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EFFECT OF EXOGENOUS MONETARY POLICY SHOCKS ON SELECTED MACROECONOMIC VARIABLES IN HUNGARY: A SVAR APPROACH

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ABSTRACT

The aim of this research paper is to estimate a structural vector autoregressive model of the Hungarian economy and present the reactions of the selected macroeconomic variables to an exogenous monetary policy shock. We estimate the model with recursive short run restrictions. We analyze monthly data of industrial production, prices, interest rates and the exchange rate ranging from 2004 to 2019. Some of our results are in accordance with economic theory. As a result of one standard deviation monetary policy shock, interest rates rise and the exchange rate appreciates. On the other hand, industrial production increases for one month before the expected decline. The price puzzle is also present, but the effects of the shocks are statistically insignificant. We also present the forecast error variance decompositions and check the robustness of our results by changing the identification scheme. The reactions of macroeconomic variables appear to be robust, except for the industrial production.

KEYWORDS

SVAR, forecast error variance decomposition, monetary policy in Hungary, Cholesky decomposition, vector autoregressive

INTRODUCTION

To design and implement monetary policy, economists need accurate information on the effectiveness of the monetary transmission mechanism.[24] This information should not be obtained by regressing selected variables on interest rate changes. Since interest rate movements are endogenous responses to economic shocks, the regression would only describe the consequences of these shocks. Economists therefore try to separate disturbances resulting from deliberate monetary policy measures and other types of shocks.[25] Thus they can conduct monetary policy better.

To separate these disturbances, economists can estimate structural vector autoregression (hereafter SVAR) models, which infer structural innovations from ordinary VAR models by imposing identifying restrictions on them. SVAR models have a couple of advantages. Firstly, impulse response functions (hereafter IRF), historical decompositions and forecast error variance decompositions (hereafter variance decomposition) can be plotted from them. These tools isolate the response of selected macroeconomic variables to various exogenous economic shocks - including monetary policy shocks (hereafter innovations) - and present their transmission over time.[24] For the purpose of this paper, an innovation represent a "*positive deviation of the interest rate from the average reaction function of the central bank for the sample period*".[18] Secondly, SVAR models are data driven and economic theory is only used for the selection of identifying restrictions. A structural model of the economy is therefore not

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required for economic analysis.[24] These are the advantages which make SVAR models popular.

VAR and SVAR models exist since 1980.[21] They have been applied many times since then, mainly because of the advantages explained above. To identify a SVAR model, long run restrictions can be combined with short run restrictions or used separately.[9] Some of the authors impose only long run restrictions on ordinary VAR models to identify demand and supply shocks, mainly in the USA.[4][5] Studies on the effects of demand shocks, supply shocks and innovations in the European Union are also available.[2][19] They yield similar results as the research conducted in the USA.[15] The estimation results are robust to different specifications. According to these studies, the reason of the similarity is that both the USA and EU have comparable, large and relatively closed economies. Other studies analyze the effectiveness of policy transmissions in different countries, noting a high degree of heterogeneity.[8][26] Their estimates are robust to other identification schemes and find that innovations result in anticipated changes in the variables.[18] These variables are usually output, prices and the interest rate, but other specifications do exist. Instead of output, the index of industrial production is used as a proxy variable, and the equation includes the exchange rate as well.[7][8] The latter are better suited for an analysis of a small open economy. The studies cited in this paragraph provide the theoretical foundation of this research paper.

Despite the advantages and popularity, SVAR models have their own limitations. Firstly, their main advantage can be a disadvantage. Since the models are data driven, economic theory is only applied when selecting identifying restrictions. This may result in three different puzzles, i.e. counterintuitive outcomes.[24] The first is the liquidity puzzle, when an unexpected expansionary monetary shock results in an increase in nominal interest rates. The second is the price puzzle, when an innovation results in an increase of the price level. The third is the exchange rate puzzle, when as a result of an innovation the exchange rate depreciates.[14] Secondly, SVAR models are subject to the Lucas-critique, that is they might result in inaccurate estimates when structural breaks are present. Thirdly, methodological problems might arise when determining the correct error bands – confidence intervals – of the IRF.[24] These limitations must be taken into consideration when interpreting the results.

The puzzles mentioned above are counterintuitive to economic theory. Innovations should have the following results instead. Firstly, prices and output should decline in the short and medium terms. When interest rates increase, central bankers expect that the real output of the economy is higher than the potential output, which creates inflationary pressure. They therefore raise the interest rate. This increases the cost of borrowing on the market and lowers the prices of financial assets. Spending and investment therefore decline along with output and prices. Secondly, the nominal exchange rate should appreciate, because the assets denominated in the domestic currency become more attractive due to higher returns, thus attracting capital inflows in the short run. On the long run, however, a nominal depreciation should occur as a result of higher interest rates. Thirdly, interest rates should either rise or decline, depending on the monetary regime. On the one hand, in case of an inflation targeting framework, expected decline in inflation should result in a decline in interest rates. On the other hand, interest rates should fall in case of an exchange rate targeting regime, since an innovation should result in the appreciation of the currency.[14] To sum up, the anticipated results are provided by economic theory, but the estimated results of the SVAR model might be different and still be acceptable, albeit counterintuitive.

The aim of this research paper is to estimate a SVAR model of the Hungarian economy and present the reactions of the selected macroeconomic variables to an innovation. This research paper consists of four sections. This first section states the purpose of the research, review the existing literature, sets the limitations of the SVAR approach, establishes the anticipated responses of the macroeconomic variables and sets the aim of the research paper. The following section discusses the methods used to obtain the results. Here we describe the data, the VAR methodology and Cholesky decomposition, IRFs, decomposition and the recursive ordering of the variables. The third section describes the statistical tests and the results. The last section concludes.

Methodology and methods

In this chapter we present our research methods, characterize the VAR models and describe our data. VAR models are suitable tools for analyzing the effect of innovations on selected macroeconomic variables.[24] A VAR model in structural form can be analytically written as follows:

$$\mathbf{\Gamma y_t} = \mathbf{B_0} + \sum_{i=1}^{p} \mathbf{B_i y_{t-i}} + u_{t},$$

where

- $\mathbf{\Gamma}$ – matrix of coefficients of endogenous variables at time *t*,
- $\mathbf{B_0}$ – vector of intercepts,
- $\mathbf{B_i}$ – matrix of mutual relationships between endogenous variables,
- **p** – number of maximum lags,
- $\mathbf{y_t}$ – vector of endogenous variables at time *t*,
- $\mathbf{u_t}$ – vector of structural error terms.

