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A BAYESIAN VAR MODEL FOR INFLATION: THE CASE OF AZERBAIJAN

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ABSTRACT

This study examines the effectiveness of Bayesian Vector Autoregressive (BVAR) models in forecasting consumer price inflation in Azerbaijan. Given the country's limited and often low-frequency macroeconomic datasets, traditional forecasting models frequently yield poor forecasting accuracy. To address this, we construct BVAR models using three alternative priors, namely Minnesota, Normal-Wishart, and Sims-Zha Normal-Wishart (dummy observations) and compare their forecasting accuracy with benchmark models: a univariate random walk and a standard unrestricted Vector Autoregressive (VAR) model. Using quarterly data from 2003Q1 to 2024Q2, the study divides the sample into estimation and pseudo-out-of-sample forecasting periods. We evaluate forecast accuracy using relative root mean squared forecasting errors (RMSFEs), while the Diebold-Mariano (DM) test is employed to assess the statistical significance of forecast differences. The models incorporate key domestic and external drivers of inflation, including the M2 money supply, manufacturing producer prices, real non-oil GDP, nominal effective exchange rates, and foreign inflation. The results show that all BVAR models outperform the random walk model across nearly all forecast horizons, while the BVAR with dummy observations prior consistently yields the lowest RMSFEs. Although Minnesota has underperformed in short-term forecasts, it improves in accuracy over longer horizons. Compared to the VAR benchmark, the Sims-Zha Normal-Wishart prior demonstrates clear superiority, confirmed by statistically significant DM test results. The study contributes to the literature on macroeconomic forecasting in developing economies and provides practical implications for policymakers. Future research may focus on extending the framework to incorporate time-varying parameters, high-frequency indicators, or density forecasts for inflation uncertainty.

Keywords: Azerbaijan, Bayesian, BVAR, forecasting performance, inflation, inflation forecasting, RMSFE, Sims-Zha Normal-Wishart prior

JEL Classification: C30, C52, C53, E31, E37

INTRODUCTION

Modelling and forecasting inflation is central to the goal of central banks, as price stability is their primary goal in most countries. Accurate inflation forecasts are essential in designing and implementing effective monetary policies and ensuring economic stability. However, predicting inflation is challenging due to the varying underlying factors that cause inflation across different countries. Furthermore, forecasting inflation becomes even more complex in developing countries due to the limited availability of reliable and long-spanning time series. Central banks and academics employ various techniques, including univariate and multivariate models, to address these challenges. The Bayesian Vector Autoregression (BVAR) model is a multivariate model that gained popularity for forecasting and policy analysis purposes, particularly in short data series environments, due to its ability to handle dimensionality problems. As a developing country, Azerbaijan often lacks high-quality, long-term economic data series with sufficient frequency. Although some indicators have been available since the mid-1990s, concerns about data quality make it challenging to model and forecast economic variables. In this regard, BVAR models can be valuable tools for modelling and forecasting Azerbaijan's economic variables, including inflation.

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Therefore, this paper aims to employ different priors to construct BVAR models for Azerbaijan's short- and medium-term inflation forecasting. We start with building an unrestricted VAR model. Then, we construct BVAR models with a Minnesota prior, a Normal-Wishart prior, and a Sims-Zha Normal-Wishart prior, also known as the dummy observations approach, to conduct the analysis. The study spans the period from 2003Q1 to 2024Q2. The sample period is split into two periods. We estimate the models using data until 2018Q2 and designate the period starting in 2018Q3 as the pseudo-out-of-sample forecasting period. This approach allows us to calculate the best-performing models with the lowest forecasting error. Hence, we choose the root mean squared forecasting error (RMSFE) as our measure of forecasting accuracy. Additionally, we generate forecasts and compute RMSFEs using random walk and standard VAR models, which serve as benchmark comparisons. We then apply the Diebold-Mariano test to assess whether the differences between the model forecasts are statistically significant.

The study reveals that the manufacturing producer price index, M2 money supply, and real non-oil GDP, alongside past inflation (inertia), are domestic drivers of inflation, while inflation in major trading partners and nominal effective exchange rates are external drivers. The results show that all Bayesian VARs generally outperform the benchmark univariate random walk model. Regarding forecasting performance between multivariate models, the BVAR model with the Sims-Zha Normal-Wishart prior has the lowest RMSFEs. The DM test also confirms its superior performance.

The rest of the paper is structured as follows: Chapter 2 is dedicated to a literature review, followed by a theoretical background in Chapter 3. The next chapter describes data and methodology, while Chapter 5 presents results and a discussion. Finally, Chapter 6 concludes the study.

LITERATURE REVIEW

The first study applying BVAR in inflation forecasting dates back to the 1980s, with pioneering studies such as Doan et al. (1984) and Litterman (1986), although the inflation variable used in those studies was not CPI; instead, it was based on the GNP deflator. Since then, these models have gained popularity and have been applied in numerous studies (such as Koop, 2013; Giannone *et al.*, 2014; Carriero *et al.*, 2015). This section focuses on a few recent studies by academicians and central bankers.

