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Sector-Specific Supply and Demand Shocks: Joint Identification

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ABSTRACT

This article proposes a technique for computing sign restrictions in large-scale models. The technique is applied to a Bayesian vector autoregression (BVAR) model with 16 industries (16 growth rates, 16 inflations), and the interest rate. The results demonstrate that the suggested technique can yield different implications for the density of relevant measures compared to the conventional random draw approach. Shocks identification is more accurate for suggested approach in experiments with simulated from DSGE model data. The usage of industry specific data and identification of demand and supply shock have large influence on identification of MP-shocks. It reveals important elements of transmission mechanics of monetary policy including differences in magnitude and shape of responses on MP-shocks, differences in historical decomposition, differences in importance of demand and supply shocks for interest rates dynamic. Variance decomposition shows decrease of relative importance of its own shocks to industries with switching from short-run to long-run decomposition. There are some similarities with input-output tables and some differences those open questions for future researches.

Keywords: sign-restriction, BVAR, VAR, SVAR.

JEL codes: C32, C51, E32, E52.

1. INTRODUCTION

VAR-type models play a crucial role in macroeconomic analysis, often employed for forecasting and nowcasting purposes [Banbura, Giannone, and Reichlin (2010); Bloor and Troy, (2010); Koop, (2013); Cimadomo et al.,(2022)]. Large-scale Bayesian vector autoregression (BVAR) models have been found to outperform factor-augmented VAR (FAVAR) models in terms of forecasting accuracy [Banbura, Giannone, and Reichlin, (2010); Koop, (2013)]. However, an essential aspect of economic analysis lies in the utilization of structural shocks, which remains a challenge, particularly in large-scale models. The primary approach in this context is the application of Cholesky ordering, as observed in studies by Bloor and Troy (2010) and Banbura, Giannone, and Reichlin (2010). Koop (2013) does not use shocks decomposition. Cimadomo et al. (2022) employ a generalized impulse response that disregards correlations between variables' forecasting errors.

Identification of structural shocks constitutes a separate issue, with three main groups of approaches: zero restrictions, instrumental variables (often derived from high-frequency data), and sign restrictions. Although this classification is not perfect, some techniques are challenging to categorize within these groups, such as the DSGE-VAR approach with an equal number of observables and shocks [Del Negro and Schorfheide, (2004)].

The first approach involves imposing linear or zero restrictions on impulse responses, which is relatively straightforward to implement but may pose challenges in terms of defining a sufficient number of restrictions, especially for large-scale models. The Cholesky ordering technique represents a specific case within this approach. For a detailed exposition of the corresponding theory and computational details, refer to Rubio-Ramírez et al. (2010).

The second approach utilizes instrumental variables, typically derived from high-frequency data, that should be correlated with the shock of interest and uncorrelated with other shocks [Gertler and Karadi, (2015); Tishin, (2019)]. This approach proves accurate when researchers can identify or construct suitable instruments. However, this can be a complex problem, and in certain models or for specific shocks of interest, it may be impossible to find such instruments.

The third approach, which offers greater intuition, involves imposing sign restrictions on impulse responses [Uhlig, (2005); Rubio-Ramirez et al., (2010)]. Different forms of sign restrictions exist, including narrative sign restrictions [Antolin-Diaz and Rubio-Ramirez, (2018)], which apply restrictions to historical decompositions instead of impulse response functions (IRFs). While these restrictions may be easier to formulate theoretically, their computational implementation is similar to other sign restriction techniques. Sign restrictions are typically employed within a Bayesian framework, but they can also be interpreted from a frequentist perspective [Granziera et al. (2019)], although this interpretation is not as straightforward as in other types of structural identification methods, and it can affect the construction of confidence intervals.

The choice of prior distribution in Bayesian approaches also influences the identification of structural shocks [Baumeister and Hamilton, (2015)]. The use of a uniform prior distribution for rotation matrices can lead to informative prior distributions for IRFs and other properties, with this effect being less pronounced in larger models. This highlights the limitation of relying heavily on uniform "non-informative" priors [Baumeister and Hamilton, (2019)].

However, the main problem related to sign restrictions is computational one. The main technique is based on random draws [Uhlig (2005); RUBIO-RAMIREZ et al (2010)]. It means that restrictions should hold for significant share of draws. So, number of restrictions should be relatively small that means small models. Only 6-7 variables are usually used at VAR models with sign restrictions due to fast growth of computational costs [Chan (2022)].

Some authors make a trick for usage of sign restriction. They identify shocks separately that means for each shock hold only restriction related to it without imposing any restriction to other shocks [Uhlig (2005); Chan (2022)]. The disadvantage of it can be illustrated by the example of model with 2 variables. If you have restrictions [+,-;-,+] and Cholesky decomposition of covariance is [1,x;0,1] with x>0 than it is impossible that all restrictions holds. However it would be possible to receive some draws where holds [+,*;-,*] or [*,-;*,+].

The initial version of penalty function approach has some undesired properties that make it almost impossible to implement without tricks. It is suggested to use linear-restrictions and simplex method [Uhlig (2005); Kilian and Lutkepohl (2017); Mountford and Uhlig (2009); Beaudry et al.(2011)]. It means problem with quadratic restriction (that rotation matrix is used). Additional problem is form of penalty function. It is suggested that undesired sign of some restriction can be compensated by large desired values related to other restriction. Such property (with naming it as additional restriction) produces critics of this approach [Kilian and Lutkepohl (2017)].

One of the key types of decomposition of shocks is dividing of them into demand and supply shocks (+ monetary policy, or other specific shocks). Such decomposition is very intuitive for any market or aggregate level. However, market includes multiple sectors-industries. It opens question about influence of demand and supply shocks from one sector to another. Influence of monetary policy shocks is different across sectors. How different would be identification of MP-shock separately vs joint identification?

The aim of the paper is to recognize influence of disaggregated data on shocks identification. It requires technique that is able to identify demand and supply shocks for sector-specific data (within large BVAR model). The next goal is comparison of suggested technique with conventional one. The last goal is investigation of influence of disaggregated data on monetary policy transmission mechanics and influence of sector-specific shocks.

Thus, the paper should expand sign-restriction identification techniques for large-scale BVAR models. The second contribution is related to monetary policy shock transmission that is usually investigated on aggregated level without sector-specific view as it done by [Uhlig (2005); Chan (2022)]. The last contribution (that is quite small) is related cross industry dependence that is usually investigated with input-output tables approach.

The rest of the paper is organized as follows. The next section describes details of BVAR models and suggested identification techniques with sign restriction (that is based on penalty function optimization with analytical derivatives). The data and results are described after that. It includes details related to computation speed, accuracy, identification of shocks, influence of MP-shocks for industries and sector specific shocks for interest rates, historical decomposition and variance decomposition. The last section is conclusion.

2. MODEL AND IDENTIFICATION TECHNIQUE

The BVAR

BVAR model can use different prior distributions. We use inverse Wishart conjugated Normal. This combination have nice property that posterior has the same distribution (with different parameters) as prior. It means that MCMC is not needed and marginal likelihood may be computed analytically. It makes possible estimation of hyper-parameters. The type of prior is Minnesota type. There are alternative priors that have advantages for much larger models [Korobilis and Pettenuzzo (2019)]. Alternative priors do not restrict usage of suggested approach for sign restrictions, but the more conventional prior would be used.

The conventional equations for this type of BVAR are below. Equation (1) is VAR-presentation for vector of endogenous variables y_t, vector of exogenous variables z_t (usually only constant) and vector of exogenous shocks ε_t. Prior for shocks covariance matrix is inverse Wishart distribution: $cov(\varepsilon_t)=\Omega \sim IW(S_0, n_0)$. Prior for matrix of parameters A is normal distribution: $vec(B) \sim N(vec(EB_0), kron(VB_0;\Omega))$. Equations (2)-(5) shows how parameters of posterior distribution depends on priors and data $Y=[y_1,\ldots,y_T]$, $X=[x_1,\ldots,x_T]$.

$$y_t = \left(\sum_{i=1}^{P} A_i y_{t-i}\right) + A_0 z_t + \varepsilon_t = B x_t + \varepsilon_t \quad (1)$$

$$VB_1 = \left((VB_0)^{-1} + XX'\right)^{-1} \quad (2)$$

$$EB_1 = \left(EB_0 (VB_0)^{-1} + YX'\right)^{-1} VB_1 \quad (3)$$

$$\mathrm{n}_1 = \mathrm{n}_0 + T \tag{4}$$

$$\mathrm{S}_1 = \mathrm{S}_0 + (\mathrm{EB}_1 - \mathrm{EB}_0)(\mathrm{VB}_0)^{-1}(\mathrm{EB}_1 - \mathrm{EB}_0)' + (Y - \mathrm{EB}_1 X)(Y - \mathrm{EB}_1 X)' \tag{5}$$

Equation (6) shows how marginal likelihood looks like. It allows to estimate hyper-parameters by maximization of marginal likelihood.

$$\mathrm{ML} = \left(\prod_{i=1}^{n_y} \frac{\gamma(\mathrm{n}_1/2 + (1-\mathrm{i})/2)}{\gamma(\mathrm{n}_0/2 + (1-\mathrm{i})/2)} \right) \frac{|S_0|^{n_0/2} |VB_1|^{n_y/2}}{|S_1|^{n_1/2} |VB_0|^{n_y/2} \pi^{Tn_y/2}} \tag{6}$$

The choice of prior parameters is an important consideration. Two approaches can be used. The fully correct approach suggests no prior information is used, while the simplified approach employs the estimation of AR(1) models to formulate the prior. For Minnesota-type priors, four hyperparameters (ψ, ψ_c, ψ_p, n_0) are suggested. In the fully correct approach, EB_0 is set to zero, and the expected covariance Ω is an identity matrix multiplied by 0.01^2 (all variables are log-growth rates). Equation (7) demonstrates how to compute the mean of the inverse Wishart distribution. The matrix VB_0 is diagonal, with elements vb_{ijl} related to dependent variable i and "regressor" j with lag l (8). If the "regressor" is exogenous (constant), the corresponding element would be $\psi\psi_c$. It is worth noting that some papers employ slightly different formulas, often using the ratio of variances, due to different types of BVAR models. For this BVAR type, the coefficient variance is the Kronecker product, implying the multiplication of shocks' variance to achieve similar prior moments.

$$\mathrm{E}_0\Omega = S_0/(\mathrm{n}_0 - \mathrm{n}_\mathrm{Y} - 1) \tag{7}$$

$$vb_{i,j,l} = \frac{\psi}{\{\Omega\}_{i,i} l^{\psi_p}} \tag{8}$$

In the simplified approach, AR(1) estimations are used to construct EB_0, setting the expected covariance matrix ($E_0\Omega$) equal to the estimated covariance matrix of the errors in the AR(1) models. All other aspects remain the same.

