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Proxy structural vector autoregressions, informational sufficiency and the role of monetary policy

Mirela S. Miescu and Haroon Mumtaz

The Department of Economics
Lancaster University Management School
Lancaster LA1 4YX
UK

Proxy structural vector autoregressions, informational sufficiency and the role of monetary policy

Mirela S. Miescu* Haroon Mumtaz†

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Abstract

We show that the contemporaneous and longer horizon impulse responses estimated using small-scale Proxy structural vector autoregressions (SVARs) can be severely biased in the presence of information insufficiency. Instead, we recommend the use of a Proxy Factor Augmented VAR (FAVAR) model that remains robust in the presence of this problem. In an empirical exercise, we demonstrate that this issue has important consequences for the estimated impact of monetary policy shocks in the US. We find that the impulse responses of real activity and prices estimated using a Proxy FAVAR are substantially larger and more persistent than those suggested by a small-scale Proxy SVAR.

JEL Classification*: C36, C38, E52*

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*Lancaster University. email: m.miescu@lancaster.ac.uk

†Queen Mary University of London. email: h.mumtaz@qmul.ac.uk

1 Introduction

The narrative approach to shock identification has become increasingly popular in empirical macroeconomic analyses. This shift is based on the argument that conventional identification strategies that rely on zero or sign restrictions on model parameters may imply assumptions that are unrealistic or hard to justify from a theoretical perspective. The seminal work of Stock and Watson [2012] and Mertens and Ravn [2013] provided a practical method to incorporate narrative information into structural vector autoregressions (SVARs) by proposing the proxy SVAR model. As is well known, proxy SVARs use narrative measures of structural shocks as instruments to estimate the contemporaneous impulse response function (IRF).

A number of applied studies have used proxy SVARs recently. Mertens and Ravn [2013] and Mertens and Ravn [2014] employ proxy SVARs to estimate the effect of tax shocks on the US economy. Gertler and Karadi [2015] derive an instrument for US monetary policy shocks using high frequency data on future rates. This measure is then used in a proxy SVAR to estimate the impact of monetary policy shocks. Piffer and Podstawski [2017] use an instrument for uncertainty shocks derived from gold prices in a proxy SVAR and show that uncertainty shocks are important for business cycle fluctuations in the US.

Most of the studies that apply proxy SVARs use small-scale VAR models with a limited number of endogenous variables.[1] Thus, an implicit assumption made by these studies is that of informational sufficiency. Informational sufficiency requires that the structural shock of interest can be obtained from current and past values of the variables included in the model (Forni and Gambetti [2014]).

In this paper we consider the importance of this assumption for proxy SVARs. Using a series of Monte-Carlo experiments we show that if the data generating process (DGP) is based on a data-rich environment, the proxy SVAR model does

[1] Stock and Watson [2012] is an early exception as they identify shocks using external instruments within a dynamic factor model framework.

not recover the true IRFs for horizons others than the impact responses. Moreover, if we assume that the instrument is correlated not only with the shock of interest but also with variables omitted from the model, the small scale VAR provides biased estimates for both the contemporaneous and the longer horizons effects of the shock. Similarly, if data is generated from a DSGE model that incorporates foresight on the part of agents, a small scale proxy VAR fails to recover the impulse responses even if the true shock is used as an instrument. This is because, foresight in the model results in non-fundamentalness and information insufficiency. In contrast a proxy factor augmented VAR (FAVAR) that incorporates a large information set performs well in both experimental settings.

We provide an empirical application on the effects of monetary policy shocks. After showing that the monetary policy shocks à la Gertler and Karadi [2015] (hereafter GK) fail the informational sufficiency test as per Forni and Gambetti [2014], we revisit the results in Bernanke et al. [2005] (BBE forthwith) and GK in a unified approach. Precisely, we compare the impulse responses for a large number of variables obtained from a proxy FAVAR, with the responses from a proxy SVAR in which the additional variables are included one at a time in the benchmark model, as in GK. The results suggest that the IRFs produced by the small scale proxy SVAR present substantial differences when compared to the ones obtained in a Proxy FAVAR framework. This holds true especially for the variables in the categories of real activity and prices. Compared to the FAVAR model of BBE identified with timing restrictions, the impulse responses from the proxy FAVAR display differences in magnitude.

Our paper is related to a growing number of studies that have considered conditions under which the proxy SVAR delivers unbiased estimates of the impulse response function. Miranda-Agrippino and Ricco [2019] derive the conditions for partial identification with external instruments under the assumption of (partial) invertibility. They discuss the effects of VAR misspecification such as omitted variables and show that impulse responses estimated from such a model can suffer from bias. Relative to their paper, our contribution is to explicitly propose and evaluate a solution (i.e. the proxy FAVAR model) for such problems with the VAR specification. In doing so we generalise the approach of Caldara and Herbst [2019] who show that results regarding the impact of a monetary policy shock depend crucially on the inclusion of proxies for financial conditions in the VAR model. We also provide a formal explanation for the difference in proxy SVAR and proxy FAVAR responses of asset prices to monetary policy shocks detected by Alessi and Kerssenfischer [2019]. Similarly, we provide simulation evidence to back the claim in Bruns [2018] that proxy FAVAR models alleviate problems of information insufficiency. More generally, our paper falls within the recent literature focusing on the informational sufficiency and invertibility in SVAR models, such as Forni and Gambetti [2014], Soccorsi [2016] and Forni et al. [2019].

The remainder of the paper is organized in three sections. Section 2 introduces the concept of informational sufficiency in proxy SVAR models, followed by Monte Carlo experiments. In section 3 we describe the empirical exercise by presenting the empirical model, data and results. Section 4 concludes.

2 Informational sufficiency in Proxy SVAR models.

In this section we discuss the relevance of the informational sufficiency in proxy SVAR models. Building on the recent contributions of Forni et al. [2019], Stock and Watson [2018] and Miranda-Agrippino and Ricco [2019], we describe the sources of bias due to informational deficiency in a misspecified Proxy SVAR framework and the potential remedies offered by a proxy FAVAR model[2]. The results of our

[2] In applied work, informational deficiency is commonly associated with an omitted variables problem. See Kilian, Lutz and Lütkepohl, Helmut [2017], Chapters 16,17

discussion are then validated using a simulation experiment.

2.1 Proxy SVAR models and partial identification

Define a proxy SVAR model:

$$\mathbf{Y}_t = \mathbf{B}\mathbf{X}_t + \mathbf{u}_t \tag{1}$$

where Y_t denotes the matrix $N \times 1$ matrix of endogenous variables, X_t=$[Y_{t-1}, ..., Y_{t-P}, 1]$ is $(NP+1)\times 1$ vector or regressors in each equation and B denotes the $N\times(NP+1)$ matrix of coefficients $B = [B_{1,...,}B_P, c]$. The covariance matrix of the reduced form residuals u_t can be written as $\Sigma = A_0 A_0^{'}$ with A_0 denoting the contemporaneous impact matrix.

