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Monetary Policy Effectiveness in Kazakhstan

Results With a Small Macro Model

Gregorio Impavido

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Monetary Policy Effectiveness in Kazakhstan: Results With a Small Macro Model
Prepared by Gregorio Impavido*

Authorized for distribution by Ali Al-Eyd
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ABSTRACT: This paper assesses the effectiveness of monetary policy in Kazakhstan using a small macro model and identifies alternative plausible economic structures consistent with priors on the sign of responses of macro variables to structural shocks. Monetary policy effectiveness has increased over time.

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WORKING PAPERS

Monetary Policy Effectiveness in Kazakhstan

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Prepared by Gregorio Impavido[1]

[1] "The author(s) would like to thank" footnote, as applicable.

Contents

Introduction

A central question in empirical macroeconomics pertains to the economy's reaction to monetary policy or other macro shocks. Since the work of Sims (1980), an extensive body of literature has addressed this issue by estimating structural parameters through the use of structural vector autoregression (SVAR) models. These models have rapidly gained popularity as a method for analyzing macroeconomic data, largely due to their emphasis on dynamic impulse response functions (IRFs) and primarily because New-Keynesian models, which assign significant importance to structural parameters in the dynamics of macroeconomic variables, have become a standard framework within the literature on monetary policy.

In the early literature on SVAR, policy and macroeconomic shocks were identified through parametric restrictions, predominantly zero restrictions, on the immediate responses of macroeconomic aggregates to these shocks. Contemporaneous zero restrictions are often justified on the grounds that some variables are sluggish to adjust to new information or that new information is observed with a delay. For instance, a tightening of monetary policy could lead to a decline in real economic activity, albeit with some delay. More recent studies have sought to relax these identification assumptions by employing sign restrictions. Unlike parametric restrictions, which necessitate specific coefficient values derived from prior knowledge of the structure of the economy, sign restrictions simply stipulate the direction of a shock's impact on macroeconomic aggregates. Hence, they are often referred to as "agnostic" identification procedures.

Prominent applications of sign restrictions to study monetary policy effectiveness include papers like Astveit et al. (2017), Canova and De Nicoló (2002), Elekdag and Han (2015), Faust (1998), and Uhlig (2005). Notably, Uhlig (2005) finds that contractionary monetary policy shocks do not exhibit a discernible effect on real GDP, suggesting that the neutrality of money is consistent with empirical data. Subsequent refinements to Uhlig's identification approach (Arias et al., 2019) and the use of identification based on external instruments (Gertler and Karadi, 2015) have tended to reaffirm the conventional view that monetary policy exerts a short-term influence on GDP, as, for instance, predicted by models incorporating price rigidities.

This paper proposes a "quasi-agnostic" identification procedure to overcome the low acceptance rates typical of agnostic identification procedures. Agnostic identification procedures based on sign restrictions typically yield a low proportion of simulated structural shocks that satisfy the imposed sign restrictions (acceptance rates). For instance, Fisher and Huh (2018), find acceptance rates of less than 1 percent using their proposed algorithm, or the one developed by Arias et al (2018). Ouliaris and Pagan (2016) algorithm also yields very low acceptance rates when applied to the Cho Moreno (2006) study. The strategy proposed in this paper is akin to an iterative grid search that employs increasingly refined identification methods to identify the plausible set of structural parameters that satisfy the imposed sign restrictions. The strategy is designated as "quasi-agnostic", reflecting the fact that, at each iteration, it narrows down the likely interval of the plausible structural parameters using the information garnered from earlier iterations. Results suggest that this strategy can significantly enhance acceptance rates, revealing a larger set of economic structures consistent with the priors on the sign of responses of macro variables to structural shocks.

The rest of the paper is organized as follows. Section I provides an overview of the data and establishes a baseline SVAR model to examine how the Kazakhstan economy responds to monetary and macroeconomic shocks through a small three-variable macroeconomic model. In Section II, this baseline model is linked to a conventional New-Keynesian framework to address potential misspecifications. Section III critiques the rationale for employing a unique set of parametric restrictions, such as zero contemporaneous restrictions, and adopts the methodology proposed by Ouliaris and Pagan (2016) for imposing sign restrictions on the IRFs at various time horizons. Section IV explores different alternative “quasi-agnostic” identification procedures, proposing that, even without comprehensive knowledge of the economic structure, higher acceptance rates than those commonly achieved through purely agnostic identification methods can be achieved. Section V concludes with a comprehensive summary of empirical results on the evolution of monetary policy effectiveness in the country.

The baseline model

We start laying out a SVAR for a small macro model with three variables as our baseline model. The variables are the output gap, inflation, and the policy rate. The output gap is estimated through a two-step process. Firstly, Harvey and Jaeger (1993) adapted for mixed frequencies data is used to estimate the log of seasonally adjusted quarterly real GDP at a monthly frequency between January 2017 and September 2024. Subsequently, Impavido (2024a) is used to extract the cyclical component employing the annual real growth of monthly loans to individuals as a proxy to assess the influence of the financial cycle on the business cycle. Inflation is computed using seasonally adjusted CPI, excluding controlled prices, for the same period between January 2017 and September 2024. The exclusion of controlled prices is deemed necessary to better reflect the impact of policy rate shocks on overall prices. The monetary policy variable is represented by the average policy rate utilized by the Central Bank to determine the monetary policy stance, with data consistent across the specified timeframe.

The model is defined as:

$$A_0 Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + B_0 \varepsilon_t \tag{1}$$

In this model, $Y = [o, \pi, r]'$ is the vector of the three endogenous variables: the output gap (o), inflation (π), and the policy rate (r); A_0 is a lower triangular matrix with ones over the diagonal capturing the contemporaneous interactions among the endogenous variables; A_1 and A_2 are full matrices of parameters for the lagged values of Y; B_0 is a diagonal matrix with the standard errors of the shocks on the diagonal;[1] $\varepsilon_t \sim (0, I_3)$ is the vector of uncorrelated and orthogonalized shocks of unit variance; and $\eta_t = B_0 \varepsilon_t$ will contain the structural equation shocks.