Giannone *et al.* (2014) construct a medium-scale BVAR model to investigate euro area inflation and conclude that the model is helpful in both real-time forecasting and scenario analysis. Berg and Henzel (2015) also evaluate the accuracy of different versions and specifications of the BVAR model in providing point and density forecasts for euro area inflation and GDP growth using quarterly data. The authors find that there is no single BVAR model that outperforms other models in terms of accuracy, suggesting that different variants of the models can be used for various purposes. However, BVAR models generally yield good density forecasts for inflation.

Stelmasiak and Szafranski (2016) examine Polish headline inflation through BVAR models: the Sims and Zha (1998) and Villani (2009) approaches. Employing monthly variables, they divide the dataset into two parts, dedicating the period from January 1999 to October 2011 for estimation and the period from November 2011 to October 2014 for evaluating the out-of-sample exercise. They also estimate the frequentist VAR model and use it as a benchmark for comparing forecasting abilities against the BVAR models. They compare the relative forecast performance of the models across different accuracy measures, such as RMSFE, MFE, Log score and Continuous Ranked Probability Scores and find that BVAR models perform superior to the frequentist model.

Mandalinci (2017) evaluates the performance of alternative univariate and multivariate models in forecasting inflation for nine emerging economies. The study reveals heterogeneity across the countries under consideration regarding the forecasting ability of the models tested. Although unobserved stochastic volatility is the best-performing model across the countries, BVAR models perform well. Notably, the latter model has the lowest RMSE in forecasting inflation on a relatively longer horizon in the case of Chile, the Philippines, and Thailand. Overall, the results suggest that BVAR models perform better in longer-term horizons.

The various central banks have extensively used BVAR models. To forecast Turkish inflation, Ogunc (2019) builds BVAR models that differ in the number of variables, with the variables being first differences or log-level. The study spans the period from 2005Q1 to 2017Q4. Alternatively, a univariate SARIMA model and a random walk model are constructed as benchmarks. The forecasting performance of the models is compared against each other and univariate models. The author concludes that models containing a relatively smaller number of variables have lower errors in forecasting inflation in Türkiye. Furthermore, conditioning the future path of the variables in the model enhances forecasting accuracy.

Papavangjeli (2019) constructs a 9-variable BVAR model for Albania using domestic and external variables from 2002Q2 to 2018Q4. Minnesota and Normal-Wishart priors are used in the estimation, and a few univariate models and a VAR model were built to compare the forecast performance of the models. The results suggest that the BVAR models outperform both the univariate and VAR models, although the differences in forecasting abilities between the models are not statistically significant. The author attributes this to the relatively short sample period.

Brazdik *et al.* (2017) developed a small-scale mean-adjusted BVAR model to compare its forecasting ability with that of the models on which the Czech National Bank's (CNB's) forecasts are based. They argue that, despite the superiority or comparability of the CNB's forecasts in other macroeconomic variables, such as GDP growth, interest rates, and exchange rates, the BVAR model exhibits lower forecast errors in terms of inflation forecasting within the monetary policy horizon. In another central bank working paper, Shapovalenko (2021), following Brazdik *et al.* (2017), utilises Bayesian VAR methodology for inflation and GDP forecasting purposes and compares the accuracy of the BVAR models with the forecasting errors from the workhorse model, the quarterly projections model (QPM), of the National Bank of Ukraine. She concludes that the BVAR model demonstrates a better forecasting ability for inflation, whereas the opposite is true for the GDP forecasting exercise.

Forecasting Swedish inflation through BVAR models, Lindholm *et al.* (2020) show that the proposed models outperform benchmark univariate models, professional forecasts and the then-BVAR forecasting model used by the Riksbank.

A few studies have previously focused on modelling Azerbaijan's inflation using BVAR models. Huseynov *et al.* (2014) employ 30 domestic and external variables at a monthly frequency, spanning from January 2003 to December 2012, to evaluate the forecasting performance of various univariate and multivariate models, including BVAR, against that of naïve models, random walk models, and 12-month-average models. They find that all models except the time-varying parameter VAR model cannot "beat" naïve models. In another study focusing on Azerbaijan's inflation, Rahimov *et al.* (2020) also show that the forecasting performance of the BVAR model is lower than that of the ARIMA model. However, it is not statistically significant across different forecasting horizons except for the four-quarter-ahead horizon.

AIMS AND OBJECTIVES

The primary objective of this study is to evaluate the effectiveness of different BVAR priors in forecasting consumer price inflation in Azerbaijan, a developing country characterised by limited availability of high-frequency and long-term macroeconomic data. Specifically, the study aims to:

- identify the primary domestic and external factors influencing inflation in Azerbaijan;
- construct BVAR models using three priors: Minnesota, Normal-Wishart, and Sims-Zha Normal-Wishart;
- compare their inflation forecasting performance of these models against standard benchmark models, such as random walk and standard VAR models;
- assess the statistical significance of the model forecasts using the Diebold-Mariano test;
- provide policy-relevant insights for relevant policymakers.