The reduced form residuals are related to the underlying structural shocks through the matrix A_0 as per (2):

$$u_t = A_0 \varepsilon_t \tag{2}$$

or:

$$u_t = A_0(1)\varepsilon_{1t} + A_0(2)\varepsilon_{2t} + ... + A_0(N)\varepsilon_{Nt}$$

where $A_0(i)$ denotes the ith column of A_0 with elements $\begin{pmatrix} A_{0,1}(i) \\ A_{0,2}(i) \\ . \\ A_{0,N}(i) \end{pmatrix}$. Denote ε_{1t} the structural shock of interest and $\varepsilon_{-t} = [\varepsilon_{2t}, ..., \varepsilon_{Nt}]$ the remaining shocks. To identify the effects of ε_{1t} the proxy SVAR approach makes use of an instrument m_t which satisfies the relevance and exogeneity conditions:

$$E(\varepsilon_{1t} m_t) = \alpha \neq 0 \text{ (Relevance condition)}$$

$$E(\varepsilon_{-t} m_t) = 0 \text{ (Exogeneity condition)}$$

Note that:

$$cov\left(m_t, u_t\right) = A_0(1)\alpha \rightarrow$$
$$\begin{pmatrix} cov\left(m_t, u_{1t}\right) \\ cov\left(m_t, u_{2t}\right) \\ . \\ cov\left(m_t, u_{Nt}\right) \end{pmatrix} = \begin{pmatrix} A_{0,1}(1) \\ A_{0,2}(1) \\ . \\ A_{0,N}(1) \end{pmatrix} \alpha$$

With an estimate of $cov\left(m_t, u_t\right)$ in hand, the normalised first column of this matrix is given by the ratio of covariances:

$$\begin{pmatrix} 1 \\ \frac{cov(m_t,u_{2t})}{cov(m_t,u_{1t})} \\ . \\ \frac{cov(m_t,u_{Nt})}{cov(m_t,u_{1t})} \end{pmatrix} = \begin{pmatrix} 1 \\ \frac{A_{0,2}(1)}{A_{0,1}(1)} \\ . \\ \frac{A_{0,N}(1)}{A_{0,1}(1)} \end{pmatrix} \tag{3}$$

In a frequentist setting (e.g. Mertens and Ravn [2013]) $cov\left(m_t, u_t\right)$ can be obtained using a regression of m_t on u_t. In a Bayesian setting, the posterior distribution of $cov\left(m_t, u_t\right)$ is estimated along with the posterior estimates of the VAR parameters using MCMC algorithms (see Drautzburg [2016] and Caldara and Herbst [2019] for recent applications of this approach).

2.2 Informational sufficiency in Proxy SVAR models

Following Forni and Gambetti [2014], define the information set X_t^* of the VAR described by (1) as the closed linear space spanned by present and past values of the variables in X_t, i.e. $X_t^* = \overline{span}\left(X_{1t-k}^*, ..., X_{Nt-k}^*, k = 1, ..., \infty\right)$, where

$$\mathbf{X}_t^* = \mathbf{X}_t + \xi_t = \mathbf{f}(\mathbf{L})\varepsilon_t + \xi_t \tag{4}$$

ξ_t being a vector of white noise measurement errors, mutually orthogonal and orthogonal to X^*_{jt-k} , $j = 1, ..., n$ and any k. Consider the theoretical projection equation of Y on X^*_t, i.e:

$$\mathbf{Y}_t = \mathbf{P}(\mathbf{Y}_t | \mathbf{X}^*_{t-1}) + \mathbf{u}_t \tag{5}$$

An estimate of u_t can be obtained by estimating a VAR model. Then the structural shocks can be recovered as a linear combination of u_t. According to Forni and Gambetti [2014], Y_t and the estimated VAR is informationally sufficient for the shocks ε_t if and only if there exists a matrix A_0^{-1} such that $\varepsilon_t = A_0^{-1} u_t$. In other words, the information in the history of Y_t is such that u_t span the structural shocks. As discussed in Forni and Gambetti [2014], sufficiency can be defined with respect to a subset of shocks that is of interest, e.g. ε_{1t} in our context. In this case, u_t is assumed to span the shock of interest. Note that sufficiency is closely related to fundamentalness. The latter concept can be defined by considering $y_t = HX_t$ that is driven by ε^y_t a sub-vector of ε_t. Then ε^y_t is fundamental for y_t and the moving average $y_t = Hf(L)\varepsilon_t = A(L)\varepsilon^y_t$ is fundamental if $\varepsilon^y_t \in \overline{span}\,(y_{1t-k}, ..., y_{1t-k}, k > 0)$. Forni and Gambetti [2014] prove that Y_t is sufficient for ε_t if there exists a linear combination of Y_t that is free of measurement error and has a fundamental representation in ε_t.

As a simple example of the effect of informational insufficiency in proxy SVARs, assume that the data generating process is defined by the following FAVAR:

$$\begin{pmatrix} Y_t \\ f_t \end{pmatrix} = \begin{pmatrix} B & \delta \\ 0 & \rho \end{pmatrix} \begin{pmatrix} X_t \\ x_t \end{pmatrix} + \begin{pmatrix} u_t \\ \nu_t \end{pmatrix} \tag{6}$$

where $\underbrace{f_t}_{K\times 1}$ denotes unobserved factors, $x_t = \left[f'_{t-1}, ..., f'_{t-P}\right]$, δ is a $N \times KP$ matrix of coefficients linking Y_t with lags of f_t, the $K \times KP$ matrix ρ holds the matrix of the autoregressive coefficients describing the dynamics of f_t and $cov \begin{pmatrix} u_t \\ \nu_t \end{pmatrix} =$

$$\begin{pmatrix} \Sigma & 0 \\ 0 & P \end{pmatrix}.$$

Assume that the econometrician erroneously estimates the proxy SVAR in equation 1 instead of the model in equation 6. If f_t is omitted from the VAR model, it is absorbed into the residuals: $\tilde{u}_t = u_t + \delta x_t$. In this case the Proxy SVAR model in equation 1 is misspecified and informationally deficient. If $\delta \neq 0$ the estimates of B and consequently the IRFs are biased as discussed in Forni and Gambetti [2014] and Forni et al. [2019]. In the case of the proxy SVAR in 1, the bias in the contemporaneous impulse response $A_0(1)$ depends on the covariance between x_t and m_t. If $cov(x_t, m_t) = 0$, then $cov(m_t, \tilde{u}_t) = cov(m_t, u_t + \delta x_t) = A_0(1)\alpha$ and the contemporaneous impact of the shock is correctly estimated. However, if $cov(x_t, m_t) \neq 0$, then $cov(m_t, \tilde{u}_t) = cov(m_t, u_t + \delta x_t) = A_0(1)\alpha + \delta cov(m_t, x_t)$ and the resulting estimate of the response is biased.[3]

Stock and Watson [2018]relate information sufficiency to invertibility of the proxy VAR model. Invertibility requires that:

$$Proj\left(Y_t|Y_{t-1}, Y_{t-2}, .., \varepsilon_{t-1}, \varepsilon_{t-2,}..\right) = Proj\left(Y_t|Y_{t-1}, Y_{t-2}, ...\right) \tag{7}$$

That is, adding the true shocks to the econometrician's information set would not improve the VAR forecast if invertibility holds. Therefore, a violation of invertibility might reflect a problem of omitted variables. Miranda-Agrippino and Ricco [2019] consider the case when only a subset of the shocks are invertible. They prove that, in this case, the proxy SVAR can accurately recover impact responses to the shock

[3]In this case, the normalised response is:

$$\begin{pmatrix} 1 \\ \frac{cov(m_t,\tilde{u}_{2t})}{cov(m_t,\tilde{u}_{1t})} \\ . \\ \frac{cov(m_t,\tilde{u}_{Nt})}{cov(m_t,\tilde{u}_{1t})} \end{pmatrix} = \begin{pmatrix} 1 \\ \frac{A_{0,2}(1)+\delta_2 cov(m_t,x_t)}{A_{0,1}(1)+\delta_1 cov(m_t,x_t)} \\ . \\ \frac{A_{0,N}(1)+\delta_N cov(m_t,x_t)}{A_{0,1}(1)+\delta_1 cov(m_t,x_t)} \end{pmatrix}$$

where δ_i denotes the coefficients in the ith row of δ. The estimated elements of $A_0(1)$ are biased with the sign and size of the bias dependent on the ratios $\frac{\delta_j}{\delta_1}$ for $j = 2, ..., N$. Thus, in this simple example, the bias depends on strength of the impact of x_t on the jth endogenous variable relative to the first.

of interest under model misspecification as long as the instrument is not correlated with non-invertible shocks. When this condition is violated, the impact response is biased. The example above (see equation 6) is a simple demonstration of Miranda-Agrippino and Ricco [2019] result.

