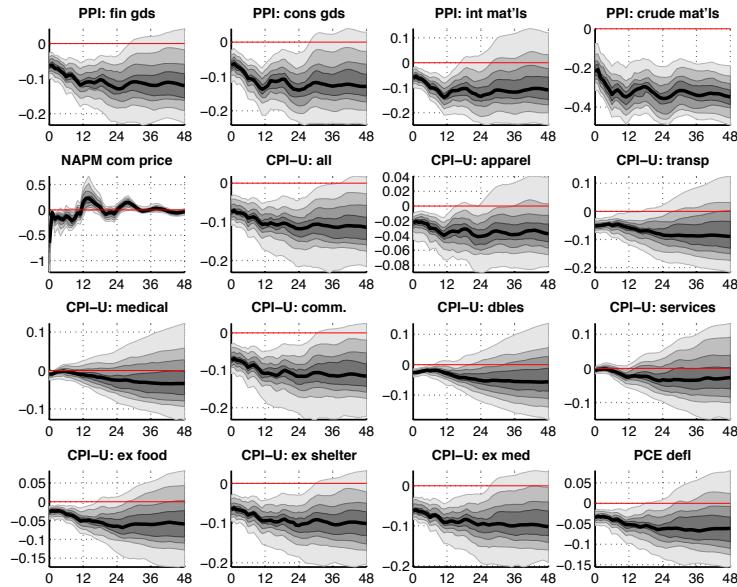
B.2. *Figures: Variation 2*

In this subsection we analyze the data for the pre Volcker period covering 1960 : 02–1979 : 09 including CPI inflation and the federal funds rate in the core VAR for the FAVAR model.

FIGURE 33.— **Output Responses: Benchmark Model**

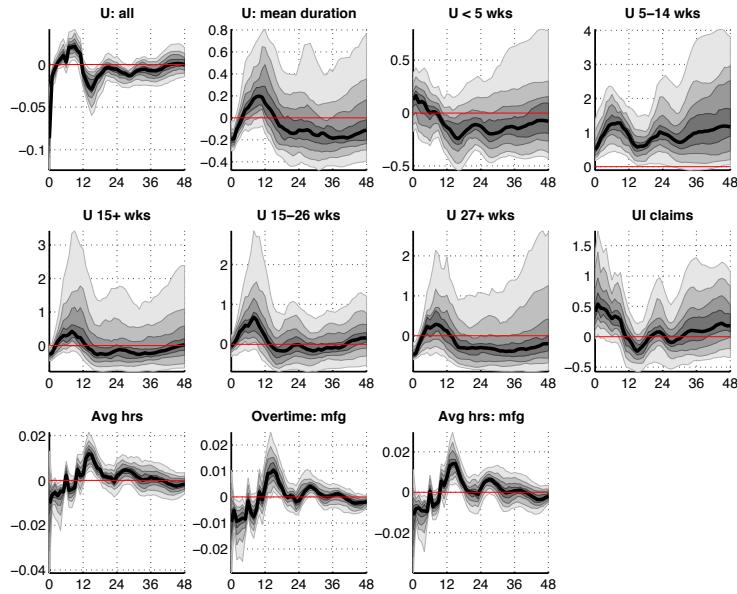
This figure provides plots of posterior IRFs for a selection of many output indicators for the benchmark model.

FIGURE 34.— Price Responses: Benchmark Model



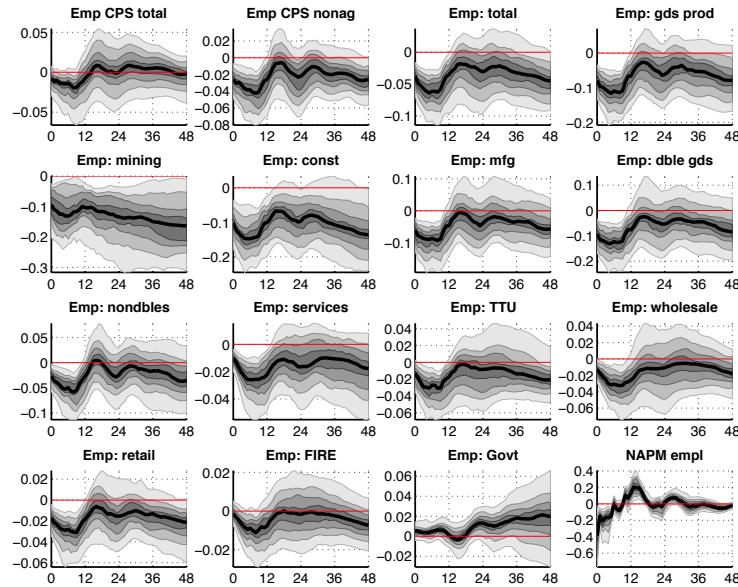
This figure provides plots of posterior IRFs for a selection of many price indicators for the benchmark model.

FIGURE 35.— **Unemployment Responses: Benchmark Model**
for the benchmark model.



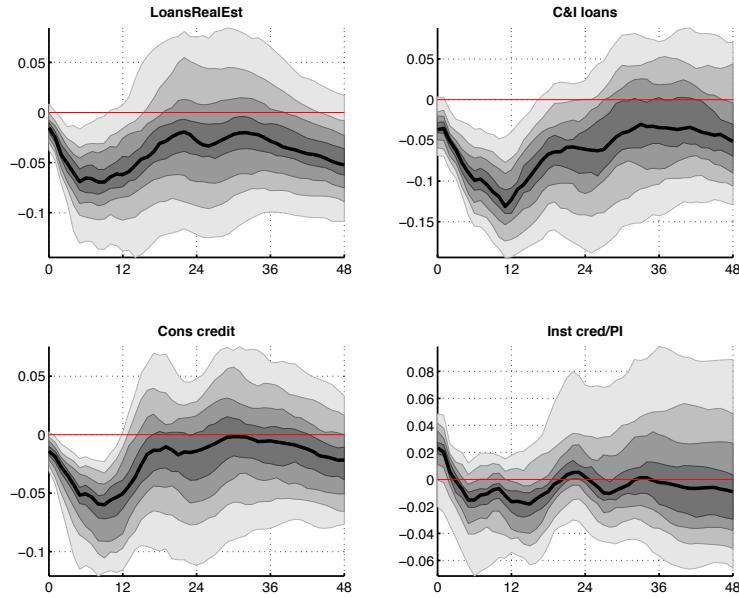
This figure provides plots of posterior IRFs for a selection of many unemployment indicators

FIGURE 36.— Employment Responses: Benchmark Model



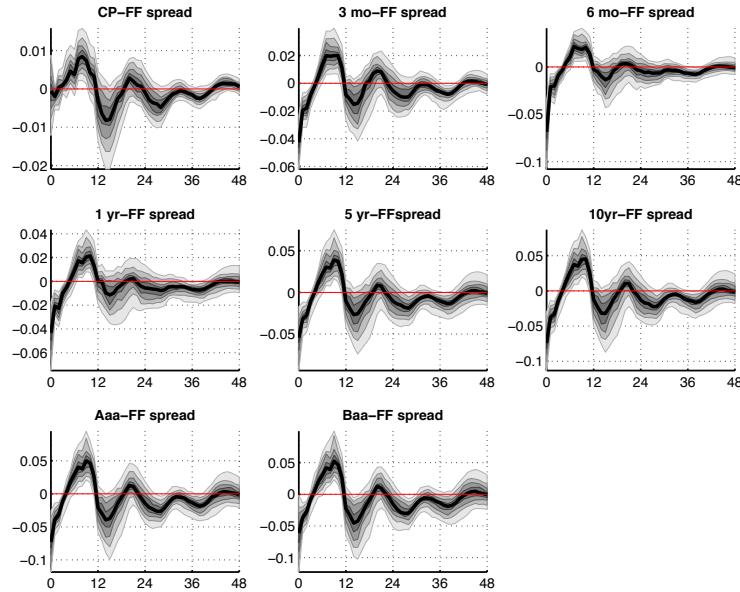
This figure provides plots of posterior IRFs for a selection of many employment indicators for the benchmark model.