METHODS

Bayesian Theoretical Framework

Bayesian VAR takes root from a standard unrestricted VAR model proposed by Sims (1980). A standard VAR model is a system of equations where each variable included in the model is dependent on lags of its own and other variables. However, VAR models can also incorporate exogenous variables determined outside the system. Following Dieppe et al. (2016), a standard VAR model with n endogenous, p lags, and m exogenous variables can be expressed in compact form as follows:

This matrix can also be expressed in compact form:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots A_p y_{t-p} + C x_t + \varepsilon_t, \tag{1}$$

where $t = 1,2,\dots,T$.

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Here $y_t = (y_{1,t}, y_{2,t}, \ldots, y_{n,t})$ represents $n \times 1$ endogenous variables vector, $A_1, A_2, \ldots, A_p$ denote p matrices of dimension $n \times n$, C is a $n \times m$ dimension matrix, x_t is a $m \times 1$ exogenous variables vector (which can include constant terms), and $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \ldots, \varepsilon_{n,t})$ are residual vectors which follow a multivariate normal distribution:

$$\varepsilon_t \sim N(0, \Sigma) \tag{2}$$

Equation (1) can also be rewritten more compactly as:

$$Y = XB + E \tag{3}$$

B in equation (3) can be estimated by applying an ordinary least square (OLS) methodology, yielding the estimated form:

$$y = \bar{X}\beta + \varepsilon, \tag{4}$$

where $y = vec(Y)$, $\bar{X} = I_n \otimes X$, $\beta = vec(B)$, $\varepsilon = vec(E)$ (5)

The multivariate normal assumption on the ε from equations (5) leads to a multivariate normal distribution of y:

$\varepsilon \sim N(0, \bar{\Sigma})$, where $\bar{\Sigma} = \Sigma \otimes I_T$ (6)

Hence, an OLS estimate of β from equation (4) can be expressed as follows:

$$\hat{\beta} = (\bar{X}'\bar{X})^{-1}\bar{X}'y \tag{7}$$

However, standard VAR models, which are considered frequentist approaches, have challenges, especially in shorter time-series environments. Since the number of parameters increases exponentially as new variables and/or lags are added, they suffer from an overfitting problem, leading to poor out-of-sample forecast performances. A large dataset might be required to handle this problem, which is not always available.

One way to address this problem is by employing BVAR models by incorporating prior distributions into VAR models. In a standard VAR approach, the goal is to estimate the coefficients of the model and the covariance matrix. However, in the BVAR framework, the econometrician conducting the study may incorporate prior information about the distribution of the parameters into the information in the data to derive posterior distributions.

For a parameter vector θ and a dataset y, the posterior distribution $\pi(\theta|y)$ can be derived by using fundamental definitions of conditional probabilities:

$$\pi(\theta|y) = \frac{\pi(\theta,y)}{\pi(y)} = \frac{\pi(\theta,y)}{\pi(y)}\frac{\pi(\theta)}{\pi(\theta)} = \frac{\pi(y,\theta)}{\pi(\theta)}\frac{\pi(\theta)}{\pi(y)} = \frac{\pi(y|\theta)}{\pi(y)} \tag{8}$$

As data density is often denoted by f instead of π, Bayes rule can also be expressed:

$$\pi(\theta|y) = \frac{f(y|\theta)\pi(\theta)}{f(y)} \tag{9}$$

Since $f(y)$ is independent of θ, it can be disregarded, simplifying the posterior to the following form:

$$\pi(\theta|y) \propto f(y|\theta)\pi(\theta) \tag{10}$$

Minnesota prior. The earlier version of the BVAR model priors is the Minnesota prior, introduced by Litterman (1986), which is often referred to as the "Minnesota prior," named after the University of Minnesota, or the "Litterman prior," taken from the author's name. In this study, this term is used as Minnesota prior. This approach assumes a fixed residual variance-covariance matrix Σ, implying that the only parameter to be estimated is β. Thus, within the framework of Bayes' rule of equation (10), to get the posterior distribution for β, the likelihood function $f(y|\beta)$ for the data and a prior distribution $\pi(\beta)$ for β are needed. The likelihood function for the data can be formulated as follows:

$$f(y|\beta, \bar{\Sigma}) = (2\pi)^{-nT/2}|\bar{\Sigma}|^{-1/2} exp\left[-\frac{1}{2}(y - \bar{X}\beta)'\bar{\Sigma}^{-1}(y - \bar{X}\beta)\right] \tag{11}$$

Equation (11) can be simplified in the following form:

$$f(y|\beta,\bar{\Sigma}) \propto exp\left[-\frac{1}{2}(y-\bar{X}\beta)'\bar{\Sigma}^{-1}(y-\bar{X}\beta)\right] \quad (12)$$

And β is assumed to follow a multivariate distribution:

$$\pi(\beta) \sim N(\beta_0, \Omega_0), \quad (13)$$

where β_0 is a vector of mostly zeros, with non-zero elements for a variable's own lag.