Given the relatively large size of the model and the high persistence of one variable (the shadow interest rate), there is a probability of generating explosive processes. To mitigate this, draws from the posterior distribution that produce explosive trajectories (eigenvalues larger than 1) are discarded. This approach is equivalent to changing the prior distribution, but dropping these trajectories is performed after computing the posterior. A minor drawback of this approach is that it slightly affects the computation of the marginal likelihood, as the marginal likelihood of the model without dropping explosive trajectories differs slightly from the true marginal likelihood.

Restrictions: signs and other

In the conventional approach for sign restrictions identification, a random draw method is commonly used [Uhlig, (2005); Rubio-Ramirez et al., (2010)]. This approach involves generating a new random rotation matrix until all sign restrictions are satisfied. Alternatively, some papers focus on checking restrictions related to specific shocks rather than all restrictions simultaneously.

However, as the size of the model increases, the number of restrictions also increases, and the probability of accepted draws approaches zero. Changing the signs of shocks, as done in Rubio-Ramirez et al. (2010), does not address this issue.

To overcome this problem, an alternative penalty approach, suggested by Uhlig (2005), can be employed. The penalty function is modified, and analytical derivatives are used to increase computation speed. The algorithm minimizes the penalty function while enforcing the restriction on the covariance matrix. An alternative version without optimization and restrictions was also examined, but the parameterization of the rotation matrix, similar to Uhlig (2005), performed poorly in large-scale cases.

The main question pertains to the appropriate restrictions for large industrial BVAR models. The idea is based on the definition of shocks. For this model, there are supply and demand shocks related to each industry. A positive demand shock leads to growth in volume and prices in the corresponding industry, while a supply shock leads to volume growth and a decrease in prices. A relatively small number of crucial restrictions are derived from this concept. The remaining group of restrictions ensures that shocks related to an industry have a larger absolute influence on that industry compared to any other industry. Monetary policy shock leads to decrease of outputs and prices and growth of interest rates.

There are also restrictions on other variables in the model. The monetary policy shock should have a reasonable effect, such as a positive impact on interest rates and negative impacts on each output and inflation. The penalty function uses squared undesired responses. For instance, if x represents the response of output to a demand shock, the corresponding penalty function term is x^2 $(x < 0)$. This formulation simplifies the analytical computation of derivatives. Additionally, there are constants denoting the relative importance of the restrictions. The demand, supply, and monetary policy shock restrictions are assigned higher importance by multiplying their errors by 10^5, while the cross-sector restrictions are less important and are multiplied by 1.

Thus, suggested approach is minimization of penalty function (9) by rotation matrix R that is written as restriction (10). Equation (11) shows relation between iid structural shocks u_t and initial shocks ε_t with covariance matrix Ω. Matrix C is computed by Cholesky decomposition of Ω. Rows w_i are coefficients that allow to compute desired sign restriction. For example raw of zeros with 10^5 corresponding to impulse response of interest rate to monetary policy shock produces summand corresponding to positive response of interest rate to MP-shock.

$$penalty = \sum_i \left(w_i vec(CR)\right)^2 \left(w_i vec(CR) < 0\right) \rightarrow \min \quad (9)$$

$$RR' = I \quad (10)$$

$$CRu_t = \varepsilon_t \quad (11)$$

An interior-point algorithm with analytical derivatives of restrictions and the penalty function is used for optimization. The fmincon() function in the optimization toolbox for Matlab, which employs an interior-point algorithm, is utilized. The initial point for optimization is random, similar to Rubio-Ramirez et al. (2010). However, instead of changing the signs of shocks to improve the fit, the optimization procedure is directly initiated. This is important due to the local nature of the optimization problem, as the penalty function may have multiple local modes. Even small problems can exhibit similar local convergence issues described in Uhlig (2005).

The suggested approach should be much faster than conventional one especially for large models. The intuition for it is following. Each additional sign restriction leads to dividing by 2 probability of successful draw when conventional approach is used. It may be slightly slower exponential growth (due to nonzero correlation of restriction signs), but it is very fast growth. Suggested optimization approach should have polynomial growth rate of computation costs depending on model dimension (it should be almost insensitive to number of restrictions). It happens due to smooth penalty function and gradient that shows direction for improving of penalty function. Thus, it is natural to expect that optimization approach that use additional information about penalty function would be faster than random draw approach if model size is large enough. It may lose only for small scale models due to computational costs of optimization algorithm and convergence to local modes (with bad value of penalty function).

Another crucial detail pertains to the prior distribution. The conventional approach suggests a uniform distribution of rotation angles, which implies a non-uniform prior distribution for impulse response functions (IRFs) and other measures [Baumeister and Hamilton, (2015)]. The suggested approach divides the space into areas, transferring the density of "bad" areas to the nearest local mode. This means that sign restrictions not only influence the size of the space where they hold but also the probabilities of different areas. However, if the restrictions hold relatively rarely, this transfer of density becomes less important due to smaller variance across trajectories where the restrictions are satisfied. Furthermore, it is challenging to predict the convergence area of a particular local mode. In other words, it is difficult to argue that such a deviation from a uniform angle distribution (where the restrictions hold) provides more informative priors for IRFs. Nevertheless, this factor may impact the results, especially if areas where restrictions holds are large.

3. THE DATA AND RESULTS

The data

What can we see and check? What would be difference in historical decomposition due to usage of industry level data? Which industry has larger response on MP-shock and which is lower? Which industry shock has larger influence on interest rate?

The first exercise would be done on US data. We use Chain-Type Quantity Indexes for Gross Output by Industry and Chain-Type Price Indexes for Gross Output by Industry from 2005q1 till 2019q4. It gives industry related growth and inflation rates. We have 2 levels of aggregation: all industries, large industries (16 industries). And shadow rate is used as interest rate [Wu and Xia (2016)].

Computation speed and related details

The model is large with usage of industry-level data. However, BVAR are good approach even for large scale models [Marta Banbura, Domenico Giannone and Lucrezia Reichlin (2008)]. The simplified approach is used for choosing priors for all and large industries. Additional tests are made for small industries case (40 industries).The fully correct approach is used for small industries due to number of endogenous variables that is greater than number of periods (that leads to no positive defined prior for shocks covariance matrix). However, small industries case produces explosive trajectories too often, so it is used only for computation speed tests.

Random draws is very inefficient for large industries case (10^6 draws computed with choosing of shocks signs such that diagonal restrictions holds). It takes 3.875 minutes and best 5 values of penalty function are 1.22, 1.34, 1.39, 1.44, 1.49. It is illustration that conventional approach is inappropriate for large scale models.

The suggested approach takes 3.85 minutes (median) for optimization (20% quintile is 2.93 minutes, 80% quintile is 5.64 minutes). Additional test was done with small industries (40 industries). The numbers increases to 100.6 minutes for median (82.7 and 117.1 minutes for 20% and 80% quintiles). However, draws of BVAR parameters are explosive, so it is used for speed computing only. Thus, 2.45 times increase of model size leads to 23.4 times slower computations. Nether the less, such values looks reasonable and makes possible to implement shock identification technique for model of such size.

The penalty function for large industries are $6.50*10^{-7}$, $4.13*10^{-7}$, $2.50*10^{-7}$ (80%, 50%, 20% quintiles). The worst value is $2.80*10^{-5}$. If we run algorithm without restriction (with rotation matrix parameterization) then it takes about 2.66 min for optimization and gives value of penalty function equal to 19.14. It means that optimization works bad due to scale of the problem and may be realization of rotation matrix parameterization. Thus, algorithm of optimization with restrictions works much better.

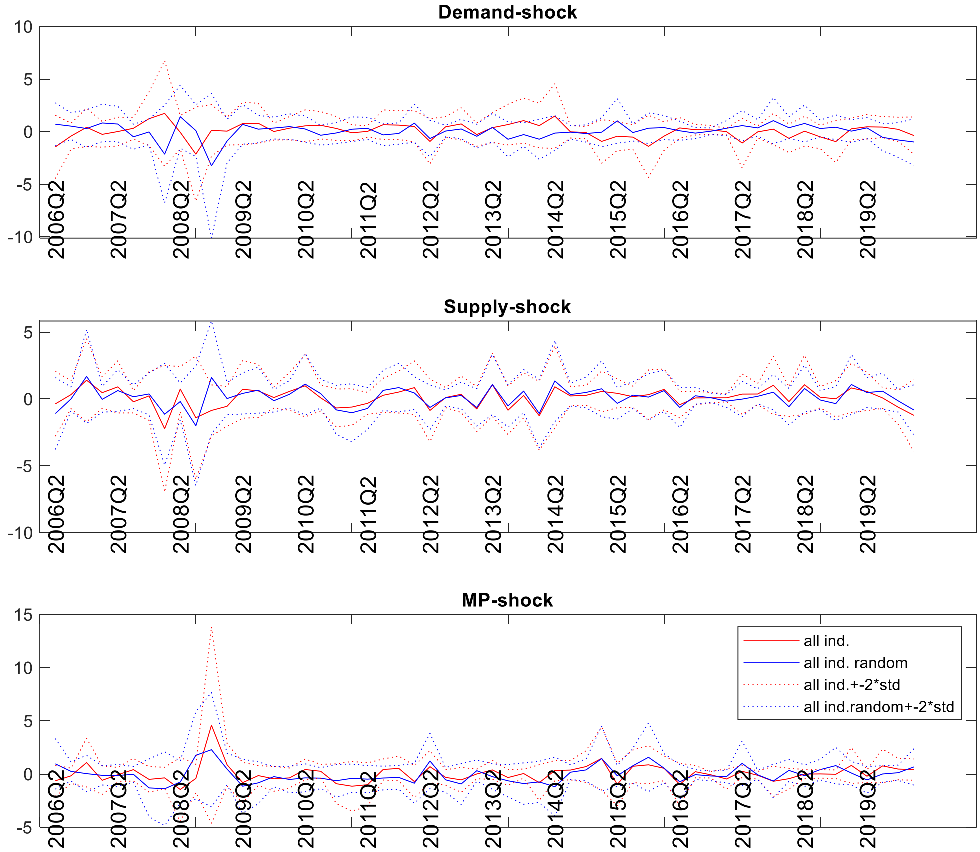
The penalty function for small industries are $3.70*10^{-7}$, $2.41*10^{-7}$, $1.44*10^{-7}$ (80%, 50%, 20% quintiles). However, if we look on all industry case the penalty function became much worse: 3.66, $3.23*10^{-2}$, $3.13*10^{-18}$ (80%, 50%, 20% quintiles). It demonstrates that number of sign restriction per parameter is larger in small scale cases that increase number of local modes with bad value of penalty function. The response on this property is taking into account only draws (after optimization) that produce good value of penalty function (smaller than 10^{-5}). We have 2522 draws for large industries (2006 that satisfy eigenvalues and penalty function restriction) and 2500 draws for all industries (2483 that satisfy eigenvalues restriction; 753 that satisfy both types of restriction).