Forni and Gambetti [2014]and Stock and Watson [2018] recommend the use of FAVAR models as a solution to the problem of information insufficiency. By expanding the VAR information set via factors extracted from a large dataset it becomes more likely the VAR disturbances span the structural shocks of interest. In the simple example above, the addition of factors purges the residuals of the covariance term $cov(m_t, x_t)$ and reduces or eliminates the bias in the estimate of $A_0(1)$. In the section below, we consider the performance of proxy FAVAR models in a series of Monte Carlo experiments.

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2.3 Monte Carlo experiments

To validate our discussion, we proceed by running two Monte Carlo experiments. The first experiment uses a Proxy FAVAR model as DGP. In the second experiment artificial data is generated from a DSGE model that incorporates forsight on the part of agents.

2.3.1 Proxy FAVAR as DGP

Artificial data is generated in accordance with the model described by the subsequent equations:

$$X_{it} = b_i F_t + v_{it} \tag{8}$$

$$F_t = BF_{t-1} + u_t \tag{9}$$

$$\varepsilon_t = A_0^{-1} u_t \tag{10}$$

$$u_t = \gamma_i M_t + \eta_t \tag{11}$$

The experiment has the following characteristics: 500 datasets are generated. Each dataset contains 50 series obtained from a factor model with 5 unobserved factors and 1 observed factor. The VAR coefficients B are calibrated to the estimates of a 1 lag VAR model containing the 5 factors extracted from the FRED-MD database and the 1 year government bond rate for US.

We generate two types of instruments M, one that is uncorrelated with lagged unobserved factors and one that is correlated with two factors. The second scenario is calibrated with the regression coefficients of the GK monetary policy shock on five factors extracted from the FRED-MD dataset. Two of the five coefficients are significant at 99% level and are used for the calibration of the correlated instrument scenario. The contamination of the GK instrument by lagged factors has been attested in Miranda-Agrippino and Ricco [2018] as well.

The sample length is set to 220 and the first 100 observations are discarded to remove the influence of initial conditions.

Figure 1 presents the comparison of the IRFs obtained with the Proxy FAVAR vs a five variables Proxy VAR across 500 datasets. The instrument is the true shock in both models. The results show that even with a perfect instrument, for three out of the five variables, the small scale VAR produces biased impulse responses due to the informational deficiency; at contrary, the Proxy FAVAR performs well for all variables.

In Figure 2 we asses the performance of the two models under the scenario of a contaminated instrument. Precisely, we assume the instrument to be correlated with the lags of two factors, in line with what obtained by regressing GK's monetary

Figure 1: Comparison between impulse responses estimated with a Proxy FAVAR vs a Proxy VAR. Blue lines represent the true IRFs; the red lines reproduce the median and 68% bands across the 500 datasets.

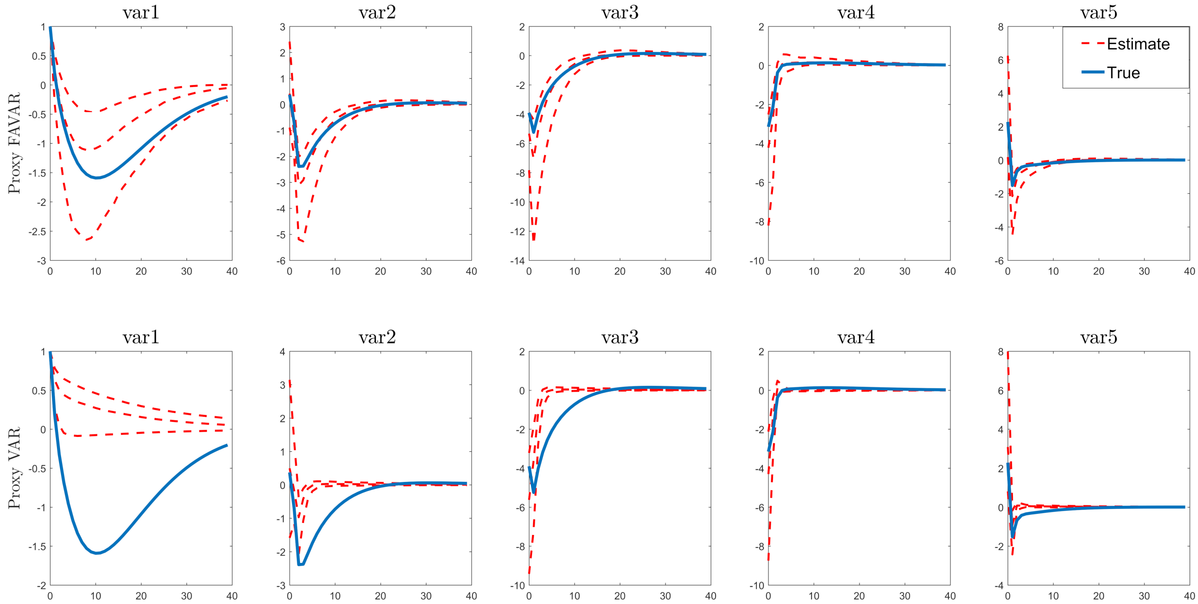
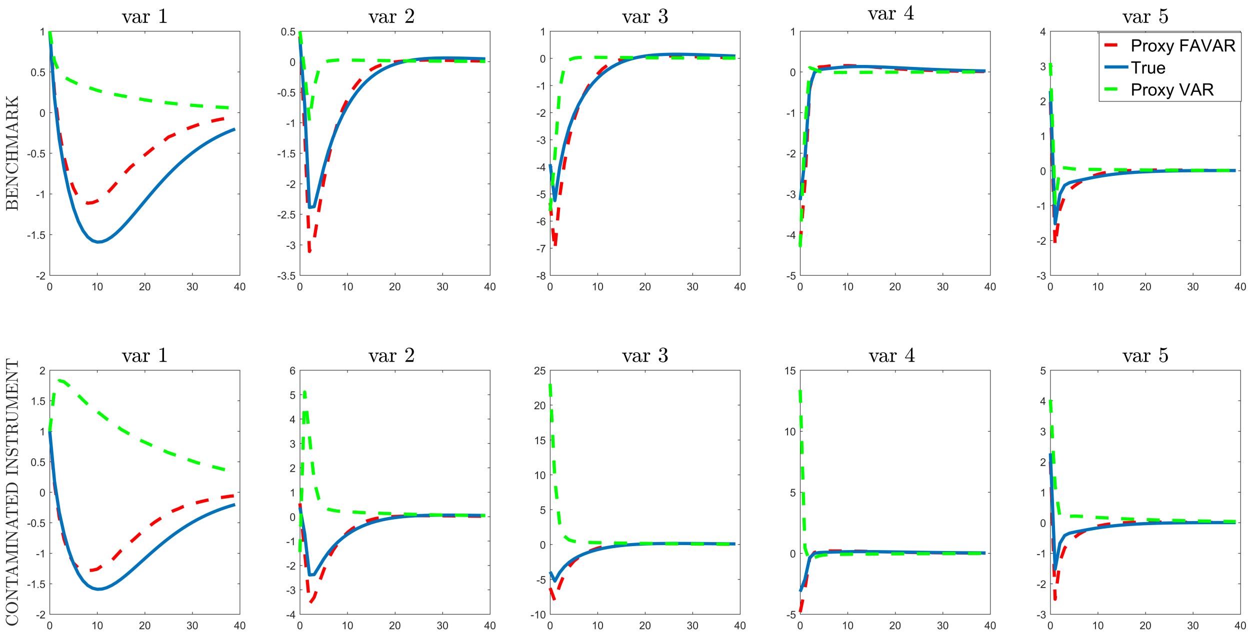


Figure 2: Comparison between impulse responses estimated with a Proxy FAVAR vs a Proxy VAR. Upper side present the uncontaminated instrument scenario; Lower side graphs describe the IRFs with contaminated instrument. Red and green lines represent the medians across 500 datasets of Proxy FAVAR and Proxy VAR estimates, blue lines are the true IRFs.



policy shocks on factors extracted from a large dataset. For ease of exposition, we report medians across the 500 datasets and the true responses. The top side of Figure 2 contains the IRFs in the perfect instrument scenario as in Figure 1, while the bottom side presents the estimates under the contaminated instrument scenario. If with a perfect instrument, the small scale VAR recovers the impact responses quite well, with a contaminated instrument the results become completely unreliable; on the other side, the Proxy FAVAR keeps performing well under this scenario too.