Given the contemporaneous correlation among shocks implied by the structure of A_0, there is an identification problem. There are 27 parameters to be estimated[2] and only 24 parameters can be estimated from the underlying VAR. Hence, three zero contemporaneous restrictions are imposed in A_0 to identify the structural shocks, making the SVAR recursive and exactly identified. I.e.:

$$A_0 = \begin{bmatrix} 1 & 0 & 0 \\ a_{21}^0 & 1 & 0 \\ a_{31}^0 & a_{32}^0 & 1 \end{bmatrix} \text{ and } B_0 = \begin{bmatrix} \sigma_o & 0 & 0 \\ 0 & \sigma_\pi & 0 \\ 0 & 0 & \sigma_r \end{bmatrix} \tag{2}$$

[1] A SVAR with standard deviations along the diagonal of B_0 and ones along the diagonal of A_0 is called *normalized*. A SVAR with ones along the diagonal of B_0 and parameters to be estimated along the diagonal of A_0 is called *unnormalized*. The two representations are equivalent.

[2] There are 6 parameters in A_0, 9 in A_1, 9 in A_2, and 3 in B_0.

Table 1 reports the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (BIC), and the Hannan and Quinn information criterion (HQIC) lag-order selection statistics for a series of SVARs of order 1 through 5. A sequence of log-likelihood (LL), likelihood-ratio test statistics (LR), and their p-values for all the full SVAR models of order less than or equal to the highest lag order are also reported. The first likelihood-ratio test that rejects the null hypothesis that the additional parameters from adding a lag are jointly zero would suggest a SVAR of order 3. The other information criteria suggest that little information is lost by additional lags between 2 and 3. A lag of 2 is chosen to minimize the risk of overfitting.[3]

The SVAR defined in equation (1), using the structural restrictions in A_0 defined in equation (2), can be estimated via FIML, or since it is exactly identified, simply via 2SLS using instrumental variables.[4] This second option is used throughout this paper as it enables us to later cover more easily cases when the contemporaneous restrictions are different from zero.[5]

The IRFs derived from the SVAR model presented in equation (1), utilizing the structural matrix A_0 as defined in equation (2) are illustrated in Figure 1. The first column indicates that a one standard deviation demand shock exerts a contemporaneous impact on the output gap equal in magnitude to the shock, and with a persistence of about 15 periods. This shock also results in a modest positive contemporaneous effect on inflation and a small immediate increase in the policy rate, which subsequently rises over time in response to an expanding output gap. In the second column, a one standard deviation supply shock has a zero contemporaneous impact on the output gap, dictated by the zero contemporaneous restriction in A_0. However, this impact increases to about twenty basis points in about 6-8 periods. This shock also elicits a positive contemporaneous response in inflation, indicating that rising production costs are rapidly transferred to consumer prices, alongside a contemporaneous increase in the policy rate that reaches about twenty-five basis points within 6-8 months before inflationary pressures abate. Lastly, in the third column, a one standard deviation monetary shock has a zero contemporaneous impact on the output gap and on inflation, again dictated by the zero contemporaneous restriction in A_0. The output gap response accelerates to about fifteen basis points in a few periods, while the response of inflation is small and positive.

These initial findings indicate that various shocks exert a durable influence on the output gap and interest rates, while their effect on inflation is minimal; with the notable exception of supply shocks, which have a more sustained impact on inflation. This marked persistence in the output gap response may be attributed to a heightened degree of habit formation in consumers' utility functions, as characterized by an autoregressive process that exceeds the influence of the forward-looking component. Similarly, the persistence observed in the policy rate can be linked to significant habit formation within the Central Bank's reaction function. The limited persistence of the inflation response may stem from a robust forward-looking component or other influences, such as substantial exchange rate pass-through. These outcomes align with prior literature suggesting that inflation in the country is predominantly imported (Hajdenberg 2024), that the interest channel

[3] In addition, all eigenvalues lie in the unit circle suggesting that the SVAR satisfies the stability condition.

[4] The estimated $\hat{A}_0$ and $\hat{B}_0$ for the SVAR defined in equation (1) using the structural identification short run restrictions defined in equation (2) can be derived from the Cholesky decomposition of the variance covariance matrix of the shocks Σ from the underlying VAR. More formally, if $\Sigma = CC'$ is the Cholesky decomposition of Σ from the VAR, then $C = \hat{A}_0^{-1}\hat{B}_0$ and, since the SVAR is exactly identified, $\hat{B}_0 = diag(C)$. It follows that $\hat{A}_0 = \left(C\left(diag(C)\right)^{-1}\right)^{-1}$.

[5] With non-zero contemporaneous restrictions one can always redefine the endogenous variables to make the SVAR recursive but the A_0 stemming from the Cholesky decomposition of the variance-covariance matrix of the shocks of the underlying VAR as described in footnote **Error! Bookmark not defined.**, would be associated to these modified endogenous variables and an additional step is needed to derive the structural matrix of the original non-redefined variables.

of monetary policy is relatively weak (Zhou 2022), and that inflation exhibits a limited response to the output gap, in turn, supporting the notion of a flat Phillips curve (Impavido 2024b).

The observation that a monetary shock leads to a positive inflation response raises concerns about potential misspecification in the model. To address this type of puzzles, typical of recursive systems, the literature suggests various corrective approaches, including (i) incorporating additional endogenous variables to better reflect the underlying economic structure, (ii) redefining existing endogenous variables to capture different relationships or effects, (iii) employing non-recursive, less strict, identification procedures, and (iv) introducing latent variables that can account for unobservable factors influencing the relationships within the model.