How accurate are computations?

First of all, the all industries case would be investigated. This case allows to compare conventional random draw approach with suggested one. The same 2500 draws of variance matrix and other BVAR coefficients are used for both approaches. The random draw keep accepted 2483 draws (discarded draws with explosive VAR parameters). For each of them it was made enough random draws for receiving zero penalty function (all restriction holds) as was suggested at [Rubio-Ramirez et al. (2010)]. The suggested optimization approach keep 753 draws due to additional penalty function limit (10^{-5}).

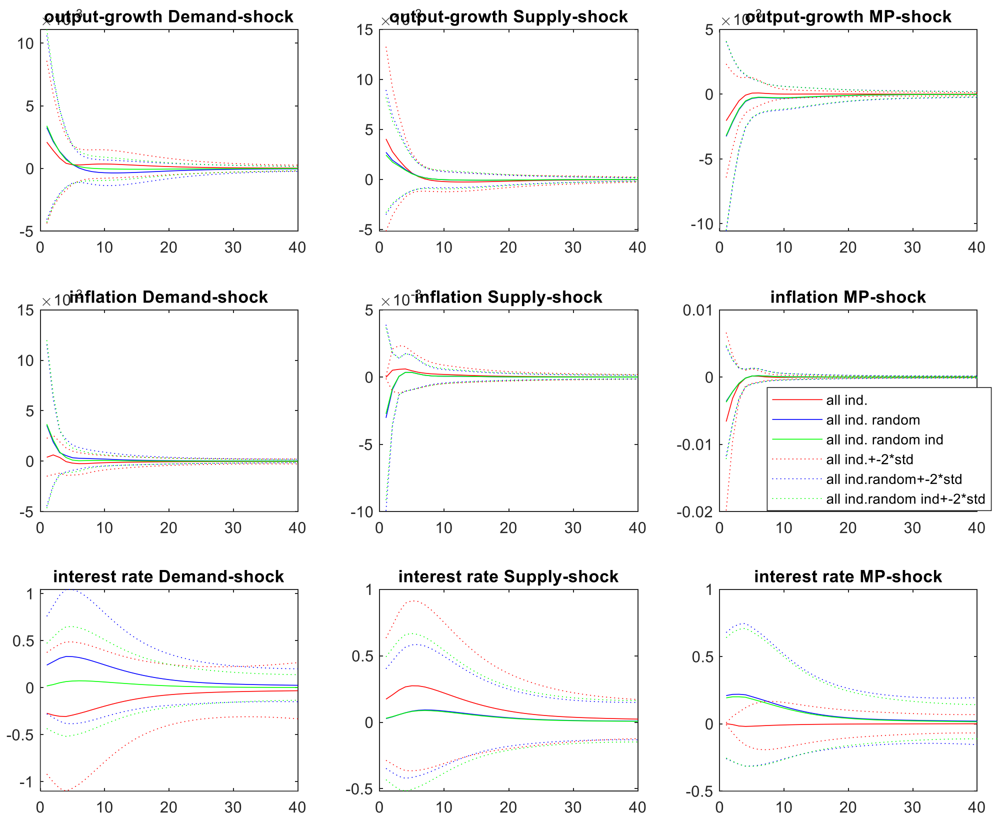
Figure 1 demonstrate expected shock and confidence intervals (per draw). It can be seen that pictures is similar. It means that changing of priors due to optimization technique is negligible. T-statistics for test of equal mean can be easily computed. The maximum absolute value for this statistic for MP-shock is 97.1 (median is 29.4). This difference is statistically significant while economical difference is small. It may be suggested that draws with higher penalty function have some specific. Robustness to this property is checked. T-statistics are computed for equal mean test (optimization vs random2) only for draws which are kept in case of optimization (753 draws). The maximum is 59.2 and median is 22.5. Results for equal mean for short and full set of draws (random vs random2) are similar (max is 61.5, median is 24.0). It means that such change of prior for IRFs is statistically significant but has small economical meaning.

Fig.1 Shocks identified with different methods for same sign restrictions



Comparison of IRFs presented at fig.2. They are suggested optimization approach, random draws and independent random draw (restrictions for each shock are checked separately, without taking into account restrictions for other shocks). It can be seen that results are different, especially for interest rate. However, the results for one method are within 2 standard deviation confidence interval computed for other method (at the most cases). It may be noted that 2 standard deviation confidence interval includes signs of response prohibited by restrictions. It is property of highly asymmetric distribution that allows to have different signs of confidence interval despite the same sign of all draws.

Fig.2 IRF with different methods for same sign restrictions



There are 2 cases where suggested approach produces quite different confidence intervals: response of interest rate to MP-shock and response of inflation on supply-shock. The response of variable is near zero for these cases in almost all draws. It means that having desired signs for almost all initial point is complicated and optimization converges with corresponding zero values. There are also some difference in mean responses. However, it is not obvious which results are better from economic point of view. Almost zero response of interest rates on MP-shock means near-optimal monetary policy that is fully driven by economy (other shocks) and do not suggest discretionary choice of interest rate (MP-shock). Response of interest rate on demand shock is more conventional in case of random draws (higher interest rate when higher inflation and growth). However, lower interest rates better corresponds to idea of forward looking policy (inflation became slightly negative in a few periods) that produces faster returning of inflation response to zero. Thus, alternative prior implied by sign restriction techniques produces alternative results, but these results have the same (or may be slightly better) level of economic theory understanding.

How accurate are computations? Simulated data.

The data based analysis shows difference of shock identification depending on method. Which method is better? The answer requires knowledge of true values of shocks. It is possible for simulated data only. So, the dynamic stochastic general equilibrium (DSGE) model is used for simulation. It is hard to construct and estimate model with large number of sectors (in additional conventional random approach would be too slow for it). So, small-scale DSGE model would be used (see appendix). The result may be sensitive to approximation of the model: linear approximation of solution can be better approximated by BVAR model. It may produce advantage for some sign identification method. The second-order pruned approximation is used as alternative simulation technique. The sample length can also have some influence. So, short and long sample are generated. The posterior mode is used as realistic parameters values. The 3 timeseries (all industries) are used for estimation. The nonlinear model has different dynamic from linear one. Thus, the both versions are estimated (linear and second order pruned approximations). The Quadratic Kalman Filter is used for estimation of nonlinear model [Ivashchenko (2014)]. The 1000 quarters sample is generated. The first 400 quarters are dropped. The short sample is next 60 quarters. The long sample is 600 quarters. All DSGE related computations are made with modified dynare [Adjemian et all (2011)].

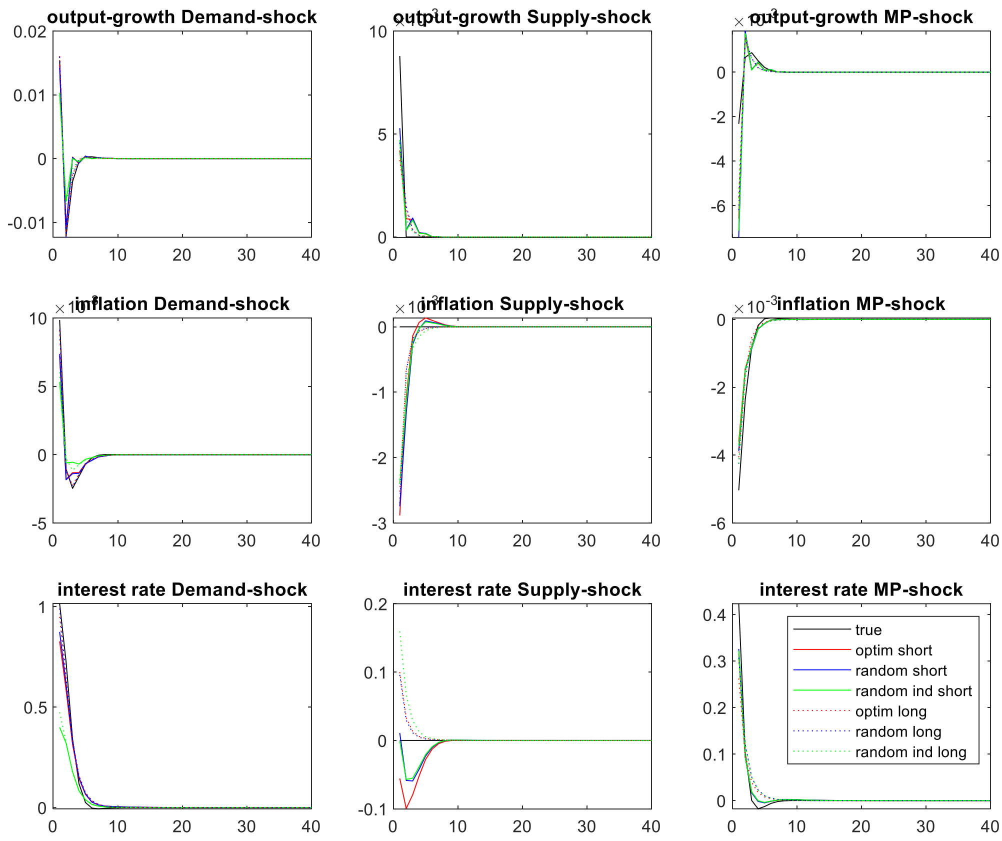
The results for all 4 cases (linear approximation, short sample (LS); linear approximation, long sample (LL); nonlinear approximation, short sample (NS); nonlinear approximation, long sample (NL)) presented at table 1. It can be seen that optimization based approach produces smaller errors of shock identification in almost all cases. There are only 3 exceptions. It is demand shock (LS case) if median absolute error or maximum absolute error is used as accuracy measure. The last exception is maximum absolute error for demand shock (NS case). However, the difference in accuracy is small for all cases. It means that for other model advantage of suggested method could become smaller.

