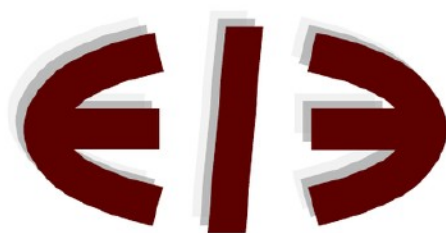


RBC SVAR for Uzbekistan

Alessandro Saccal

EERI Research Paper Series No 10/2026

ISSN: 2031-4892



EERI

Economics and Econometrics Research Institute

Avenue Louise

1050 Brussels

Belgium

Tel: +32 2271 9482

Fax: +32 2271 9480

www.eeri.eu

RBC SVAR for Uzbekistan

Alessandro Saccal*

Westminster International University in Tashkent

August 25, 2026

Abstract

The present work provides the first structural decomposition of business cycle fluctuations in Uzbekistan using a Real Business Cycle (RBC) Structural Vector Auto-Regression (SVAR). Employing a recursive identification scheme on a core vector of macroeconomic variables one is to recover the inaugural set of Orthogonalised Impulse Response Functions (OIRFs) and Forecast Error Variance Decompositions (FEVDs) for the Uzbek economy. The findings furnish a critical empirical benchmark for Uzbekistan, scrutinise the theoretical relevance of the RBC framework for transition economies and lay the essential empirical foundation for the subsequent development and parametrisation of a structural Dynamic Stochastic General Equilibrium (DSGE) model. The analysis thereby bridges a significant gap in the scientific literature, moving the study of Central Asian business cycles from empirical causality to structural explanation.

JEL classification codes: C22; C60; E13; E32; E37.

MSC codes: 91B51; 91B55; 91B62; 91B84.

Keywords: capital; consumption; labour; RBC; TFP; VARs; Uzbekistan.

1. INTRODUCTION

The empirical dissection of business cycle fluctuations stands as a central preoccupation of contemporary macroeconomics. In developed economies such an endeavour has long been facilitated by a rich ecosystem of structural time series models, amongst which SVARs occupy a pre-eminent position.

By imposing theoretically grounded identification restrictions, be they short run, long run or sign driven, SVARs enable the recovery of structural shocks from the reduced form covariance matrix of observable variables. Such a methodology has been instrumental in quantifying the relative importance of supply, demand, monetary and financial shocks in

*asacal@wiut.uz. Disclaimer: the author has no declaration of interest related to this research; all views and errors in this research are the author's. ©Copyright 2025 Alessandro Saccal

driving the cyclical dynamics of such nations or blocs as the United States of America (Christiano, Eichenbaum and Evans, 2005) and the Euro Area (Smets and Wouters, 2003).

Subsequent methodological refinements, including Bayesian VARs (BVARs), which incorporate prior information to mitigate over-parametrisation, Time Varying Parameter VARs (TVP VARs), which capture evolving economic structures, and Dynamic Factor Models (DFMs), which distil common movements from large datasets, have further enriched the empirical toolkit, providing nuanced, data consistent narratives of business cycle origins and propagation.

Conversely, the application of such a sophisticated empirical apparatus to the business cycles of emerging and transition economies remains conspicuously underdeveloped. The existing scientific literature is often bifurcated. One strand employs non-theoretical, reduced form VARs to describe empirical causality without an explicit structural interpretation; another strand parameterises DSGE models, yet frequently neglects the critical step of confronting such models with empirically identified structural shocks from the data in question.

For the post-Soviet economies of Central Asia, such as Kazakhstan, such a gap is particularly pronounced. While studies have examined determinants of economic growth, inflation or exchange rate adjustments, a foundational empirical analysis of the structural sources of business cycle fluctuations, disentangling supply from demand, transitory from permanent and domestic from external impulses, is virtually inexistent.

Aitymbetova *et al.* (2025) employ a VAR to study the Kazakh interactions between oil price, exchange rates and foreign direct investment; Barma (2025) comparably explores the Kazakh interdependencies of exchange rates and net exports by means of VARs.

Katenova (2025) makes use of a VAR to appraise the linkages between stock market and economic growth in Kazakhstan and Impavido (2025) correspondingly exploits an SVAR to assess Kazakh monetary policy. Orlov (2021) assembles a BVAR for Kazakhstan and Abilov (2021) finally constructs a Kazakh DSGE model estimated by means of Bayesian methods.

Uzbekistan, a pivotal regional economy undergoing profound structural transformation since its 2010s reforms, epitomises such an analytical void even more. Its macroeconomic dynamics, shaped by a legacy of state directed investment, commodity dependence and a rapidly liberalising institutional framework, have yet to be systematically decomposed into their constituent structural shocks through the lens of an SVAR.

Indeed, Abrorov *et al.* (2025) adopt VARs to analyse the impact of the digital economy on Uzbek economic development. Ataniyazov *et al.* (2025) deploy VARs to assess the effect of renewable energy on exports in Uzbekistan.

Isakov (2024) employs VARs to forecast non-performing loans of Uzbek commercial banks, while Kasimov (2025) utilises them to analyse the relationship between education and economic growth in Uzbekistan, as do Maaz and Nuriddinova (2025) in the orbit of Uzbekistan's environmental hurdles.

A more promising avenue is that travelled by Boymirzaev (2025), who develops factor augmented VARs and BVARs to explicate Uzbek near term forecast inflation. Davlatov *et al.* (2025) similarly utilise an Uzbek SVAR to attempt resolving price and exchange rate puzzles.

By the same token, Wang and Zhao (2025) adopt VARs to evaluate the effects of monetary policy on the economy of Uzbekistan; to date, however, notwithstanding the efforts of Inogamov and Makhmudov (2023), there exists no public and complete DSGE model for Uzbekistan.

It is within such a context that the present research makes its primary and inaugural contribution: the production of the first identified RBC SVAR for Uzbekistan, complete with OIRFs and FEVDs. Such an empirical benchmark is constructed using a parsimonious vector of core macroeconomic aggregates distinctive of an RBC model, being Total Factor Productivity (TFP), capital, labour and consumption, identified via a standard Cholesky recursive ordering consistent with the causal hierarchy of a canonical RBC model; the resulting OIRFs reveal the dynamic causal impact of TFP, capital, labour and consumption shocks on the Uzbek economy, while the FEVDs quantify their relative importance at various forecast horizons.

Such an empirical exercise is not an end in itself, but serves a dual, pivotal purpose. First, it directly addresses the aforementioned gap in the scientific literature by providing a structured, causal narrative for Uzbekistan's business cycle grounded in its own data.

Second, it more fundamentally establishes the essential empirical target against which a theoretical RBC model for Uzbekistan should be validated. The patterns embedded within such OIRFs constitute the quantitative stylised facts which any credible theory of the Uzbek business cycle should explain.

By first establishing such facts through a rigorous SVAR methodology the present research lays an indispensable empirical foundation. It thereby bridges the prevailing chasm between the abstract theoretical literature on DSGE models for emerging markets and the sparse, often non-structural, empirical work on Central Asian economies.

The subsequent phase of such an enterprise, that is, the development and parametrisation of a fully specified RBC model for Uzbekistan, is to draw its legitimacy and discipline from such a very empirical contribution, ensuring the theory may be regulated by the identified dynamics of the economy it seeks to elucidate.

2. EMPIRICAL FORECASTING MODELS AND FOUNDATIONS

As outlined, the formulation of an empirical model for the present forecasting purposes is to pass by the construction of an SVAR beginning from first principles, wherewith the present section is concerned. In detail, a time series is to be firstly formalised in the measure theoretical environment of a probability space; the notions of a white noise and of the weak stationarity of a time series are to follow; VARs in extended and reduced form then ensue along with the notion of causality in terms of stability analysis; SVARs are thus defined in the optic of a Sims (1980) orthogonalisation through Cholesky decompositions, whereupon SVMAs and OIRFs are introduced; SVMA forecast errors and their variance decompositions finally emerge. Difference stationarity, co-integration and the spurious regression are ulteriorly presented to the end of justifying the employment of log-levels data for the SVAR at hand.

2.1 Time series and probability space. A time series is $\{x_t\}_{t \in S} \subset \mathbb{R}^n$ such that, $\forall n, T \in \bar{\mathbb{N}}_+, \{\cdot\} : S \subseteq \bar{\mathbb{Z}} \rightarrow \mathbb{R}^n$; it is a sequence of stochastic or data generation processes. Its sample size is cardinality $n(\{x_t\}_{t \in S}) = n(S) = T \in \bar{\mathbb{N}}_+$.

For probability space $[\{x_{tw}\}_{t \in S}, \mathcal{G}, p]$ and fixed discrete event $\omega \in \Omega \subset \mathbb{R}$: time series realisation or process $x_{tw} \in \{x_{tw}\}_{t \in S} \subset \mathbb{R}^n$, in which $\{x_{tw}\}_{t \in S}$ is the time series or sample space; the sigma-algebra $\mathcal{G} \subseteq \mathcal{P}(\{x_{tw}\}_{t \in S}) = 2^{\{x_{tw}\}_{t \in S}}$; the probability measure is $p : \mathcal{G} \rightarrow [0, 1] \subset \mathbb{R}_+$ such that $p(x_{tw}) \in [0, 1] \subset \mathbb{R}_+$ for $\sum_{\omega \in \Omega} p(x_{tw}) = 1$.

2.2 White noise. A white noise $\varepsilon_t \sim WN(0, \sigma^2)$ is such that, $\forall j \in \mathbb{Z} \setminus \{0\}$, $\mathbb{E}(\varepsilon_t) = 0$, $Var(\varepsilon_t) = \sigma^2 \in \mathbb{R}_{++}$ and $Cov(\varepsilon_t \varepsilon_{t-j}) = 0$.

2.3 Weak stationarity. Weak stationarity is such that $x_t \sim WS(\mu, \gamma_0) : \forall x_t \in \mathbb{R}, j \in \mathbb{Z} \setminus \{0\}$,

$$\left. \begin{array}{l} \mathbb{E}(x_t) = \mu \\ Var(x_t) = \gamma_0 \\ Cov(x_t x_{t-j}) = \gamma_j \end{array} \right\} < \infty.$$

2.4 Autoregression. An autoregression $x_t \sim AR(p)$ is such that, $\forall p \in \bar{\mathbb{N}}_+$, $x_t, \mu_x \in \mathbb{R}$, $\{x_{t-j}\}_{j=1}^p, \{\rho_j\}_{j=1}^p \subset \mathbb{R}$, $\varepsilon_t \sim WN(0, \sigma^2)$,

$$x_t = \mu_x + \sum_{j=1}^p \rho_j x_{t-j} + \varepsilon_t$$

and $AR(0)$ such that $x_t = \mu_x + \varepsilon_t$.