Approach (i), the addition of new endogenous variables, is a viable strategy to address the price puzzle, as it can be informed by theoretical or intuitive considerations. For instance, incorporating a monetary aggregate into the model can help resolve the price puzzle by accounting for the implicit money demand, which is currently absent. I.e., it is believed that there is an implicit money supply represented by the interest rule in the model but not a money demand; and its absence allows prices to increase when the interest rate increases. Additionally, there could be a hidden exchange rate puzzle that is not evident because the exchange rate is missing as additional endogenous variable. I.e., the monetary shock would depreciate the currency (rather than appreciating it, as it is normally the case) and this causes prices to increase through the exchange rate passthrough. Or additionally still, the monetary shock would cause inflation expectations to increase because (say) of low credibility of the Central Bank and, through this channel, increase current prices. However, adding more endogenous variables increases the number of parameters to be estimated exponentially. It also increases the number of shocks and hence, it requires identifying additional restrictions,[6] and additional puzzles may arise. Approach (iv), introducing latent variables, is conceptually similar to approach (i); it increases the number of shocks relative to the observed variables and can help resolve observed puzzles. It also comes with similar drawbacks. In addition, when it is believed that latent variables are present, estimation typically involves casting the model in its state space representation and estimating impulse response functions via MLE using the Kalman filter; all beyond the scope of this paper. Therefore, we leave approaches (i) and (iv) for future research and in the next section we follow approach (ii) to solve the price puzzle while the subsequent section follows approach (iii) to relax the identifying restrictions.

The baseline model respecified

In this section we suspect that inflation expectations are somehow poorly anchored and that they are the cause of the price puzzle just discussed. In order to devise a strategy for redefining the endogenous variables to purge them of the effects of inflation expectations, we need to lay down the small New Keynesian model implicit in the previous section:

$$\begin{aligned} gap_t &= \gamma E_t ogap_{t+1} + (1-\gamma) ogap_{t-1} - \delta(r_t - E_t \pi_{t+1}) + \varepsilon_{IS,t} \\ \pi_t &= \alpha E_t \pi_{t+1} + (1-\alpha)\pi_{t-1} + \beta gap_t + \varepsilon_{AS,t} \\ r_t &= \phi r_{t-1} + (1-\phi)(\lambda E_t \pi_{t+1} + \mu gap_t) + \varepsilon_{MP,t} \end{aligned} \tag{3}$$

[6] The number of additional identifying restrictions required increases by $\left(\frac{d(d-1)}{2} + nd\right)$ where n is the number of original endogenous variables and d is the number of endogenous added to the system.

The first equation is the IS equation in which the output gap depends on a forward-looking component and past habit formation of consumers, the monetary policy channel captured by the ex-ante real interest rate, and ε_{IS} is the aggregate demand shock. The second equation is the aggregate supply equation in the spirit of Calvo (1983) in which inflation is a function of past and expected inflation, as well as the output gap, and ε_{AS} is the aggregate supply shock. The third equation is the Central Bank reaction function with habit formation and in which the policy rate reacts also to expected inflation and the output gap, and ε_{MP} is the monetary policy shock. The system in (3) is estimated using the SUR estimator. Then, the expected inflation multiplied by the relevant estimated parameters is subtracted from the original endogenous variables. For simplicity, such modified variables will still be referred to as output gap, inflation, and the policy rate in the rest of the paper. In addition, a dummy for the COVID shock and the log of oil prices are added to the output gap equation as exogenous variable to control for the large output gap generated by the covid shock in 2020 and the procyclical impact of fiscal policy, typical of an oil exporting country.[7] Ultimately, parameters of the underlying VAR non statistically different from zero are dropped from the estimation.

The re-specified constrained SVAR with exogenous variables is given by:

$$A_0 Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \Gamma X_t + B_0 \varepsilon_t \tag{4}$$

where A_0 and B_0 are defined in equation (2), $A_1 = \begin{bmatrix} a_{11}^1 & a_{12}^1 & a_{13}^1 \\ a_{21}^1 & a_{22}^1 & a_{23}^1 \\ a_{31}^1 & a_{32}^1 & a_{33}^1 \end{bmatrix}$, $A_2 = \begin{bmatrix} 0 & 0 & 0 \\ 0 & a_{22}^2 & a_{23}^2 \\ 0 & 0 & a_{33}^2 \end{bmatrix}$, $\Gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$, and $X = [covid, oil\ ]'$ is the vector of exogenous variables.

The SVAR model presented in equation (4) is then re-estimated yielding the following estimated structural matrix and standard deviation of the shocks:

$$\hat{A}_0 = \begin{bmatrix} 1 & 0 & 0 \\ -0.0218 & 1 & 0 \\ -0.0770 & -0.1196 & 1 \end{bmatrix} \text{ and } \hat{B}_0 = \begin{bmatrix} 0.4902 & 0 & 0 \\ 0 & 0.2590 & 0 \\ 0 & 0 & 0.2988 \end{bmatrix} \tag{5}$$

The estimated IRFs are reported in Figure 2. Results are qualitatively similar to the ones of the baseline model with original variables, so the interpretation provided in the previous section remains valid. The notable distinction is the resolution of the price puzzle, supporting the idea that the previous misspecification was primarily due to the exclusion of inflation expectations as an additional endogenous variable.