2.3.2 DSGE as DGP

We follow Forni and Gambetti [2014] and consider a model that incorporates anticipation effects in fiscal policy. This real business cycle model is taken fromLeeper et al. [2013] (LWY forthwith). As described in LWY, the model is an extended version of the one presented in Chari et al. [2008] and features distortionary taxes on labour and capital. The government in the model satisfies the following flow budget constraint:

$$G_t + Z_t = \tau_t^L w_t l_t + \tau_t^L r_t^K k_{t-1} \tag{12}$$

where G_t denotes government spending, Z_t are transfers, τ_t^L is the labour tax, τ_t^K is the capital tax, l_t is labour supply, k_t denotes the capital stock, with wages and return on capital denoted by w_t and r_t^K. The evolution of capital tax rates is governed by the following equation:

$$\hat{\tau}_t^K = \rho\hat{\tau}_{t-1}^K + \sum_{j=0}^{J} \theta_j \left[\sigma^K \varepsilon_{t-j}^K + \xi\sigma^L \varepsilon_{t-j}^L\right] \tag{13}$$

where $\varepsilon_{t-j}^L, \varepsilon_{t-j}^K$ represent news about labour and capital taxes, ξ allows for correlation between the taxes and θ are the moving average coefficients. LWY show that different types of information flows regarding taxes can be embedded via this set-up. We focus on a simple case where $J = 8$, $\theta_j = 1$ for $j \neq 1$ and $\theta_1 = 1$. This implies that agents in the model have one quarter perfect foresight. The remaining sections of the model are standard and described in LWY. As discussed in LWY, the presence of foresight can lead to non-fundamental equilibrium representations.

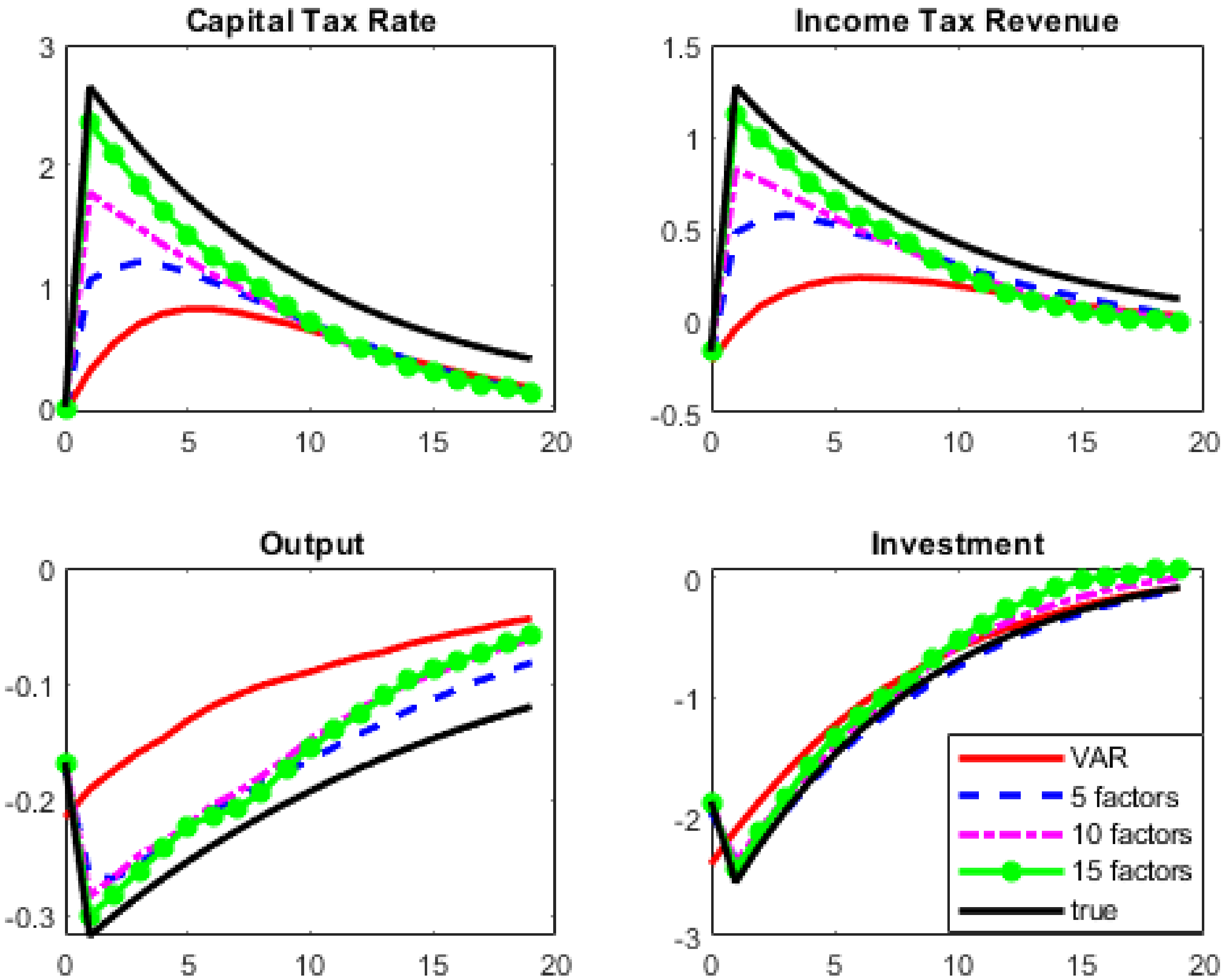
As in LWY we generate artificial data from the model employing their calibration for this purpose. The simulated values for the capital tax rate, income tax rate, investment and output are used to estimate a VAR model employing 300 observations. The shock to capital taxes is identified by using the simulated shock to capital taxes as an instrument. The experiment is repeated 1000 times. Figure 3 compares the true impulse responses to a capital tax shock to the median estimate obtained from the proxy VAR model (lines labelled 'VAR'). The estimated responses are biased at all horizons. The contemporaneous response of output and investment is larger in magnitude than the true response with the VAR model missing the anticipation effect. At the medium horizon, the VAR response of taxes and revenue is severely downward biased.

Following Forni and Gambetti [2014], we then investigate the impact of expanding the information set. We assume that the econometrician has access to a panel of data that is a linear function of the endogenous variables and shocks in the model. In particular, we construct the following variables:

$$z_{it} = \Lambda_i Z_t + \Psi_t \tag{14}$$

where Z_t denotes the model variables not included in the VAR model and all the structural shocks, $\Lambda_i \tilde{} U(0,1)$ and the measurement error $\Psi_t \tilde{} N(0,1)$. We assume that $i = 1, 2, ..., 100$. These 100 variables provide noisy information about the structural shocks that are not spanned by the VAR model and can be thought of as a simulation counterpart of survey variables (see Forni and Gambetti [2014]). We recursively add $5, 10$ and 15 principal components taken from $z_t = [z_{1t}, z_{2t}, ..., z_{100t}]$ to small scale VAR in the first simulation and use the same external instrument to estimate the shock. The median responses from these FAVAR models clearly show

Figure 3: Comparison between impulse responses estimated with a Proxy FAVAR vs a Proxy VAR. Black lines represent the true IRFs; the median across 1000 replications is reported for the Proxy VAR and the Proxy FAVAR .



two results. First, by expanding the information set, the contemporaneous response becomes much closer to the DGP. Second, the response at longer horizons improves considerably in the FAVAR models with the econometrician able to match the shape of the IRFs. Thus FAVARs can be an effective solution to insufficient information when identification is carried out using an external instrument.