With regard to variance Ω_0, Litterman (1986) identified three cases, namely endogenous, cross-variable and exogenous variable variances:

$$\sigma^2_{\alpha_{ii}} = \left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2 \quad (14)$$

$$\sigma^2_{\alpha_{ij}} = \left(\frac{\sigma_i^2}{\sigma_j^2}\right)\left(\frac{\lambda_1\lambda_2}{l^{\lambda_3}}\right)^2 \quad (15)$$

$$\sigma^2_{c_i} = \sigma_i^2(\lambda_1\lambda_4)^2 \quad (16)$$

According to Dieppe *et al.* (2016), in the literature for λ_1, λ_2, λ_3, and λ_4, mostly used values are 0.1, 0.5, 1 or 2 and 10^2 to ∞, respectively.

The normality assumption implies that its density is given by:

$$\pi(\beta) = (2\pi)^{-nk/2}|\Omega_0|^{-1/2}exp\left[-\frac{1}{2}(\beta-\beta_0)'\Omega_0^{-1}(\beta-\beta_0)\right] \quad (17)$$

The posterior distribution for β is obtained by combining the likelihood (12) and the prior (17):

$$\pi(\beta|y) \propto f(y|\beta)\pi(\beta) \propto exp\left[-\frac{1}{2}(y-\bar{X}\beta)'\bar{\Sigma}^{-1}(y-\bar{X}\beta)\right] \times exp\left[-\frac{1}{2}(\beta-\beta_0)'\Omega_0^{-1}(\beta-\beta_0)\right]$$

$$= \left[-\frac{1}{2}\{(y-\bar{X}\beta)'\bar{\Sigma}^{-1}(y-\bar{X}\beta) + (\beta-\beta_0)'\Omega_0^{-1}(\beta-\beta_0)\}\right] \quad (18)$$

Normal-Wishart prior. The normal-Wishart assumes a normal prior for $(\beta|\Sigma)$ and an improper prior for Σ. The likelihood function derives from equation (11):

$$f(y|\beta,\Sigma) \propto |\bar{\Sigma}|^{-1/2}exp\left[-\frac{1}{2}(y-\bar{X}\beta)'\bar{\Sigma}^{-1}(y-\bar{X}\beta)\right] \quad (19)$$

Similar to the Minnesota prior, β is assumed to follow a multivariate normal distribution:

$$\beta \sim N(\beta_0, \Sigma \otimes \Phi_0) \quad (20)$$

Variances for own and cross lags are defined as:

$$\sigma^2_{\alpha_{ij}} = \left(\frac{1}{\sigma_j^2}\right)\left(\frac{\lambda_1}{l^{\lambda_3}}\right)^2, \quad (21)$$

while for exogenous variables, it is defined as:

$$\sigma^2_{c_i} = (\lambda_1\lambda_4)^2 \quad (22)$$

The conditional posterior for β is:

$$\pi(\beta,\Sigma|y) \propto |\,\Sigma|^{-k/2}exp\left[-\frac{1}{2}(\beta-\bar{\beta})'(\Sigma\otimes\bar{\Phi})^{-1}(\beta-\bar{\beta})\right] \times |\,\Sigma|^{-(\bar{\alpha}+n+1)/2}xp\left[-\frac{1}{2}tr\{\Sigma^{-1}\bar{S}\}\right] \quad (23)$$

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Posterior density for Σ is:

$$\pi(\Sigma|y) \propto |\Sigma|^{-(\bar{\alpha}+n+1)/2} exp\left[-\frac{1}{2}tr\{\Sigma^{-1}\bar{S}\}\right] \tag{24}$$

Sims-Zha Normal-Wishart (dummy observations) prior. Sims-Zha Normal-Wishart prior (also known as dummy observations prior), popularised by Sims-Zha (1998), is an expansion of the Minnesota prior by allowing for an unknown variance-covariance matrix Σ. In order to improve forecasting capability, Sims and Zha (1998) added dummy observations to the BVAR model. The posterior distribution takes the following form:

$$f(\beta,\Sigma|y) \propto |\Sigma|^{-\frac{T+n+1}{2}} exp\left[-\frac{1}{2}tr\{\Sigma^{-1}(B-\hat{B})'(X'X)(B-\hat{B})\}\right] \times exp\left[-\frac{1}{2}tr\{\Sigma^{-1}(Y-X\hat{B})'(Y-X\hat{B})\}\right] \tag{25}$$

Expression (25) combines a matrix normal distribution with an inverse Wishart distribution.