2.5 Moving average. A moving average $y_t \sim MA(q)$ is such that, $\forall q \in \bar{\mathbb{N}}_+$, $y_t, \mu_y \in \mathbb{R}$, $\{\varepsilon_{t-j}\}_{j=0}^q \sim WN(0, \sigma^2)$, $\{\theta_j\}_{j=1}^q \subset \mathbb{R}$,

$$y_t = \mu_y + \varepsilon_t + \sum_{j=1}^q \theta_j \varepsilon_{t-j}$$

and $MA(0)$ such that $y_t = \mu_y + \varepsilon_t$.

2.6 Autoregressive moving average. An autoregressive moving average $x_t \sim ARMA(p, q)$ such that, $\forall x_t \sim AR(p)$, $y_t \sim MA(q)$,

$$x_t = \sum_{j=1}^p \rho_j x_{t-j} + \mu_x + \varepsilon_t + \sum_{j=1}^q \theta_j \varepsilon_{t-j}$$

and $ARMA(0, 0)$ such that $x_t = \mu_x + \varepsilon_t$.

2.7 Wold decomposition. The Wold decomposition is such that, $\forall y_t \sim WS(\mu, \gamma_0)$, $\eta_t \equiv \hat{\varepsilon}_t = P(\varepsilon_t | y_{t-1}, \dots) \in \mathbb{R}$, $j \in \bar{\mathbb{N}}$, $\{\varepsilon_{t-j}\}_{j=0}^\infty \sim WN(0, \sigma^2)$, $\{\theta_j\}_{j=0}^\infty \subset \mathbb{R}$,

$$y_t = \eta_t + \sum_{j=0}^\infty \theta_j \varepsilon_{t-j}$$

coefficient $\theta_0 = 1$ and sum $\sum_{j=0}^\infty \theta_j^2 < \infty$.

2.8 Stability. Stability is such that, $\forall \{\lambda_i\}_{i=1}^q, \{z_i\}_{i=1}^q \subset \mathbb{C}$,

$$y_t = \varepsilon_t + \sum_{j=1}^q \theta_j \varepsilon_{t-j}$$

is stable if and only if modulus eigenvalue $|\lambda_i| < 1$ if and only if modulus root $|z_i| > 1$ such that eigenvalue $\lambda_i = \frac{1}{z_i}$. In practice, one is to use substitution $\varepsilon_{t-j} = z^j$, $\forall j \in \mathbb{N}$, set $y_t = 0$, solve for roots $\{z_j\}_{j=1}^{\tilde{q}_i} \in \mathbb{C}$ and check whether $|z_i| > 1$, recalling that modulus root $|z| = \sqrt{a^2 + b^2}$, $\forall z = a \pm bi$, $a, b \in \mathbb{R}$ and $i = \sqrt{-1}$.

2.9 Causality and invertibility. Causality and invertibility are such that $\forall \{\lambda_i\}_{i=1}^{p,q}, \{z_i\}_{i=1}^{p,q} \subset \mathbb{C}$, $ARMA(p, q)$ process

$$x_t = \sum_{j=1}^p \rho_j x_{t-j} + \varepsilon_t + \sum_{j=1}^q \theta_j \varepsilon_{t-j}$$

is causal and invertible if and only if $|\lambda_i| < 1$ if and only if $|z_i| > 1$ such that $\lambda_i = \frac{1}{z_i}$. Causal and invertible $x_t \sim ARMA(p, q)$ process is rewritable as $ARMA(\infty, \infty)$ process $\prod_{i=1}^q \left[\sum_{j=0}^{\infty} (-\lambda_i^j) L^j \right] x_t = \prod_{i=1}^p \left(\sum_{j=0}^{\infty} \lambda_i^j L^j \right) \varepsilon_t$; in practice, one is to use x_{t-j} , $\varepsilon_{t-j} = z^j$, $\forall j \in \mathbb{N}$, set $\{\varepsilon_{t-j}, x_{t-j}\}_{j=0}^{p,q} = 0$, solve for $\{z_j\}_{j=1}^{p,q} \in \mathbb{C}$ and check whether $|z_i| > 1$.

2.10 VAR. A VAR is such that $x_t \sim VAR(p)$ such that, $\forall p, n, T \in \bar{\mathbb{N}}_+$, $x_t \in \mathbb{R}^n$, $\mu_x = 0$, $\{P_j\}_{j=1}^p \subset \mathbb{R}^{n \times n}$, $\varepsilon_t \sim MWN(0, \Sigma)$,

$$\begin{bmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{nt} \end{bmatrix} = \sum_{j=1}^p \begin{bmatrix} \rho_{j11} & \rho_{j12} & \cdots & \rho_{j1n} \\ \rho_{j21} & \rho_{j22} & \cdots & \rho_{j2n} \\ \vdots & \ddots & \ddots & \vdots \\ \rho_{j n1} & \rho_{j n2} & \cdots & \rho_{j nn} \end{bmatrix} \begin{bmatrix} x_{1t-j} \\ x_{2t-j} \\ \vdots \\ x_{nt-j} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{nt} \end{bmatrix}$$

$$x_t = \sum_{j=1}^p P_j x_{t-j} + \varepsilon_t \longrightarrow$$

$$x_t - \sum_{j=1}^p P_j x_{t-j} = (I_n - \dots - P_p L^p) x_t = P(L) x_t = \varepsilon_t$$

for $\{x_{it}\}_{i=1}^n \subset \mathbb{R}^T$ and $\varepsilon_{it} \sim WN(0, \sigma^2) \vee MWN(0, \Sigma)$.

2.11 VAR estimation. $VAR(p)$ process $x_t = \sum_{j=1}^p P_j x_{t-j} + \varepsilon_t$ is rewritten as

$$\begin{aligned}
x_t &= \sum_{j=1}^p P_j x_{t-j} + \varepsilon_t = \underbrace{\begin{bmatrix} P_1 & P_2 & \cdots & P_p \end{bmatrix}}_{P \sim (n \times np)} \underbrace{\begin{bmatrix} x_{t-1} \\ x_{t-2} \\ \vdots \\ x_{t-p} \end{bmatrix}}_{z_t \sim (np \times 1)} + \varepsilon_t \\
\begin{bmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{nt} \end{bmatrix} &= \underbrace{\begin{bmatrix} x_{1t-1} I_n & x_{2t-1} I_n & \cdots & x_{nt-p} I_n \end{bmatrix}}_{[z^\top \otimes I_n] \sim (n \times n^2 p)} \underbrace{\begin{bmatrix} \rho_{111} \\ \rho_{121} \\ \vdots \\ \rho_{pnn} \end{bmatrix}}_{\text{vec}(P) \sim (n^2 p \times 1)} + \underbrace{\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{nt} \end{bmatrix}}_{\varepsilon_t \sim (n \times 1)} \\
\begin{bmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{nt} \end{bmatrix} &\downarrow \begin{matrix} x_t \\ Y \sim [(T-p)n \times 1] \end{matrix} = \underbrace{\begin{bmatrix} z_t^\top & \otimes & I_n \\ (1 \times np) & & (n \times n) \end{bmatrix}}_{\downarrow X \sim [(T-p)n \times n^2 p]} \underbrace{\text{vec}(P)}_{\downarrow \beta \sim (n^2 p \times 1)} + \underbrace{\varepsilon_t}_{\downarrow U \sim [(T-p)n \times 1]}
\end{aligned}$$

$$Y = X\beta + U,$$

for regressand and error $Y, U \in \mathbb{R}^{(T-p)n \times 1}$, regressor $X \in \mathbb{R}^{(T-p)n \times n^2 p}$ and coefficient $\beta \in \mathbb{R}^{n^2 p \times 1}$ such that OLS estimator $\hat{\beta} = (X^\top X)^{-1} X^\top Y \in \mathbb{R}^{n^2 p \times 1}$, OLS sample variance $\hat{V}ar(\hat{\beta}|X) = \hat{\sigma}^2 (X^\top X)^{-1} \in \mathbb{R}_+^{n^2 p \times n^2 p}$, OLS error sample variance $\hat{\sigma}^2 = [(T-p)n - n^2 p]^{-1} \hat{U}^\top \hat{U} \in \mathbb{R}_+$ and residual $\hat{U} = Y - \hat{Y} = Y - X\hat{\beta}$; specifically, degrees of freedom $(T-p)n - n^2 p > 0 \rightarrow T-p > np \rightarrow T > (n+1)p$ for OLS.

2.12 Reduced form VAR. A reduced form VAR is such that $VAR(p)$ process $x_t = \sum_{j=1}^p P_j x_{t-j} + \varepsilon_t$ can be reduced to a $VAR(1)$ process:

$$\begin{aligned}
\begin{bmatrix} x_t \\ x_{t-1} \\ \vdots \\ x_{t-p+1} \end{bmatrix} &= \begin{bmatrix} P_1 & P_2 & \cdots & P_p \\ I_n & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & I_n & 0 \end{bmatrix} \begin{bmatrix} x_{t-1} \\ x_{t-2} \\ \vdots \\ x_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \\
\underline{x}_t &= A \underline{x}_{t-1} + \underline{\varepsilon}_t
\end{aligned}$$

for $\underline{x}_t \in \mathbb{R}^p$, $A \in \mathbb{R}^{p \times p}$ and $\underline{\varepsilon}_t \sim MWN(0, \Sigma)$. For simplicity, $\underline{x}_t = A \underline{x}_{t-1} + \underline{\varepsilon}_t$ is merely rewritten as $x_t = A x_{t-1} + \varepsilon_t$.

2.13 Reduced form causality. Reduced form causality is such that, $\forall \lambda_{A(\lambda)}, z_{A(z)} \in \mathbb{C}$, $VAR(1)$ reduced form

$$x_t = A x_{t-1} + \varepsilon_t$$

is causal if and only if modulus eigenvalue $|\lambda_{A(\lambda)}| < 1$ if and only if modulus root $|z_{A(z)}| > 1$ such that eigenvalue $\lambda_{A(\lambda)} = z_{A(z)}^{-1}$. Causal $x_t \sim VAR(1)$ reduced form is

rewritable as $VMA(\infty)$ reduced form $x_t = \sum_{j=0}^{\infty} A^j \varepsilon_{t-j}$; in practice, one is to solve for roots $z_{A(z)} \in \mathbb{C}$ in determinant $\det[A(z)] = \det(I_p - Az) = 0$ and check whether $|z_{A(z)}| > 1$.