3 Revisiting the effects of monetary policy shocks in the US

In this section we illustrate the implications of the informational deficiency in small Proxy SVAR models with an empirical application. We first show that the GK's monetary policy shocks are predicted by the principal components extracted from a large dataset, which makes the small scale VAR results questionable. We then assess the effects of monetary policy shocks on a large set of variables by performing a comparison between the Proxy SVAR model and the Proxy FAVAR model.

3.1 Empirical model, data and estimation

We adopt the non-stationary factor model setting of Barigozzi et al. [2016]. Working in this framework allows us to include data on key variables in log levels and thus offers a direct comparison with the VAR model of GK. Consider a panel of M possibly non-stationary time-series X_t. The factor model is defined as:

$$X_t = c + b\tau + \Lambda F_t + \xi_t \tag{15}$$

where c is an intercept, τ denotes a time-trend, F_t are the R non-stationary factors, Λ is a $M \times R$ matrix of factor loadings and ξ_t are idiosyncratic components that are allowed to $I(1)$ or $I(0)$. As described in Barigozzi et al. [2016], the factors can be consistently estimated using a principal components (PC) estimator. In particular, the factor loadings are estimated via PC analysis of the first differenced data ΔX_t. With these in hand, the factors are estimated as $\hat{F}_t = \hat{\Lambda}' \left(X_t - \hat{c} - \hat{b}\tau \right)$. The Bai and Ng [2002] criteria suggest the presence of 9 to 13 factors. In the benchmark model we set the number of factors to 13.[4]The factor dynamics are given by the VAR:

$$\tilde{Y}_t = \tilde{c} + \sum_{j=1}^{P} \tilde{\beta}_j \tilde{Y}_{t-j} + \tilde{u}_t \tag{16}$$

where $\tilde{Y}_t = \begin{pmatrix} R_t^1 \\ \hat{F}_t \end{pmatrix}$ with R_t^1 denotes the one year government bond yield. The monetary policy shock is identified using an updated version of the measure of monetary policy surprises used in GK[5]. In particular, we use the change in three month federal funds futures around FOMC announcements as our main instrument.

The results from the FAVAR are compared with those from the small scale proxy SVAR used in GK:

$$z_t = c + \sum_{j=1}^{P} \beta_j z_{t-j} + v_t \tag{17}$$

where $z_t = \begin{pmatrix} R_t^1 \\ IP_t \\ CPI_t \\ EBP_t \end{pmatrix}$ where IP, CPI and EBP denote industrial production, consumer price index and the excess bond premium respectively.

We adopt a Bayesian approach to estimation using the algorithm of Caldara and Herbst [2019]. Under this approach the FAVAR and VAR, respectively, are augmented with an equation describing the relationship between the instrument m_t and the structural shock of interest denoted by ε_{1t} :

$$m_t = \beta \varepsilon_{1t} + \sigma v_t, \quad v_t \sim \mathcal{N}(0, 1) \tag{18}$$

[4]The framework of Barigozzi et al. [2016] allows for F_t to be reduced rank with their space spanned by $Q \leq R$ dynamic factors. As we use an identification scheme based on external instruments we follow Alessi and Kerssenfischer [2019] and set $R = Q$.

[5]We are grateful to Refet Gurkaynak for sharing the updated shock series with us.

where $E(v_t \varepsilon_t) = 0$. The instrument is assumed to be relevant ($\beta \neq 0$) and exogenous ($E(m_t \varepsilon_{-t}) = 0$). We assume a non-informative prior for β and σ. The posterior distribution of the parameters of the VAR models in equations 16 and 17 is approximated using a Metropolis within Gibbs algorithm (see Caldara and Herbst [2019] for details). The algorithm uses 100,000 iterations, with a burn-in of 50,000 with every remaining 10th draw retained for inference. The technical appendix presents inefficiency factors that suggest convergence of the algorithm.

The final dataset for the FAVAR model contains 135 macroeconomic and financial series and runs at a monthly frequency from January 1990 to August 2016. We extend the FRED-MD dataset with a measure of excess bond premium, a mortgage rate and dollar exchange rates for Belgium, France, Germany and Italy. [6]

3.2 Results

Before discussing the impulse responses, we perform a test of "structuralness" of a shock as per Forni and Gambetti [2014] in a Bayesian framework. Specifically, we consider two regression models. In the first one, the monetary policy shocks from the small scale VAR are regressed against principal components, one at a time, extracted from FRED-MD. In the second one, the shocks are projected on a constant only. The probability that β_k, the coefficient of regression corresponding to the k^{th} principal component, is equal to zero, is computed by means of Bayes factors.

The results in Figure 4 suggest that the probability that the factors extracted from FRED-MD have no predictive power for the monetary policy shock, is rejected with a probability close to 1 for two out of the fifteen factors. As such, the test points towards the informational deficiency of the small scale Proxy SVAR employed by GK. In contrast, when the shock identified by the FAVAR is used, the probability that $\beta_k = 0$ reaches a minimum at 0.14, thus suggesting that evidence

[6] The data file and the corresponding transformations are available at the following link: https://www.dropbox.com/s/3mxmfdngb2uj12t/data.xlsx?dl=0

for predictability is substantially smaller in this case[7].

Figure 4: Predictability of shocks by lagged factors.

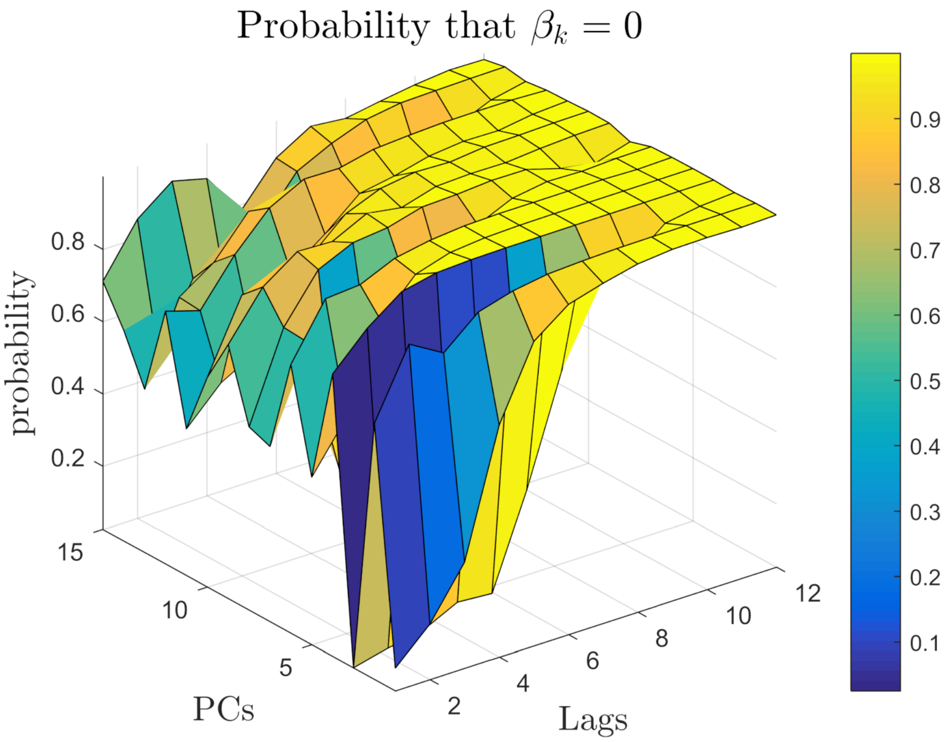


Figure 5 shows the impulse responses for the baseline model. For comparison, in each graph we report the results for both the Proxy FAVAR model and the four variables Proxy SVAR, along with the 68 HPDIs. Since the identification strategy is the same across the two models, the differences in the responses between the two approaches should be mainly attributed to the information deficiency of the small scale VAR, as mentioned in BBE.