Data

We use quarterly data spanning from 2003Q1 to 2024Q2. Figure 1 plots the yearly inflation rates of Azerbaijan over the period 2004Q1 and 2024Q2. As can be seen, Azerbaijan experienced a double-digit inflation rate at the beginning of the sample period, surpassing 20%, due to a booming economy and a massive increase in government expenditures and the money supply before turning negative in the second quarter of 2009. This period coincided with the Global Financial Crisis and declining oil prices. With the recovery of the real economies around the world, inflation started to pick up and remained low and stable for about 5 years. However, as the oil prices began to decline in mid-2014, the Central Bank (CBAR) devalued the currency in February and December 2015 and announced the adoption of a managed floating exchange rate regime. Manat lost half of its value against the USD. Consequently, the inflation rate accelerated at the end of 2015 and reached double-digit levels in 2016. As the depreciation continued gradually through early 2017, the inflation rate remained elevated in 2017 before dropping to 2-3% in 2018 and staying there through 2020. The latest consumer price shock occurred in 2021, following a supply shock coupled with pent-up demand after the COVID-19 pandemic and later supply chain disruptions due to geopolitical tensions, which caused inflation to reach the 13-14% band in 2022. However, starting in the second half of 2023, the inflation rate began to decline significantly, reaching below 1% by the end of the sample.

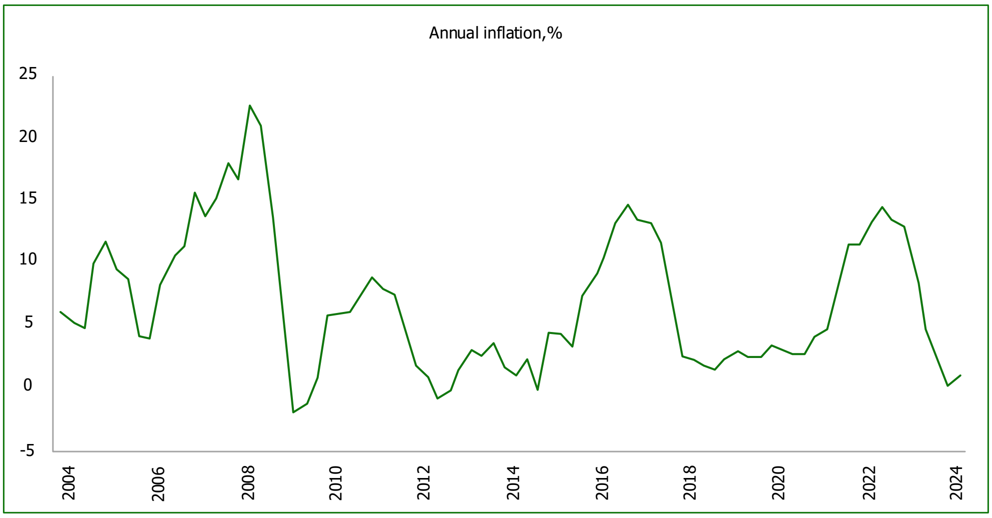

Figure 1. Annual inflation dynamics (2004Q1-2024Q2). *(Source: The State Statistics Committee of the Republic of Azerbaijan)*

After examining various domestic and external variables and based on earlier studies, we identify the following variables as the primary drivers of inflation in the model. The annual change in the manufacturing PPI is used as a measure of supply shock and is sourced from the Azerbaijan State Statistics Centre (SSCRA) database. In fact, Rahimov (2024) finds a relationship between inflation and manufacturing PPI. The M2 money supply is used to capture the fiscal and monetary shocks. The source for this variable is the Central Bank of Azerbaijan (CBAR). Rahimov *et al.* (2016) show that this variable is one of the determinants of inflation in Azerbaijan. Since Azerbaijan is a fiscal-dominant country, so this variable can be considered a fiscal shock, as Ahmadov et al. (2013) suggested. The real non-oil GDP, which was retrieved from the SSCRA, is another variable used in this study. Although Azerbaijan is an oil-rich country, with oil and gas accounting for approximately 90% of exports and around 35% of the economy, oil does not directly impact inflation. Because up to 10% of consumer baskets are administered goods and services, and fuel prices and utilities are among the administered services. The oil revenues are directed to the State Oil Fund, and a portion of them is transferred to the State budget to finance government expenditures, which we assume is captured by the M2 variable. Another channel through which the oil price impact can be transmitted is indirectly through its trading partners. Hence, inflation in trading partners is used as an exogenous variable. We calculate this series using official statistics on the non-oil import trade-weighted nominal effective exchange rate (NEER), a real effective exchange rate (REER), published by the CBAR, and official CPI by the SSCRA. It is an exogenous variable since Azerbaijan is a small-open country and cannot influence inflation in its trading partners. Another exogenous variable is the non-oil import trade-weighted NEER, as Azerbaijan's de facto exchange rate regime is pegged to the USD. Therefore, we use NEER as an exogenous variable.