FIGURE 37.— Loan Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many loan indicators for the benchmark model.

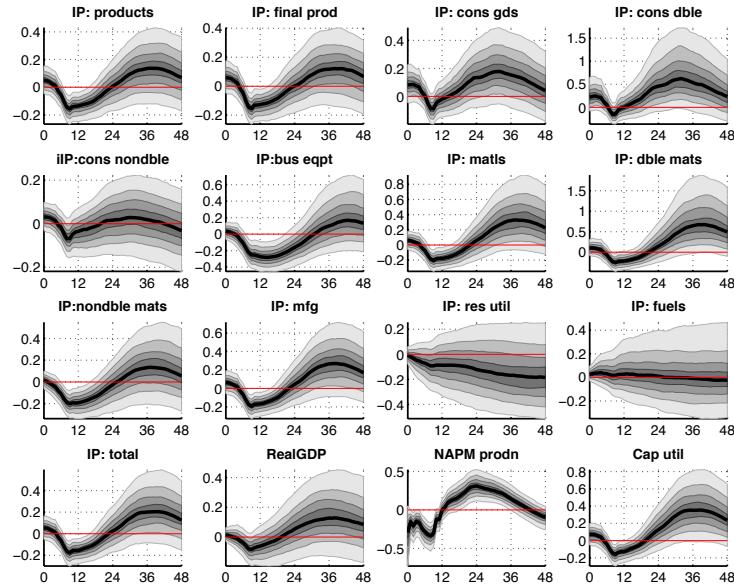
FIGURE 38.— Spread Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many spread indicators for the benchmark model.

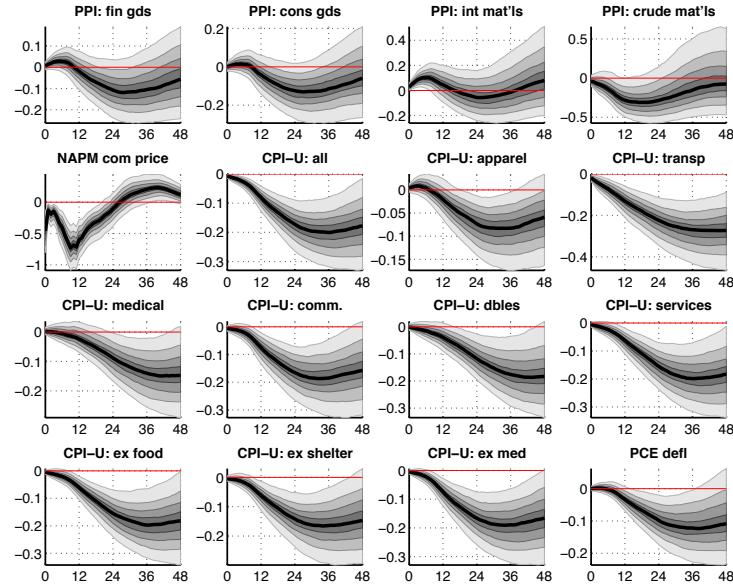
B.3. *Figures: Variation 3*

In this subsection we analyze the data for the pre Volcker period covering 1960 : 02–1979 : 09 including only the federal funds rate in the core VAR for the FAVAR model.

FIGURE 39.— **Output Responses: Benchmark Model**

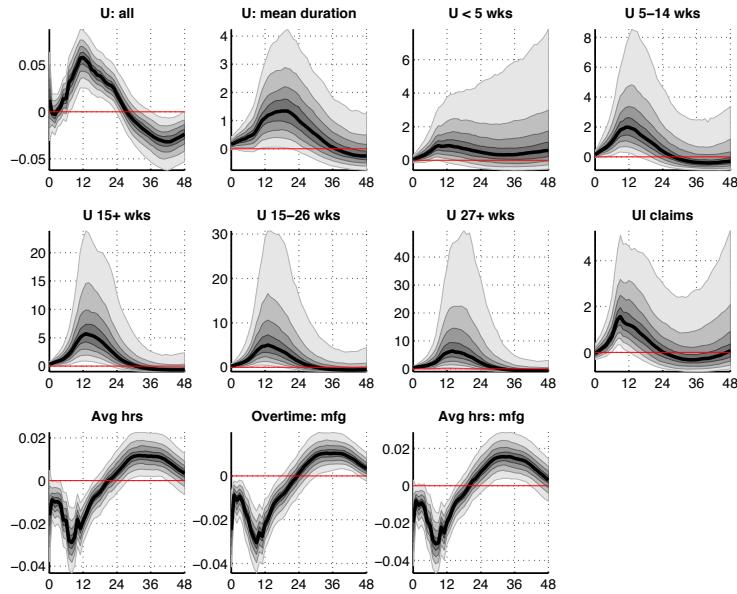
This figure provides plots of posterior IRFs for a selection of many output indicators for the benchmark model.

FIGURE 40.— Price Responses: Benchmark Model



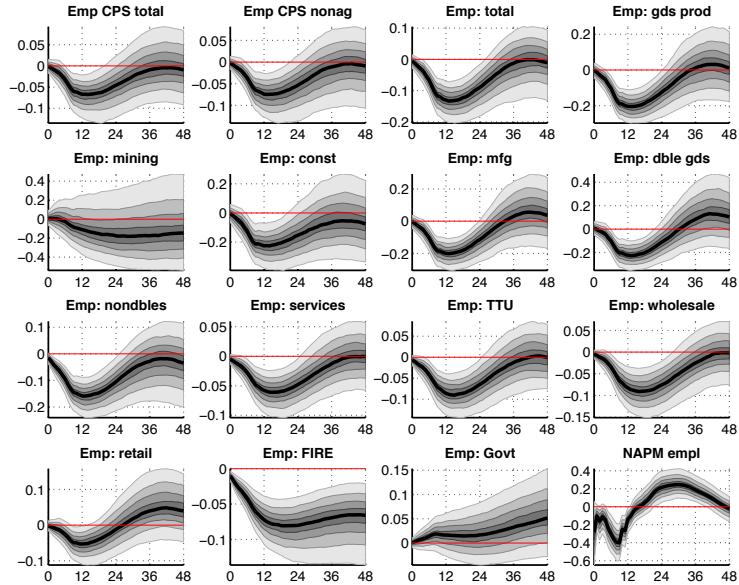
This figure provides plots of posterior IRFs for a selection of many price indicators for the benchmark model.