The most striking difference in the impulse responses comes from the reaction of the industrial production. Following a contractionary monetary policy shock, the industrial production falls substantially in the factor model case, while it displays a (counter intuitive) negligible and non-significant reaction in the small scale VAR

[7]The full results for predictability of the shock identified using the FAVAR are available on request.

scenario. In both cases, the effects of the monetary policy shock are not associated with evidence of a price puzzle, but a more persistent reaction of the consumer price index is observed in the FAVAR case.

It is interesting to notice that although the small scale VAR setting follows closely GK, the responses are quite different. In particular, GK reports a significant fall in the industrial production and no significant reaction of prices following a monetary tightening. One potential explanation for such difference comes from the fact that in the current application the shock series and the VAR data cover the same range of time, while GK employ a longer sample for the VAR. We next consider the effects of a monetary policy shock on data at a more disaggregated level. The variables are grouped in four categories, namely real activity, prices, interest rates and asset prices. The responses in the small scale VAR are computed as per GK, by adding one variable at a time to the baseline model.

Figures 6 and 7 present the IRFs for the real activity and prices variables. In the small scale model, the reaction of several real activity variables to the contractionary monetary shock is muted or counterintuitive (see for example the responses of Real Personal Income, Real estate loans, Average hourly earnings, Civilian Labor force, New Orders) and the decline in prices is small or absent. At contrary, when the impulse responses are computed with the Proxy FAVAR model, the monetary tightening has a clear contractionary and deflationary effect for most of the variables under consideration; the Average hourly earnings initially increase and then decline, similar to what has been found in BBE.

The IRFs for interest rates are shown in Figure 8. In line with the results presented in Alessi and Kerssenfischer [2019], the responses of most of the spread variables display a considerably lower magnitude for the contemporaneous impact in the small scale model.

We next turn our attention to the asset prices variables. In particular, we detect relevant differences across the two models in the behavior of the real exchange rates (see Figure 9). This is far from surprising considering that a well established anomaly in the empirical open economy literature is the so-called "exchange rate puzzle". As reported in Grilli and Roubini [1995] and Eichenbaum and Evans [1995], the "exchange rate puzzle" is associated to an expansionary/contractionary monetary shock that leads to a persistent depreciation/appreciation of the currency rather than a persistent appreciation/depreciation after the initial depreciation/appreciation, as predicted by Dornbusch's "overshooting theory".

Along these lines, our findings are in agreement with the contributions of Mumtaz and Surico [2009], Forni and Gambetti [2010] and Alessi and Kerssenfischer [2019] who attribute such exchange rate anomaly to the informational deficiency of the small scale VAR model. Consequently, the results we obtained with the Proxy FAVAR model are in accordance with the Dornbusch's "overshooting theory" while the responses of the real exchange rates in the small scale model are still hard to square with the basic theory predictions.

Finally, there might be concerns that the GK's monetary policy shocks are contaminated by central bank information shocks, as argued by Jarocinski and Karadi [2018]. To address this issue, we compute a series of "pure" monetary policy shocks by removing the FOMC announcements that generate positive co-movement between the three month federal funds future and the S&P 500. Overall, the effects of the "pure" monetary policy shock are similar to the baseline (see Figure 10).To sum up, our findings show that the identification strategy is a necessary but not sufficient condition to recover the effects of monetary policy shocks, reason why the small scale Proxy SVAR produces results at odds with the theory. If in change, a valid identification strategy is complemented with a large information set, as is the case in the Proxy FAVAR scenario, the impulse responses of a large set of variables are in line with the theory and there is no evidence of "price and delayed overshooting" puzzles.

Figure 5: Baseline model. Comparison between IRFs obtained with the Proxy FAVAR (red line) vs the Proxy SVAR (blue line). Bands represent 68 HPDI.

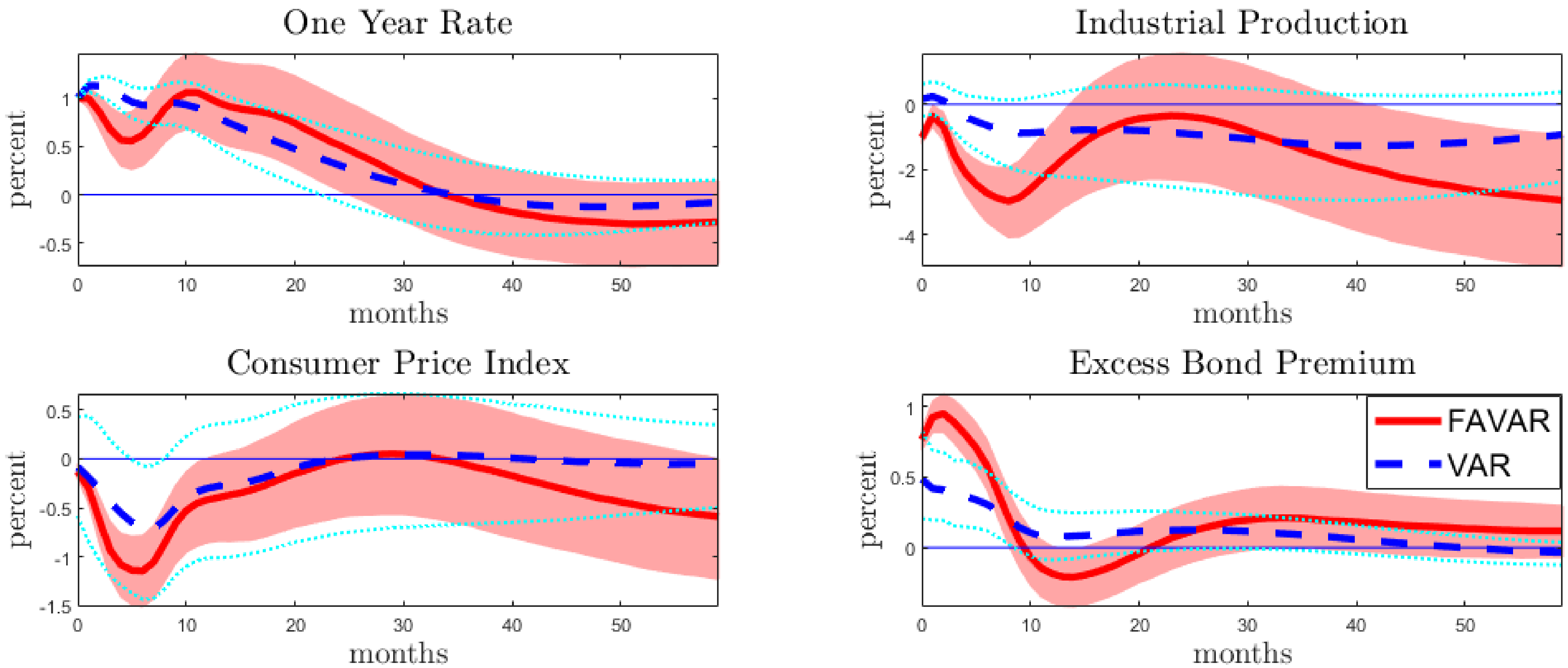


Figure 6: Real activity variables. The small scale Proxy SVAR responses are obtained including one additional variable at a time to the baseline model. Bands represent 68 HPDI.