Estimation Procedure

We include the variables in the model at annual growth rates. Hence, there is no need for seasonal adjustments. However, like the VAR model, which requires the variables to be stationary, BVAR models also require stationarity conditions. We apply the Augmented Dickey-Fuller (ADF) test (1979) to determine whether the series exhibits unit roots. All the variables used in the model are integrated of order zero, i.e. I(0), meaning there is no unit root and all variables are stationary.

Another critical step in building the models is determining the optimal number of lags to include. We perform standard lag selection procedures, such as the Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), Hannan-Quinn Information Criterion (HQ), Sequential modified LR test statistic and Final prediction error (FP). We obtain mixed results, where AIC, FPE, and AIC suggest two lags, while SC and HQ procedures suggest one lag as the optimal selection. However, as a rule of thumb, we prefer to include two lags for both endogenous and exogenous variables. We apply the grid search optimisation procedure introduced by Giannone et al. (2015) to determine hyperparameters. The hyperparameter values for this study, suggested by the grid search optimisation approach, align with the standard hyperparameters often preferred in standard statistical software packages. Thus, we use $\lambda_1 = 0.10$, $\lambda_2 = 0.99$, $\lambda_3 = 0.997$ and $\lambda_4 = \infty$.

To assess the forecasting performance of the models, we produce pseudo-out-of-sample forecasts for one-, two-, four-, six-, and eight-period ahead horizons. Therefore, we split the data into two periods: 2004Q1-2018Q2 as the estimation period and 2018Q3-2024Q2 as the forecasting period. Since the time series is relatively short, we use an expanding forecasting method.

We choose the root mean squared forecasting error (RMSFE) to evaluate model performance. For forecasts produced over h periods for variable i, RMSFE is expressed as follows:

$$RMSFE_i = \sqrt{(1/h)\sum_{i=1}^{h}(y_{T+i} - \tilde{y}_{T+i})^2}, \tag{26}$$

where y_{T+i} is the actual value, while $\tilde{y}_{T+i}$ is the forecasted value.

However, RMSFE in this study is expressed in a relative form, implying that it is calculated as the RMSFE from a BVAR model divided by the RMSFE from the benchmark model. A relative value below 1 represents a lower forecast error or better performance. Conversely, a relative value above 1 indicates a higher forecast error or worse performance.

It is worth noting that our goal is to build Bayesian models, so we chose a random walk model and a standard VAR model as benchmark models. That is why it is essential to determine whether the differences between these models are significant. To determine if the differences between forecast errors are significant, we apply the Diebold-Mariano (DM) test (1995). The DM test starts with calculating the loss differentials between the forecast errors:

$$d_\tau = g\left(e_\tau^{(2)}\right) - g\left(e_\tau^{(1)}\right), \tag{27}$$

where $e_\tau^{(i)}$ is the difference between the actual value and the forecasted value, while g is a generic loss function.

The DM test is calculated as follows:

$$DM = \frac{\bar{d}}{\sqrt{\frac{Var(d_\tau)}{n}}}, \tag{28}$$

where $\bar{d}$ is the mean of d_τ defined in equation (28), $Var(d_\tau)$ is the variance of d_τ, and n is the number of observations.

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The null hypothesis in this test is that the model of interest does not have lower significant errors than the benchmark model.

RESULTS

This section is dedicated to presenting the empirical findings of the paper. The forecasting performance of the BVAR models with different priors, Minnesota, Normal-Wishart and Sims-Zha Normal-Wishart, is evaluated against two benchmark models: a univariate random walk (RW) model and a standard VAR model. The evaluation is based on the relative RMSFEs and DM test for statistical significance.

Figure 2 illustrates the deviation of forecasted inflation from actual inflation over the pseudo-out-of-sample period. A notable observation is that all BVAR models broadly track inflation trends effectively, although accuracy diminishes at longer horizons. The sharp decline in inflation in the last four quarters of the sample has resulted in significant forecasting errors. This situation reflects a combination of domestic inflationary policies, such as tighter monetary policy, along with a global moderation in commodity prices and the normalisation of the supply chain following post-pandemic disruptions. This phenomenon underscores a common limitation of statistical models, as they are better at capturing gradual trends than sudden regime shifts or policy-induced changes.