2.14 SVAR and SVMA. An SVAR is such that $x_t = Ax_{t-1} + D\eta_t$ is an $SVAR(1)$ representation. An SVMA is such that $x_t = \sum_{j=0}^{\infty} A^j D\eta_{t-j}$ is an $SVMA(\infty)$ representation if and only if its $SVAR(1)$ representation is stable. Matrix D can proceed from Sims' orthogonalisation: for $n \in \mathbb{N}_+$ and $VMA(\infty)$ representation $x_t = \sum_{j=0}^{\infty} A^j \varepsilon_{t-j}$ then

$$\begin{aligned} \text{Var}(\varepsilon_t) &= \mathbb{E}\{[\varepsilon_t - \mathbb{E}(\varepsilon_t)][\varepsilon_t - \mathbb{E}(\varepsilon_t)]^\top\} = \mathbb{E}(\varepsilon_t \varepsilon_t^\top) = \Sigma = DD^\top = \\ &= \begin{bmatrix} \sigma_1^2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_n^2 \end{bmatrix} = \begin{bmatrix} d_{11} & \dots & 0 \\ \vdots & \ddots & \vdots \\ d_{n1} & \dots & d_{nn} \end{bmatrix} \begin{bmatrix} d_{11} & \dots & d_{n1} \\ \vdots & \ddots & \vdots \\ 0 & \dots & d_{nn} \end{bmatrix} \in \mathbb{R}^{n \times n} \end{aligned}$$

such that $D \in \mathbb{R}^{n \times n}$ is lower triangular by Cholesky decomposition of Σ , being positive semi-definite. Indeed, $\eta_t = D^{-1}\varepsilon_t \longrightarrow \varepsilon_t = D\eta_t \longrightarrow x_t = \sum_{j=0}^{\infty} A^j \varepsilon_{t-j} = \sum_{j=0}^{\infty} A^j D\eta_{t-j}$ such that

$$\begin{aligned} \mathbb{E}(\eta_t \eta_t^\top) &= \mathbb{E}[D^{-1}\varepsilon_t (D^{-1}\varepsilon_t)^\top] = \\ \mathbb{E}(D^{-1}\varepsilon_t \varepsilon_t^\top D^{-\top}) &= D^{-1}\mathbb{E}(\varepsilon_t \varepsilon_t^\top) D^{-\top} = \\ D^{-1}DD^\top D^{-\top} &= I_n. \end{aligned}$$

It orders the entries of x_t from the most causal to the least in the short run for the $VAR(1)$ representation $x_t = Ax_{t-1} + \varepsilon_t$.

2.15 OIRFs. The short run OIRF coefficients for Sims orthogonalisation are such that for $n \in \mathbb{N}_+$, $SVMA(\infty)$ representation $x_t = \sum_{j=0}^{\infty} A^j D\eta_{t-j}$ and Sims orthogonalisation matrix $D \in \mathbb{R}^{n \times n}$ then

$$\frac{\partial \mathcal{I}_j}{\partial \eta_t} = \frac{\partial x_{t+j}}{\partial \eta_t} = \frac{\partial x_t}{\partial \eta_{t-j}} = A^j D.$$

2.16 SVMA forecast error. The h -lead forecast error of an SVMA process is such that for $SVMA(\infty)$ process $x_t = \sum_{j=0}^{\infty} A^j D\eta_{t-j}$ and lead index $h \in \mathbb{N}_+$ then

$$\begin{aligned}
e_{t+h} &\equiv e_t(h) = x_{t+h} - x(t+h) = x_{t+h} - \mathbb{E}(x_{t+h} | \{x_t\}_{t \in S}) = \\
&\sum_{j=0}^{\infty} A^j \varepsilon_{t-j+h} - \mathbb{E} \left(\sum_{j=0}^{\infty} A^j \varepsilon_{t-j+h} | \{x_t\}_{t \in S} \right) = \\
&\sum_{j=0}^{\infty} A^j \varepsilon_{t-j+h} - \mathbb{E} \left(\sum_{j=0}^{h-1} A^j \varepsilon_{t-j+h} | \{x_t\}_{t \in S} \right) - \mathbb{E} \left(\sum_{j=h}^{\infty} A^j \varepsilon_{t-j+h} | \{x_t\}_{t \in S} \right) = \\
&\sum_{j=0}^{\infty} A^j \varepsilon_{t-j+h} - \sum_{j=h}^{\infty} A^j \varepsilon_{t-j+h} = \sum_{j=0}^{h-1} A^j \varepsilon_{t-j+h} = \sum_{j=0}^{h-1} A^j D \eta_{t-j+h},
\end{aligned}$$

as

$$\mathbb{E}(\varepsilon_{t-j+h} | \{x_t\}_{t \in S}) = \begin{cases} \varepsilon_{t-j+h}, & j \geq h \text{ (non-future)} \\ 0, & j < h \text{ (future)} \end{cases}.$$

2.17 SVMA FEVD. The h -lead forecast error variance of an SVMA process is such that for $SVMA(\infty)$ process $x_t = \sum_{j=0}^{\infty} A^j D \eta_{t-j}$ and lead index $h \in \mathbb{N}_+$ then

$$\begin{aligned}
\mathbb{E}(e_{t+h}) &= \mathbb{E} \left(\sum_{j=0}^{h-1} A^j D \eta_{t-j+h} \right) = \\
&\mathbb{E} \left(\sum_{j=0}^{h-1} A^j D D^{-1} \varepsilon_{t-j+h} \right) = \mathbb{E} \left(\sum_{j=0}^{h-1} A^j \varepsilon_{t-j+h} \right) = \\
&A^j \mathbb{E} \left(\sum_{j=0}^{h-1} \varepsilon_{t-j+h} \right) = 0
\end{aligned}$$

as

$$\mathbb{E}(\varepsilon_{t-j+h} | \{x_t\}_{t \in S}) = \begin{cases} \varepsilon_{t-j+h}, & j \geq h \text{ (non-future)} \\ 0, & j < h \text{ (future)} \end{cases},$$

whence

$$\begin{aligned}
Var(e_{t+h}) &= \mathbb{E}(e_{t+h}^2) - \mathbb{E}(e_{t+h})^2 = \mathbb{E}(e_{t+h}^2) = \\
&\mathbb{E} \left(\sum_{j=0}^{h-1} A^j D \eta_{t-j+h} \eta_{t-j+h}^{\top} D^{\top} A^{\top j} \right) = \mathbb{E} \left(\sum_{j=0}^{h-1} A^j D D^{-1} \varepsilon_{t-j+h} \varepsilon_{t-j+h}^{\top} D^{-\top} D^{\top} A^{\top j} \right) = \\
&\mathbb{E} \left(\sum_{j=0}^{h-1} A^j \varepsilon_{t-j+h} \varepsilon_{t-j+h}^{\top} A^{\top j} \right) = A^j \mathbb{E} \left(\sum_{j=0}^{h-1} \varepsilon_{t-j+h} \varepsilon_{t-j+h}^{\top} \right) A^{\top j} = \sum_{j=0}^{h-1} A^j \Sigma A^{\top j}.
\end{aligned}$$

The h -lead FEVD of an SVMA process is such that for $SVMA(\infty)$ process $x_t =$

$\sum_{j=0}^{\infty} A^j D \eta_{t-j}$ and lead index $h \in \mathbb{N}_+$ they are ratios of diagonal $\text{diag} \left(\sum_{j=0}^{h-1} A^j \Sigma A^{\top j} \right)$ in

$$\begin{aligned} \text{Var}(e_{t+h}) &= \sum_{j=0}^{h-1} A^j \Sigma A^{\top j} = \\ &= \sum_{j=0}^{h-1} \begin{bmatrix} a_{11}^{(j)} & \dots & a_{1n}^{(j)} \\ \vdots & \ddots & \vdots \\ a_{n1}^{(j)} & \dots & a_{nn}^{(j)} \end{bmatrix} \begin{bmatrix} \sigma_1^2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_n^2 \end{bmatrix} \begin{bmatrix} a_{11}^{(j)} & \dots & a_{n1}^{(j)} \\ \vdots & \ddots & \vdots \\ a_{1n}^{(j)} & \dots & a_{nn}^{(j)} \end{bmatrix} = \\ &= \sum_{j=0}^{h-1} \begin{bmatrix} a_{11}^{(j)} \sigma_1^2 & \dots & a_{1n}^{(j)} \sigma_n^2 \\ \vdots & \ddots & \vdots \\ a_{n1}^{(j)} \sigma_1^2 & \dots & a_{nn}^{(j)} \sigma_n^2 \end{bmatrix} \begin{bmatrix} a_{11}^{(j)} & \dots & a_{n1}^{(j)} \\ \vdots & \ddots & \vdots \\ a_{1n}^{(j)} & \dots & a_{nn}^{(j)} \end{bmatrix} = \\ &= \sum_{j=0}^{h-1} \begin{bmatrix} a_{11}^{(j)} \sigma_1^2 a_{11}^{\top(j)} + \dots + a_{1n}^{(j)} \sigma_n^2 a_{1n}^{\top(j)} & \dots & a_{11}^{(j)} \sigma_1^2 a_{n1}^{\top(j)} + \dots + a_{1n}^{(j)} \sigma_n^2 a_{nn}^{\top(j)} \\ \vdots & \ddots & \vdots \\ a_{n1}^{(j)} \sigma_1^2 a_{11}^{\top(j)} + \dots + a_{nn}^{(j)} \sigma_n^2 a_{1n}^{\top(j)} & \dots & a_{n1}^{(j)} \sigma_1^2 a_{n1}^{\top(j)} + \dots + a_{nn}^{(j)} \sigma_n^2 a_{nn}^{\top(j)} \end{bmatrix}; \end{aligned}$$

in other words: $\forall i, k \in [1, n] \subset \mathbb{N}_+$,

$$\varpi_{x_i|\varepsilon_k} \equiv \mathcal{F}_{ik} = \frac{\sum_{j=0}^{h-1} a_{ik}^{(j)} \sigma_k^2 a_{ik}^{\top(j)}}{\sum_{j=0}^{h-1} \text{diag} (A^j \Sigma A^{\top j})_i} = \frac{\sum_{j=0}^{h-1} a_{ik}^{(j)} \sigma_k^2 a_{ik}^{\top(j)}}{\sum_{j=0}^{h-1} (A^j \Sigma A^{\top j})_{ii}}.$$

2.18 Difference stationarity. Difference stationarity is such that for an autoregressive integrated moving average (ARIMA) process, $\forall p, q \in \mathbb{N}_+$, $x_t, \mu_x \in \mathbb{R}$, $\{\rho_j\}_{j=1}^p, \{\theta_j\}_{j=1}^q \subset \mathbb{R}$, $\varepsilon_t \sim WN(0, \sigma^2)$, $d \in \mathbb{N}$, $j \in \mathbb{Z}$, $x_t L^j = x_{t-j}$,

$$\begin{aligned} x_t &\sim ARIMA(p, d, q) \longrightarrow \\ \rho(L) \Delta^d x_t &= \rho(L) (1 - L)^d x_t = \\ \mu_x + \theta(L) \varepsilon_t &\sim ARIMA(p, 0, q) \sim WS_d \end{aligned}$$

and $x_t \sim I(d)$, in which d is the order of integration or number of unit roots.