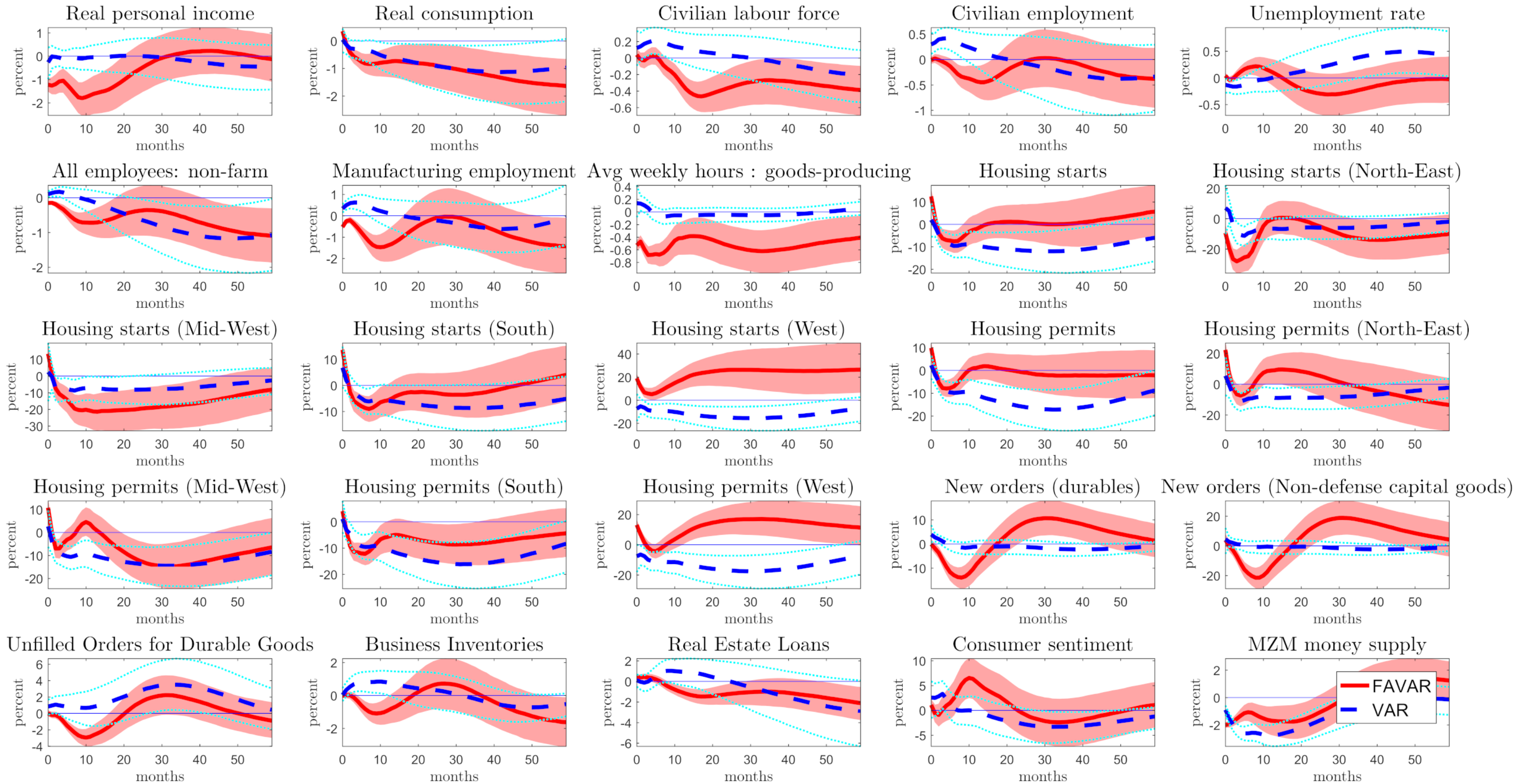


Figure 7: Prices variables. The small scale Proxy SVAR responses are obtained including one additional variable at a time to the baseline model. Bands represent 68 HPDI.

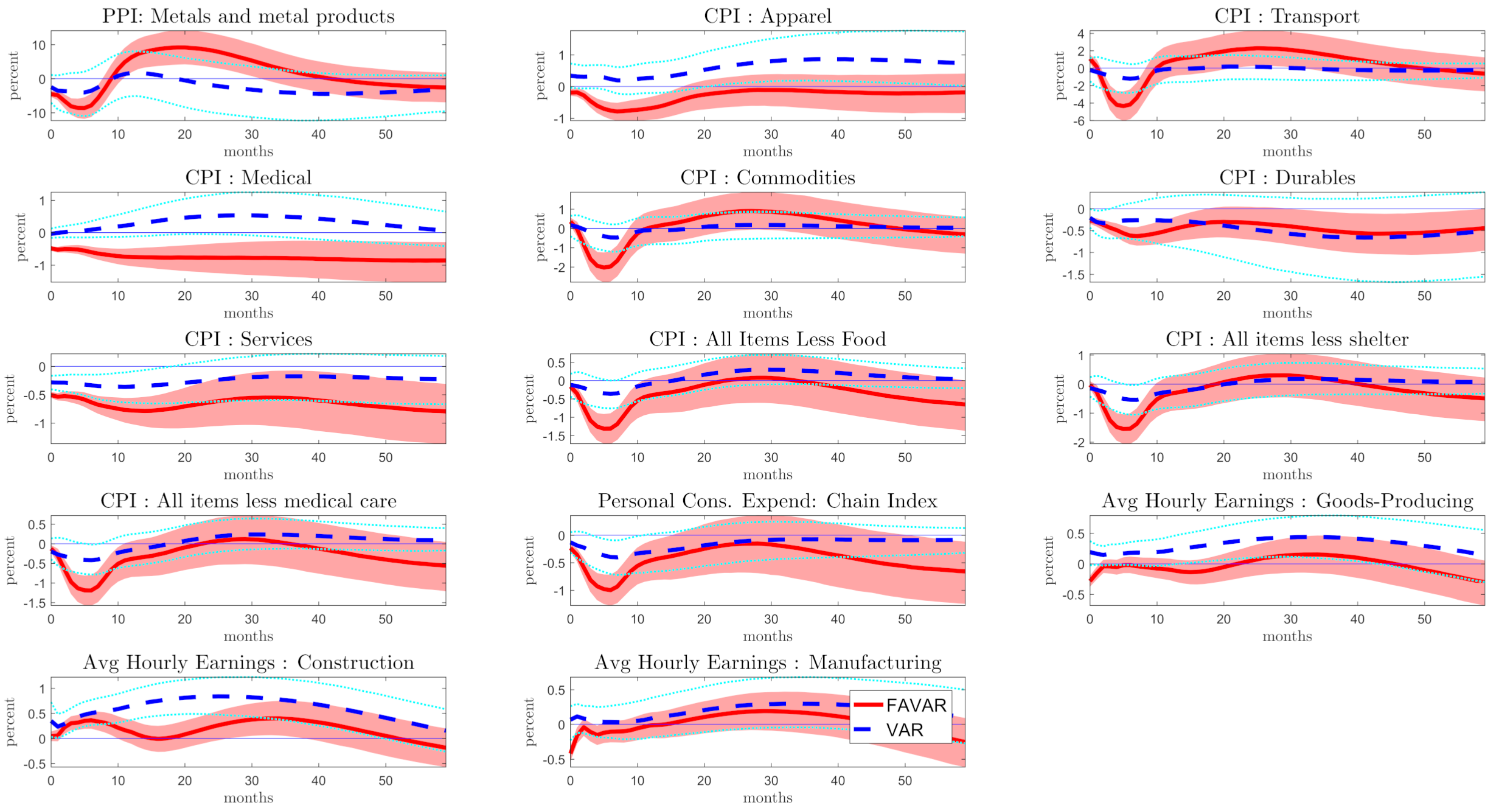


Figure 8: Interest rates. The small scale Proxy SVAR responses are obtained including one additional variable at a time to the baseline model. Bands represent 68 HPDI.