FIGURE 41.— Unemployment Responses: Benchmark Model
for the benchmark model.



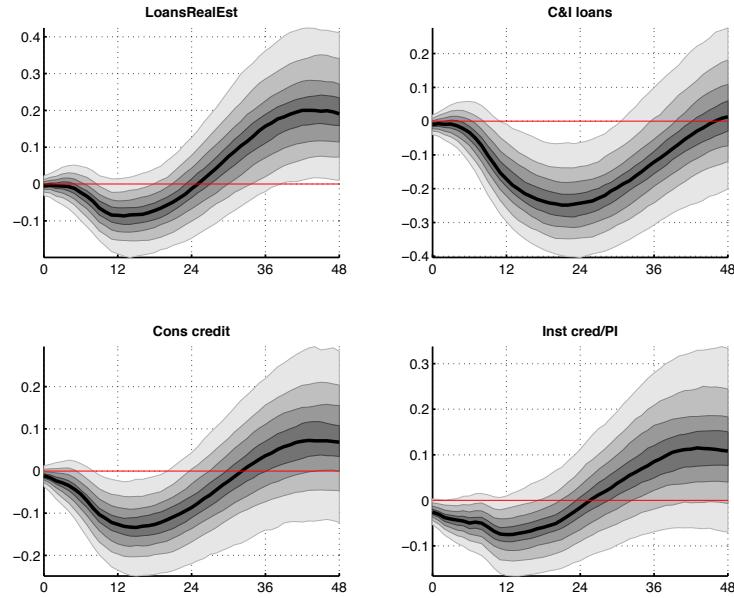
This figure provides plots of posterior IRFs for a selection of many unemployment indicators

FIGURE 42.— Employment Responses: Benchmark Model



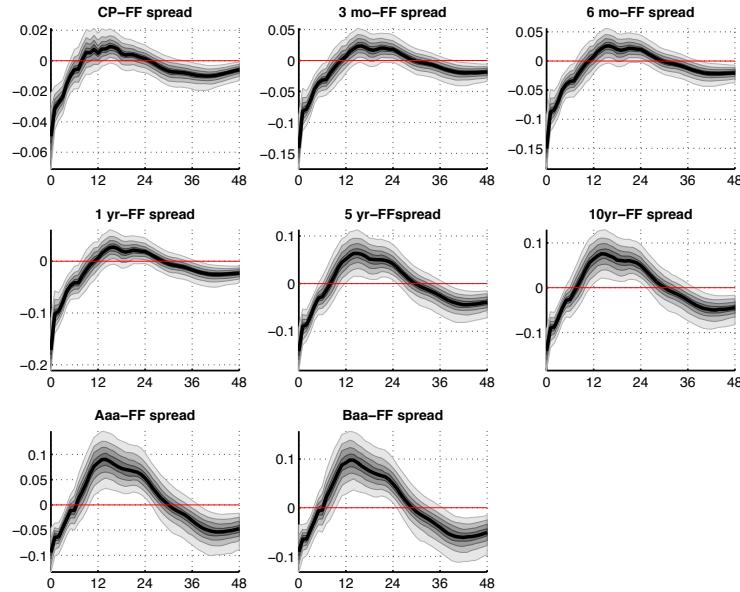
This figure provides plots of posterior IRFs for a selection of many employment indicators for the benchmark model.

FIGURE 43.— Loan Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many loan indicators for the benchmark model.

FIGURE 44.— Spread Responses: Benchmark Model

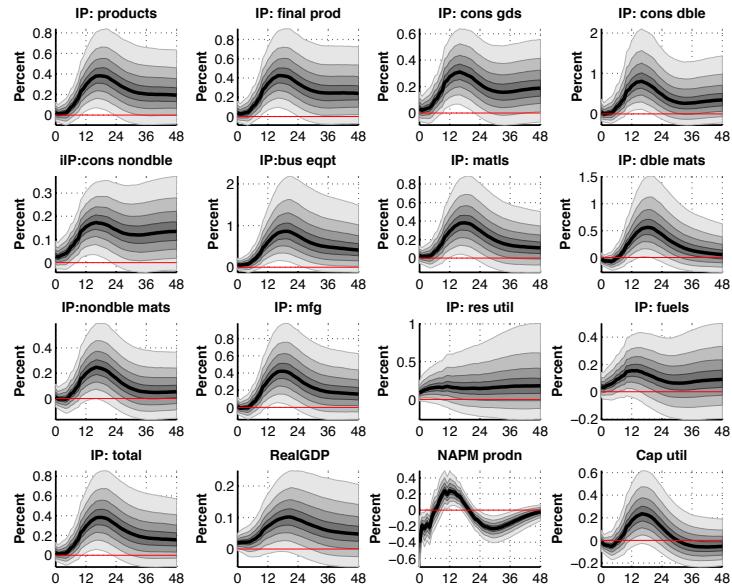


This figure provides plots of posterior IRFs for a selection of many spread indicators for the benchmark model.

B.4. Figures: Variation 4

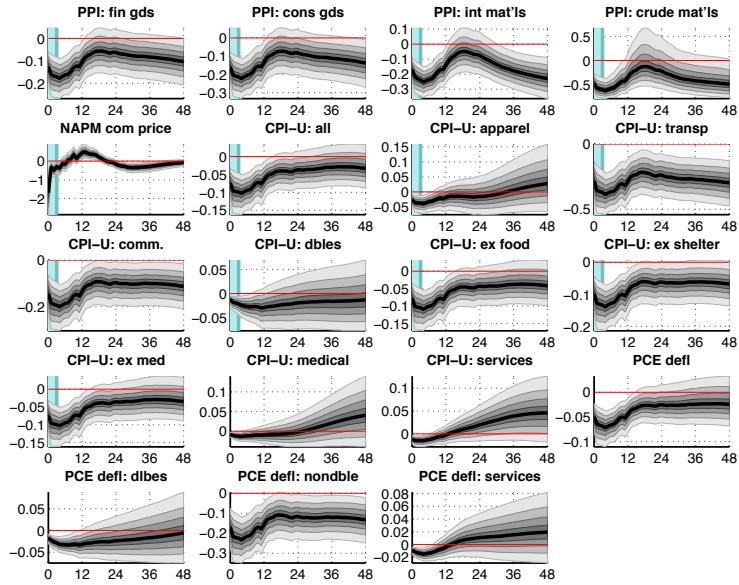
In this subsection we analyze the data for the post Volcker period covering 1984 : 02 – 2010 : 06 including the recent financial crisis with CPI inflation and the federal funds rate in the core VAR of the FAVAR model.