Table 1. Accuracy of shock identification

	'demand shock optim'	'suply shock optim'	'MP-shock optim'	'demand shock random'	'suply shock random'	'MP-shock random'
'LS RMSE'	**0.866**	**0.670**	**0.722**	0.883	0.730	0.773
'LS MedianAE'	0.542	**0.397**	**0.553**	**0.536**	0.447	0.597
'LS MaximumAE'	2.384	**2.045**	**1.806**	**2.311**	2.265	1.910
'LL RMSE'	**0.900**	**0.747**	**0.785**	0.918	0.861	0.879
'LL MedianAE'	**0.584**	**0.492**	**0.537**	0.587	0.563	0.616
'LL MaximumAE'	**3.033**	**3.289**	**2.501**	3.182	3.793	2.885
'NS RMSE'	**0.825**	**0.689**	**0.734**	0.850	0.743	0.783
'NS MedianAE'	**0.526**	**0.411**	**0.533**	0.540	0.450	0.586
'NS MaximumAE'	2.104	**1.898**	**1.598**	**2.082**	2.077	1.715
'NL RMSE'	**0.895**	**0.738**	**0.779**	0.910	0.852	0.875
'NL MedianAE'	**0.570**	**0.494**	**0.525**	0.582	0.555	0.595
'NL MaximumAE'	**3.080**	**3.259**	**2.450**	3.326	3.762	2.809

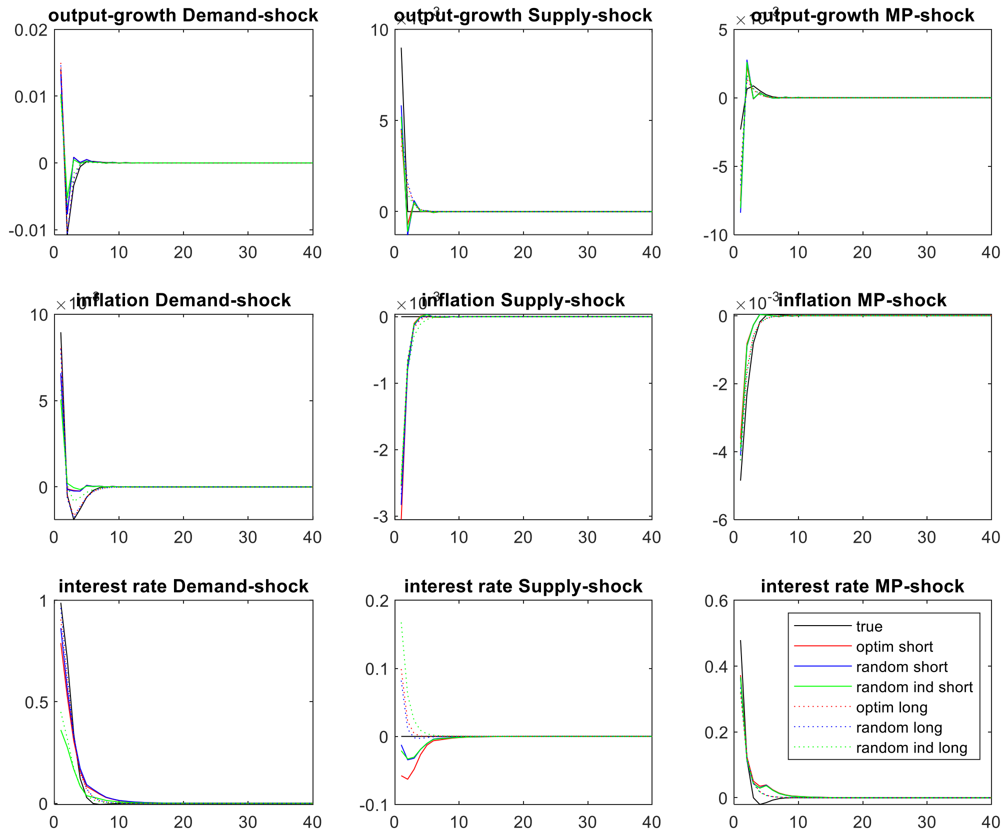
Another interesting detail is related to higher errors related to long sample. It may be related to impossibility to reproduce exact autocorrelation matrixes with BVAR model with 4 lags. In case of large sample errors of approximation would be interpreted by BVAR model as part of shocks. In case of small sample these errors would be partly interpreted as uncertainty of parameters and have smaller effect of shocks identification.

Fig 3. IRF for simulated data from linearized DSGE



The IRFs on simulated data can be compared too. The results presented on figures 3 and 4. It can be seen that similar to the real data IRFs looks very similar for the most variables and shocks. However, variable-shock of the largest difference is other for simulated data. It is response of interest rate to supply shock. All methods greatly increase sensitiveness of inflation and interest rate to supply-shock in contrast to real data cases. Linear and nonlinear pictures look very similar. It should be noted that IRF for nonlinear model can be defined in different ways (it depends on size of the shocks and state of the economy). The output of dynare computations of IRFs for non-linear pruned model is used as true IRFs.

Fig 4. IRF for simulated data from nonlinear DSGE



Monetary policy shocks from different models

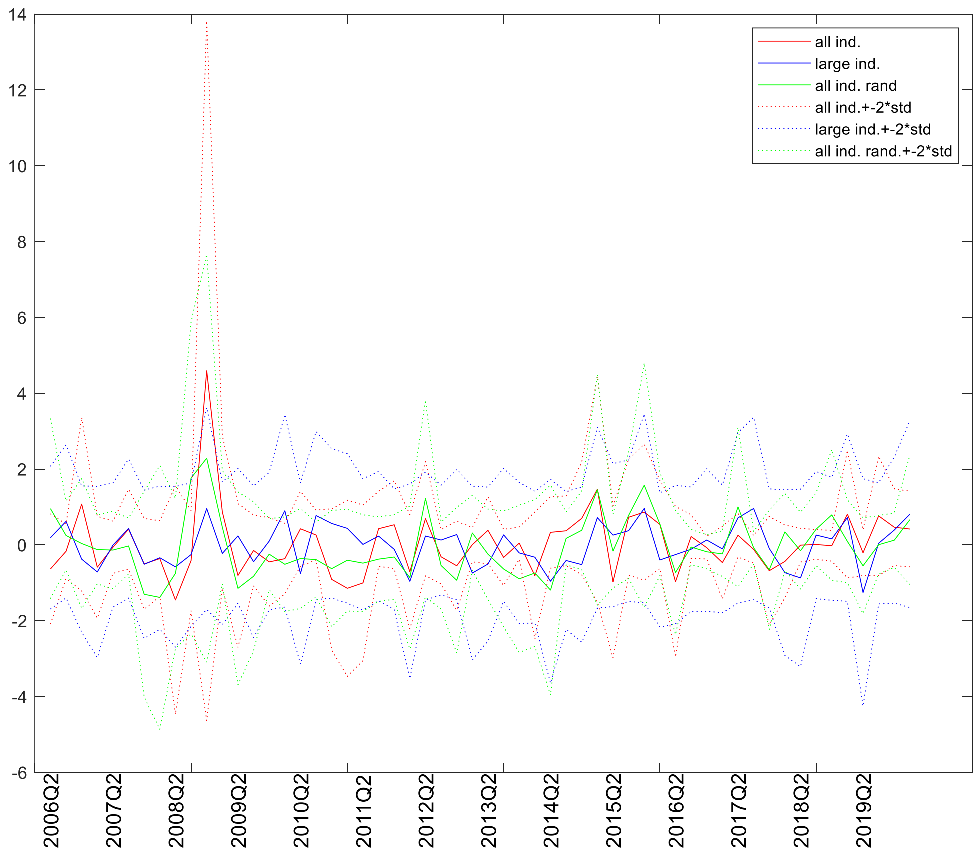
The next view is values of monetary policy shocks from different models (see fig.5). The more detailed data produces different shock identification. Correlation of identified shocks is not high (27.8% for all vs large and 39.3% for all random vs large). Difference is significant (see table 2). Standard deviation of expected MP-shock is 0.882 (0.780 for random) for all industry and 0.555 for large industry model.

Table 2. Difference in MP shocks (large industries vs all industries)

	'value'	'value/mean std model0'	'value/mean std model2'
'root-mean-squared abs difference(all vs large) in MP shocks'	0.89	1.31	0.89
'median abs difference(all vs large) in MP shocks'	0.59	0.86	0.59
'max abs difference(all vs large) in MP shocks'	3.64	5.33	3.64
'root-mean-squared abs difference(all random vs large) in MP shocks'	0.75	0.94	0.75
'median abs difference(all random vs large) in MP shocks'	0.60	0.75	0.60
'max abs difference(all random vs large) in MP shocks'	2.02	2.52	2.02

It should be noted that standard deviation of expected MP-shock that is computed "across time dimension" is much smaller for more detailed data (large industries). It means that monetary policy became more predictable in case of more detailed description of the economy. However, the standard deviation of MP-shock at each period of time (that is computed "across draw dimension") is larger in case of large industries. It means that uncertainty about larger number of parameters produces larger uncertainty about the values of each shock. There are few periods when uncertainty is smaller. The most obvious is 2008-2009 crises.