The structural form above cannot be estimated. The reduced form of the VAR model must be expressed from the structural equation. To do that, the structural form is multiplied by the matrix $\mathbf{\Gamma^{-1}}$. [13] This results in the following equations:

$$\mathbf{\Gamma^{-1}\Gamma y_t} = \mathbf{\Gamma^{-1}B_0} + \mathbf{\Gamma^{-1}} \sum_{i=1}^{p} \mathbf{B_i y_{t-i}} + \mathbf{\Gamma^{-1}} u_{t},$$

$$\mathbf{y_t} = \mathbf{\Pi_0} + \sum_{i=1}^{p} \mathbf{\Pi_i y_{t-i}} + v_{t}.$$

The main issue arising from the estimation of the reduced VAR model is the problem of identifying multi equation models. This means that from the reduced from fewer parameters can be estimated than from the structural form. The ordinary VAR model is therefore unidentified. Structural VAR (SVAR) models are used to solve this problem. The SVAR model introduces identifying restrictions on VAR estimates in order to detect structural shocks in the original VAR model.[24] The identifying restrictions are called the Cholesky decomposition of the matrix $\mathbf{\Gamma}$. This results in a matrix with $(n^2\text{-}n)/2$ short run restrictions, where *n* is the number of exogenous variables in the reduced form VAR model. To receive the fully identified structural form of the VAR model, therefore, the matrix presented on the 1. figure must be estimated.

Model: Ae = Bu where E[uu']=I

A =

1	0	0	0
C(1)	1	0	0
C(2)	C(4)	1	0
C(3)	C(5)	C(6)	1

B =

C(7)	0	0	0
0	C(8)	0	0
0	0	C(9)	0
0	0	0	C(10)

1. figure: Cholesky decomposition. Source: Developed by author.

To apply the Cholesky decomposition to the VAR model, the variables must be ordered recursively. This means that the form of IRF depends on the order of the individual variables in the SVAR model, since this ordering implicitly determines the relationships between the variables. The first place is usually taken by the variable that, according to theory or a priori information, does not depend on any other variable in the VAR model. Consequently, the last place is taken by the variable who reacts to the changes in all the other variables. Different ordering of the same variables might therefore result in different estimated coefficient values. Ordering is thus important.

The graphical output of the VAR model estimate is the IRF, which expresses the impact of the exogenous shock of the *i*-th variable on the value of one of the endogenous variables. To express these effects, it is necessary to calculate, using the moving average matrix and the matrix $\mathbf{\Gamma^{-1}}$, the following relationship:

$$\left(\mathbf{I} - \sum_{i=1}^{p} \mathbf{\Pi_i} \mathrm{L}^i\right)\left(\mathbf{I} + \sum_{i=1}^{\infty} \boldsymbol{\theta}_i \mathrm{L}^i\right) = \mathbf{I}$$

This relationship is then derived for lag *k*, which is the lag length that the VAR model has. As an example, the form of the relation for lag *k=1* is:

$$(\mathbf{I}-\mathbf{\Pi_1}\mathrm{L})(\mathbf{I}+\boldsymbol{\theta}_1\mathrm{L}+\boldsymbol{\theta}_2\mathrm{L}^2+\boldsymbol{\theta}_3\mathrm{L}^3+\cdots+\boldsymbol{\theta}_\infty\mathrm{L}^\infty) = \mathbf{I}$$
$$\mathbf{I}+\boldsymbol{\theta}_1\mathrm{L}+\boldsymbol{\theta}_2\mathrm{L}^2+\boldsymbol{\theta}_3\mathrm{L}^3+\cdots+\boldsymbol{\theta}_\infty\mathrm{L}^\infty-\mathbf{\Pi_1}\mathrm{L}-\mathbf{\Pi_1}\boldsymbol{\theta}_1\mathrm{L}^2-\mathbf{\Pi_1}\boldsymbol{\theta}_2\mathrm{L}^3\ldots = \mathbf{I}$$
$$(\boldsymbol{\theta}_1-\mathbf{\Pi_1})\mathrm{L}+(\boldsymbol{\theta}_2-\mathbf{\Pi_1}\boldsymbol{\theta}_1)\mathrm{L}^2+(\boldsymbol{\theta}_3-\mathbf{\Pi_1}\boldsymbol{\theta}_2)\mathrm{L}^3+\cdots = 0.$$

The equation above is the moving averages formulation of the model, where each parenthesis must equal to zero. Subsequently, if the matrix $\boldsymbol{\theta}_i$ is multiplied by the matrix $\mathbf{\Gamma^{-1}}$, the matrix of short-term multipliers of the responses to the impulse $\mathbf{\Psi_i}$ is obtained. Long-term multipliers, i.e. long-term responses of variables to an exogenous shock are obtained by summing the short-term responses. The graphical representation of these multipliers is then the IRF.

Another useful tool of VAR analysis is the variance decomposition. It shows "*the proportion of the movements in a variable due to its 'own' shock versus shocks to the other variables*".[20] First, the forecast error for *m* periods must be calculated, as shown below:

$$\mathbf{y}_{\mathbf{t+m}} - E_t\left(\mathbf{y}_{\mathbf{t+m}}\right) = \boldsymbol{\mu} + \sum_{k=0}^{\infty} \boldsymbol{\Psi}_{\mathbf{k}} \mathbf{u}_{\mathbf{t-k+m}} - \left(\boldsymbol{\mu} + \sum_{k=m}^{\infty} \boldsymbol{\Psi}_{\mathbf{k}} \mathbf{u}_{\mathbf{t-k+m}}\right) = \sum_{k=0}^{m-1} \boldsymbol{\Psi}_{\mathbf{k}} \mathbf{u}_{\mathbf{t-k+m}}$$

An endogenous variable is then selected, for which the equation above can be rewritten as follows:

$$y_{t+m,1} - E_t\left(y_{t+m,1}\right) = \sum_{k=0}^{m-1}\left(\Psi_{11}^{(k)} u_{t-k+m,1} + \Psi_{12}^{(k)} u_{t-k+m,2} + \ldots + \Psi_{1n}^{(k)} u_{t-k+m,n}\right)$$