FIGURE 45.— Output Responses: Benchmark Model



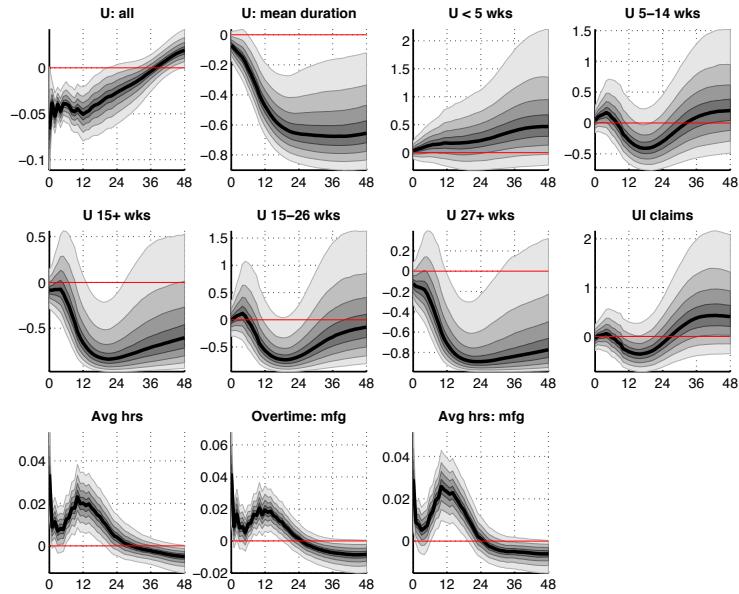
This figure provides plots of posterior IRFs for a selection of many output indicators for the benchmark model.

FIGURE 46.— Price Responses: Benchmark Model



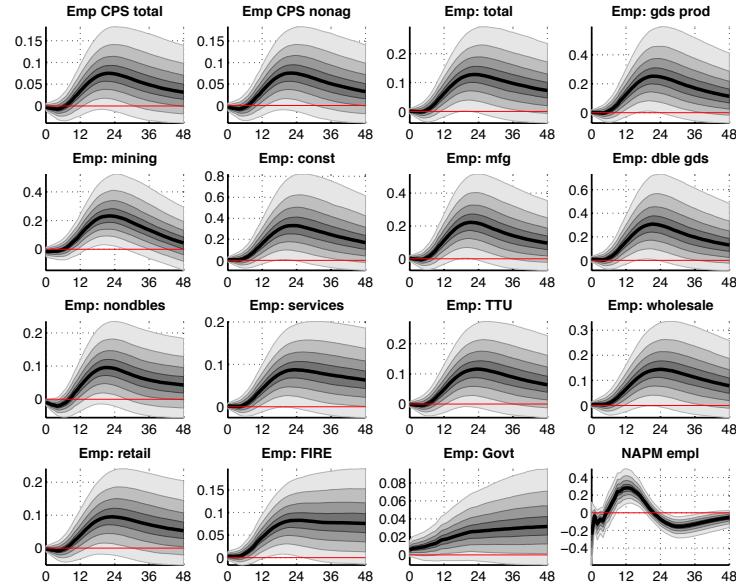
This figure provides plots of posterior IRFs for a selection of many price indicators for the benchmark model.

FIGURE 47.— **Unemployment Responses: Benchmark Model**
for the benchmark model.



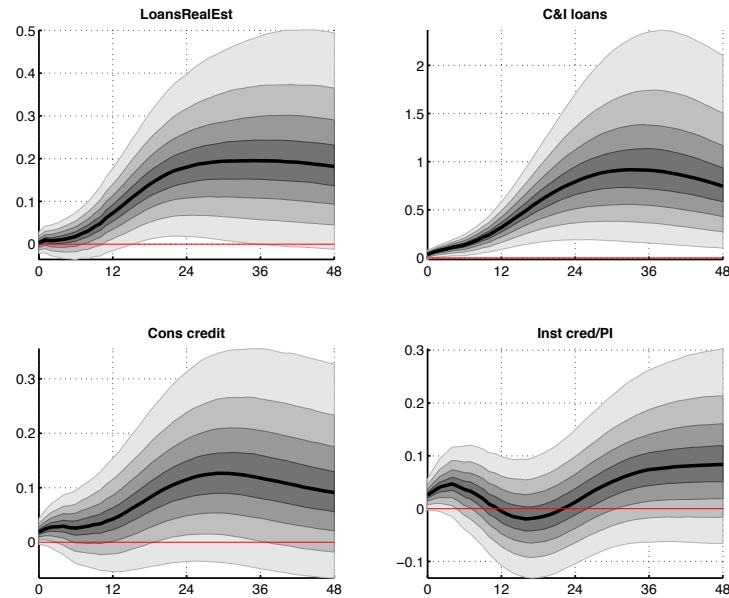
This figure provides plots of posterior IRFs for a selection of many unemployment indicators

FIGURE 48.— Employment Responses: Benchmark Model



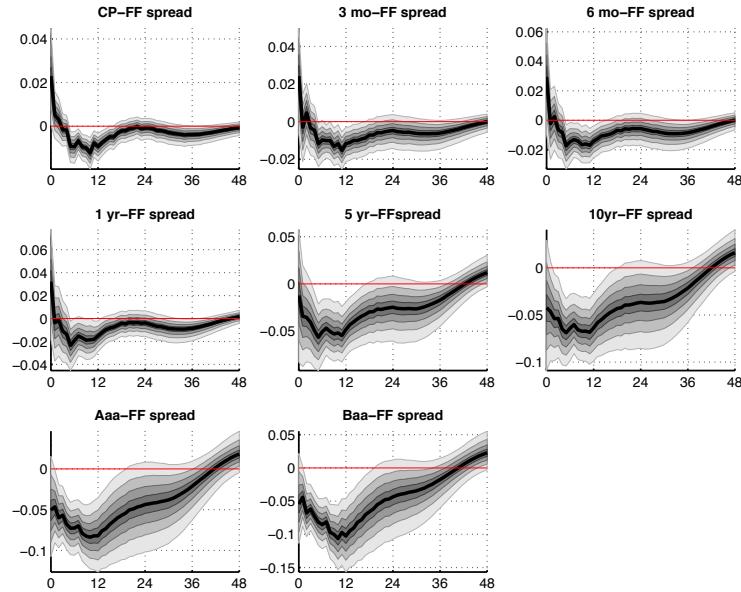
This figure provides plots of posterior IRFs for a selection of many employment indicators for the benchmark model.

FIGURE 49.— Loan Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many loan indicators for the benchmark model.

FIGURE 50.— Spread Responses: Benchmark Model

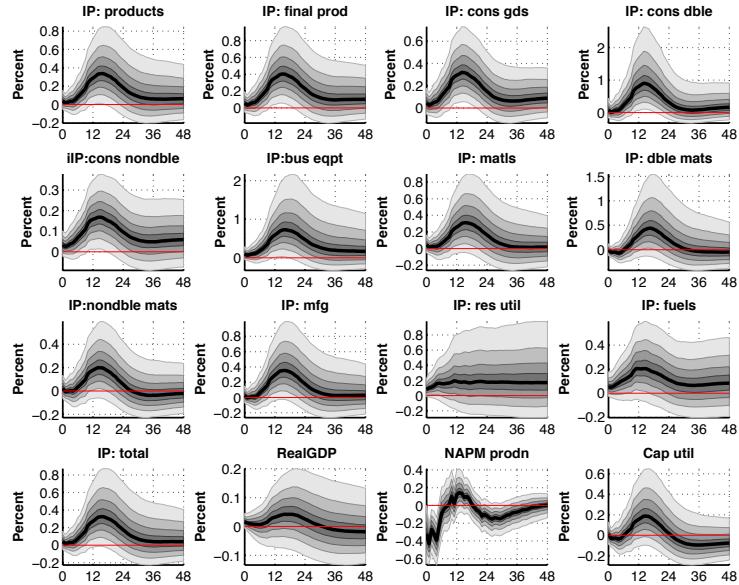


This figure provides plots of posterior IRFs for a selection of many spread indicators for the benchmark model.