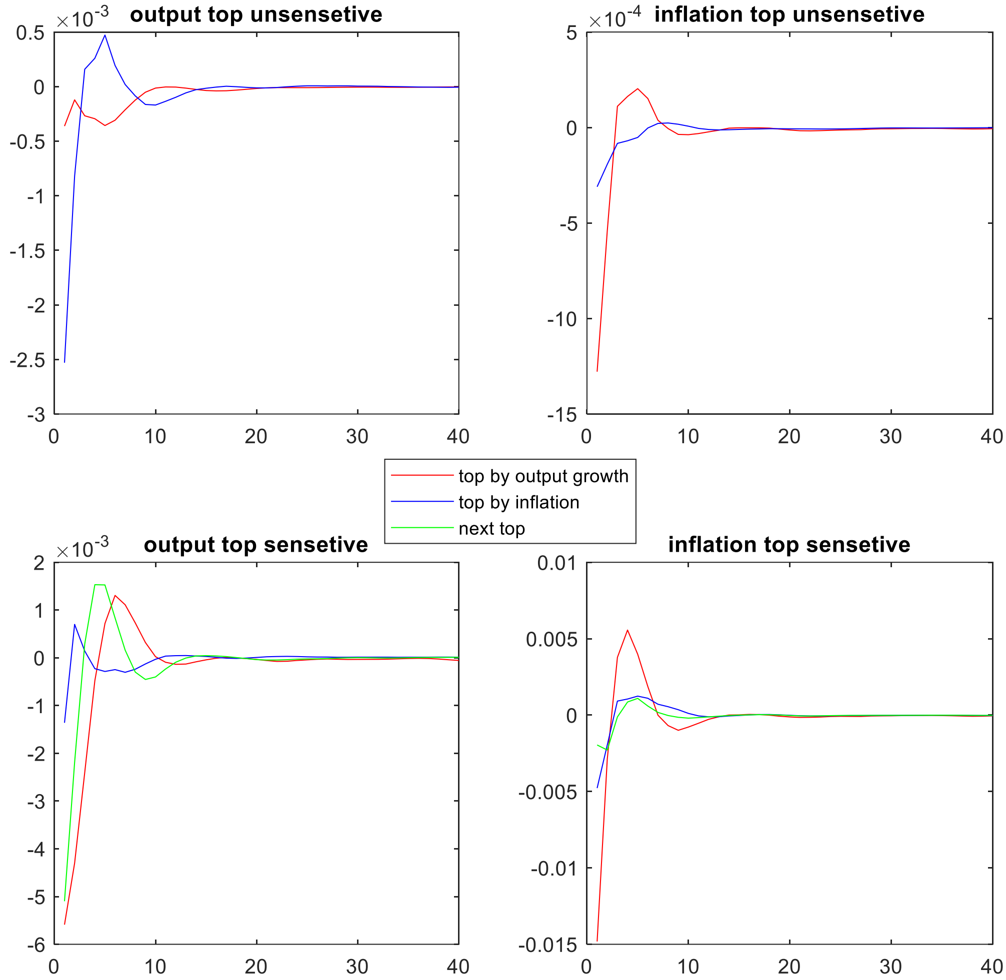
Fig.5 MP-shocks



MP-shock influence on different industries

The next view is comparison of IRFs. The MP-shock has different influence on different industries. Fig.6 shows IRFs for most and less sensitive industries. "Wholesale trade" has minimal sensitiveness of output growth (maximal absolute response of output growth is minimal). "Agriculture, forestry, fishing, and hunting" has minimal sensitiveness of inflation. "Finance, insurance, real estate, rental, and leasing" has maximal sensitiveness of growth to MP-shock ("Transportation and warehousing" is second best). "Finance, insurance, real estate, rental, and leasing" has maximal sensitiveness of inflation too. "Manufacturing" is second most sensitive inflation (it is presented as top by inflation).

Fig.6 IRF for MP-shock (1 std)

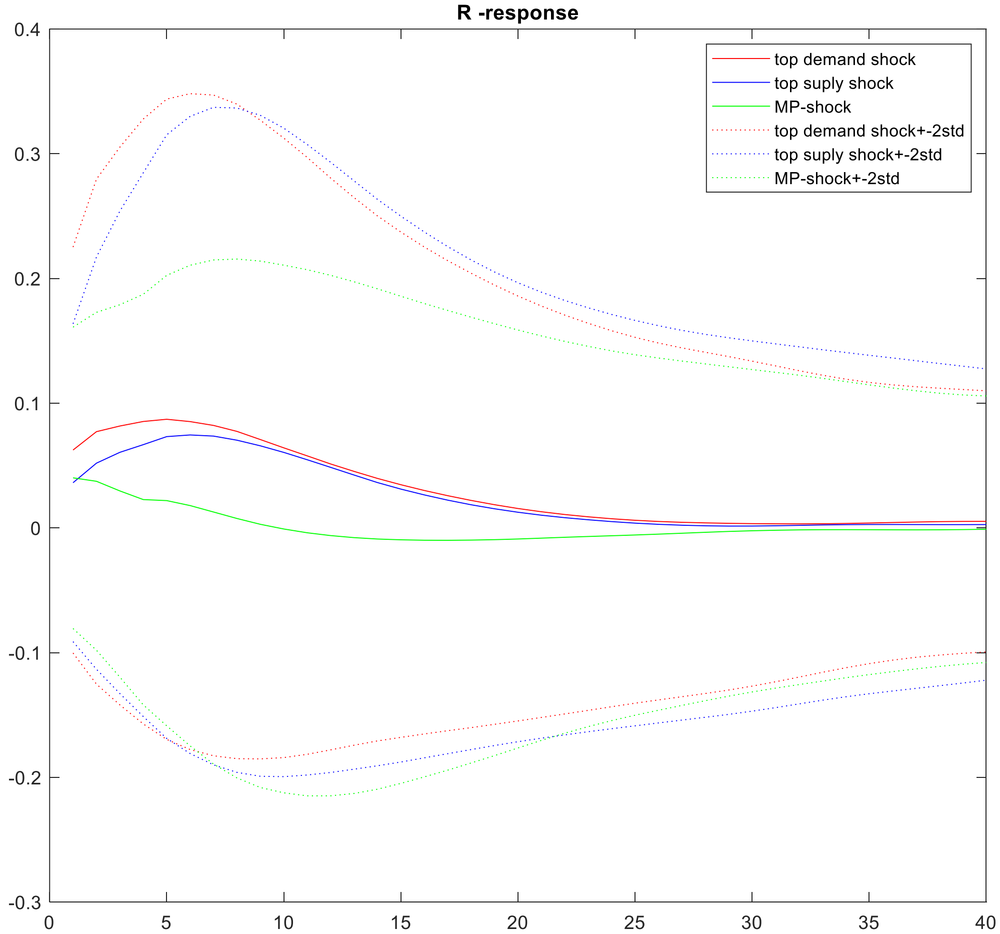


It demonstrates how different response in terms of magnitude and shape is. The difference in transmission mechanics produces 10-100 times difference in responses. Such difference is too large for ignoring at model level (by assuming homogenous production).

Influence of different demand and supply shocks on interest rates

The different industries have different influence on interest rates. The most important demand shock (for interest rates) is "Retail trade". The most important supply shock is "Wholesale trade". The corresponding results (with confidence intervals) presented at fig.7

Fig.7 IRF of interest rate on different shocks (1 std)



The top response of interest rate on supply shock ("Wholesale trade") is 0.0745. The most unimportant supply shock ("Professional and business services") has maximum influence equal to 0.0048 that is almost 20 times lower. Thus, interest rate has quite different response for shock in different industries.

Historical decomposition of interest rate

The historical decomposition of interest rates provides insights into the factors driving interest rate dynamics. Fig.8 shows decomposition for all industry, Fig.9 shows decomposition for all industry random, Fig.10 for large industry. The picture is quite different. The random draw produces much higher influence of MP-shocks on interest rate dynamic. It is related to different interpretation produced by different priors that were discussed above. The suggested approach implies interpretation that interest rates are driven by responses to demand and supply shocks. The industry related data significantly increase importance of supply shocks.

Fig.8 Historical decomposition of interest rate(all industry)

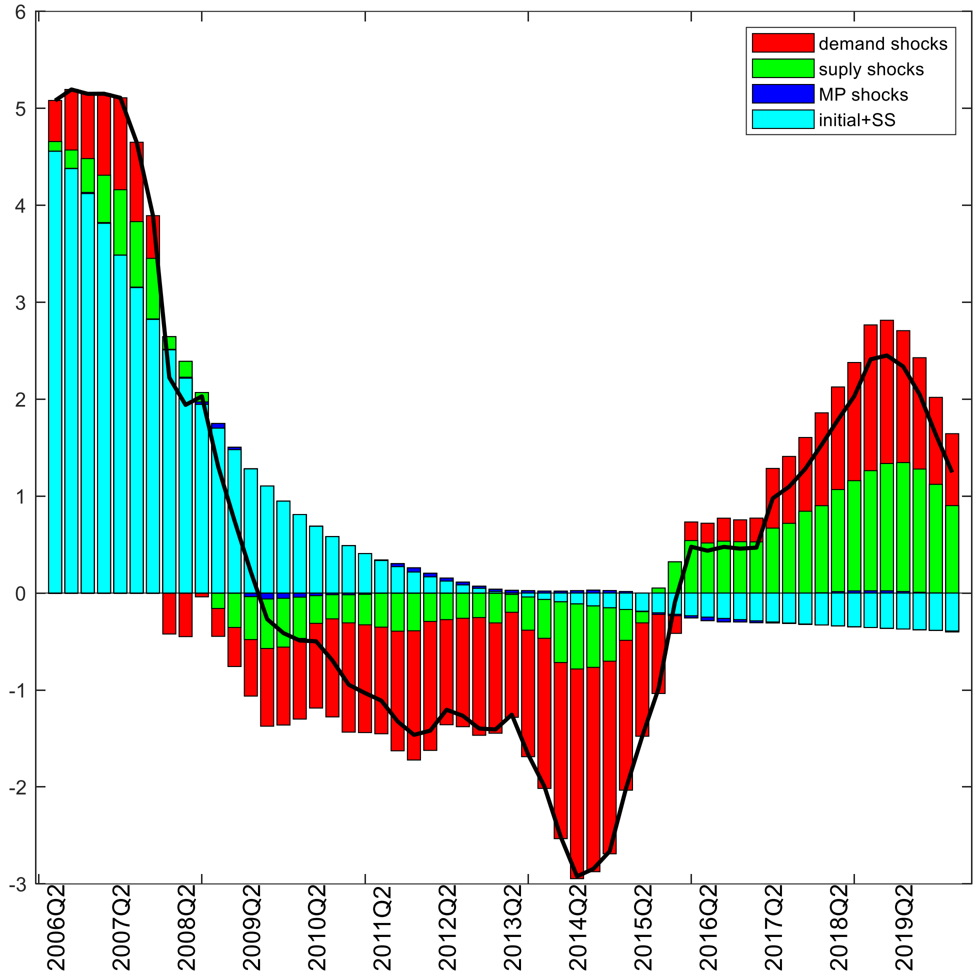


Fig.9 Historical decomposition of interest rate(all industry random)