From the equation above the variance of the endogenous variable can be derived:

$$\sigma^2\left(y_{t+m,1}\right) = \operatorname{var}\left(u_1\right)\sum_{k=0}^{m-1}\left(\Psi_{11}^{(k)}\right)^2 + \operatorname{var}\left(u_2\right)\sum_{k=0}^{m-1}\left(\Psi_{12}^{(k)}\right)^2 + \ldots + \operatorname{var}\left(u_n\right)\sum_{k=0}^{m-1}\left(\Psi_{1n}^{(k)}\right)^2$$

This shows that a variance of a particular endogenous variable is impacted by the variance of the individual exogenous shocks, and that the effect of the individual shocks can be separated and analyzed.[13]

However, the decomposition of the forecast errors cannot be used to identify the variables and shocks which drive the business cycle. In addition, it does not provide information on the importance of exogenous shocks in the historical sample.[24] Another method was developed to identify the individual contributions of exogenous shocks to the movements in the selected macroeconomic variables. This method is called the historical decomposition.[21] To calculate the historical decomposition of the variables, first a VAR(1) model has to be derived:

$$\mathbf{y_t} = \mathbf{c} + \mathbf{A}\mathbf{y_t} + u_t.$$

Then, the endogenous variables at each time t are calculated as the sum of initial values and the sum of all exogenous shocks:

$$\mathbf{y_t} = \mathbf{A}^{\mathbf{T}}\,\mathbf{y_0} + \sum_{k=1}^{T} \mathbf{A}^{\mathbf{T-k}} + \boldsymbol{u_k}.$$

The equation above therefore identifies the shocks which were the driving force in the development of the endogenous variables during the historical sample period. All the tools used in this research paper are presented above. The following paragraphs describe the data and the identification schemes.

In our research, the vector of the endogenous variables consisted of output (y_t), prices (p_t), interest rate (i_t) and the exchange rate ($neer_t$). Out of these four variables three characterized the state of the economy, while we considered the interest rate as the policy variable. The output was proxied by the index of industrial production. This index expresses the rate of change in the volume of industrial production. Prices were measured by CPI inflation. Interest rate was the 1-month money market rate. We could have proxied it by near money, but the results were similar.[16] We could have also used it as a fifth variable, but to save degrees of freedom, we decided to exclude it from the analysis. The exchange rate was measured by the nominal effective exchange rate towards the important trading partners. We used monthly data for the period of 2004M01:2019M11, which we obtained from Eurostat, the National Bank of Hungary and the International Financial Statistics database of the International Monetary Fund. All the variables were in log levels, except the interest rate. The data was not seasonally adjusted, therefore we included seasonal dummies along with a constant in the SVAR estimation as exogenous variables.

As mentioned before, ordering of the variables was important. We tested two ordering schemes to ensure the robustness of the SVAR estimates. The schemes were based on two different studies. [1][3] The first scheme assumed that output could only be affected by supply shocks. Inflation was affected by both supply and inflation shocks, the interest rate was impacted by the shocks of itself, output and inflation, while the exchange rate was immediately impacted by all the shocks in the endogenous variables. This was the scheme which is accepted by macroeconomic theory and can be written in the following matrix form:

$$\begin{pmatrix} y_t \\ p_t \\ i_t \\ neer_t \end{pmatrix} = B(L) \begin{pmatrix} u_y \\ u_p \\ u_i \\ u_{neer} \end{pmatrix}$$

where

- **B(L) –** matrix of Cholesky decomposition presented on the 1. figure,
- **u** – shock of the selected macroeconomic variable at time *t*.

The second scheme was theoretical, since most central bankers would not have accepted the presumptions of this scheme. We assumed that, firstly, the interest rate was only affected by the innovations, and the other variables in the model had no effect on it. Secondly, the nominal exchange rate was affected by the interest rate, because a fall in interest rates caused the exchange rate to weaken and rising interest rates had the opposite effect. Third, inflation was affected by both the interest rate and the exchange rate. An increase in the interest rate was followed by a decrease in consumption and thus, according to Fisher's equation, a decrease in inflation as the savings rate increased. Furthermore, the exchange rate affected the domestic price level through imported inflation. The appreciation of the exchange rate caused a reduction in imported inflation and thus a decline in the domestic price level and vice versa. Fourth, we assumed that shocks in industrial production did not affect the endogenous variables, but the shocks of these other variables affected this index. This second scheme was used only as a robustness check and it is unlikely that will ever be considered in practice.[3] The second scheme in matrix form is presented below:

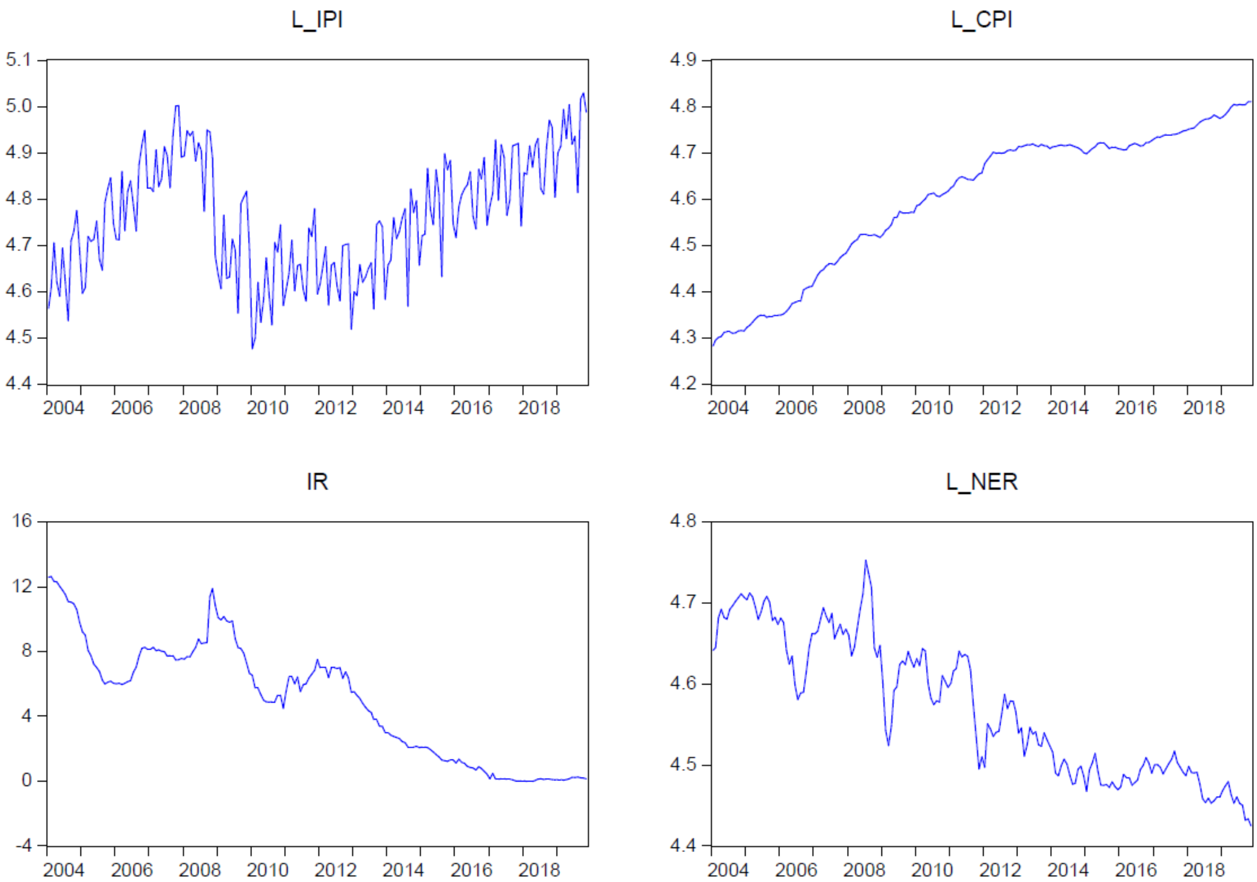
$$\begin{pmatrix} i_t \\ neer_t \\ p_t \\ y_t \end{pmatrix} = B(L) \begin{pmatrix} u_i \\ u_{neer} \\ u_p \\ u_y \end{pmatrix}$$

The SVAR models, which included industrial production (l_ipi), inflation (l_cpi), interest rate (ir) and exchange rate (l_ner), were estimated in EViews. We applied the methodology described above using this software and our results are presented in the next chapter.

Results and discussion

Before we estimated our SVAR models, we looked at the data in log levels. The time series contained useful information. Firstly, we looked for structural breaks, which could affect the estimated parameters of the SVAR models. Secondly, we would have preferred to do the analysis on covariance stationary series. The data is presented on the 2. figure.

We began our analysis by looking for structural breaks. As stated before, the data was available from 2004M01. It was logical to look for the first structural breaks at 2004M05, when Hungary joined the European Union. The series, however, represent a smooth transition. Then we analyzed the graphs separately. The first graph presents the initial increase in industrial production, then a rapid decline and recovery during the 2008-2009 financial crisis. Inflation did not have serious structural breaks during the sample period and remained stable even during the crisis. The third graph presents the interest rate which peaked just before the crisis hit and it had been in an almost constant decline since then, converging to zero. The last graph presents the exchange rate with a huge structural break in 2008. This break was caused by two factors. The first and obvious one is the global financial crisis. The second, and maybe lesser known factor is that Hungary had besides the inflation targeting a managed floating regime, which was abandoned in only 2008. To sum up, there is a structural break during the financial crisis.



2. figure: Data. Source: Developed by author.

We then tried to determine whether the series are stationary or not. It was enough to look at the data and conclude the absence of stationarity. However, we also used the Augmented Dickey-Fuller test (ADF) to test our hypothesis of non-stationary series. The test estimated the following equation presented on the 3. figure:

$$\Delta x_t = \mu + \gamma t + \alpha x_{t-1} + \sum_{j=1}^{k-1} \beta_j \Delta x_{t-j} + u_t$$

3. figure: ADF test. Source:[27]

where

- Δ - difference operator
- $\mathbf{x_t}$ – time series of endogenous variables

- ***u*** – white noise error term

the test examines the negativity of *alfa* based on its regression *t* ratio and tests the null hypothesis of the existence of a unit root.[27] First, we tested the log levels of their series and they were non-stationary. We therefore tested the first differences of each of the series as well, which were stationary. This means that the series were integrated of order one.

Generally, SVAR models are estimated using stationary series. In our case this would have meant estimating them using the first differences of the variables, which we did not do. On the one hand, when VAR models are used for forecasting, all variables should be stationary to avoid the spurious regression problem. On the other hand, in the case of structural identification, which was our aim, we were interested in consistent estimates of parameters. In addition, we wanted to clarify the interrelationships between the selected endogenous variables. For this reason, we opted for a different method, which was advocated by the inventor of the VAR models. In accordance with this approach, non-stationarity should not be considered when selecting the suitable VAR model. If the series are non-stationary and a unit root is present, estimates using the maximum likelihood method still delivers consistent estimates of VAR parameters. In this case we can implicitly assume that there is enough cointegration for the individual variables to be covariance stationary together. [21][6] This way the additional information in the variable levels - which would have been lost if we had estimated the VAR using differences - could be used.[23][11]

We thus continued our analysis using log levels of the variables instead of their differences. To apply identifying restrictions and obtain a SVAR model, first the unrestricted ordinary VAR had to be estimated. We estimated it with 8 lags, which was not optimal. To find the optimal lag length, we took into consideration multiple information criteria. The optimal number of lags proposed by each of them are presented on the 4. figure.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	183.7466	NA	2.03e-06	-1.756509	-1.484067	-1.646157
1	1433.216	2394.270	4.99e-12	-14.67241	-14.12753*	-14.45171
2	1465.548	60.60155	4.21e-12	-14.84343	-14.02611	-14.51238
3	1484.623	34.95504	4.08e-12	-14.87563	-13.78587	-14.43423
4	1520.613	64.44219	3.31e-12	-15.08495	-13.72274	-14.53319*
5	1535.799	26.55594	3.35e-12	-15.07643	-13.44178	-14.41432
6	1562.156	44.98592*	3.01e-12*	-15.18488*	-13.27778	-14.41242
7	1567.192	8.385095	3.39e-12	-15.07007	-12.89054	-14.18726
8	1580.558	21.69297	3.51e-12	-15.04249	-12.59051	-14.04932