2.19 Random walk and Dickey-Fuller test. A random walk is such that $x_t \sim RW$, and, $\forall x_t \in \mathbb{R}$, $\varepsilon_t \sim WN(0, \sigma^2)$, then

$$x_t = x_{t-1} + \varepsilon_t.$$

It is integrated of order one: $x_t \sim RW$ such that

$$x_t = x_{t-1} + \varepsilon_t \sim I(1) \longrightarrow \Delta x_t = (1 - L)x_t = \varepsilon_t \sim I(0),$$

whence $x_t \sim ARIMA(1, 1, 0)$ and $\Delta x_t \sim ARIMA(0, 0, 0)$. The Dickey-Fuller test is such that, $\forall x_t = \rho_1 x_{t-1} + \varepsilon_t \sim AR(1)$, unit root $d = 1$ is tested on $\Delta x_t = x_t - x_{t-1} = (\rho_1 - 1)x_{t-1} + \varepsilon_t = \varrho_1 x_{t-1} + \varepsilon_t$ and

$$\begin{aligned} h_0 : \varrho_1 = 0 &\longrightarrow \rho_1 = 1 \text{ if and only if } d = 1 \\ h_1 : \varrho_1 < 0 &\longrightarrow \rho_1 < 1 \text{ if and only if } d = 0. \end{aligned}$$

2.20 Trend stationarity. Trend stationarity is such that, $\forall x_t \in \mathbb{R}$, $\alpha, \beta \in \mathbb{R}$, $t \in S$, $\varepsilon_t \sim WN(0, \sigma^2) \sim I(0)$, then

$$x_t = \alpha + \beta t + \varepsilon_t \longrightarrow x_t - \beta t = \alpha + \varepsilon_t \sim WS_t.$$

2.21 Co-integration and spurious regression. Co-integration is such that for $n, T \in \bar{\mathbb{N}}_+$, $\{x_{it}\}_{i=1}^n \subset \mathbb{R}^T$, $x_{1t}, \dots, x_{nt} \sim I(d)$, $x_t = [x_{1t} \cdots x_{nt}]^\top$, $\beta = [\beta_1 \cdots \beta_n]^\top$ and $d \geq b \in \mathbb{N}$ then

$$y_t = \beta^\top x_t = x_t^\top \beta = \sum_{i=1}^n \beta_i x_{it} = \beta_1 x_{1t} + \dots + \beta_n x_{nt} \sim I(d - b),$$

whereby $\{x_{it}\}_{i=1}^n \sim CI(d, b)$, $\beta^\top x_t$ contains co-integrating relations of order (d, b) and β is a co-integrating vector. The spurious regression is such that for $x_{1t} = x_{1t-1} + \varepsilon_{1t} + \delta_1 \sim RWD \sim (1)$ and $x_{2t} = x_{2t-1} + \varepsilon_{2t} + \delta_2 \sim RWD \sim I(1)$ then $x_{1t} = \beta_2 x_{2t} + u_t \sim I(1)$ and $\hat{\beta}_2$ estimated by Ordinary Least Squares (OLS) could be statistically significant (spuriously, given no linear dependence).

The solution, supposing verified unit roots for $x_{1t} = \rho_{11}x_{1t-1} + \varepsilon_{1t} + \delta_1$ and $x_{2t} = \rho_{21}x_{2t-1} + \varepsilon_{2t} + \delta_2$ through Dickey-Fuller test, is for $\Delta x_{1t} = x_{1t} - x_{1t-1} = \varepsilon_{1t} + \delta_1$ and $\Delta x_{2t} = x_{2t} - x_{2t-1} = \varepsilon_{2t} + \delta_2$ to estimate $\Delta x_{1t} = \beta_2 \Delta x_{2t} + u_t$ by OLS for $\hat{\beta}_2$ and re-examine statistical significance. Integrated variables, of the same, reduced order if different, but not linearly dependent and thus not co-integrated, are robust to spurious regression only with lags: for

$$\begin{aligned} x_{1t} &= x_{1t-1} + \varepsilon_{1t} \sim RW \sim I(1), \\ x_{2t} &= x_{2t-1} + \varepsilon_{2t} \sim RW \sim I(1) \text{ and} \\ u_t &\neq x_{1t} - \beta_2 x_{2t} \end{aligned}$$

then $\{x_{it}\}_{i=1}^2 \not\sim CI(1, 1)$ such that $x_{1t} = \beta_2 x_{2t} + u_t$ is a spurious regression (i.e. not co-integrated), but Auto-Regressive Distributed Lag (ARDL) process $x_{1t} = \beta_1 x_{1t-1} + \underbrace{\beta_2 x_{2t} + u_t}_{\varepsilon_{1t}}$

is not (co-integrated in lags), as $\varepsilon_{1t} = x_{1t} - \beta_1 x_{1t-1} \sim I(0)$ and

$$\lim_{n \rightarrow \infty} \hat{\beta}_1 = \lim_{n \rightarrow \infty} \frac{\sum_{t=1}^n x_{2t}^2 \sum_{t=1}^n x_{1t-1} x_{1t} - \sum_{t=1}^n x_{1t-1} x_{2t} \sum_{t=1}^n x_{2t} x_{1t}}{\sum_{t=1}^n x_{1t-1}^2 \sum_{t=1}^n x_{2t}^2 - (\sum_{t=1}^n x_{1t-1} x_{2t})^2} = \beta_1 = 1 \text{ and}$$

$$\lim_{n \rightarrow \infty} \hat{\beta}_2 = \lim_{n \rightarrow \infty} \frac{\sum_{t=1}^n x_{1t-1}^2 \sum_{t=1}^n x_{2t} x_{1t} - \sum_{t=1}^n x_{1t-1} x_{2t} \sum_{t=1}^n x_{1t-1} x_{1t}}{\sum_{t=1}^n x_{1t-1}^2 \sum_{t=1}^n x_{2t}^2 - (\sum_{t=1}^n x_{1t-1} x_{2t})^2} = \beta_2,$$

in view of $x_{1t-1}, x_{2t} \sim RW$; Distributed Lag (DL) process $x_{1t} = \beta_2 x_{2t} + \beta_3 x_{2t-1} + u_t \longrightarrow x_{2t} = \frac{-\beta_3 x_{2t-1}}{\beta_2} + \underbrace{\frac{x_{1t}}{\beta_2}}_{\varepsilon_{2t}} + u_t$ alternatively, as $\varepsilon_{2t} = x_{2t} + \frac{\beta_3 x_{2t-1}}{\beta_2} \sim I(0)$ for $\beta_2 = 1$ and $\beta_3 = -1$.

2.22 Vector Error Correction Model (VECM) The VECM is such that for $VAR(p)$

$$\begin{aligned} x_t &= P_1 x_{t-1} + \dots + P_p x_{t-p} + \varepsilon_t \longrightarrow (I_n - \dots - P_p L^p) x_t = P(L) x_t = \varepsilon_t \\ [\Gamma(L)(1 - L) - PL] x_t &= \Gamma(L)(1 - L) x_t - PL x_t = \varepsilon_t \longrightarrow \\ \Gamma(L) \Delta x_t &= (I_n - \dots - \Gamma_{p-1} L^{p-1}) \Delta x_t = P x_{t-1} + \varepsilon_t \longrightarrow \\ \Delta x_t &= P x_{t-1} + \sum_{j=1}^{p-1} \Gamma_j L^j \Delta x_t + \varepsilon_t \\ \Delta x_t &= P x_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta x_{t-j} + \varepsilon_t \sim I(0) \text{ (VECM)} \end{aligned}$$

and $P(L) = \Gamma(L)(1 - L) + P(1) = \Gamma(L)(1 - L) - P = \Gamma(L)(1 - L) - PL$, $\Gamma(L) = (I_n - \dots - \Gamma_{p-1} L^{p-1})$, $\Gamma_j = \sum_{k=j+1}^p (-P_k)$ and $P = \sum_{j=1}^p P_j - I_n$. Indeed, $\{\Gamma_j \Delta x_{t-j}\}_{j=0}^{p-1} \sim I(0)$, whence $P x_{t-1} \sim I(0)$ such that $y_t = \beta^\top x_{t-1} \sim I(0)$ even if $x_{it-1} \sim I(d)$ for $CI(d, d) \sim \{x_{it-1}\}_{i=1}^n \subset \mathbb{R}^T$ and $n \in \mathbb{N}_+ \setminus \{1\}$. The Johansen likelihood ratio tests (trace or maximum eigenvalue) are such that

$$\begin{aligned} \lambda_{tr}(r) &\equiv -t_{max} \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i) \text{ or} \\ \lambda_{max}(r, r+1) &\equiv -t_{max} \ln(1 - \hat{\lambda}_{r+1}) \end{aligned}$$

for $t_{max} \in S \subseteq \bar{\mathbb{Z}}$ and $rk(P) = r \in [0, n]$. Indeed, $r = 0$ means x_{it} are integrated, but not co-integrated; $r = n$ means x_{it} are difference stationary; $r \in (0, n)$ means some x_{it} are co-integrated. It is best to run a $VAR(p)$ in levels: for integrated variables, of the same, reduced order if different, (i) it avoids spurious regression (i.e. lags) if not co-integrated and (ii) it avoids failure of the VECM (i.e. levels) if co-integrated; for trend non-stationary variables; for stationary variables.

In practice, if the $VAR(p)$ in levels is unstable for difference non-stationary variables then one should run the Johansen likelihood ratio tests to check for co-integration such

that: (i) if co-integrated then one should use the VECM; (ii) if not co-integrated then one should use differences; if still unstable in either case then one should acknowledge instability (or de-trend if trend non-stationary, acknowledging instability afresh if yet unstable).

3. RBC DATA FOR UZBEKISTAN

Data were collected from the National Statistics Committee of the Republic of Uzbekistan¹. The variables of interest are GDP at constant prices (production² or expenditure³ method), final consumption of households at constant prices (expenditure⁴ method), employment (millions of persons⁵) and gross capital formation at constant prices⁶.