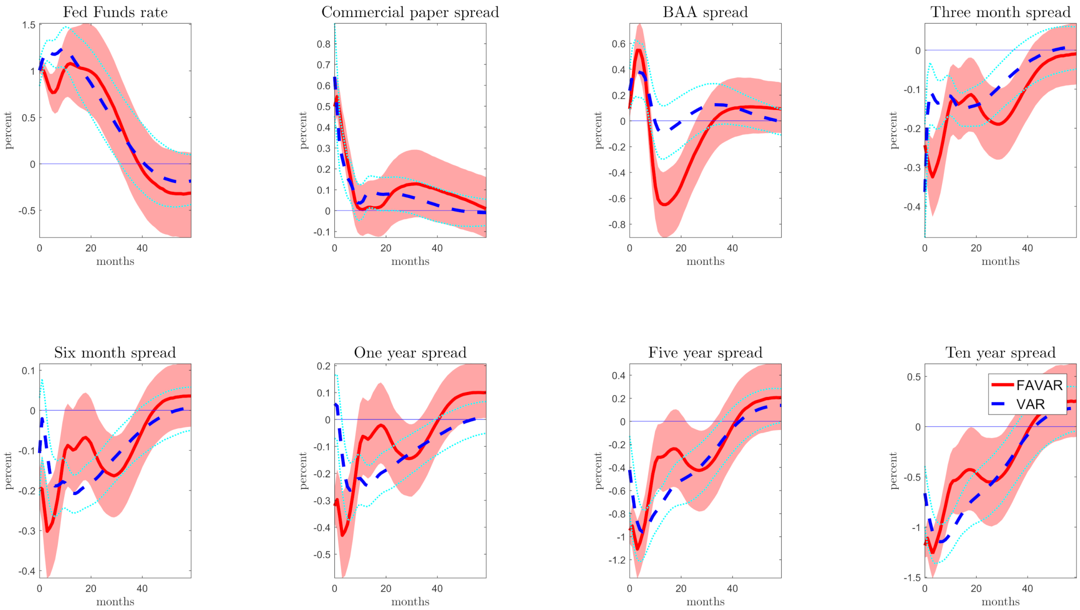


Figure 9: Asset prices. The small scale Proxy SVAR responses are obtained including one additional variable at a time to the baseline model. Bands represent 68 HPDI.

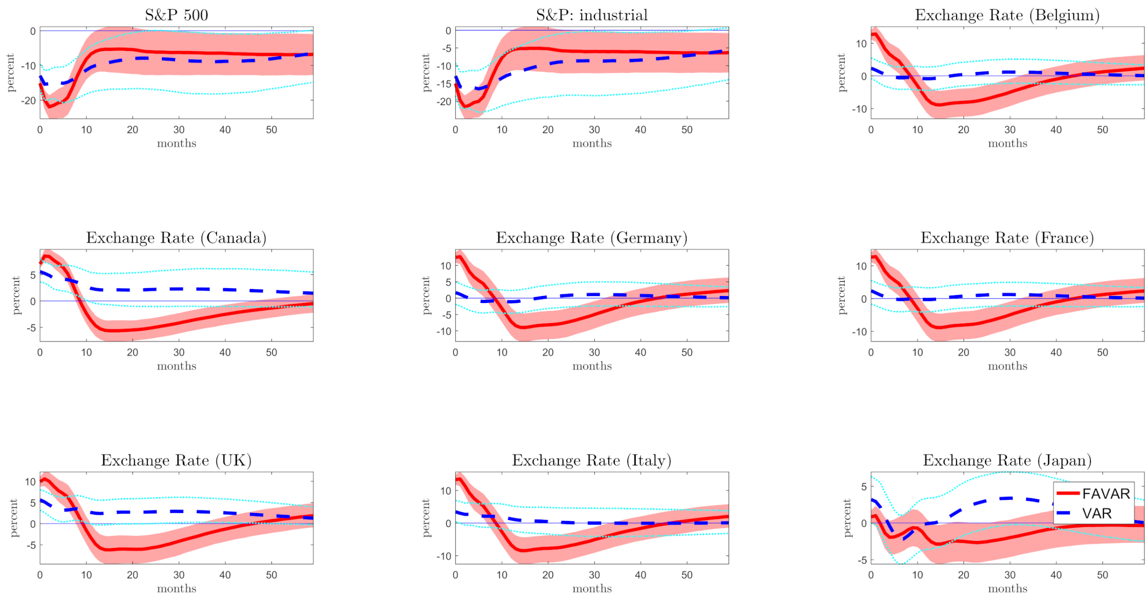
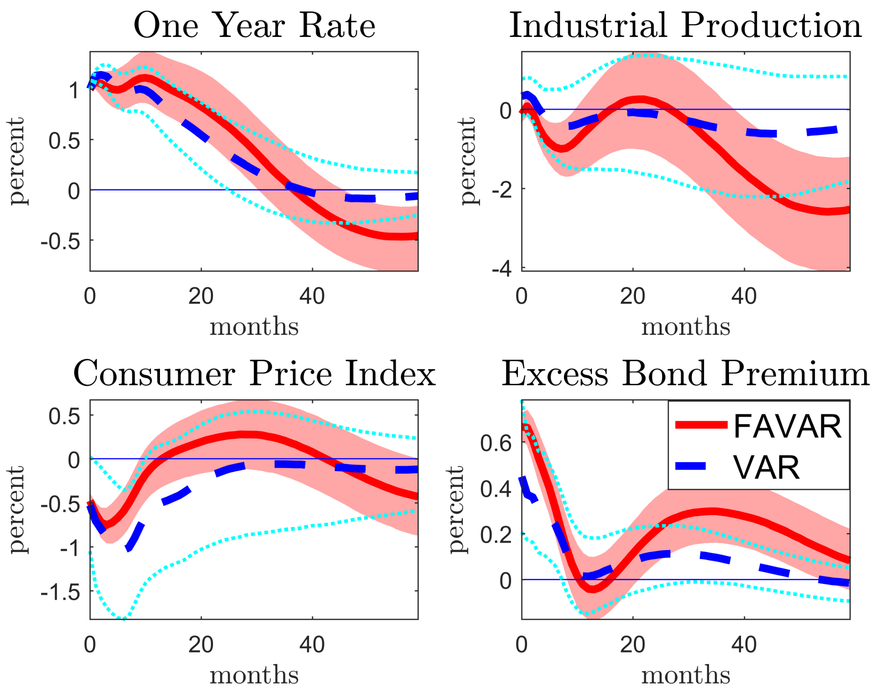


Figure 10: Benchmark scenario with "pure" monetary policy shock.



4 Conclusions

We propose the use of a Proxy FAVAR model in which an instrumental variable identification is complemented with a large information set. Using Monte Carlo experiments, we show that a small scale Proxy SVAR model provides unreliable results if relevant variables are omitted from the model; on the other hand, in a FAVAR framework the informational deficiency is less of a problem by construction.

In an empirical exercise we revisit the effects of monetary policy shocks in US through the lenses of the Proxy FAVAR model. We show that despite a strong identification strategy, the small scale VAR model employed by GK has informational problems and produces results that are often puzzling. At contrary, the impulse responses obtained with the Proxy FAVAR model are in line with basic theory predictions and are purged from the "price and delayed overshooting" puzzles.

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