Imposing agnostic sign restrictions

The recursive assumption stemming from the zero contemporaneous restrictions and the specific ordering of the endogenous variables used in Y need to be justified. Without additional information on the structure of the economy and on how shocks propagate in the economy, it is not possible to answer these two fundamental questions. There could be an infinite number of combinations of restrictions that are compatible with our priors regarding the responses of macro variables to structural shocks. How to find these combinations of restrictions is the objective of the literature on sign restrictions. In particular, Ouliaris and Pagan (2016) propose an

[7] Alternative specifications using in addition, or alternatively, the nominal exchange rate or the import deflator in the inflation equation to capture the high dependence of domestic inflation on external shocks, produced similar qualitative results.

identification procedure based on sign restrictions of generated coefficients (SRC) according to which the zero contemporaneous restrictions in A_0 are imposed using random coefficients of the form $a_{ij} = \frac{\theta}{1-abs(\theta)}$ with $\theta \sim U(-1,1)$.

The SRC procedure is implemented as follows:

- We take the SVAR defined by equation (4), using an unrestricted structural matrix $A_0 = \begin{bmatrix} 1 & a_{12}^0 & a_{13}^0 \\ a_{21}^0 & 1 & a_{23}^0 \\ a_{31}^0 & a_{32}^0 & 1 \end{bmatrix}$.

- Next, we then simulate 1,200 combinations of parameters a_{12}^0, a_{13}^0, and a_{23}^0 using the SRC procedure.

- For each combination of parameters, we estimate B_0 and the remaining parameters in A_0 using 2SLS, and we use OLS to estimate the parameters of A_1 and A_2.

- Next, the signs of the contemporaneous $IRF_{h=0} = \hat{A}_0^{-1}\hat{B}_0$ are then compared with our priors on the signs of the responses of macro variables to positive structural shocks reported in Table 1, and IRFs inconsistent with priors are discarded.

- Ultimately, the acceptance rate is computed as the number of combinations consistent with priors over total draws.

The IRFs derived from this procedure are illustrated in Figure 3. Several points can be noted:

- A one standard deviation monetary shock has a negative impact on the output gap of anything between zero and thirty basis points and negative impact on inflation of anything between zero and fifteen basis points. The inflation response increases to about twenty-five basis points after three periods before dissipating.

- The low acceptance rate suggests in principle that the model specification can be further improved. While this is generally always the case, it will be argued in the next section that the acceptance rate is also dependent on the method adopted to impose sign restrictions, leaving the question of the relative contribution of these two factors to such low acceptance rates unanswered.

- Sign restrictions solve the structural identification problem but are not helpful in solving the model identification problem. Each IRF reported in Figure 3 is generated by a unique set of structural parameters and the lack of a unique model raises the question of which one to use. Summary statistics like median, percentiles, or average values of the IRFs fail to acknowledge the model identification problem. In the absence of prior knowledge on how to reject implausible IRFs, the range of models can be narrowed by imposing sign restrictions on more than just contemporaneous impulse responses. This is done in the first line of Figure 3 and Table 2, which reports the acceptance rate of the SRC($-\infty, +\infty$) procedure with sign restrictions imposed at lag zero, three and six. Clearly, this narrows the range of plausible models quite sharply.

- Ultimately, sign restrictions alone permit variation in the magnitude of the standard deviation of the structural shocks across different models. This does not matter for the shape of the IRFs, which does not depend on the standard deviation of the shock. However, it matters for contemporaneous responses. Fortunately, in our analysis, this variability is minimal, as reported by the panels along the diagonal of Figure 3. Furthermore, it is always possible to normalize the IRFs to solve this issue.

Imposing "quasi-agnostic" sign restrictions

The SRC($-\infty, +\infty$) is characterized by its capacity to generate an extensive array of parameters; however, this advantage is mitigated by the elevated standard deviations associated with these parameters, resulting in a significant proportion of values that fall outside of a plausible range, thereby yielding a low acceptance rate. The delineation of a plausible range is inherently contingent upon the specific model employed. Nevertheless, even in the absence of detailed insights into the economic structure, it remains feasible to develop a strategy for effectively constraining the range of structural parameters to enhance the acceptance rate. The proposed approach to refine the range of plausible structural parameters resembles a grid search across progressively refined identification procedures. These procedures are designated as "quasi"-agnostic, reflecting their adaptive nature, wherein subsequent methodologies are adapted based on the insights garnered from the results of earlier procedures regarding the likely interval of plausible structural parameters.

Figure 4 and Table 2 to Table 6 are useful to illustrate the strategy. In the first line of Figure 4 the SRC($-\infty, +\infty$) procedure is applied to sign restrict the IRFs at lag zero, three and six. Each panel reports, for each parameter a_{12}^0, a_{13}^0, and a_{23}^0, the median of the distribution (represented by the line in the box), the first and third quartiles (represented by the top and bottom of the box), the first and last quintiles (represented by the whiskers), eventual outliers, and the acceptance rate stemming from 1200 simulations. For easier reading, Table 2 reports similar numerical values and in addition, the mean, and the number of successful combinations of parameters. Several things can be noted: the median of all three parameters lies in the $(0,1)$ interval; all a_{13} parameters are positive; very few successful a_{12}^0, and a_{23}^0 parameters are negative and in any case, very close to zero; when we sign restrict the IRFs at lag six, the number of successful negative parameters diminishes; the standard deviation of a_{23}^0 is very small suggesting that all successful parameters are concentrated around the mean; and the standard deviation of a_{12}^0 is quite high suggesting that successful parameters are quite dispersed around the mean. All this suggests that plausible parameters are likely to be positive and for a_{23}^0, very close to its mean.

With this information, it seems natural to modify the procedure to limit the random draws to the $(0, +\infty)$ interval. This is done in the second line of Figure 4 and Table 3 where the absolute values of the SRC($-\infty, +\infty$) procedure are taken. This new procedure, labeled here as SRC($0, +\infty$), yields higher acceptance rates at all time horizons. It also reveals new (larger) plausible parameters for a_{13} which, however, tend to disappear when IRFs are restricted at higher time horizons. By construction, however, it excludes our baseline model and plausible negative values for a_{12}^0.