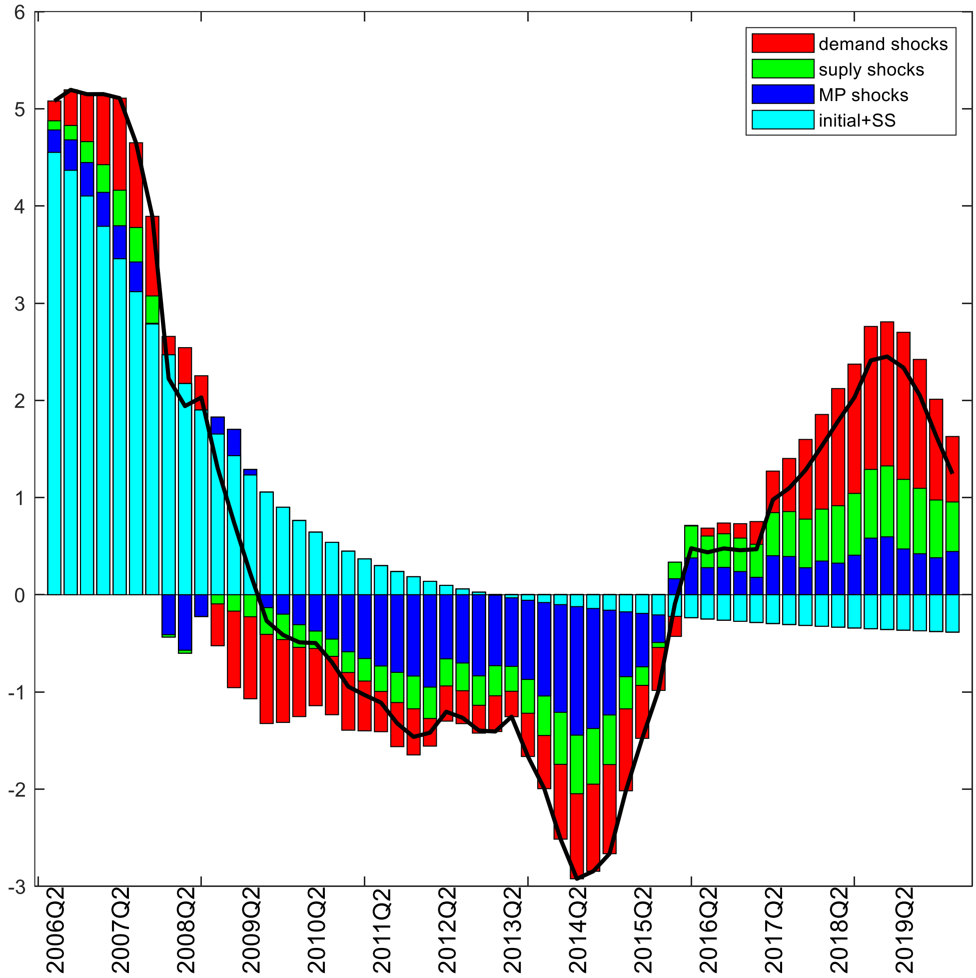
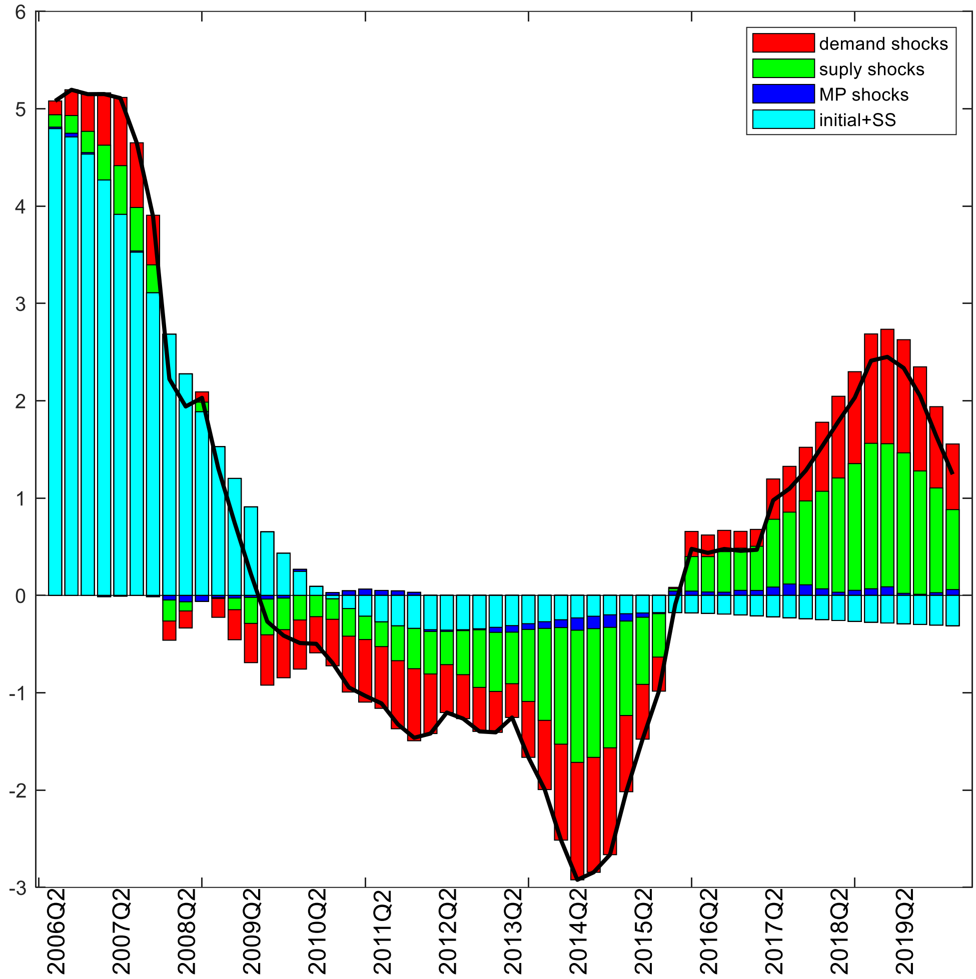


Fig.10 Historical decomposition of interest rate(large industry)



Variance decomposition

Additional interesting view is variance decomposition. Which share of variance is explained by demand and supply shocks of industry itself? Which is explained by other industries? The answer depends on horizon. But it also depends on definition and understanding of variance decomposition. The first possible understanding is computing of variance decomposition for each draw and computing mean of shares. The second one is simplified version that implies usage of mean IRFs (computing squared mean response of variable to each iid shock and normalizing it). The first approach is much more correct. However, the costs of simplification would be demonstrated too. Table 3 presents conditional variance decomposition for 1 period.

Table 3. Variance decomposition for 1 period

Variable	mean variance decomposition					variance decomp. corresponding mean IRFs				
	Demand-shock o industry'	Supply-shock o industry'	Demand-shocks f other industrie	Supply-shocks o other industries'	'MP-shock'	Demand-shock o industry'	Supply-shock o industry'	Demand-shocks f other industrie	Supply-shocks o other industries'	'MP-shock'
DY 'Manufacturing'	21.9%	32.4%	27.0%	17.5%	1.3%	12.6%	18.4%	33.7%	34.0%	1.3%
DY 'Finance+'	43.8%	29.2%	9.9%	6.5%	10.6%	22.3%	15.4%	30.0%	25.5%	6.8%
DY 'Transportation+'	48.9%	30.4%	6.8%	5.5%	8.5%	25.5%	16.2%	27.7%	24.6%	6.0%
DY 'Prof.+serv.'	30.4%	36.1%	20.2%	7.8%	5.5%	15.8%	18.8%	33.2%	27.9%	4.3%
DY 'health+'	20.6%	28.4%	28.4%	21.5%	1.1%	11.8%	16.3%	35.5%	35.1%	1.3%
DY 'entertainment+'	16.5%	31.9%	31.0%	16.6%	4.0%	9.6%	18.8%	34.5%	33.7%	3.4%
DY 'Retail'	17.1%	46.9%	17.2%	16.6%	2.2%	8.3%	22.8%	27.7%	39.4%	1.8%
DY 'Information'	25.6%	27.6%	22.0%	19.7%	5.0%	14.0%	15.2%	33.4%	33.6%	3.8%
DY 'Federal'	16.6%	40.4%	18.5%	23.2%	1.2%	8.0%	19.2%	30.9%	40.8%	1.2%
DY 'Mining'	30.3%	22.2%	24.7%	20.6%	2.2%	15.3%	11.3%	36.3%	35.2%	2.0%
DY 'Agriculture+'	20.1%	26.3%	27.3%	15.4%	10.8%	11.1%	14.5%	35.2%	32.0%	7.2%
DY 'State+'	28.6%	24.7%	29.0%	14.8%	3.0%	14.0%	12.2%	38.9%	32.6%	2.3%
DY 'Other'	20.0%	29.0%	21.5%	25.4%	4.2%	11.9%	17.1%	31.3%	36.2%	3.5%
DY 'Utilities'	25.2%	29.4%	21.8%	20.2%	3.5%	13.4%	15.6%	33.1%	35.1%	2.9%
DY 'Construction'	27.4%	43.3%	20.9%	6.2%	2.2%	11.5%	18.2%	35.1%	33.3%	1.8%
DY 'Wholesale'	13.8%	30.1%	29.2%	24.5%	2.4%	6.7%	14.5%	34.9%	42.0%	1.9%
DP 'Manufacturing'	19.6%	33.7%	20.2%	21.6%	4.8%	12.0%	20.3%	29.4%	34.2%	4.2%
DP 'Finance+'	19.6%	18.4%	27.1%	26.7%	8.2%	12.5%	11.8%	33.0%	35.5%	7.2%
DP 'Transportation+'	40.3%	31.6%	10.2%	16.5%	1.5%	21.4%	17.0%	29.1%	30.8%	1.7%
DP 'Prof.+serv.'	29.3%	30.7%	24.9%	10.3%	4.8%	11.4%	12.0%	38.0%	35.6%	2.9%
DP 'health+'	11.5%	17.2%	30.6%	30.7%	10.0%	7.9%	11.9%	34.1%	37.5%	8.6%
DP 'entertainment+'	23.3%	42.3%	20.3%	12.4%	1.7%	10.1%	18.3%	32.4%	37.9%	1.4%
DP 'Retail'	17.5%	51.2%	5.1%	24.3%	1.9%	7.4%	21.1%	24.2%	45.9%	1.4%
DP 'Information'	18.0%	16.8%	31.4%	16.6%	17.2%	11.5%	10.8%	36.1%	29.7%	12.0%
DP 'Federal'	17.3%	33.1%	23.1%	23.8%	2.8%	7.7%	14.6%	33.3%	42.5%	1.9%
DP 'Mining'	19.6%	16.6%	38.0%	19.1%	6.7%	10.9%	9.3%	41.9%	33.1%	4.8%
DP 'Agriculture+'	15.7%	22.6%	26.6%	27.5%	7.7%	6.5%	9.1%	38.6%	41.3%	4.5%
DP 'State+'	16.9%	15.8%	28.4%	19.0%	19.8%	8.9%	8.3%	37.8%	35.2%	9.8%
DP 'Other'	24.1%	27.0%	27.1%	15.3%	6.5%	8.7%	9.7%	39.9%	38.3%	3.4%
DP 'Utilities'	12.3%	16.9%	17.2%	43.4%	10.3%	6.8%	8.7%	32.3%	46.2%	5.9%
DP 'Construction'	21.1%	26.6%	32.6%	17.4%	2.3%	9.9%	12.5%	38.3%	37.5%	1.7%
DP 'Wholesale'	8.9%	20.7%	30.9%	29.0%	10.6%	5.8%	13.4%	34.0%	39.0%	7.9%
'interest rate'	0.0%	0.0%	75.4%	17.5%	7.2%	0.0%	0.0%	54.0%	43.0%	2.9%

DY is output growth. DP is inflation. 'Manufacturing' is 'Manufacturing'. 'Finance+' is 'Finance, insurance, real estate, rental, and leasing'. 'Transportation+' is 'Transportation and warehousing'. 'Prof.+serv.' is 'Professional and business services'. 'health+' is 'Educational services, health care, and social assistance'. 'entertainment+' is 'Arts, entertainment, recreation, accommodation, and food services'. 'Retail' is 'Retail trade'. 'Information' is 'Information'. 'Federal' is 'Federal'. 'Mining' is 'Mining'. 'Agriculture+' is 'Agriculture, forestry, fishing, and hunting'. 'State+' is

'State and local'. 'Other' is 'Other services, except government'. 'Utilities' is 'Utilities'. 'Construction' is 'Construction'. 'Wholesale' is 'Wholesale trade'.