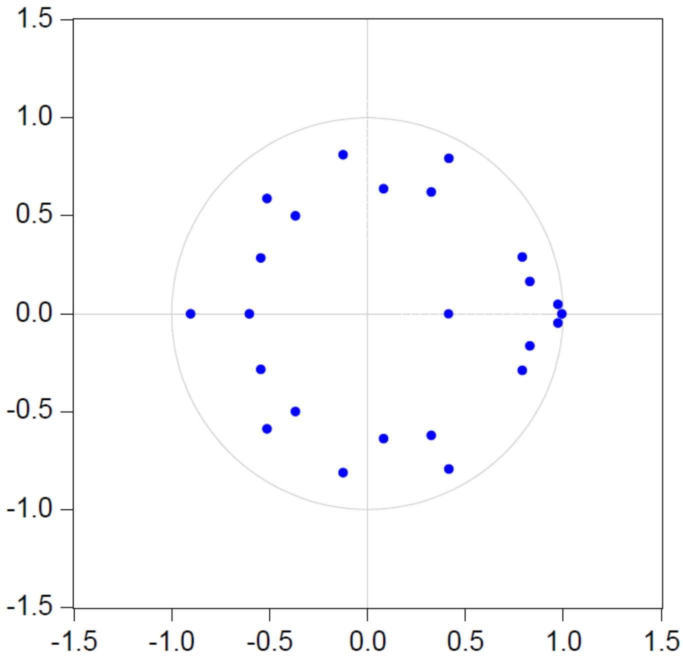
4. figure: Information criteria. Source: Developed by author.

The optimal number of lags is marked by an asterisk in the table. The LR, FPE and AIC criteria all proposed 6 lags. We had monthly data, so we first considered the HQ criteria and estimated the unrestricted VAR with 4 lags.[10] The LM autocorrelation test found significant autocorrelation in almost every lag. The model was therefore re-estimated with 6 lags, as proposed by LR, FPE and AIC. The estimation results were convincing, albeit autocorrelation was still present in the 6^{th} lag. Since adding more lags or including further dummy variables did not solve the issue, and that short-term lags had satisfactory p-values, as presented on the 5. figure, we continued with 6 lags in the unrestricted VAR specification.[20]

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
Null hypothesis: No serial correlation at lag h						
1	16.10329	16	0.4458	1.008584	(16, 477.2)	0.4459
2	17.86923	16	0.3316	1.121243	(16, 477.2)	0.3317
3	25.49276	16	0.0616	1.612334	(16, 477.2)	0.0616
4	21.76080	16	0.1511	1.370963	(16, 477.2)	0.1512
5	26.21721	16	0.0510	1.659405	(16, 477.2)	0.0511
6	16.58186	16	0.4131	1.039074	(16, 477.2)	0.4132
7	19.40475	16	0.2482	1.219537	(16, 477.2)	0.2483
8	31.46944	16	0.0117	2.002782	(16, 477.2)	0.0117
9	19.54695	16	0.2413	1.228656	(16, 477.2)	0.2414
10	18.31371	16	0.3058	1.149663	(16, 477.2)	0.3059

5. figure: LM autocorrelation test. Source: Developed by author.

After taking autocorrelation into account, the stability of the model had to be tested as well. If the model had not been stable, the standard deviations of the IRF would not have been accurate. For the model to be stable, none of the inverse roots should lie outside of the unit root circle. Based on the 6. figure we concluded we that the model was stable and appropriate for further study.



6. figure: Stability test. Source: Developed by author.

Since our VAR model was considered fit for estimation, we applied the identifying restrictions of the first identification scheme to it and estimated our SVAR model. The scheme was described in the methodology and methods section in more detail. The results are presented on the 7. figure.

Estimated A matrix:

1.000000	0.000000	0.000000	0.000000
-0.005680	1.000000	0.000000	0.000000
-0.923846	-1.405762	1.000000	0.000000
-0.008058	0.381991	0.002598	1.000000

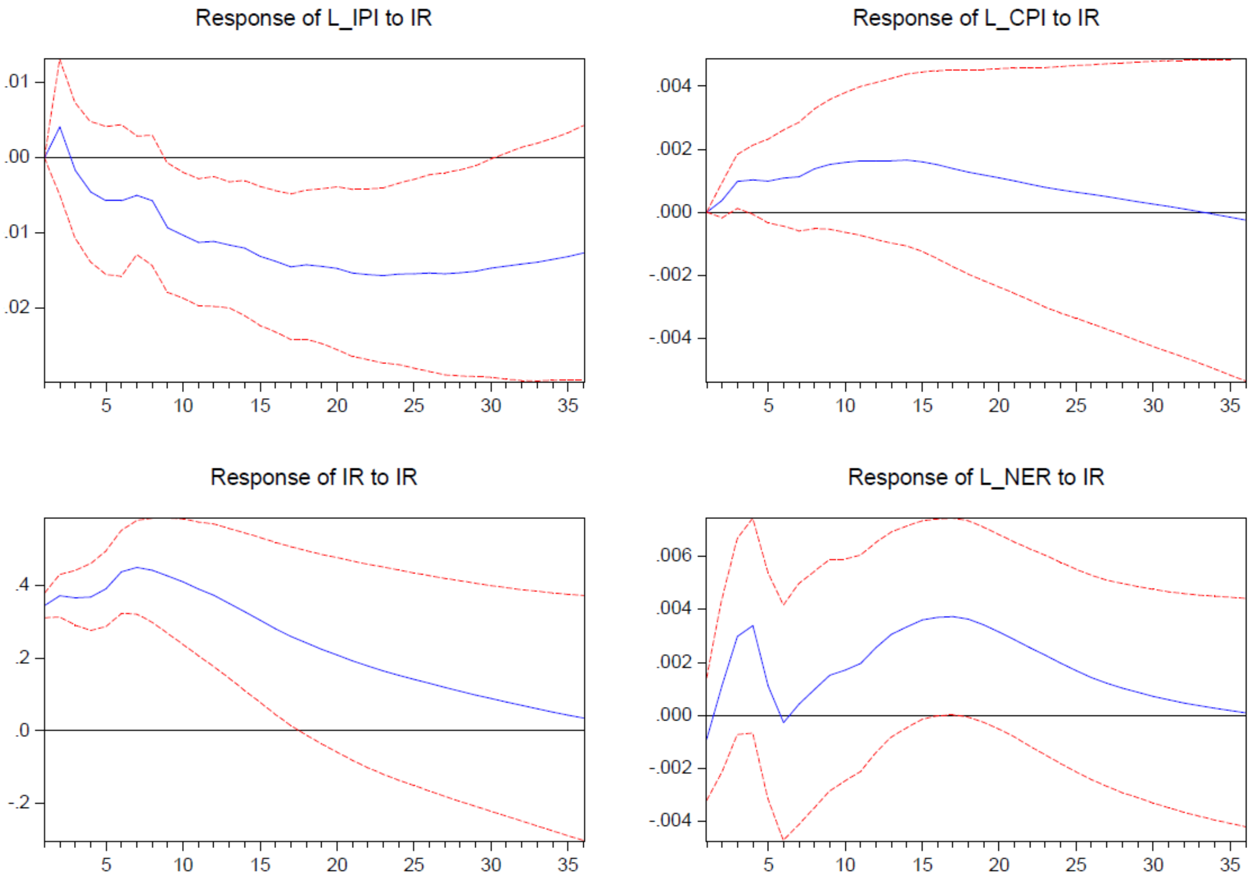
Estimated B matrix:

0.063979	0.000000	0.000000	0.000000
0.000000	0.003919	0.000000	0.000000
0.000000	0.000000	0.344443	0.000000
0.000000	0.000000	0.000000	0.015289

7. figure: SVAR matrix results. Source: Developed by author.

Before we plotted the IRFs, one more issue had had to be addressed. Despite the unrestricted VAR model being stable, a couple of its roots were very close to one. This made us question whether the asymptotic confidence intervals of the IRFs - which were calculated automatically by EViews - were still accurate. We could not prove or disprove this assumption, so instead of taking the risk of incorrect confidence intervals we opted for a bootstrapping technique. The confidence intervals were thus calculated using a Monte Carlo simulation method with 1000 repetitions for a 36 months long horizon. We then plotted the IRFs which are presented on the 8. figure. These IRFs showed us how the individual variables in the system responded to innovations. Their response expressed the dynamic interaction between individual endogenous variables and the VAR process. With the issue addressed, we then moved onto interpretation of the results

On the 8. figure below we plotted the responses of each variable to the structural shock of monetary policy and we can study the monetary transmission mechanism. One thing to be aware of was that in the sample period until 2008 the Hungarian National Bank followed an inflation targeting regime, along with a managed floating policy. Knowing this, we could compare our results to the expectations we set in the first chapter. Firstly, industrial production slightly rose at the beginning of the estimation period, then fell sharply after the second month and had been declining since then, save for a small recovery period. Except for the first month, the industrial production index reacted to the innovation as expected. Secondly, inflation initially rose during the first 15 months. We, therefore, found evidence of the price puzzle in the data, because we would not expect inflation to rise after the interest rate had also risen. On the contrary, inflation should have declined as a result of the innovation, as we stated in the introduction. This result left doubt about the effectiveness of the inflation targeting regime to control inflation. Thirdly, the interest rate initially rose as expected for seven months and the effect of the innovations decreased over time. Fourthly, the exchange rate suddenly appreciated for the first three months and then fell below its initial level, before it was sharply rising again, returning to its initial value at the end of the period. This was expected as well. To sum up, all our expectations were met, except for the inflation, whose reaction was a price puzzle.



8. figure: IRFs of the first identification scheme. Source: Developed by author.

The findings above were promising at first glance, but we could not safely interpret them without accounting for the confidence intervals of plus minus two standard deviations generated by the Monte Carlo simulations. We could thus analyze the significance of the response of the variables to the innovation. None of the variables showed a significant response to the innovation, except for the interest rate itself, which significantly reacted for up to 18 months after the innovation happened. There can be numerous reasons why reactions were insignificant. For example, frequent changes in the monetary policy regime could have been the main reason for their insignificance. The monetary policy regime in Hungary changed several times during the sample period. We have already mentioned the managed floating regime. In addition, multiple structural breaks were present in the data. These changes could significantly affect the results of the estimation, thus obtaining unconventional results.[24]

After the IRF analysis we proceeded with variance decompositions, which helped us determine the relative importance of each structural shock in influencing the variables in the SVAR model. This decomposition showed us what percentage of the variability of each variable can be attributed to his own shocks, and how the variability was influenced by the shocks of other variables. A couple of interesting results emerged, which are presented in the tables below.

1. table: variance decomposition of industrial production. Source: Developed by author.

L_IPI	L_IPI	L_CPI	IR	L_NER
1	100	0.00	0.00	0.00

6	86.16	12.23	1.81	0.80
12	79.89	10.53	7.98	1.60
18	68.45	11.05	17.44	3.06
24	57.09	12.42	26.05	4.43
30	48.25	13.99	31.94	5.83
36	42.55	15.32	35.23	6.90

The 1. table presents that, firstly, inflation explained between 10 and 15 percent of the variance of industrial production during the sample period. Secondly, the dominant source of fluctuations in the volume of industrial production were interest rates. In the six-month horizon, which we considered the short run, the interest rate explained only 1.81 percent of the fluctuations of the industrial production. Despite having little impact on the volume of industrial production on the short run, its influence was steadily growing. On the long run, in the 36-month horizon, the interest rate accounted for a substantial 35.23 percent of the variability of the industrial production. Thirdly, we found that the nominal exchange rate had the lowest impact of all the variables, reaching only 6.9 percent in 36 months. This finding was interesting, because Hungary is considered a small, export oriented open economy. We expected that the exchange rate would have a higher impact on industrial production. To sum up, the variability of industrial production could mainly be explained by the shocks of interest rate besides itself.

Another study had completely different results, which represented conventional wisdom. It found that, being an export-oriented economy, the exchange rate had greatly impacted the variability of Hungarian output. What is more, the interest rate had almost no impact on the variability of GDP, thus showing that the real economy was indifferent to the efforts of the Hungarian National Bank. We had to keep in mind, however, that they used quarterly data, GDP instead of industrial production, in a different sample period, with different identification schemes.[17]

2. table: variance decomposition of inflation. Source: Developed by author.