In order to re-include zero or negative values, the exercise is re-conducted using random draws from a normal distribution with zero mean and a standard deviation of one. Results reported in line three of Figure 4 and Table 4 broadly comparable to the SRC($-\infty, +\infty$) method simply because the ratio of two uniform distributions approximates a normal distribution. Two more rounds of this grid search strategy are conducted by lowering the standard deviation of the random draws and shifting their mean roughly around the mean or median of plausible parameters from earlier procedures. Results are reported in the last two lines of Figure 4, and Table 5 and Table 6. Clearly, the acceptance rate tends to increase the more parameters are drawn around the mean of plausible parameters.

The IRFs derived from the SVAR model presented in equation (4) and using the N(0.5,0.25) identification procedure at time lag six, are illustrated in Figure 5. Results suggest that there are many plausible structures of the economy in which a one standard deviation monetary policy shock reduces contemporaneous output gap between zero and twenty-five basis points and contemporaneous inflation between four and twelve basis points. The response of the output gap decreases over time while the response of inflation increases to about eighteen basis points in the first two periods before declining as the output gap closes.

Monetary policy effectiveness over time

The effectiveness of the monetary policy in containing inflation has increased over time and the exchange rate channel of monetary transmission has likely strengthened. The structure of the economy yielding the strongest inflation response from the previous section was taken.[8] This is given by:

$$A_0 = \begin{bmatrix} 1 & 0.1015 & 0.6809 \\ a_{21}^0 & 1 & 0.3361 \\ a_{31}^0 & a_{32}^0 & 1 \end{bmatrix} \quad (6)$$

The SVAR model, presented in equation (4) with the structural matrix A_0 defined in equation (6), was then re-estimated across six time periods, each extending an additional 12 months starting with a first sample ending in 2019m12. Figure 6 illustrates the response of the output gap and inflation to a one standard deviation monetary policy shock. There is a substantial increase in the contemporaneous impact of the shock on the output gap, more than doubling from eight to seventeen basis points between 2019 and 2024. Concurrently, the inflation response exhibits an even higher increase, rising from four to twelve basis points across the same timeframe.[9] This shift may be attributable to factors such as enhanced central bank credibility, reduced dollarization, and improved communication strategies. Furthermore, the relationship between the output gap and inflation demonstrates temporal variation. Early periods (2019-2020) exhibit a faster convergence of inflation back to its trend compared to the output gap, whereas later periods (2023-2024) display the inverse. Both patterns suggest a relatively flat Phillips curve: a weak inflation response to the output gap beyond the immediate impact. However, the observed change in the relationship indicates a possible change in the relative importance of different monetary policy transmission channels, with potentially a stronger exchange rate channel over time.

Conclusions

The structural parameters of a small macro model for Kazakhstan using output gap, inflation, and policy rate are estimated using an exactly identified recursive SVAR. Results indicate that identified shocks exert a

[8] The same exercise was conducted using structural restrictions yielding the median and the minimum contemporaneous inflation response to a monetary policy shock and results are comparable.

[9] Part of the impact is due to an increase in the variance of the shocks over time. However, this does not affect the shape of the IRFs that show higher persistence of the inflation response over time.

durable influence on the output gap and interest rates, while their effect on inflation is minimal; with the notable exception of supply shocks, which have a more sustained impact on inflation. Results support the priors that inflation in the country is predominantly imported, that the interest channel of monetary policy is relatively weak, and that inflation exhibits a limited response to the output gap, in turn, supporting the notion of a relatively flat Phillips curve.

The recursive nature of the model cannot be justified with available knowledge of the structure of the economy. Hence, short term restrictions are relaxed, and sign restrictions are imposed on impulse response functions at different time horizons using the SRC algorithm proposed by Ouliaris and Pagan (2016). Results suggest that there are plausible structures of the economy that yield stronger responses to monetary policy shocks than the recursive model. However, the procedure yields very low acceptance rates suggesting either model misspecification, or identification procedure limitations.

To overcome possible identification procedure limitations, this study proposes a strategy aimed at identifying a greater number of plausible economic structures. The proposed strategy is akin to a grid search across progressively refined identification procedures. These procedures are designated as “quasi”-agnostic, reflecting their adaptive nature, wherein subsequent methodologies are informed by the insights garnered from the results of earlier procedures regarding the likely interval of plausible structural parameters. Results suggest that this strategy can significantly enhance acceptance rates, revealing a larger set of economic structures consistent with the priors on the sign of responses of macro variables to structural shocks. Results also leave open the question of the relative importance of possible model misspecification in determining the acceptance rate of any given sign restriction procedure.

Ultimately, results suggest a notable enhancement in monetary policy effectiveness, with the contemporaneous impact of a monetary policy shock on the output gap more than doubling between 2019 and 2024. Concurrently, the inflation response to such shocks has nearly tripled. These changes may be attributed to factors such as heightened central bank credibility, a decline in dollarization, and more effective communication strategies. Preliminary findings also indicate a potential shift in the relative strength of monetary transmission channels, with the exchange rate channel possibly assuming a more prominent role towards the end of this period.