B.5. Figures: Variation 5

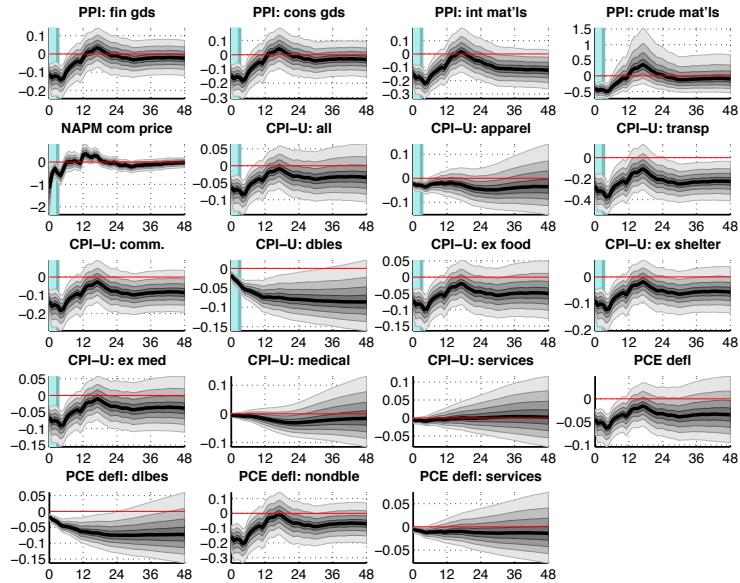
In this subsection we analyze the data for the post Volcker period covering 1984 : 02 – 2010 : 06 including the recent financial crisis with the federal funds rate in the core VAR of the FAVAR model.

FIGURE 51.— Output Responses: Benchmark Model



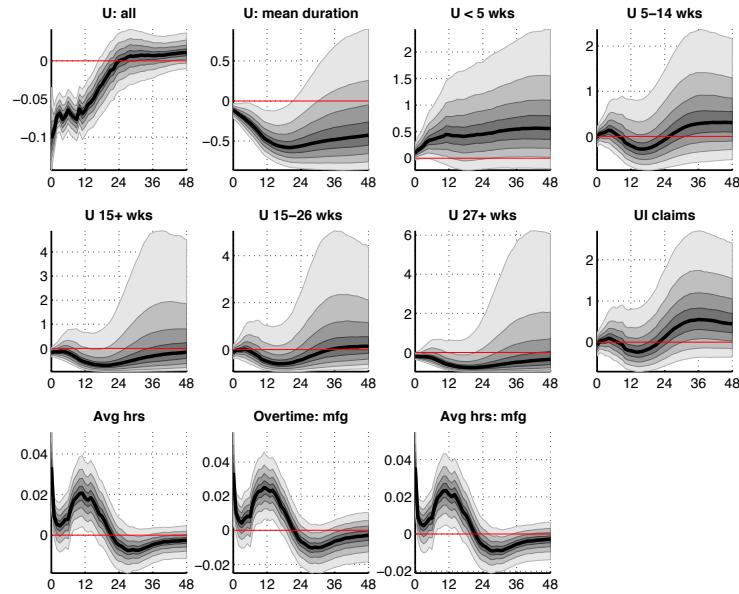
This figure provides plots of posterior IRFs for a selection of many output indicators for the benchmark model.

FIGURE 52.— Price Responses: Benchmark Model



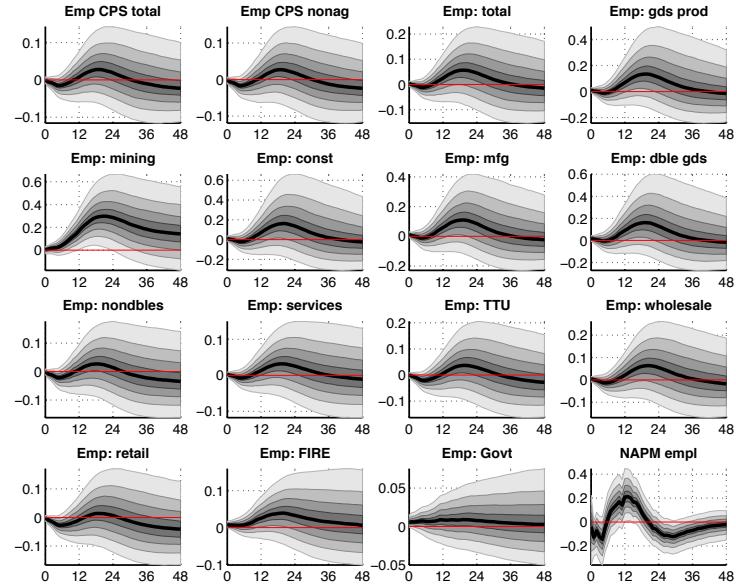
This figure provides plots of posterior IRFs for a selection of many price indicators for the benchmark model.

FIGURE 53.— Unemployment Responses: Benchmark Model
for the benchmark model.



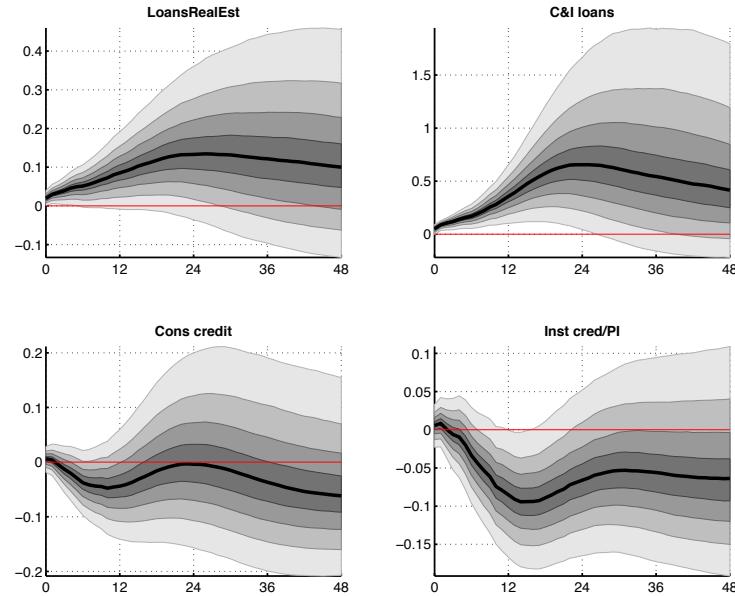
This figure provides plots of posterior IRFs for a selection of many unemployment indicators