The variance decomposition varies across industries significantly. It is also quite different depending on method of computing. The simplified method underestimates influence of MP-shocks and shocks of industries itself. The main focus is related to more accurate approach. The additional view is conditional variance decomposition for 2 and 40 periods presented at table 4.

Moving to long-run variance decomposition leads to decreasing of influence of shocks related to industries itself. It happens for industries with large influence (such as 'Transportation+') and with small influence (such as 'Wholesale'). MP-shocks almost keep its importance (it decreases for slightly more than 50% industries). Another interesting detail is that average influence of demand shocks is lower than average influence of supply shocks. Demand shock of industry has lower influence than corresponding supply shocks for majority of industries. However, in case of other industries shocks the picture is opposite.

The variance decomposition at this BVAR model has some similarity with input-output tables. The both approaches allow to understand relation between output in one industry with all other. However, BVAR based approach talks about shocks (demand and supply) while IO-tables talks about total production (suggesting varies in demand with fixed production function). Nevertheless, ratio of final use to commodity output can be interpreted as analog of influence of industry related shocks. Table 5 demonstrates corresponding values for different years.

Table 4. Mean variance decomposition for 2 and 40 periods

Variable	2 periods					40 periods				
	Demand-shock o industry'	Supply-shock o industry'	Demand-shocks f other industrie	Supply-shocks o other industries'	'MP-shock'	Demand-shock o industry'	Supply-shock o industry'	Demand-shocks f other industrie	Supply-shocks o other industries'	'MP-shock'
DY 'Manufacturing'	20.5%	30.3%	29.3%	18.5%	1.5%	19.0%	28.1%	30.5%	20.7%	1.6%
DY 'Finance+'	38.0%	21.6%	14.9%	13.7%	11.8%	29.5%	15.2%	23.0%	22.5%	9.8%
DY 'Transportation+'	42.3%	26.4%	11.1%	11.5%	8.6%	33.1%	20.6%	17.9%	20.4%	8.0%
DY 'Prof.+serv.'	29.0%	35.0%	21.0%	9.8%	5.2%	25.7%	30.3%	24.3%	15.1%	4.7%
DY 'health+'	20.3%	24.2%	29.9%	24.6%	0.9%	15.3%	24.5%	31.7%	26.3%	2.3%
DY 'entertainment+'	16.7%	27.9%	29.5%	22.2%	3.7%	13.2%	22.4%	31.5%	28.3%	4.5%
DY 'Retail'	14.3%	40.3%	17.6%	24.9%	2.8%	12.6%	33.9%	21.1%	29.4%	3.0%
DY 'Information'	22.2%	21.2%	27.4%	23.6%	5.6%	17.9%	18.0%	29.9%	29.2%	4.9%
DY 'Federal'	14.7%	37.8%	19.1%	27.3%	1.2%	12.4%	32.0%	22.0%	31.7%	1.9%
DY 'Mining'	26.4%	18.9%	26.7%	25.3%	2.7%	23.9%	17.1%	28.3%	28.1%	2.7%
DY 'Agriculture+'	16.7%	20.9%	29.1%	23.8%	9.5%	14.3%	17.9%	29.9%	29.5%	8.5%
DY 'State+'	26.6%	22.7%	29.6%	18.3%	2.9%	25.2%	21.4%	30.9%	19.6%	2.9%
DY 'Other'	19.0%	27.8%	23.3%	25.7%	4.3%	17.4%	25.3%	25.2%	28.0%	4.0%
DY 'Utilities'	22.7%	26.6%	23.4%	23.2%	4.0%	19.1%	22.2%	26.5%	27.9%	4.2%
DY 'Construction'	25.0%	38.4%	25.1%	9.6%	1.9%	21.3%	32.7%	29.1%	15.0%	1.9%
DY 'Wholesale'	11.7%	28.5%	32.3%	25.6%	1.9%	11.2%	21.6%	35.3%	26.9%	5.0%
DP 'Manufacturing'	17.9%	28.5%	23.8%	25.1%	4.6%	15.8%	24.2%	26.2%	29.1%	4.7%
DP 'Finance+'	17.0%	18.2%	27.4%	30.7%	6.7%	15.5%	15.8%	28.1%	33.2%	7.4%
DP 'Transportation+'	35.0%	26.5%	16.2%	19.3%	2.9%	30.7%	23.2%	18.9%	23.9%	3.2%
DP 'Prof.+serv.'	26.4%	21.6%	32.0%	13.4%	6.6%	14.8%	10.9%	38.9%	29.8%	5.5%
DP 'health+'	12.2%	13.3%	30.0%	36.0%	8.5%	11.1%	13.4%	31.0%	36.1%	8.4%
DP 'entertainment+'	21.6%	37.6%	20.7%	18.0%	2.1%	19.1%	33.5%	23.0%	21.8%	2.6%
DP 'Retail'	14.2%	42.3%	12.9%	27.0%	3.7%	13.2%	39.1%	15.3%	28.8%	3.6%
DP 'Information'	15.7%	11.7%	33.8%	25.3%	13.6%	13.4%	10.1%	34.7%	30.2%	11.6%
DP 'Federal'	15.7%	30.9%	25.7%	25.2%	2.6%	13.4%	26.6%	29.0%	28.1%	3.0%
DP 'Mining'	18.7%	13.4%	37.3%	25.1%	5.5%	16.1%	11.5%	37.3%	30.2%	4.9%
DP 'Agriculture+'	16.3%	18.4%	29.4%	27.7%	8.2%	15.0%	13.7%	31.3%	33.3%	6.7%
DP 'State+'	16.1%	14.6%	29.4%	21.4%	18.6%	13.1%	12.3%	35.0%	24.5%	15.0%
DP 'Other'	22.5%	24.1%	28.3%	18.1%	7.0%	18.7%	20.4%	32.2%	22.6%	6.1%
DP 'Utilities'	13.4%	14.1%	20.2%	43.0%	9.2%	11.7%	12.0%	26.1%	42.1%	8.1%
DP 'Construction'	17.9%	20.9%	34.4%	24.1%	2.8%	15.4%	17.6%	35.0%	28.9%	3.1%
DP 'Wholesale'	7.1%	18.4%	33.7%	31.8%	9.0%	6.5%	16.4%	34.8%	34.0%	8.2%
'interest rate'	0.0%	0.0%	71.7%	22.9%	5.4%	0.0%	0.0%	59.1%	39.8%	1.0%

It is impossible to have values for 'Mining' that would be similar to produces from IO-tables. However, for other industries values are closer. Output growth rate of 'Utilities' have 41.3% variance explained by industries shocks that is in line with IO. In case of Construction long-run industry influence is 54%, but short run is 70.7%. There are industries with larger differences in long-run influence on output growth rate compare to IO: 'Transportation+' have 53.7%, 'Prof.+serv.' have 55.9%, 'Wholesale' have 32.8%.

Table 5. Final uses/commodity output from IO-tables

	1997	2007	2010	2017	2021
Agriculture, forestry, fishing, and hunting	18.6%	20.0%	19.2%	18.8%	18.9%
Mining	-19.7%	-36.5%	-35.3%	3.1%	6.0%
Utilities	46.2%	44.4%	41.7%	40.9%	38.1%
Construction	87.3%	84.6%	78.9%	82.1%	83.2%
Manufacturing	36.2%	33.0%	35.1%	34.0%	31.3%
Wholesale trade	50.2%	53.8%	56.8%	55.3%	55.7%
Retail trade	89.5%	88.7%	90.0%	88.5%	89.3%
Transportation and warehousing	39.4%	37.9%	37.9%	36.4%	34.6%
Information	52.8%	55.6%	55.4%	54.6%	55.4%
Finance, insurance, real estate, rental, and leasing	58.1%	53.7%	56.9%	54.5%	53.7%
Professional and business services	29.1%	27.7%	28.5%	27.2%	28.3%
Educational services, health care, and social assistance	96.6%	97.9%	97.2%	96.9%	96.5%
Arts, entertainment, recreation, accommodation, and food services	75.8%	77.0%	77.6%	75.4%	75.2%
Other services, except government	60.3%	70.2%	71.1%	70.8%	65.6%
Government	95.3%	96.3%	96.7%	96.6%	97.1%
Scrap, used and secondhand goods	-209.7%	-134.6%	-257.5%	-352.7%	-261.6%
Noncomparable imports and rest-of-the-world adjustment [1]	-5212.6%	-6390.3%	-5120.4%	-4081.3%	-3081.2%

These differences in influence of industry related shocks with IO-results are predictable as IO-results are analog with quite different definitions and interpretation (unpredicted shocks from set of periods with fully determined world total output). But results are much more similar than it may be expected taking into account additional information that are used for construction of IO-tables. Moreover, it opens additional group of possible sign restrictions that could make identification of structural shocks in such BVAR models even more accurate.

4. CONCLUSIONS

The structural identification of shocks is key element of economic analysis based on VAR-type of models. The existing techniques are very computationally expensive that restrict their usage by small scale models. Alternative technique is suggested that able to work with much larger models. It is tested on BVAR model with 16 industries (16 growth rates, 16 inflations and interest rate). It takes 3-5 minutes per draw while conventional random draw approach is not able to find something close to solution within same time (10^6 tries).