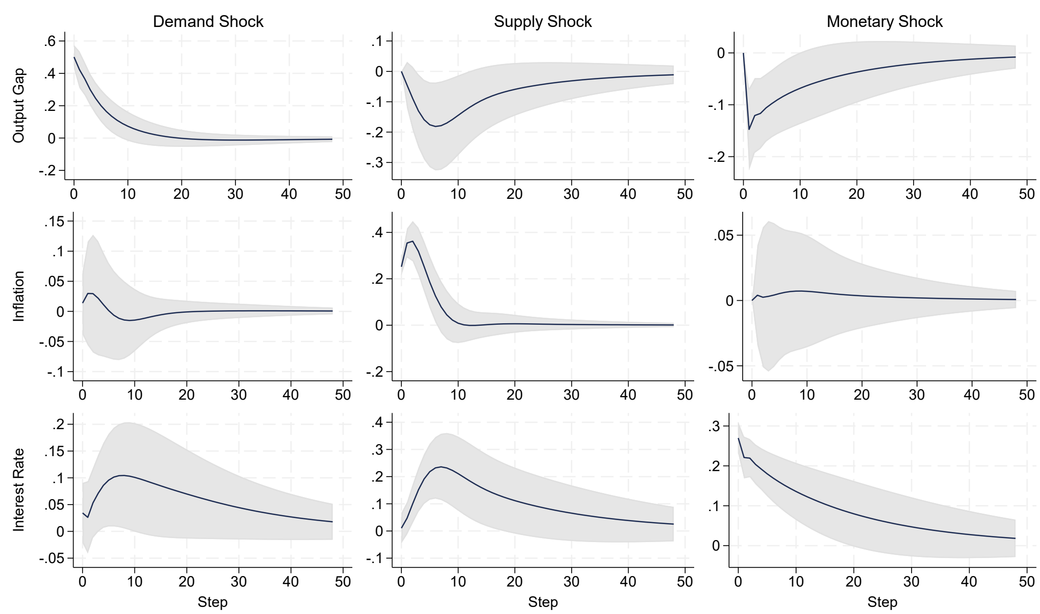
Annex I. Tables and Figures

Table 1. Lag selection

Horizon	LL	LR	Pval	FPE	AIC	HQIC	SBIC
0	-403.377			4.047	9.912	9.947	10.000
1	-99.710	607.333	0.000	0.003	2.725	2.866	3.077
2	-52.662	94.097	0.000	0.001	1.797	2.044	2.413
3	-42.677	19.970	0.018	0.001	1.773	2.126	2.653
4	-34.222	16.910	0.050	0.001	1.786	2.245	2.931
5	-26.164	16.116	0.064	0.001	1.809	2.374	3.218

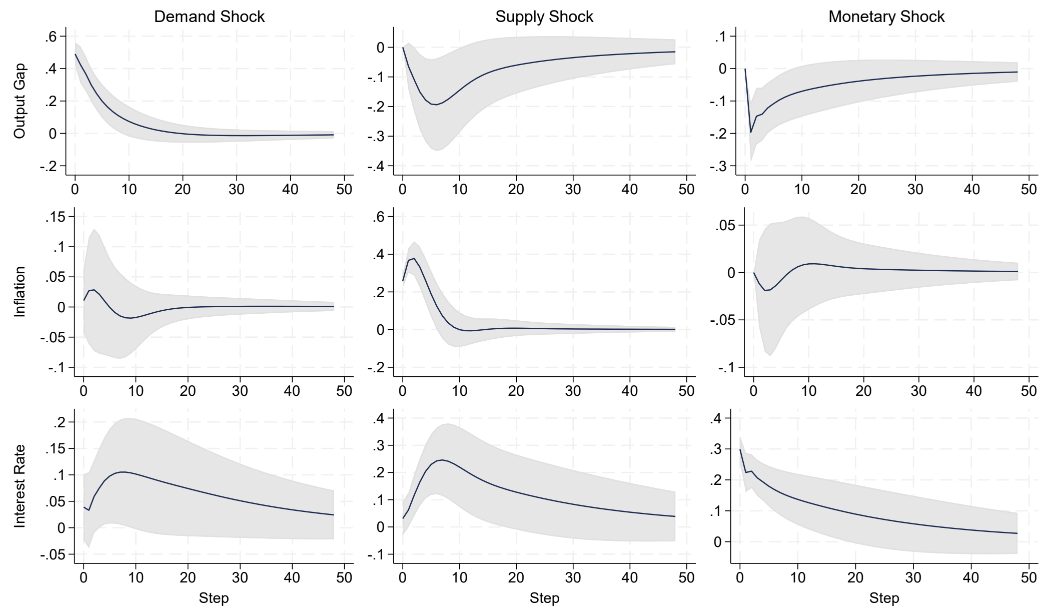
Source: Authors' calculations.

Figure 1. Structural impulse responses – baseline model



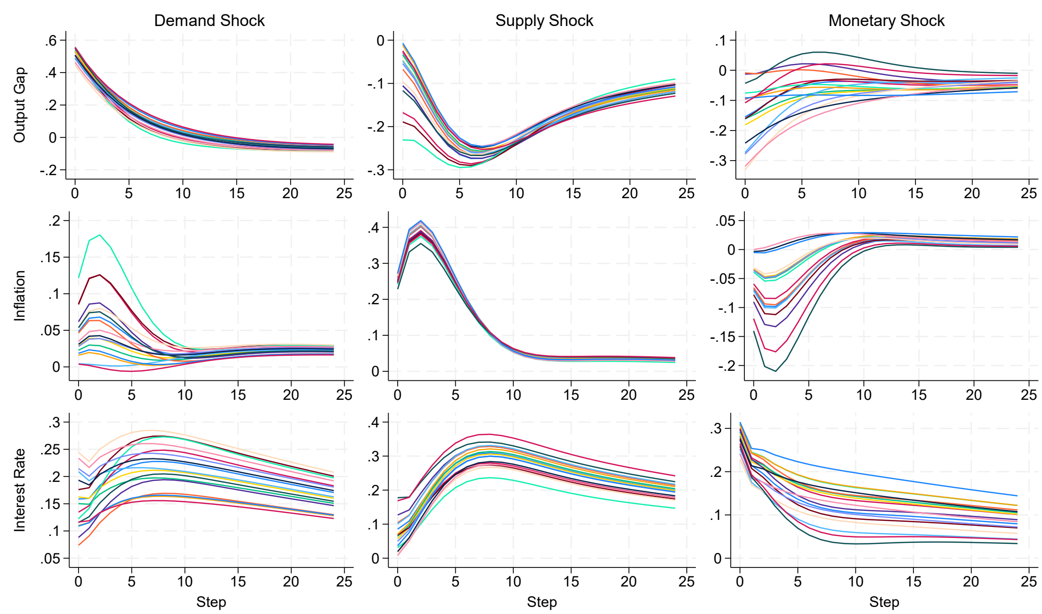
Source: Authors' calculations.