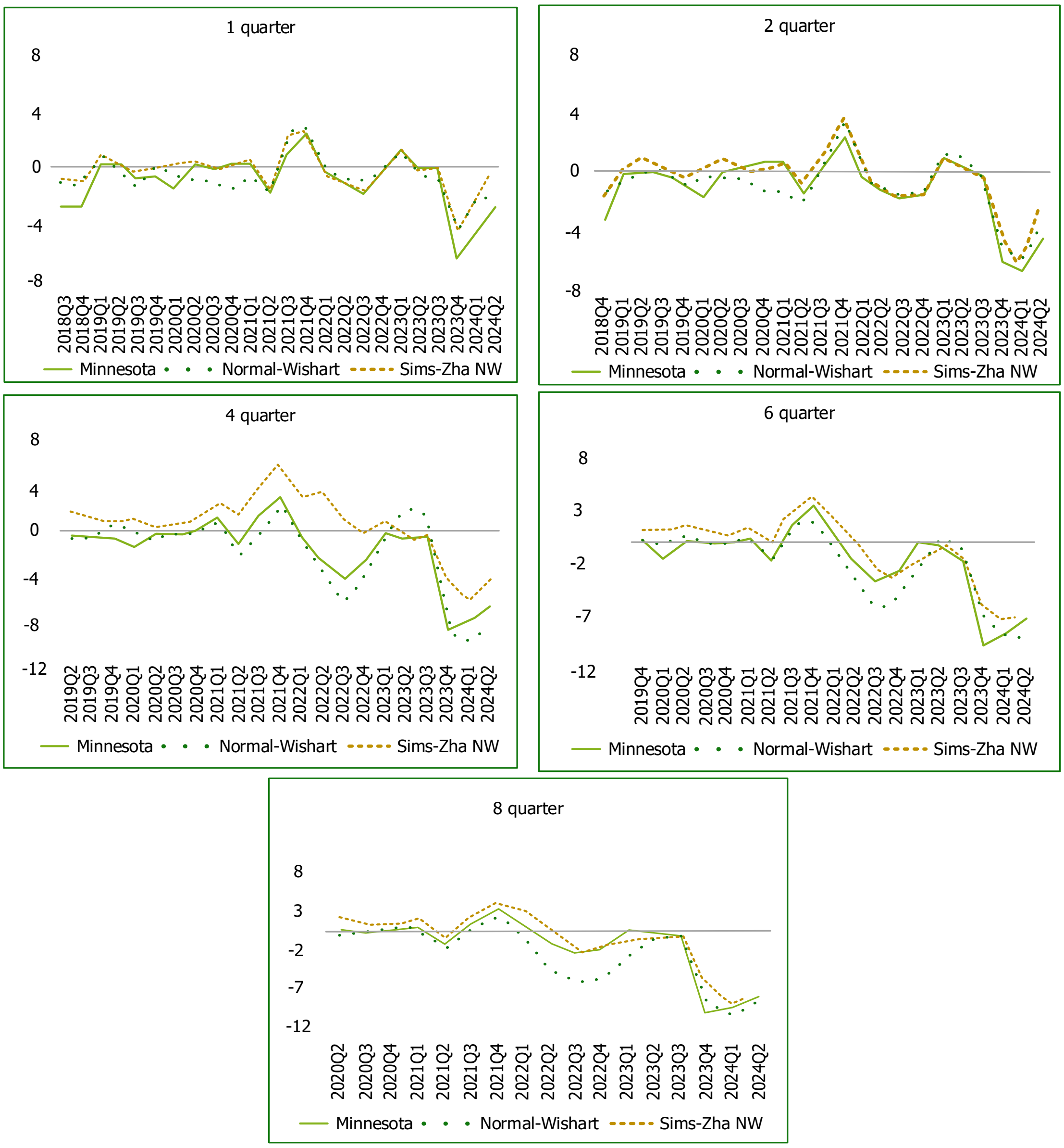

Figure 2. The deviation of the forecasted inflation from the actual inflation.

Table 1 reports relative RMSFEs between the BVAR and the RW models for one-, two-, four-, six-, and eight-period-ahead forecasts. In most cases, the RMSFEs are below 1, indicating that BVARs generally outperform RW models. The Minnesota prior slightly underperforms the random walk for the one-quarter-ahead forecast. This may be attributed to its strong shrinkage of coefficients, which limits its responsiveness to recent changes in inflation. However, for forecasts beyond the one-quarter horizon, the model with Minnesota prior shows significant improvement. The superior performance of Minnesota over the RW model is also confirmed by the DM test.

The Normal-Wishart prior consistently outperforms the RW model, demonstrating significant improvements across all forecasting horizons. The DM test confirms that the differences in RMSFEs between the Normal-Wishart BVAR and the RW model are statistically significant at the standard 5% level for the two-, four-, six- and eight-quarter-ahead forecasts. This prior offers greater flexibility in the variance-covariance matrix, effectively capturing more of the uncertainty inherent in inflation dynamics compared to the Minnesota prior.

The best performing model across all horizons is the BVAR with the Sims-Zha Normal-Wishart prior. Its flexibility, derived from dummy observations that simulate prior beliefs about inflation persistence and co-movements, improves its forecasting ability. The DM test confirms that improvements in predictive accuracy are statistically significant across all forecast periods. This robustness implies that inflation in Azerbaijan has features, such as time-varying volatility and structural shifts, that are better captured by priors incorporating more sophisticated information structures.

Table 1. Relative RMSFEs between respective BVAR models and the RW model. Note: *, **, *** denote the significance between the RMSFEs at 10%, 5% and 1% significance levels, respectively.