L_CPI	L_IPI	L_CPI	IR	L_NER
1	0.85	99.15	0.00	0.00
6	1.81	94.23	2.55	1.42
12	0.88	91.49	4.63	3.00
18	0.81	91.59	5.36	2.25
24	1.10	92.73	4.65	1.52
30	1.67	93.06	3.98	1.28
36	2.35	92.95	3.50	1.20

The 2. table present the variance decomposition of the CPI inflation. This variance decomposition yields the results which we expected based on the IRFs above. Firstly, none of the other endogenous variables could substantially impact the variability of the CPI inflation. Its past values were almost the sole determinants of the variability of the series. Here we

witnessed another interesting result. Namely, that interest rate shocks had almost no discernable effects on inflation. This meant that the controllability of the inflation by the central bank was relatively low. This conclusion was different than the one reached by another study.[17] In addition, the low values of the exchange rate suggested that Hungary did not import much inflation in the sample period. To sum up, our findings were still in contrast to conventional wisdom.

3. table: variance decomposition of the interest rate. Source: Developed by author.

IR	L_IPI	L_CPI	IR	L_NER
1	2.91	0.02	97.08	0.00
6	1.70	0.82	96.78	0.69
12	1.47	3.73	88.52	6.28
18	1.74	6.55	80.44	11.27
24	2.43	7.15	77.35	13.07
30	3.27	6.98	75.99	13.77
36	3.97	6.91	75.10	14.02

The 3. table presents the variance decomposition of the interest rate. A couple of interesting results stood out. Firstly, on the long run, inflation explains 6.91 percent of the variability of the interest rate. This suggests that feedback loops did exist in Hungary during the sample period. Secondly, the effect of industrial production is a mere 3.97 percent, despite having the highest impact on the short run, i.e. in the first 6 months. Thirdly, exchange rates had the highest overall impact on the variability of the interest rate, despite having the lowest impact on the short run. This was, however, not unexpected, since Hungary had a managed floating regime until 2008. To sum up, this variance decomposition had the results we expected.

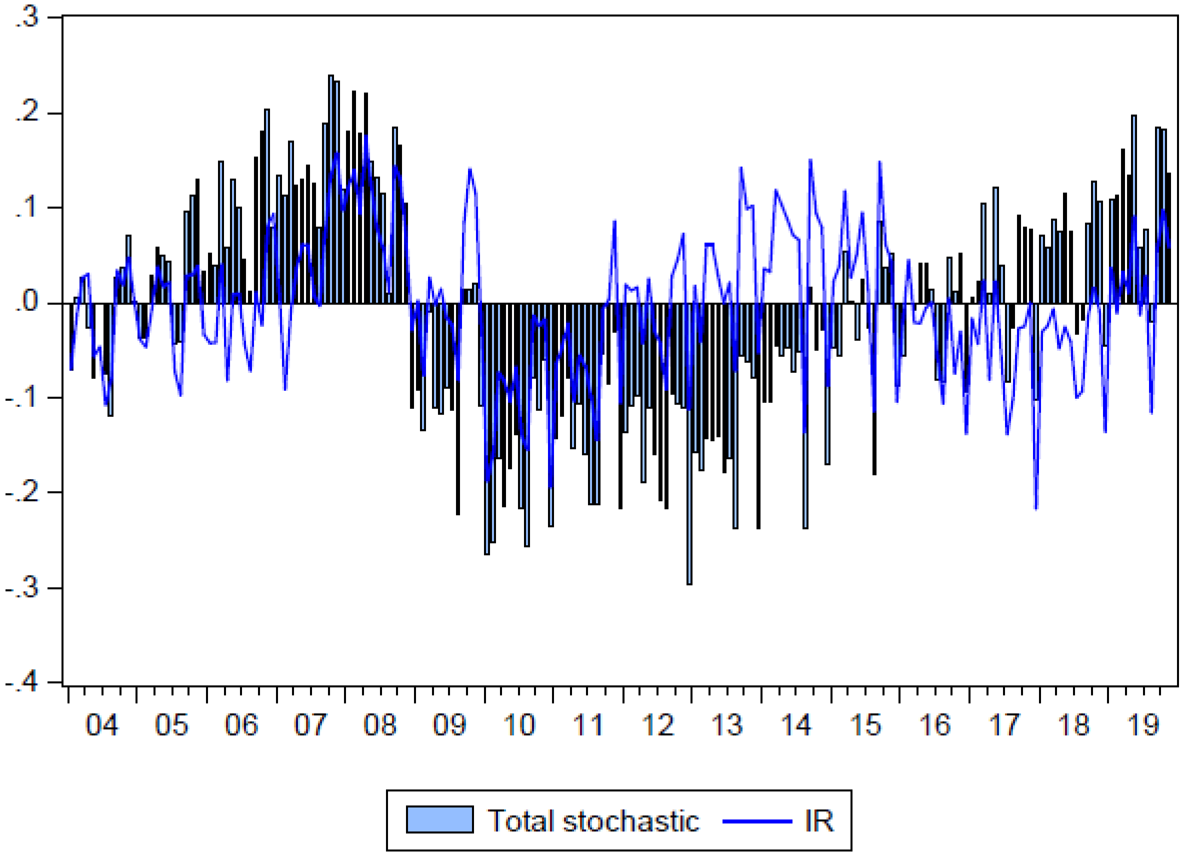
4. table: variance decomposition of the exchange rate. Source: Developed by author.

L_NER	L_IPI	L_CPI	IR	L_NER
1	0.02	0.96	0.34	98.68
6	1.92	5.60	2.01	90.48
12	2.18	7.40	3.15	87.26
18	2.87	7.69	8.27	81.17
24	3.31	7.43	10.91	78.35
30	3.51	7.51	11.28	77.57
36	3.70	8.50	11.18	76.63

The 4. table presents the variance decomposition of the exchange rate. The exogenous monetary policy shock was the dominant contributor to the variability of the exchange rate. This suggested that the international competitiveness of Hungary was mainly determined by the development of the interest rate. Again, industrial production did not affect the exchange rate

much. The CPI had the highest impact on the short run. These conclusions were supported by other studies as well. [12][14]