Figure 2. Structural impulse responses – baseline model respecified



Source: Authors' calculations.

Figure 3. Contemporaneous sign restrictions on IRFs SRC(−∞, +∞) /1



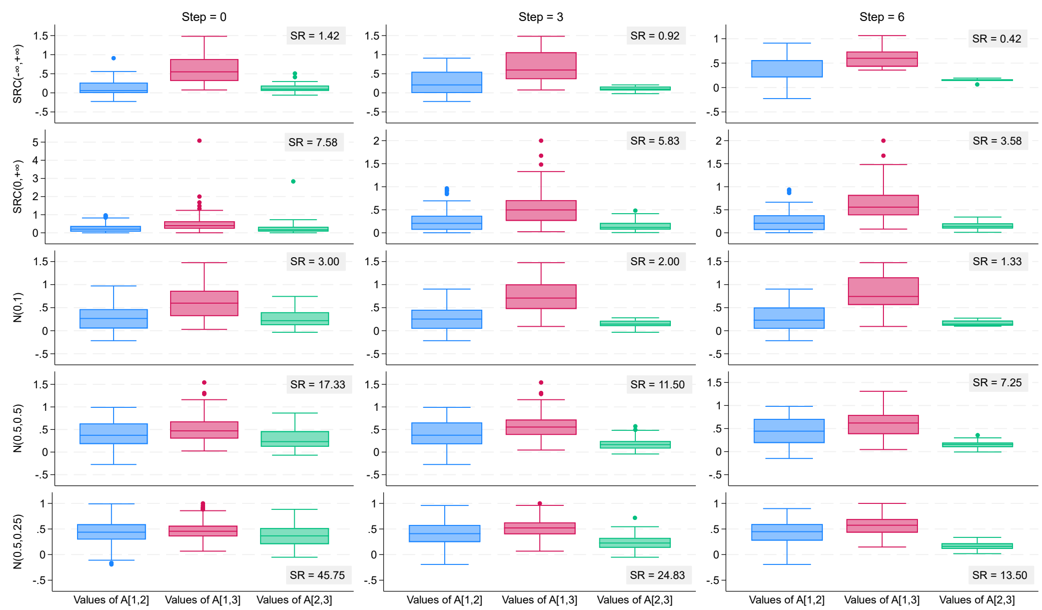
Source: Authors' calculations.

/1 Acceptance rate of 1.42 percent based on 1,200 simulations and sign restrictions tested up to horizon 0.

Table 2. Sign restrictions for positive structural shocks

	Demand Shock	Supply Shock	Monetary Shock
$ogap$	+	-	-
π	+	+	-
r	+	+	+

Figure 4. Distribution of restricted parameters using alternative identification procedures /1



Source: Authors' calculations.
/1 Stemming from 1,200 simulations.

Table 3. Summary statistics of restricted parameters from SRC($-\infty, +\infty$)

Horizon	Parameter	No	Min	max	mean	sd	median
0	a^0_{12}	17	-0.226	0.909	0.180	0.289	0.058
	a^0_{13}	17	0.076	1.482	0.626	0.416	0.551
	a^0_{23}	17	-0.060	0.507	0.137	0.154	0.096
3	a^0_{12}	11	-0.226	0.909	0.227	0.332	0.208
	a^0_{13}	11	0.076	1.482	0.666	0.409	0.599
	a^0_{23}	11	-0.022	0.209	0.109	0.069	0.096
6	a^0_{12}	5	-0.226	0.909	0.401	0.429	0.552
	a^0_{13}	5	0.357	1.064	0.637	0.281	0.599
	a^0_{23}	5	0.063	0.193	0.142	0.049	0.153

Source: Authors' calculations.

Table 4. Summary statistics of restricted parameters from SRC(0, +∞)

Horizon	Parameter	No	Min	max	mean	sd	median
0	a_{12}^{0}	91	0.001	0.964	0.268	0.256	0.204
	a_{13}^{0}	91	0.004	5.081	0.525	0.619	0.395
	a_{23}^{0}	91	0.002	2.834	0.249	0.330	0.167
3	a_{12}^{0}	70	0.001	0.964	0.277	0.262	0.206
	a_{13}^{0}	70	0.024	1.999	0.547	0.409	0.497
	a_{23}^{0}	70	0.006	0.482	0.154	0.114	0.118
6	a_{12}^{0}	43	0.002	0.939	0.273	0.257	0.208
	a_{13}^{0}	43	0.082	1.999	0.662	0.436	0.557
	a_{23}^{0}	43	0.011	0.342	0.151	0.081	0.139

Source: Authors' calculations.

Table 5. Summary statistics of restricted parameters from N(0,1)

Horizon	Parameter	No	Min	max	mean	sd	median
0	a_{12}^{0}	36	-0.217	0.971	0.295	0.337	0.265
	a_{13}^{0}	36	0.028	1.476	0.634	0.398	0.598
	a_{23}^{0}	36	-0.034	0.743	0.250	0.188	0.217
3	a_{12}^{0}	24	-0.217	0.903	0.279	0.320	0.253
	a_{13}^{0}	24	0.092	1.476	0.759	0.418	0.708
	a_{23}^{0}	24	-0.034	0.279	0.143	0.091	0.143
6	a_{12}^{0}	16	-0.217	0.903	0.265	0.334	0.229
	a_{13}^{0}	16	0.092	1.476	0.803	0.424	0.743
	a_{23}^{0}	16	0.098	0.273	0.160	0.056	0.143

Source: Authors' calculations.