It is shown that suggested technique could have influence on density of interesting measures that is different from conventional random draw approach. However, the resulting IRFs are corresponds to economic intuition for 3 variables model (despite difference with conventional approach). Moreover, simulated from DSGE model data shows that shocks identification with suggested approach is more accurate (the results are closer to simulated shocks).

The usage of industry specific data and identification of demand and supply shock have great influence on identification other measures of interest. It changes identification of historical MP-shocks. Correlation of expected MP-shocks (identified with different models) is high but significant differs from 1. Corresponding time series have different variance and their absolute difference significantly differs from zero.

The industry specific data reveal important elements of transmission mechanics of monetary policy. Different industries have quite different response on output growth and inflation (up to 10-100 times in terms of maximum absolute reaction on MP-shock). The shape of reaction is different too. The most sensitive are "Finance+", "Transportation+" and "Manufacturing". At the same time influence of demand and supply shocks of different industries is different too. "Wholesale+" and "Professional and business services" are the most important shocks for interest rate.

The industry specific data have large influence on historical decomposition. It reveals (increases) importance of supply shocks in compare to 3 variable case for interest rate. The variance decomposition shows differences across industries. Some of them are more driven by its own shocks, while other is more driven by other industries demand and supply shocks. Relative importance of its own shocks decreases when long-run variance decomposition is investigated. There are some similarity between variance decomposition and IO-tables. It opens additional sources for sign restrictions for such model from one side. But decomposition suggestions are very different from IO from other side that means creation of alternative explanation of industry dynamic.

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APPENDIX DSGE MODEL

This model is simple small-scale DSGE model of closed economy. Model includes 3 types of agents: households, firms and government.

Households solve problems (A.1)-(A.2). They maximize expected utility function (A.1) with budget restriction (A.2).

$$U_t = E\left(\sum_{s=0}^{\infty}\beta^s\left(\begin{array}{l}\frac{Z_{C,t}\left(\left(C_{t+s}/Z_{trY,t+s}\right)/\left(C_{h,t+s-1}/Z_{trY,t+s-1}\right)^h\right)^{1-\omega_c}}{(1-\omega_c)}+\\ \frac{\mu_M\left(M_{t+s}/\left(P_{t+s}Z_{trY,t+s}\right)\right)^{1-\omega_M}}{(1-\omega_M)}-\frac{\mu_L\left(L_{t+s}\right)^{1+\omega_l}}{(1+\omega_l)}\end{array}\right)\right)=$$

$$=\left(\left(\begin{array}{l}\frac{Z_{C,t}\left(\left(C_t/Z_{trY,t}\right)/\left(C_{h,t-1}/Z_{trY,t-1}\right)^h\right)^{1-\omega_c}}{(1-\omega_c)}+\\ \frac{\mu_M\left(M_t/(P_tZ_{trY,t})\right)^{1-\omega_M}}{(1-\omega_M)}-\frac{\mu_L\left(L_t\right)^{1+\omega_l}}{(1+\omega_l)}\end{array}\right)\right)+E_t\beta U_{t+1}\rightarrow \max_{C,L,K} \quad (A.1)$$

$$P_tC_t+M_t+B_t/R_t=(1-\tau)W_tL_t+M_{t-1}+B_{t-1}+T_t \quad (A.2)$$

C_t is consumption, $C_{h,t}$ is habit (that is equal to consumption but it is not controlled by individual households), L_t is labor, M_t is money, W_t is wage, R_t is interest rate in domestic currency, $B_{H,t}$ is bond/deposit savings in domestic currency, T_t is transfers from government, $Z_{trY,t}$ is exogenous process of TFP growth (that is supply shock), $Z_{C,t}$ is exogenous demand shock process.

This model use unconventional form of habit. It is done for preventing theoretical possibility of complex numbers (situation when current consumption is below habit related level). Such situation could happen with near-zero probability (taking into account approximation errors). Suggested approach produce similar effects to conventional one: dependence on previous period consumption and higher nonlinear effects (but this effect may be much smaller).

Additional detail is existence of stochastic trend with drift in all real variables. It comes from exogenous unit root TFP process. All summands of utility function should be cointegrated. So, it is impossible to have C_t without dividing by Z_t. Dropping of stochastic trend from the model is very bad practice (it would eliminate microeconomic foundation that is one of the main advantages of DSGE models).

Firms have monopolistic competition and solves problem (A.3)-(A.6). They maximize expected discounted dividends flow with price rigidity effect in Rotemberg form. The restrictions are following: budget (A.4), production function (A.5) and demand (A.6) that come from CES-aggregation.

$$E\left(\sum_{t=0}^{\infty}\left(\mathop{\Pi}_{k=0}^{t-1}R_k\right)^{-1}\left(D_{f,t}-e^{\varphi_p}P_{F,t}Y_{D,t}\left(\frac{P_{f,t}}{P_{f,t-1}}-e^{\bar{p}}\right)^2\right)\right)\rightarrow \max_{D,L,Y} \quad (A.3)$$

$$D_{f,t}+W_t L_{f,t}=P_{f,t}Y_{f,t} \tag{A.4}$$

$$Y_{f,t}=Z_{trY,t}Z_{Y,t}\left(L_{f,t}\right)^{1-\alpha_k} \tag{A.5}$$

$$Y_{f,t}=\left(\frac{P_{f,t}}{P_{F,t}}\right)^{-z_{\theta,t}}Y_{D,t} \tag{A.6}$$

Government equations.

Government has budget restriction (A.7). Monetary policy rule of Taylor type is (A.9) and rule for transfers (A.8). There are definitions of two variables that are used in the rules. The first is future inflation $p_{EXP,t}$ that is described by rule (A.10). It is done for possibility to control which inflation is more important factor for Taylor rule (next period or future one). The next variable is households domestic currency assets $A_{H,t}$ that is described by (A.11). It is liabilities of government (minus assets) that effect on its fiscal policy. Such variable allows to decrease number of state variable.

$$B_{t-1}+T_t=D_t+M_t-M_{t-1}-B_t/R_t+\tau(W_tL_t) \tag{A.7}$$

$$T_t/(P_tZ_t)=\gamma_{tr}T_{t-1}/(P_{t-1}Z_{t-1})+(1-\gamma_{tr})(\gamma_{try}(y_{D,t}-\overline{y_D})+\gamma_{trA}(a_{H,t}-\overline{a_H})+z_{tr,t}) \tag{A.8}$$

$$r_{H,t}=\gamma_r r_{H,t-1}+(1-\gamma_r)(\gamma_{rp}E_t(p_{EXP,t+1}-\overline{p})+\gamma_{ry}(y_{D,t}-\overline{y_D})+z_{r,t}) \tag{A.9}$$

$$p_{EXP,t}=\gamma_{\exp}p_t+(1-\gamma_{\exp})E_tp_{EXP,t+1} \tag{A.10}$$

$$a_{H,t}=\frac{A_{H,t}}{P_tZ_t}=\frac{B_{H,t}+M_{H,t}}{P_tZ_t}=b_{H,t}+m_{H,t} \tag{A.11}$$

There are balance equations. Balance equations are following:

$$Y_{f,t}=C_t \tag{A.12}$$

$$L_{f,t}=L_t \tag{A.13}$$

Exogenous process rules (they are independent, normal with nonzero mean):

$$\log(Z_{C,t})=z_{C,t}=\eta_{0,C}+\varepsilon_{C,t} \tag{A.14}$$

$$\log(Z_{R,t})=z_{R,t}=\eta_{0,R}+\varepsilon_{R,t} \tag{A.15}$$

$$\log(Z_{trY,t}/Z_{trY,t-1})=z_{trY,t}=\eta_{0,trY}+\varepsilon_{trY,t} \tag{A.16}$$

All other $z_{*,t}$ are equal to corresponding constants $\eta_{0,*}$.

Estimation results presented at table A1. All computations are made with modified dynare [Adjemian et all (2011).].

Table A1. Estimation

Parameter	Posterior mode(line)	Posterior mode (second order)	Lower bound	Upper bound	Density	Prior mean	Prior std
stderr ε_C	4.111E-02	3.725E-02	0.0003	10	inv_gamma_pdf	0.01	3
stderr ε_R	5.036E-03	5.943E-03	0.0003	10	inv_gamma_pdf	0.01	3
stderr ε_{trY}	8.789E-03	8.997E-03	0.0003	10	inv_gamma_pdf	0.01	3
α_K	5.893E-01	5.684E-01	0.3	0.8	normal_pdf	0.6	0.05
$\ln(\beta)$	-1.006E-05	-1.000E-05	-0.01	-1.00E-05	normal_pdf	0.005	5.00E-03
φ_P	3.052E+00	3.059E+00	-5	5	normal_pdf	0	10
γ_r	6.405E-01	6.476E-01	0.6	0.999	normal_pdf	0.8	0.15
γ_{rp}	1.000E+00	1.485E+00	1	5	normal_pdf	1.5	0.5
γ_{ry}	5.266E-01	5.745E-01	-1	1	normal_pdf	0	0.15
γ_{tr}	8.000E-01	8.000E-01	0.6	0.999	normal_pdf	0.8	0.15
γ_{trA}	-1.000E-01	-9.999E-02	-1	0	normal_pdf	-0.1	0.15
γ_{try}	9.202E-07	-7.666E-06	-1	1	normal_pdf	0	0.15
h	9.990E-01	9.990E-01	0	0.999	normal_pdf	0.7	0.15
μ_L	7.192E-05	-8.078E-04	-5	5	normal_pdf	0	10
μ_M	-1.537E-04	-1.185E-03	-5	5	normal_pdf	0	10
$\eta_{0,R}$	3.333E-03	3.333E-03	0.003333	0.008333	normal_pdf	0.005	0.005
$\eta_{0,\theta,F}$	7.988E+00	8.119E+00	4	12	normal_pdf	8	2
$\eta_{0,tr}$	9.826E-05	8.998E-04	-5	5	normal_pdf	0	10
$\eta_{0,trY}$	9.554E-04	1.032E-03	-0.01	0.02	normal_pdf	0.01	0.01
$\eta_{0,YF}$	2.089E-04	-4.902E-04	-10	10	normal_pdf	0	10
ω_C	1.922E+00	1.955E+00	1	5	normal_pdf	1.5	1.50E-01
ω_L	1.484E+00	1.450E+00	1	5	normal_pdf	1.5	1.50E-01
ω_M	1.500E+00	1.500E+00	1	5	normal_pdf	1.5	1.50E-01
τ	4.000E-01	4.000E-01	0	0.8	normal_pdf	0.4	5.00E-02
γ_{exp}	3.020E-01	2.900E-01	0.001	0.999	normal_pdf	0.5	0.25