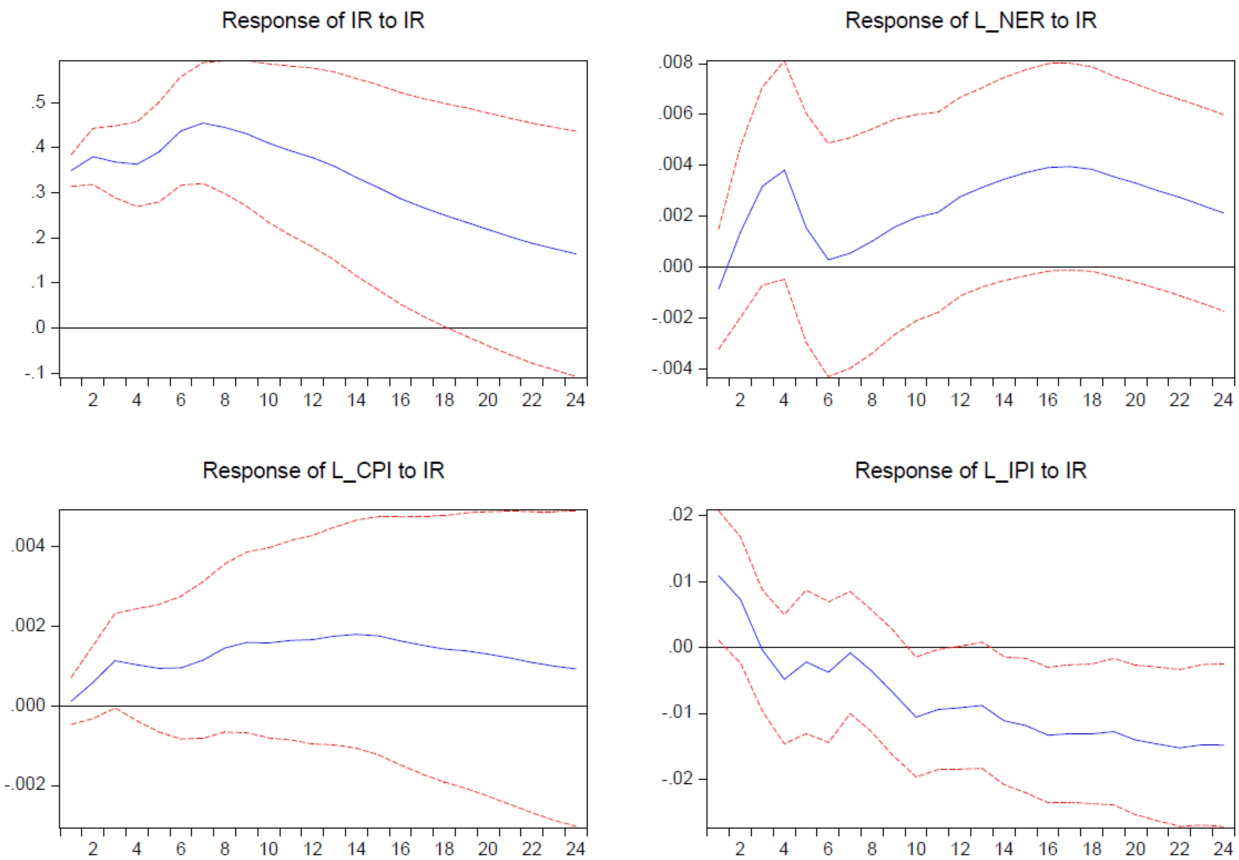
As stated above, based on the variance decomposition of the Hungarian industrial production we concluded that the interest rate shocks accounted for a substantial amount of the variability of industrial production. Since this is not what other authors found, we wanted to ensure the accuracy of the estimates. Because of this we included the graph of the historical decomposition of the industrial production on the 9. figure. It seems that the decomposition of historical results yields similar results than the variance decomposition.



9. figure: Historical decomposition of industrial production. Source: Developed by author.

As we mentioned at the beginning, two identification schemes were applied to the ordinary VAR model. The second, theoretical scheme served as an assurance that the estimation results are robust to different identification schemes. This robustness was tested by changing the ordering of the variables. New IRFs which Monte Carlo simulated confidence intervals were estimated afterwards. The results are presented on the 10. figure.

It appears that the endogenous macroeconomic variables reacted the same way to a one standard deviation innovation as they did in the case of the first identification scheme, except for the index of industrial production. Here, the index did not suddenly increase as it did when the first identification scheme was applied. Instead, it gradually declined from the beginning. This gradual decline was in accordance with economic theory and the sudden peak which was observed in the first case was not present here. What is more, during the first two months, an innovation's negative impact on the volume of the industrial production is statistically significant. Because of these results we might had concluded that this identification scheme was better, since it had more in common with conventional economic theory. However, this second identification scheme did not gain mainstream recognition among central bankers, since it assumed that the interest rate is only impacted by its own innovations, and that supply shocks or inflation had no effect on it. This was the reason why we decided to analyze the first identification scheme instead of the second. In conclusion, the estimates are mostly robust, and the results of the theoretical identification scheme were in accordance with mainstream economic thought, save for the CPI price puzzle.



10. figure: IRFs of the second identification scheme. Source: Developed by author.

Conclusion

In this paper we estimated a structural vector autoregressive model of the Hungarian economy using Cholesky decomposition. We analyzed the impact of exogenous monetary policy shocks on a set of macroeconomic variables.

Generally, the results of impulse response analysis were consistent with economic theory, except for the case of industrial production and inflation. Firstly, the innovation resulted in an increase in inflation during the first 15 months after the shock, which is the so-called "price puzzle". Fortunately, we did not find any sign of the liquidity or exchange rate puzzles. Secondly, the impact of the innovation on the exchange rate was in line with economic theory, as the exchange rate suddenly appreciated during the first months. Thirdly, the innovation caused a sharp increase in industrial production during the first month, but then the industrial production started to decline as expected. Fourthly, the innovation had a statistically significant effect on the interest rate up to 18 months after the shock. The other effects were, however, statistically insignificant with confidence bands calculated using a Monte Carlo simulation. The reactions of inflation, exchange rate and interest rate were robust to different identifying schemes. The reaction of industrial production, however, changed. Failure to meet some of the assumptions, as well as the statistical insignificance signaled by the IRFs may be due to relatively frequent changes in Hungary's monetary policy.

The forecast error variance decomposition had similarly interesting results. Two of them stood out. Firstly, innovations had a substantial impact on the variability of the Hungarian industrial production. This contrasted the findings of another study, but there were some differences between the two approaches. Secondly, it seemed that the controllability of inflation was relatively low.

In the future this analysis should be extended to the systematic component of monetary policy as well and accommodate the effects of foreign interest rate shocks.

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