They are yearly and their time interval ranges from 2010 to 2024. GDP at constant prices and final consumption of households at constant prices are to respectively measure real output Y_t and real consumption C_t . In the absence of aggregate Uzbek data on labour hours the number of employed persons in Uzbekistan is to proxy labour l_t .

Similarly, gross capital formation at constant prices is to proxy real investment I_t , accounting for all forms of capital accumulation. Specifically, capital K_t is backed out via the Perpetual Inventory Method (PIM), whereby the law of motion for capital is

$$K_t = (1 - \delta)K_{t-1} + I_{t-1}.$$

In greater detail, such a law of motion stipulates that present capital K_t is the sum of depreciated past capital $(1 - \delta)K_{t-1}$ and past investment I_{t-1} , whereby past investment models present capital as an end of period variable. By contrast, present capital is a beginning of period variable such that it is a function of present investment I_t ; the choice of either one is a matter of practical convention: the present one in favour of the former is dictated by the PIM for the calculation of inception capital, hereunder.

In greater detail, capital depreciation rate $\delta = 0.06$ controls for the rapid and asymmetric obsolescence typical of developing economies; it reflects a sustained depreciation rate of the broad capital stock and is a standard value in the RBC literature for yearly models (see [Kydland and Prescott, 1982](#)). The PIM lays down that inception capital

$$K_0 = \frac{I_0}{g_I + \delta},$$

in which $g_I = \left(\frac{I_t - I_{t-1}}{I_{t-1}}\right) \times 100$ is the investment growth rate, from which capital streams $\{K_t\}_{t \in \mathbb{N}_+}$ are calculated following $K_t = (1 - \delta)K_{t-1} + I_{t-1}$. On consideration that in the long run capital accumulates at a parametric investment growth rate, that is,

$$K_t = (1 + g_I)K_{t-1},$$

¹stat.uz

²api.siat.stat.uz

³api.siat.stat.uz

⁴api.siat.stat.uz

⁵api.siat.stat.uz

⁶api.siat.stat.uz

the logic behind $K_0 = \frac{I_0}{g_I + \delta}$ is that such an equation holds at the economy's growing steady state:

$$\begin{aligned} K_t &= (1 + g_I)K_{t-1} = (1 - \delta)K_{t-1} + I_{t-1} \longrightarrow \\ [(1 + g_I) - (1 - \delta)]K_{t-1} &= I_{t-1} \longrightarrow \\ K_{t-1} &= \frac{I_{t-1}}{g + \delta} \longrightarrow K_0 = \frac{I_0}{g_I + \delta} \end{aligned}$$

at the growing steady state. TFP a_t is finally proxied as the Solow residual of a Cobb Douglas production function regression, in which Y_t , K_t and l_t are measured as formerly relayed: $\forall \kappa \in \mathbb{R}$, $\alpha \in (0, 1) \subset \mathbb{R}_{++}$,

$$\begin{aligned} Y_t &= \kappa a_t K_t^\alpha l_t^{1-\alpha} \longrightarrow \\ \ln Y_t &= \ln \kappa + \alpha \ln K_t + (1 - \alpha) \ln l_t + \ln a_t = \beta_0 + \beta_1 \ln K_t + \beta_2 \ln l_t + u_t \longrightarrow \\ \hat{u}_t &= \hat{\ln a}_t = \ln Y_t - \ln \hat{Y}_t \text{ for } \ln \hat{Y}_t = \hat{\beta}_0 + \hat{\beta}_1 \ln K_t + \hat{\beta}_2 \ln l_t, \end{aligned}$$

in which $\{\hat{\beta}_j\}_{j=0}^2 \subset \mathbb{R}$ is estimated by Feasible Generalised Least Squares (FGLS), thereby accounting for the possibility of non-spherical errors. Specifically, for regressand and error $Y^* = GY$, $U^* = GY \in \mathbb{R}^{(T-p)n \times 1}$, regressor $X^* = GX \in \mathbb{R}^{(T-p)n \times n^2 p}$ such that FGLS estimator

$$\beta^* = (X^{*\top} X^*)^{-1} X^{*\top} Y^* = (X^\top \hat{O}_{(T-p)n}^{-1} X)^{-1} X^\top \hat{O}_{(T-p)n}^{-1} Y^* \in \mathbb{R}^{n^2 p \times 1}$$

for symmetric $O_{(T-p)n}^{-1} = G^\top G$, FGLS sample variance $\hat{Var}(\beta^* | X^*) = \tilde{\sigma}^2 (X^{*\top} X^*)^{-1} \in \mathbb{R}_+^{n^2 p \times n^2 p}$, FGLS error sample variance $\tilde{\sigma}^2 = [(T - p)n - n^2 p]^{-1} \hat{U}^{*\top} \hat{U}^* \in \mathbb{R}_+$ and residual $\hat{U}^* = Y^* - \hat{Y}^* = Y^* - X^* \beta^*$.

In greater detail, for $\hat{O}_{(T-p)n}^{-1} = F_{(T-p)n}(\hat{\phi}_{(T-p)n}) = [f_{ii}(\hat{\phi}_{(T-p)n})] \in \mathbb{R}_{++}^{(T-p)n \times (T-p)n}$ and $\hat{\phi} \in \mathbb{R}$ such that $O_{(T-p)n}^{-1} = F_{(T-p)n}(\phi_{(T-p)n}) = [f_{ii}(\phi_{(T-p)n})] \in \mathbb{R}_{++}^{(T-p)n \times (T-p)n}$, $\phi \in \mathbb{R}$ and $\hat{O}_{(T-p)n}^{-1} \xrightarrow{p} O_{(T-p)n}^{-1}$ only if $\hat{\phi} \xrightarrow{p} \phi$.

Table 1: Uzbek RBC data

Variable	Mean	Variance	Maximum	Minimum
a_t	0	0.09	0.44	-0.48
K_t	12.12	4.27	14.42	6.36
l_t	9.48	0	9.57	9.36
C_t	12.3	0.79	13.7	10.8

Note. This table reports the descriptive statistics for Uzbek RBC data in log-levels throughout the period 2010 – 2024; specifically, the mean, variance, maximum and minimum values of TFP, capital, labour and consumption. All figures are rounded to two decimal places.

4. UZBEK RBC SVAR

The RBC SVAR for Uzbekistan is constructed such that vector $x_t = [a_t \ K_t \ l_t \ C_t]^\top$. The choice of such four variables specifically refers to a centralised RBC. The sample's relative meagreness suggests the impossibility of properly detecting co-integration, as Johansen's likelihood ratio tests rely on large samples; following [Sims, Stock and Watson \(1990\)](#), data are therefore entered in log-levels lest the VECM be failed. Owing to the yearly nature of the data order $p = 1$, capturing a year's worth of lags and thereby accounting for ordinary cyclicity while striving to elude parametric overfitting. There follows that the VAR corresponds to that in reduced form:

$$\underbrace{\begin{bmatrix} a_t \\ \vdots \\ C_t \end{bmatrix}}_{x_t} = \underbrace{\begin{bmatrix} \mu_1 \\ \vdots \\ \mu_4 \end{bmatrix}}_{\mu} + \underbrace{\begin{bmatrix} \rho_{111} & \cdots & \rho_{114} \\ \vdots & \ddots & \vdots \\ \rho_{141} & \cdots & \rho_{144} \end{bmatrix}}_{P_1=A} \underbrace{\begin{bmatrix} a_{t-1} \\ \vdots \\ C_{t-1} \end{bmatrix}}_{x_{t-1}} + \underbrace{\begin{bmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{4t} \end{bmatrix}}_{\varepsilon_t} \sim VAR(1)$$

for $\{a_t, K_t, l_t, C_t\} \subset \mathbb{R}^{14}$, $\{\mu_i\}_{i=1}^4 \subset \mathbb{R}$, $\{\rho_{1ij}\}_{i,j=1}^4 \subset \mathbb{R}$, $x_t \in \mathbb{R}^4$, $\mu \in \mathbb{R}^4$, $P_1 = A \in \mathbb{R}^{4 \times 4}$ and $\varepsilon_{it} \sim WN(0, \Sigma)$, $\forall i \in [1, 4] \subset \mathbb{N}_+$.

The FGLS estimates of intercept vector μ and companion matrix A are reported in Table 2. The F-statistic p-values of all $VAR(1)$ regressions bear out their statistical significance. Adjusted centred regression $\hat{R}^2$ values are correspondingly all in the environs of unity.

By the t-statistic's p-values coefficient estimates are statistically significant beyond a 0.1 significance level for (i) TFP on TFP, capital and labour, (ii) capital on capital, (iii) labour on capital, (iv) consumption on labour and consumption and (v) the intercepts of capital and labour. Such an intermittence in individual statistical significance lies at odds with that of each regression and is best justified by invoking the limitations of a meagre sample.

Notably, FGLS estimation is attained by the satisfaction of condition $T > (n+1)p \longleftrightarrow 14 > (4+1)1 = 5$. Degrees of freedom $(T-p)n - n^2p > 120$ ensure that despite non-normal errors estimators $\hat{\mu}$ and $\hat{A}$ may be still be asymptotically normal such that the t-statistic is approximated by a Standard Normal distribution.

Degrees of freedom are hereby $(14-1)4 - 4^2 = 13 \times 4 - 16 = 52 - 16 = 46$, however, the hurdle of error non-normality is minimised by the FGLS estimation's robustness to non-spherical errors, which together with the regressor exogeneity a VAR naturally yields (i.e. $\mathbb{E}(\varepsilon_t|x_{t-1}) = 0$ as ε_t is a white noise) is to guarantee estimator normality and valid statistical inference.

The attendant $SVAR(1)$ spells

$$x_t = \mu + Ax_{t-1} + D\eta_t$$

for $\eta_t = D^{-1}\varepsilon_t$ and a lower triangular orthogonalisation matrix $D \in \mathbb{R}^{4 \times 4}$. In detail, the entries of x_t are instantaneously ordered from the most causal to the least in the short run such that a_t is instantaneously ordered as being the most causal and C_t as the least.