FIGURE 54.— Employment Responses: Benchmark Model



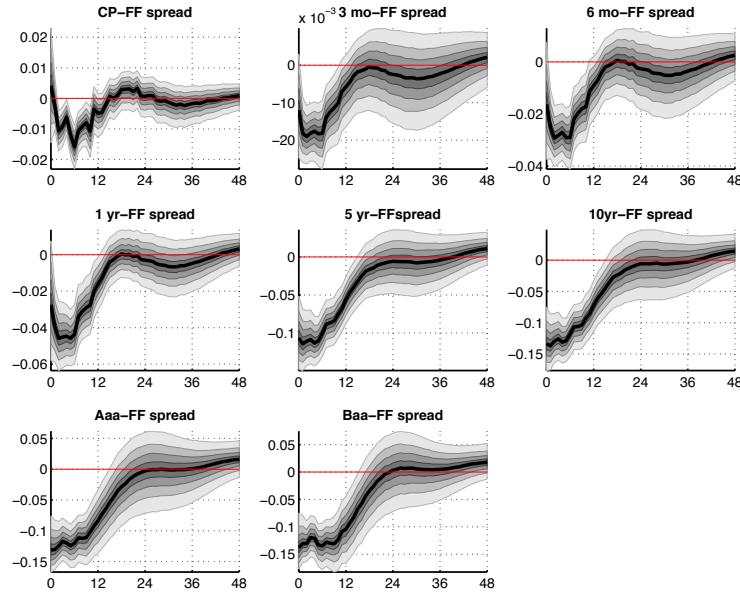
This figure provides plots of posterior IRFs for a selection of many employment indicators for the benchmark model.

FIGURE 55.— Loan Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many loan indicators for the benchmark model.

FIGURE 56.— Spread Responses: Benchmark Model

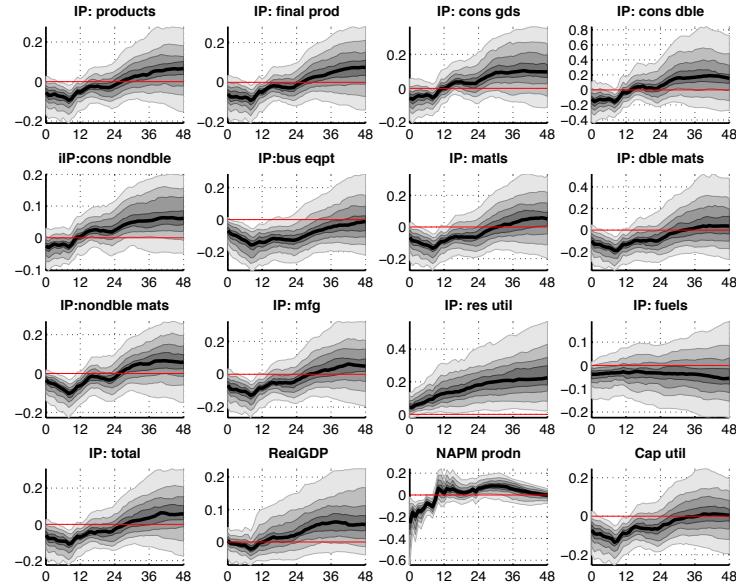


This figure provides plots of posterior IRFs for a selection of many spread indicators for the benchmark model.

B.6. *Figures: Variation 6*

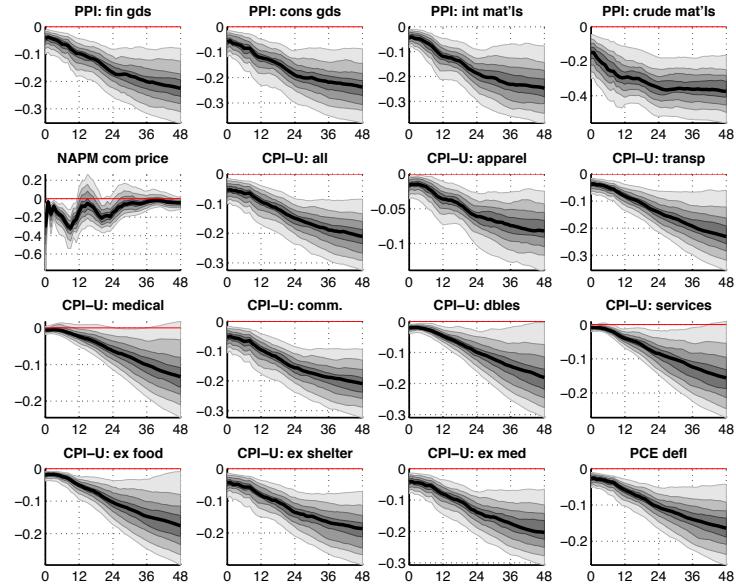
In this subsection we analyze the data for the post Volcker period covering 1984 : 02 – 2007 : 01 including the recent financial crisis with CPI inflation and the federal funds rate in the core VAR of the FAVAR model.

FIGURE 57.— Output Responses: Benchmark Model



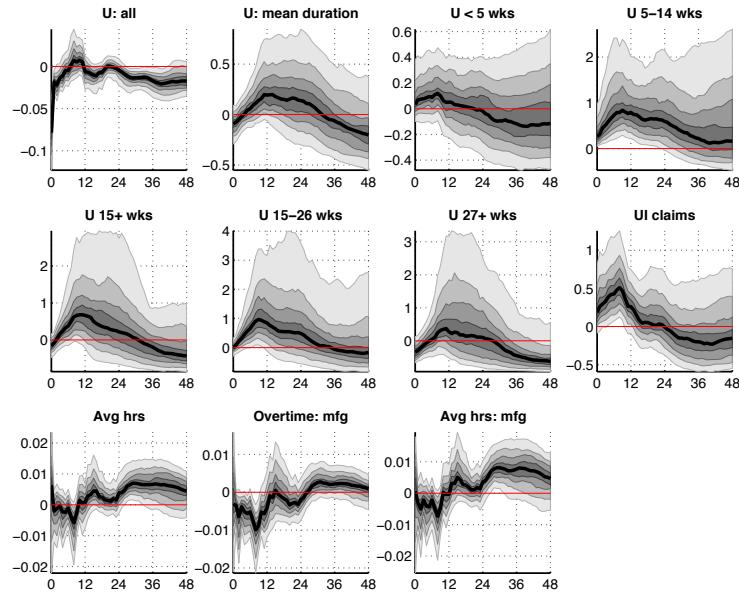
This figure provides plots of posterior IRFs for a selection of many output indicators for the benchmark model.