Table 6. Summary statistics of restricted parameters from N(0.5,0.5)

Horizon	Parameter	No	Min	max	mean	sd	median
0	a_{12}^{0}	208	-0.275	0.991	0.404	0.300	0.372
	a_{13}^{0}	208	0.025	1.542	0.505	0.266	0.470
	a_{23}^{0}	208	-0.069	0.864	0.288	0.225	0.232
3	a_{12}^{0}	138	-0.275	0.991	0.411	0.307	0.374
	a_{13}^{0}	138	0.045	1.542	0.572	0.273	0.554
	a_{23}^{0}	138	-0.043	0.572	0.177	0.125	0.165
6	a_{12}^{0}	87	-0.148	0.982	0.468	0.319	0.444
	a_{13}^{0}	87	0.045	1.309	0.591	0.279	0.621
	a_{23}^{0}	87	-0.008	0.356	0.156	0.069	0.157

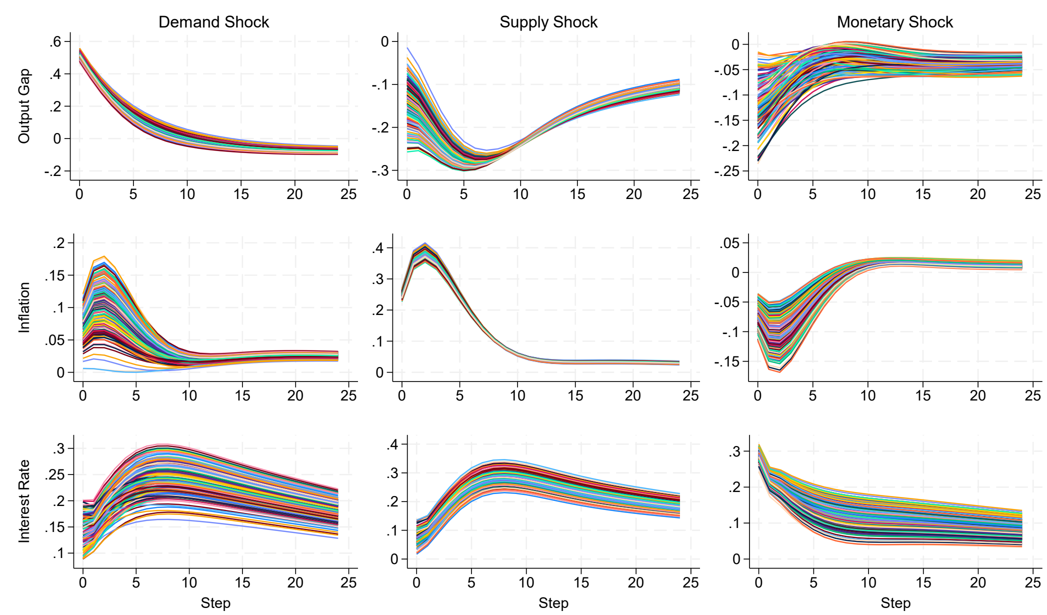
Source: Authors' calculations.

Table 7. Summary statistics of restricted parameters from N(0.5,0.25)

Horizon	Parameter	No	Min	max	mean	sd	median
0	a_{12}^{0}	549	-0.192	0.992	0.442	0.221	0.438
	a_{13}^{0}	549	0.067	1.000	0.465	0.164	0.456
	a_{23}^{0}	549	-0.052	0.883	0.366	0.203	0.366
3	a_{12}^{0}	298	-0.192	0.959	0.417	0.228	0.409
	a_{13}^{0}	298	0.067	1.000	0.516	0.172	0.520
	a_{23}^{0}	298	-0.052	0.717	0.228	0.126	0.226
6	a_{12}^{0}	162	-0.192	0.898	0.441	0.226	0.447
	a_{13}^{0}	162	0.148	1.000	0.557	0.192	0.573
	a_{23}^{0}	162	0.018	0.336	0.165	0.068	0.161

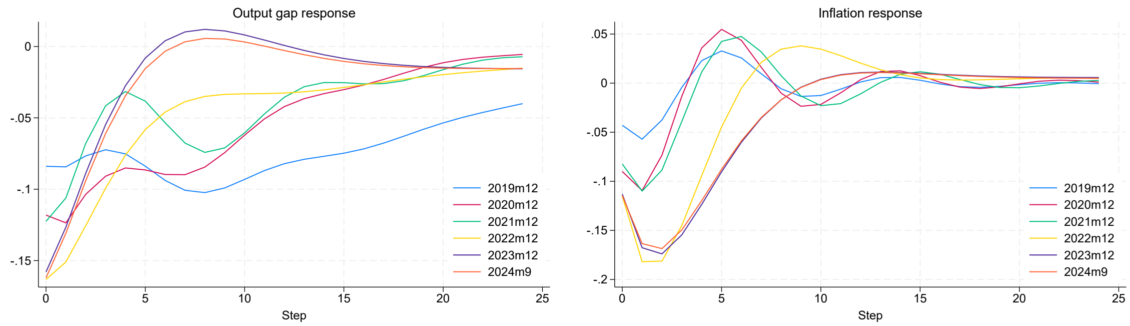
Source: Authors' calculations.

Figure 5. Period six sign restrictions on IRFs using N(0.5,0.25) /1



Source: Authors' calculations.
/1 Acceptance rate of 13.50 percent based on 1,200 simulations and sign restrictions tested up to horizon 6.

Figure 6. Impact of monetary policy over time



Source: Authors' calculations.

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