Indeed, a_t is TFP and as such an exogenous supply innovation for production inputs K_t and l_t , which in turn affect C_t ; K_t is causal relative to l_t insofar as labour, but not capital, may be an argument of the household's optimisation problem, which incarnates the demand

Table 2: Uzbek RBC $VAR(1)$ estimates

Coefficient	Estimate (Standard error)	t p-value	$\hat{R}^2$	F p-value
μ_1	-284.5 (165.83)	0.12	0.8	0*
ρ_{111}	3.1 (1.47)	0.06*		
ρ_{112}	0.26 (0.16)	0.15		
ρ_{113}	33.23 (19.48)	0.12		
ρ_{114}	-2.73 (1.68)	0.14		
μ_2	-233.97 (74.17)	0.012*	1	0*
ρ_{121}	2.05 (0.66)	0.01*		
ρ_{122}	0.37 (0.07)	0*		
ρ_{123}	26.93 (8.71)	0.01*		
ρ_{124}	-1.06 (0.75)	0.19		
μ_3	31.31 (12.66)	0.04*	0.96	0*
ρ_{131}	-0.24 (0.11)	0.07*		
ρ_{132}	-0.02 (0.01)	0.14		
ρ_{133}	-2.65 (1.49)	0.11		
ρ_{134}	0.29 (0.13)	0.05*		
μ_4	25.04 (39.99)	0.55	1	0*
ρ_{141}	-0.11 (0.35)	0.76		
ρ_{142}	-0.02 (0.04)	0.66		
ρ_{143}	-2.87 (4.7)	0.56		
ρ_{144}	1.21 (0.41)	0.02*		

Note. This table reports the FGLS estimates of μ and A for an Uzbek RBC $VAR(1)$ profiling TFP, capital, labour and consumption. Asterisks denote statistical significance at a significance level of 0.1 All figures are rounded to two decimal places.

side of the economy and is deemed to be the most endogenous in the new neo-classical orbit of the RBC. The associated $SVMA(\infty)$ is

$$\begin{aligned} x_t &= \sum_{j=0}^{\infty} A^j L^j \mu + \sum_{j=0}^{\infty} A^j D \eta_{t-j} = \sum_{j=0}^{\infty} A^j \mu + \sum_{j=0}^{\infty} A^j D \eta_{t-j} = \\ &= (I - A)^{-1} \mu + \sum_{j=0}^{\infty} A^j D \eta_{t-j} = A^{-1}(1) \mu + \sum_{j=0}^{\infty} A^j D \eta_{t-j} \end{aligned}$$

and it is obtained from the $SVAR(1)$ if and only if A 's modulus eigenvalues $|\lambda_{A(\lambda)}| < 1$, from which there follow OIRFs

$$\frac{\partial x_{t+j}}{\partial \eta_t} = A^j D.$$

Indeed, the eigenvalues of A are $\lambda_{A(\lambda)} = 0.996, 0.526, 0.526, 0.013$ (3 *d.p.*), confirming stability and causality of the $SVAR(1)$. The h -lead forecast error of the $SVMA(\infty)$ for $h \in \mathbb{N}_+$ is

$$e_{t+h} = \sum_{j=0}^{h-1} A^j D \eta_{t-j+h}$$

and its variance accordingly

$$Var(e_{t+h}) = \sum_{j=0}^{h-1} A^j \Sigma A^{\top j} = \sum_{j=0}^{h-1} \begin{bmatrix} a_{11}^{(j)} \sigma_1^2 a_{11}^{\top(j)} + \dots + a_{14}^{(j)} \sigma_4^2 a_{14}^{\top(j)} & \dots & a_{11}^{(j)} \sigma_1^2 a_{41}^{\top(j)} + \dots + a_{14}^{(j)} \sigma_4^2 a_{44}^{\top(j)} \\ \vdots & \ddots & \vdots \\ a_{41}^{(j)} \sigma_1^2 a_{11}^{\top(j)} + \dots + a_{44}^{(j)} \sigma_4^2 a_{14}^{\top(j)} & \dots & a_{41}^{(j)} \sigma_1^2 a_{41}^{\top(j)} + \dots + a_{44}^{(j)} \sigma_4^2 a_{44}^{\top(j)} \end{bmatrix}.$$

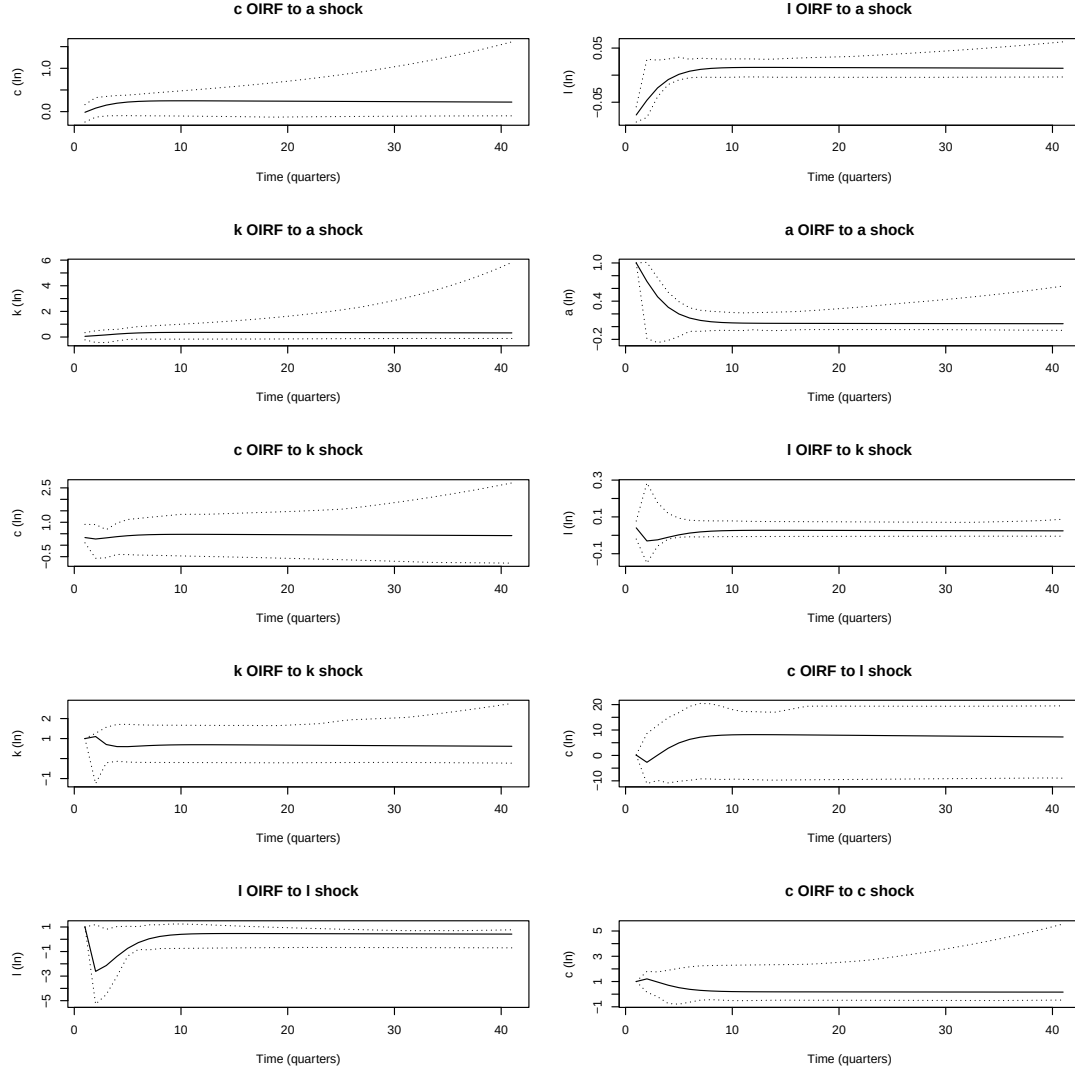
It follows that, $\forall i, k \in [1, 4] \subset \mathbb{N}_+$, the h -lead FEVD of the $SVMA(\infty)$ is

$$\varpi_{x_i|\varepsilon_k} = \frac{\sum_{j=0}^{h-1} a_{ik}^{(j)} \sigma_k^2 a_{ik}^{\top(j)}}{\sum_{j=0}^{h-1} (A^j \Sigma A^{\top j})_{ii}}.$$

5. OIRFs, FEVDs AND POLICY PRESCRIPTIONS

5.1 Uzbek RBC SVAR OIRFs. The OIRFs and the FEVDs of the centralised RBC SVAR for Uzbekistan are displayed in Figures 1 and 2, respectively. In Figure 1, owing to the imposition of a Sims orthogonalisation: the first four graphs present OIRFs in C_t , l_t , K_t and a_t to ε_{1t} shocks, that is, OIRFs of all four variables to shocks in TFP; graphs 5 to 7 present OIRFs in C_t , l_t and K_t to ε_{2t} shocks, that is, OIRFs of the last three variables to shocks in capital; graphs 8 and 9 present OIRFs in C_t and l_t to ε_{3t} shocks, that is, OIRFs of the last two variables to shocks in labour; graph 10 presents the OIRF of C_t to its own shock ε_{4t} .

Figure 1: Uzbek RBC $SVAR(1)$ OIRFs



Note. This figure exhibits the OIRFs for an Uzbek RBC $SVAR(1)$. The OIRFs specifically pertain to TFP, capital, labour and consumption to shocks in the same variables according to a Sims orthogonalisation whereby TFP is ordered as the most causal and consumption is ordered as the least.

TFP shocks give rise to permanent positive departures from the economy's steady state in all three endogenous variables, the starkest of which appear to be consumption and capital. Specifically, for a unit increase in TFP at $t = 0$, absent any reaction upon impact, as of the fifth quarter consumption and capital seem to settle on new steady state log-levels of 0.2 and 0.25, respectively; around the same time and following an initial plunge of almost 0.08, indicative of dismissals for a fixed demand, labour seems to adjust and settle on 0.01.

Accordingly, from the fifth quarter onwards TFP appears to regress to a new steady state log-level of 0.1. All of such suggests the presence of a unit process behind TFP, other than confirming the importance of stimulating TFP by means of the rule of law, trade policies and education.

Capital shocks generate permanent positive departures from the steady state in all three variables, albeit that of labour may be severely less pronounced. In detail, for a unit increase in capital at $t = 0$ consumption and capital appear to settle on new steady state log-levels of 0.4 and 0.75, respectively, posterior to similar quantified reactions upon impact; contrarily, labour increases by 0.05 on impact and appears to settle ever so slightly above zero as of the fifth quarter too.

Such all surmises the presence of a unit process behind capital as well and generally confirms Say's law whereby an increase in supply is eventually translated into higher demand; specifically, consumption and leisure, indirectly measured through labour, are permanently higher; policies oriented towards the sustained expansion of Uzbekistan's capital supply, nationally and internationally, are thus to be certainly upheld.

A shock to labour at $t = 0$ is met with no immediate reaction on the part of consumption, a slight recession until the second or third quarter and a gradual expansion thereon, which becomes permanent and settles on a new steady state log-level of 7 as of the fifth quarter.