FIGURE 58.— Price Responses: Benchmark Model



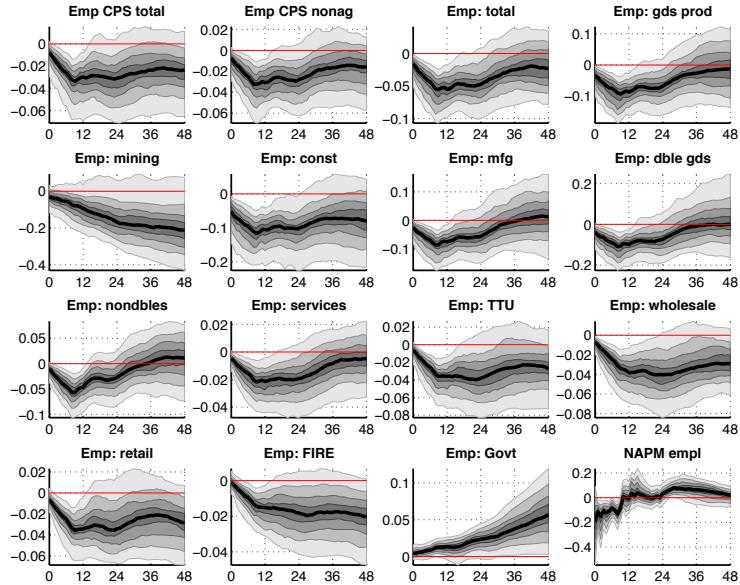
This figure provides plots of posterior IRFs for a selection of many price indicators for the benchmark model.

FIGURE 59.— **Unemployment Responses: Benchmark Model**
for the benchmark model.



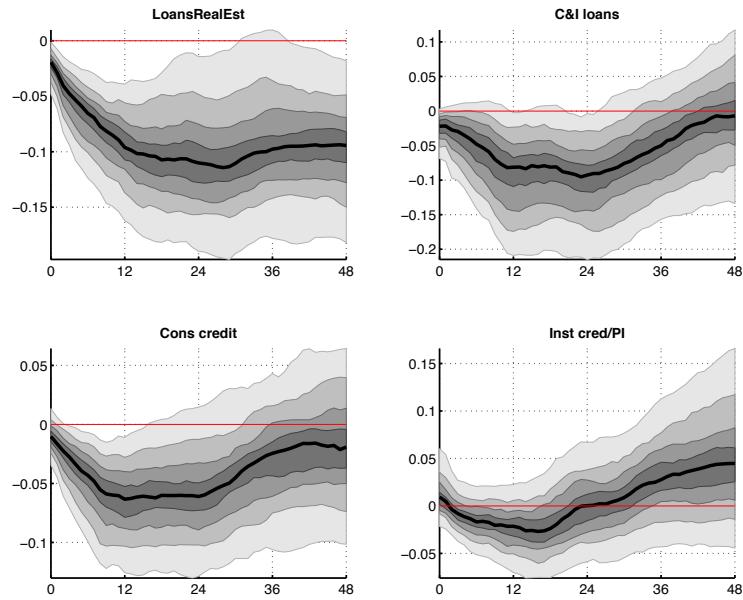
This figure provides plots of posterior IRFs for a selection of many unemployment indicators

FIGURE 60.— Employment Responses: Benchmark Model



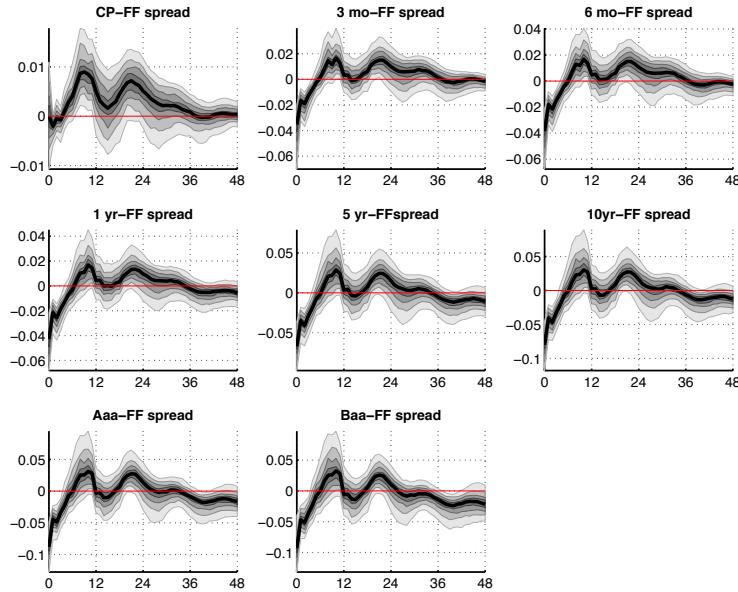
This figure provides plots of posterior IRFs for a selection of many employment indicators for the benchmark model.

FIGURE 61.— Loan Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many loan indicators for the benchmark model.

FIGURE 62.— Spread Responses: Benchmark Model



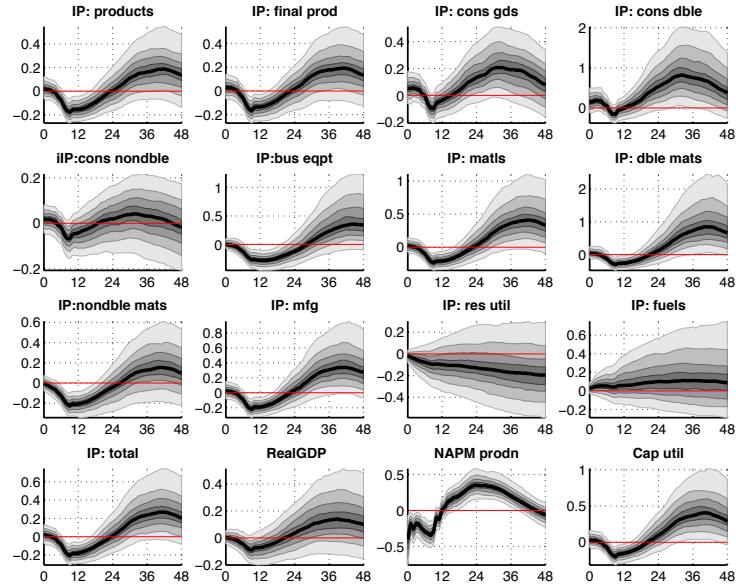
This figure provides plots of posterior IRFs for a selection of many spread indicators for the benchmark model.

B.7. Figures: Variation 7

In this subsection we analyze the data for the post Volcker period covering 1984 : 02 – 2003 : 12⁹ including the recent financial crisis with CPI inflation and the federal funds rate in the core VAR of the FAVAR model.

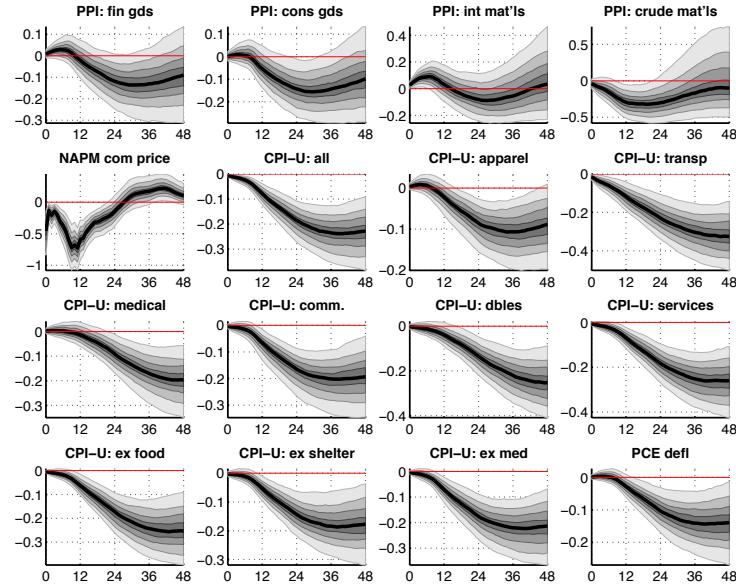
⁹The end period of the sample is consistent with Stock and Watson (2005).

FIGURE 63.— Output Responses: Benchmark Model



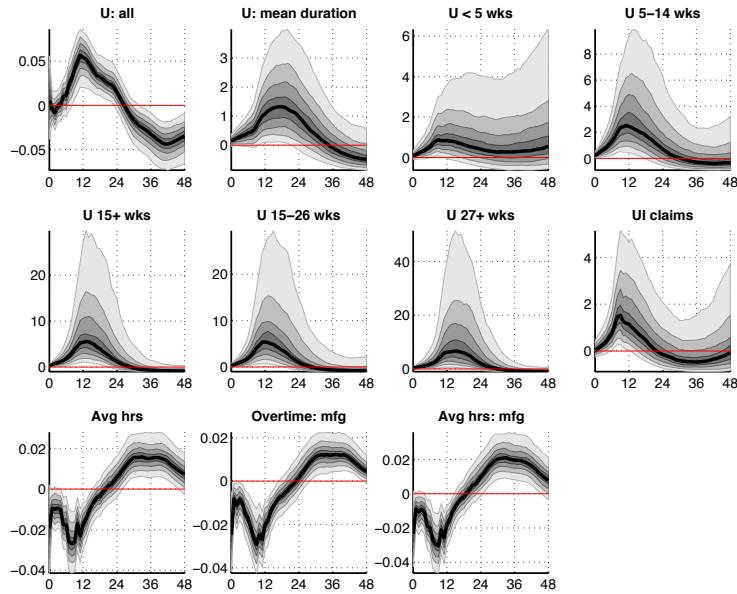
This figure provides plots of posterior IRFs for a selection of many output indicators for the benchmark model.

FIGURE 64.— Price Responses: Benchmark Model



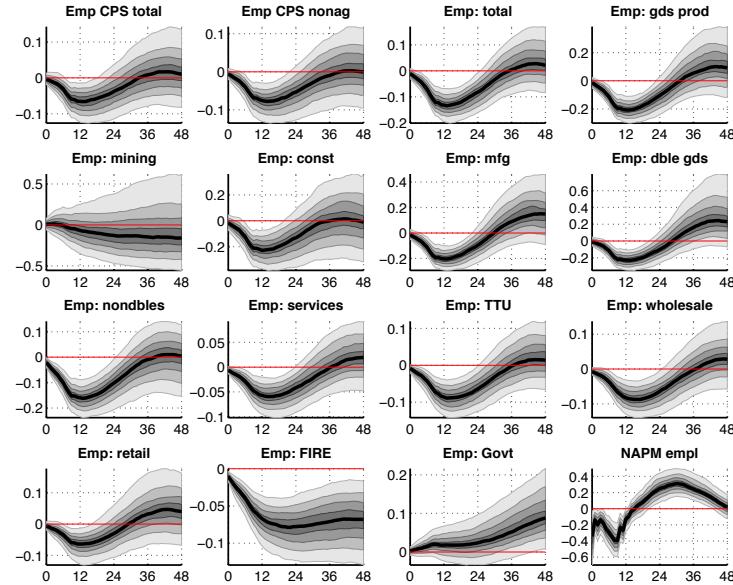
This figure provides plots of posterior IRFs for a selection of many price indicators for the benchmark model.

FIGURE 65.— Unemployment Responses: Benchmark Model
for the benchmark model.



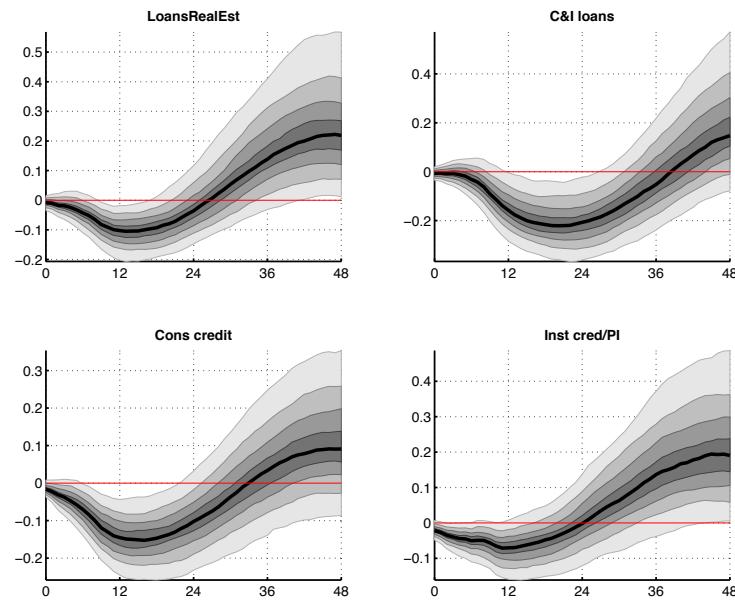
This figure provides plots of posterior IRFs for a selection of many unemployment indicators

FIGURE 66.— Employment Responses: Benchmark Model



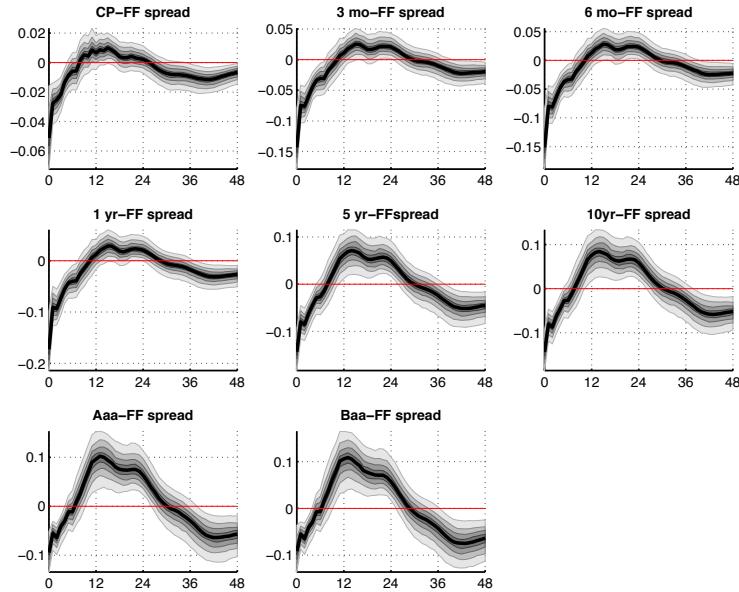
This figure provides plots of posterior IRFs for a selection of many employment indicators for the benchmark model.

FIGURE 67.— Loan Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many loan indicators for the benchmark model.

FIGURE 68.— Spread Responses: Benchmark Model



This figure provides plots of posterior IRFs for a selection of many spread indicators for the benchmark model.