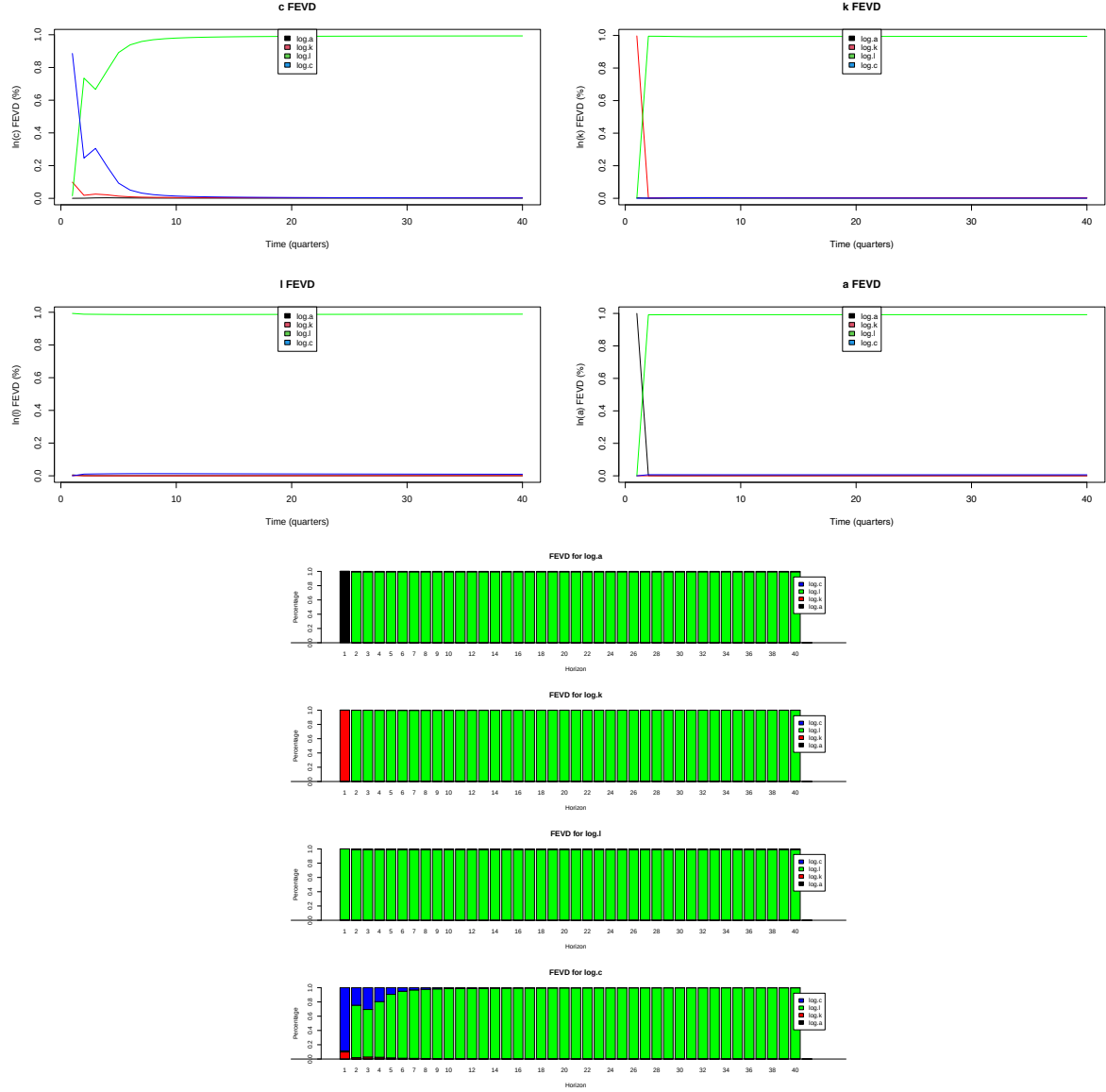
The same pattern of behaviour is exhibited by labour itself, with the exceptions that it increases upon impact and that as of the fifth quarter it settles on a much lower steady state log-level of about 0.1. In closing, a shock to consumption at $t = 0$ is met with an immediate reaction of 1 and a gradual reversion to a new steady state log-level of about 0.2.

5.2 Uzbek RBC SVAR FEVDs and policy prescriptions. Net of the initial business cycle, which is less smoothed out than that of capital owing to the greater flexibility the labour market normally suffers, the two permanent positive adjustments for a shock to labour are once again characteristic of Say's law and thereby speak to policies aimed at broadening the labour supply, particularly in those sectors in which the accompanying rise in TFP is more likely to be verified.

In an attempt to stabilise the attendant business cycle generated by surges in the labour supply the Uzbek government is also advised to strive to minimise the precariat phenomenon. The cruciality of such policy prescriptions is overall buttressed by Figure 2, in which labour shocks emerge as preponderant in the prediction of consumption, labour, capital and TFP.

Specifically, as of the second quarter the prediction of TFP, capital and labour is entirely explained by shocks to labour, being explained by its own one theretofore; the prediction of consumption is predominantly explained by its own shock and partially by that of capital throughout the first quarter, its explanation on the part of labour reaches about 0.75 during the second quarter, oscillates for a few quarters more and finally settles on approximate unity.

Figure 2: Uzbek RBC $SVAR(1)$ FEVDs



Note. This figure exhibits the FEVDs for an Uzbek RBC $SVAR(1)$. The FEVDs specifically pertain to TFP, capital, labour and consumption to prospected shocks in the same variables, their colours respectively being black, red, green and blue.

6. CONCLUSION

The present study has undertaken the inaugural empirical task of structurally decomposing the business cycle of Uzbekistan through the lens of an RBC SVAR. By imposing a recursive identification scheme on a parsimonious system comprising TFP, capital, labour and consumption one has recovered the first set of OIRFs and FEVDs which delineate the causal dynamics and relative importance of fundamental macroeconomic shocks in such a pivotal transition economy.

Such carries profound implications: it firstly provides a long missing empirical benchmark for Uzbekistan, shifting macroeconomic discourse from empirical causality to structural analysis; secondly and most critically for the broader research agenda it offers a resounding empirical scrutiny of the theoretical primacy of the RBC paradigm in such a context.

The dominance of labour shocks and the RBC consistent transmission mechanism they engender furnish a robust justification for the subsequent development of a fully specified RBC model for Uzbekistan. The OIRFs presented herein constitute the quantitative stylised facts which such a theoretical model should attempt to replicate.

In conclusion, such an SVAR analysis has successfully illuminated the core machinery of the Uzbek business cycle; it establishes that the economy's fluctuations are principally driven by supply side labour impulses, amplified through TFP. By bridging the gap between abstract theory and the specific dynamics of a Central Asian transition economy such a work lays the essential empirical foundation upon which a structurally coherent and policy relevant understanding of Uzbekistan's macroeconomics can be built.

REFERENCES

- [1] ABILOV N. (2021) "A medium-scale Bayesian DSGE model for Kazakhstan with incomplete exchange rate pass-through", *International Economic Journal* 35 (4): 486-522.
- [2] ABROROV S., ASADOV A., IRGASHEVA G., JUMAEV N., MAKHMUDOV N., MAKHMUDOV S. AND ZAYNIDDINOV R. (2025) "The influence of the digital economy on economic development evidence from Uzbekistan", *Association for Computing Machinery, Eighth International Conference on Future Networks and Distributed Systems: Proceedings*: 831-839.
- [3] AITYMBETOVA A., ABDIBEKOV S., BAINEYEVA P., DUISENBEEK D., SARSENOVA A., TURLYBEKOVA A. AND TAZHIBAYEVA, R. (2025) "Oil price shocks, exchange rate fluctuations, foreign direct investment inflows, and macroeconomic stability: evidence from Kazakhstan using a Vector Autoregressive approach", *International Journal of Energy Economics and Policy* 16 (1): 774-780.
- [4] ATANIYAZOV J., IBADULLAEV E., MASHARIPOVA M., NURJANOV A., XOLMURATOV X., XOLMUROTOV F. AND YUSUPOVA F. (2025) "The impact of renewable energy consumption on export performance in Uzbekistan: a Vector Autoregression approach", *Business Perspectives* 16 (2): 186-198.
- [5] BARMA S. (2025) "Exploring the dynamic interdependencies of exchange rates, exports, and imports in Kazakhstan: Johansen cointegration and a Vector Autoregression analysis", *International Journal on Science and Technology* 16 (3).
- [6] BOYMIRZAEV T. (2025) "Development of the near-term forecast of inflation for Uzbekistan: application of FAVAR and BVAR models", *Geneva Graduate Institute of International and Development Studies, International Economics Department, Working Paper Series, HEIDWP06-2025*.
- [7] CHRISTIANO L., EICHENBAUM M. AND EVANS C. (2005) "Nominal rigidities and the dynamic effects of a shock to monetary policy", *Journal of Political Economy* 113 (1): 1-45.
- [8] DAVLATOV E., DUSKOBILOV U. AND SÁGI J. (2025) "Resolving price and exchange rate puzzles with the structural VAR model: evidence from Uzbekistan", *Post-Communist Economies*: 1-21.

- [9] IMPAVIDO G. (2025) “Monetary policy effectiveness in Kazakhstan: results with a small macro model”, IMF Working Paper WP/25/173.
- [10] INOGAMOV S. AND MAKHMUDOV S. (2023) “Dynamic Stochastic General Equilibrium (DSGE) model for Uzbekistan and its implementation in practice”, The Central Bank of the Republic of Uzbekistan.
- [11] ISAKOV O. (2024) “Forecasting NPL of commercial banks in Uzbekistan using VAR model *[sic]*”, International Journal of Economics and Innovative Technologies 12 (6): 1-9.
- [12] KASIMOV O. (2025) “Analysing the relationship between education and economic growth in Uzbekistan: a VAR model approach”, Hungarian Statistical Review 8 (1): 31-47.
- [13] KATENOVA M. (2025) “Stock market and economic growth in Kazakhstan: is there a mutual dependence?”, CES Working Papers I, 17 (1).
- [14] KYDLAND F. AND PRESCOTT E. (1982) “Time to build and aggregate fluctuations”, Econometrica 50 (6): 1345-1370.
- [15] MAAZ A. AND NURIDDINOVA M. (2025) “Economics growth with environmental hurdles in Uzbekistan: testing the EKC hypothesis”, Frontiers in Environmental Sciences 13:1589766.
- [16] ORLOV K. (2021) “Building a large Bayesian Vector Autoregression model for Kazakhstan”, National Bank of Kazakhstan, Monetary Policy Department Working Paper 2021-1.
- [17] SIMS C. (1980) “Macroeconomics and reality”, Econometrica 48 (1): 1-48.
- [18] SIMS C., STOCK J. AND WATSON M. (1990) “Inference in linear time series models with some unit roots”, Econometrica 58 (1), 113-144.
- [19] SMETS F. AND WOUTERS R. (2003) “An estimated Dynamic Stochastic General Equilibrium model of the Euro Area”, Journal of the European Economic Association 1 (5): 1123-1175.
- [20] WANG W. AND ZHAO M. (2025) “Impact of monetary policy on the macroeconomy in Uzbekistan”, International Trade, Politics and Development 9 (3): 162-179.

APPENDIX

This is the R code for the Uzbek RBC SVAR.

```

1 # Data charge
2
3 Data <- read.csv("path/file.ext", header=TRUE)
4
5 # Variables elaboration
6
7 names(Data) [c(1, 2, 3, 4, 5, 6)] <- c("t", "y", "c", "l", "i", "k")
8
9 Data$log.i <- log(Data$i)
10 Data$log.k <- log(Data$k)
11 Data$log.l <- log(Data$l)
12 Data$log.c <- log(Data$c)
13 Data$log.y <- log(Data$y)

```

```

14
15 # Panel data packages installation
16
17 install.packages(c("Formula", "plm"))
18 library(Formula)
19 library(plm)
20
21 # FGLS regression, productivity and variables reordering
22
23 FGLS <- pggls(log.y~log.k+log.l, data=Data, index=c("t"), model="pooling")
24 summary(FGLS)
25 confint(FGLS)
26
27 log.a <- FGLS$residuals
28 Data$log.a <- (log.a)
29
30 install.packages(c("dplyr"))
31 library(dplyr)
32
33 Data <- Data %>% relocate(log.a, .before=log.i)
34 Data <- Data %>% relocate(k, .before=i)
35
36 # VAR data preparation
37
38 DataTS <- ts(Data, start=c(2010, 1), end=c(2024, 1), frequency=1)
39 DataS1 <- DataTS[, c(7, 9:11)]
40
41 summary(DataS1)
42 var(DataS1)
43
44 # VARs
45
46 install.packages(c("vars", "reshape"))
47 library(vars)
48 library(reshape)
49
50 var1 <- VAR(DataS1, p=1, type="const")
51 summary(var1)
52 roots(var1)
53
54 # SVARs, IRFs and FEVDs
55
56 bmat <- matrix(c(1, NA, NA, NA, 0, 1, NA, NA, 0, 0, 1, NA, 0, 0, 0, 1), ...
57               ncol=4, nrow=4)
58 svar1B <- SVAR(x=var1, estmethod="direct", Amat=NULL, Bmat=bmat, ...
59               hessian=TRUE, method="BFGS")

```

```

59
60 svar1B.ir2 <- irf(svar1B, impulse="log.a", response=c("log.c"), ...
    boot=TRUE, n.ahead=40)
61 svar1B.ir3 <- irf(svar1B, impulse="log.a", response=c("log.l"), ...
    boot=TRUE, n.ahead=40)
62 svar1B.ir4 <- irf(svar1B, impulse="log.a", response=c("log.k"), ...
    boot=TRUE, n.ahead=40)
63 svar1B.ir6 <- irf(svar1B, impulse="log.a", response=c("log.a"), ...
    boot=TRUE, n.ahead=40)
64
65 svar1B.ir13 <- irf(svar1B, impulse="log.k", response=c("log.c"), ...
    boot=TRUE, n.ahead=40)
66 svar1B.ir14 <- irf(svar1B, impulse="log.k", response=c("log.l"), ...
    boot=TRUE, n.ahead=40)
67 svar1B.ir15 <- irf(svar1B, impulse="log.k", response=c("log.k"), ...
    boot=TRUE, n.ahead=40)
68
69 svar1B.ir17 <- irf(svar1B, impulse="log.l", response=c("log.c"), ...
    boot=TRUE, n.ahead=40)
70 svar1B.ir18 <- irf(svar1B, impulse="log.l", response=c("log.l"), ...
    boot=TRUE, n.ahead=40)
71
72 svar1B.ir20 <- irf(svar1B, impulse="log.c", response=c("log.c"), ...
    boot=TRUE, n.ahead=40)
73
74 svar1B.fevd <- fevd(svar1B, n.ahead=40)
75
76 # IRFs graphs
77
78 irf12 <- data.frame(svar1B.ir2$irf$log.a[, 1], svar1B.ir2$Lower$log.a[, ...
    1], svar1B.ir2$Upper$log.a[, 1])
79 irf13 <- data.frame(svar1B.ir3$irf$log.a[, 1], svar1B.ir3$Lower$log.a[, ...
    1], svar1B.ir3$Upper$log.a[, 1])
80 irf14 <- data.frame(svar1B.ir4$irf$log.a[, 1], svar1B.ir4$Lower$log.a[, ...
    1], svar1B.ir4$Upper$log.a[, 1])
81 irf16 <- data.frame(svar1B.ir6$irf$log.a[, 1], svar1B.ir6$Lower$log.a[, ...
    1], svar1B.ir6$Upper$log.a[, 1])
82
83 irf113 <- data.frame(svar1B.ir13$irf$log.k[, 1], ...
    svar1B.ir13$Lower$log.k[, 1], svar1B.ir13$Upper$log.k[, 1])
84 irf114 <- data.frame(svar1B.ir14$irf$log.k[, 1], ...
    svar1B.ir14$Lower$log.k[, 1], svar1B.ir14$Upper$log.k[, 1])
85 irf115 <- data.frame(svar1B.ir15$irf$log.k[, 1], ...
    svar1B.ir15$Lower$log.k[, 1], svar1B.ir15$Upper$log.k[, 1])
86
87 irf117 <- data.frame(svar1B.ir17$irf$log.l[, 1], ...
    svar1B.ir17$Lower$log.l[, 1], svar1B.ir17$Upper$log.l[, 1])

```

```

88 irf118 <- data.frame(svar1B.ir18$irf$log.l[, 1], ...
    svar1B.ir18$Lower$log.l[, 1], svar1B.ir18$Upper$log.l[, 1])
89
90 irf120 <- data.frame(svar1B.ir20$irf$log.c[, 1], ...
    svar1B.ir20$Lower$log.c[, 1], svar1B.ir20$Upper$log.c[, 1])
91
92 pdf("uz-rbc-svar-irfs.pdf", width=10, height=10)
93 par(mfrow=c(5, 2), bg="white")
94 matplot(irf12, type="l", lty=c("solid", "dotted", "dotted"), col="black", ...
    main="c OIRF to a shock", xlab="Time (quarters)", ylab="c (ln)")
95 matplot(irf13, type="l", lty=c("solid", "dotted", "dotted"), col="black", ...
    main="l OIRF to a shock", xlab="Time (quarters)", ylab="l (ln)")
96 matplot(irf14, type="l", lty=c("solid", "dotted", "dotted"), col="black", ...
    main="k OIRF to a shock", xlab="Time (quarters)", ylab="k (ln)")
97 matplot(irf16, type="l", lty=c("solid", "dotted", "dotted"), col="black", ...
    main="a OIRF to a shock", xlab="Time (quarters)", ylab="a (ln)")
98
99 matplot(irf113, type="l", lty=c("solid", "dotted", "dotted"), ...
    col="black", main="c OIRF to k shock", xlab="Time (quarters)", ...
    ylab="c (ln)")
100 matplot(irf114, type="l", lty=c("solid", "dotted", "dotted"), ...
    col="black", main="l OIRF to k shock", xlab="Time (quarters)", ...
    ylab="l (ln)")
101 matplot(irf115, type="l", lty=c("solid", "dotted", "dotted"), ...
    col="black", main="k OIRF to k shock", xlab="Time (quarters)", ...
    ylab="k (ln)")
102
103 matplot(irf117, type="l", lty=c("solid", "dotted", "dotted"), ...
    col="black", main="c OIRF to l shock", xlab="Time (quarters)", ...
    ylab="c (ln)")
104 matplot(irf118, type="l", lty=c("solid", "dotted", "dotted"), ...
    col="black", main="l OIRF to l shock", xlab="Time (quarters)", ...
    ylab="l (ln)")
105
106 matplot(irf120, type="l", lty=c("solid", "dotted", "dotted"), ...
    col="black", main="c OIRF to c shock", xlab="Time (quarters)", ...
    ylab="c (ln)")
107 dev.off()
108
109 # FEVDs graphs
110
111 fevd12 <- data.frame(svar1B.fevd$log.c)
112 fevd13 <- data.frame(svar1B.fevd$log.l)
113 fevd14 <- data.frame(svar1B.fevd$log.k)
114 fevd16 <- data.frame(svar1B.fevd$log.a)
115
116 pdf("uz-rbc-svar-fevds.pdf", width=10, height=10)

```

```

117 par(mfrow=c(2, 1), bg="white", xpd=NA)
118
119 matplot(fevd12, type="l", lty=1, col=c("black", "red", "green", "blue", ...
      "yellow"), main="c FEVD", xlab="Time (quarters)", ylab="ln(c) FEVD (%)")
120 nn2 <- ncol(fevd12)
121 legend("top", colnames(fevd12), col=seq_len(nn2), cex=0.8, fill=seq_len(nn2))
122
123 matplot(fevd13, type="l", lty=1, col=c("black", "red", "green", "blue", ...
      "yellow"), main="l FEVD", xlab="Time (quarters)", ylab="ln(l) FEVD (%)")
124 nn3 <- ncol(fevd13)
125 legend("top", colnames(fevd13), col=seq_len(nn3), cex=0.8, fill=seq_len(nn3))
126
127 matplot(fevd14, type="l", lty=1, col=c("black", "red", "green", "blue", ...
      "yellow"), main="k FEVD", xlab="Time (quarters)", ylab="ln(k) FEVD (%)")
128 nn4 <- ncol(fevd14)
129 legend("top", colnames(fevd14), col=seq_len(nn4), cex=0.8, fill=seq_len(nn4))
130
131 matplot(fevd16, type="l", lty=1, col=c("black", "red", "green", "blue", ...
      "yellow"), main="a FEVD", xlab="Time (quarters)", ylab="ln(a) FEVD (%)")
132 nn6 <- ncol(fevd16)
133 legend("top", colnames(fevd16), col=seq_len(nn6), cex=0.8, fill=seq_len(nn6))
134
135 dev.off()
136
137 pdf("uz-rbc-svar-fevds-2.pdf", width=10, height=10)
138 par(mfrow=c(2, 2), bg="white", xpd=NA)
139 plot(svar1B.fevd, col=c("black", "red", "green", "blue", "yellow")) #lty=1
140 dev.off()

```