	1p	2p	4p	6p	8p
Minnesota	1.17	0.77*	0.63***	0.63***	0.70**
Normal-Wishart	0.90	0.72**	0.74**	0.67***	0.80**
Sims-Zha Normal-Wishart	0.74*	0.62***	0.53***	0.55***	0.62***

As random walk models are not typically considered effective for long-term predictions, we also compare the performance of BVAR models with a standard VAR model, which serves as a multivariate benchmark model, to assess their forecasting abilities. In Table 2, we present the relative RMSFEs between BVAR models and the standard VAR model. The results indicate that the performance of Minnesota's prior model performs worse than the VAR model for up to two-quarter-ahead forecasts, but it shows better performance for the remainder of the forecasting period. However, the differences are statistically significant only in the four-quarter and eight-quarter-ahead forecast periods at a 10% significance level. Additionally, the Normal-Wishart BVAR model performs nearly as well as the standard VAR model in predicting inflation across all forecasting periods.

The Sims-Zha Normal-Wishart model consistently outperforms the VAR model across all forecasting horizons. This could be due to its ability to adapt to shifts in monetary transmission, fiscal behaviour, or external price shocks, which are common in oil-exporting, import-dependent economies like Azerbaijan. The DM test results reinforce the superiority of the Sims-Zha Normal-Wishart model in all forecasting periods at a 5% significance level, with the exception of the two-quarter-ahead forecasting period, which shows significance at a 10% level.

Table 2. Relative RMSFEs between respective BVAR models and the VAR model. Note: *, **, *** denote the significance between the RMSFEs at 10%, 5% and 1% significance levels, respectively.

	1p	2p	4p	6p	8p
Minnesota	1.31	1.07	0.84*	0.93	0.88*
Normal-Wishart	1.00	1.00	0.99	0.99	1.00
Sims-Zha Normal-Wishart	0.83**	0.87*	0.71**	0.80**	0.78**

The strong performance of the Sims-Zha Normal-Wishart prior indicates that inflation dynamics in Azerbaijan are influenced by both persistent structural components and periodic shocks, such as currency devaluations (for example, in 2015), fluctuations in oil prices, and changes in global food prices. The dummy observations approach generates artificial data points that reflect prior beliefs or stylised facts, which helps the model to better anchor inflation expectations and account for trends that are not fully observed in short time series.

The BVAR models successfully captured the influence of domestic variables, such as manufacturing PPI, M2 money supply, and non-oil GDP, on inflation. The significance of M2 highlights the monetarist perspective that excess liquidity drives

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prices upward, which is particularly relevant in fiscally dominant economies. The role of real non-oil GDP reflects demand-side pressures, while manufacturing PPI serves as a proxy for cost-push inflation. External variables, particularly inflation in major trading partners and the nominal effective exchange rate, also significantly affect inflation forecasts. Azerbaijan's high dependence on imports, particularly for food and consumer goods, makes it vulnerable to imported inflation. The exchange rate pass-through continues to impact domestic prices, especially during periods of depreciation.

DISCUSSION

The findings provide valuable insights for policymakers. The superior performance of BVAR models indicates their usefulness in central bank forecasting efforts. In a limited data environment with exposure to external shocks, models that effectively balance prior beliefs with responsiveness to data offer a more reliable foundation for inflation targeting and monetary policy planning. Additionally, the fact that BVAR models outperformed both the random walk and standard Vector Autoregression (VAR) models highlights the necessity for regular updates and validation using statistical and economic diagnostics. As Azerbaijan's economy diversifies and data quality improves, BVAR models can be recalibrated with revised priors to better reflect changing macroeconomic conditions.

The novelty of this paper lies in its application of structured BVAR models for inflation forecasting in Azerbaijan. Unlike previous studies that relied on frequentist or univariate models, this paper demonstrates that well-constructed BVAR models can produce superior forecasts even in data-constrained environments. Additionally, the use of the Sims-Zha Normal-Wishart prior, which is rarely applied in studies focused on Azerbaijan, proves to be particularly effective.

Compared to earlier works such as Huseynov et al. (2014) or Rahimov et al. (2020), this study achieves lower forecasting errors across most horizons, backed by statistical validation through the Diebold-Mariano test. Notably, while previous studies typically failed to beat naïve models, this paper confirms the predictive strength of BVARs with appropriate prior calibration. The analysis is further strengthened by including both domestic and external factors, such as M2, real non-oil GDP, NEER (nominal effective exchange rate), and foreign inflation. This comprehensive approach reflects the open nature of Azerbaijan's economy.

CONCLUSIONS

In this paper, we construct BVAR models with different priors to forecast inflation in Azerbaijan. We use quarterly domestic and external variables from 2003Q1 to 2024Q2 for our study. Our findings indicate that manufacturing PPI, M2, and real non-oil GDP, alongside their own lags, are domestic drivers of inflation. Additionally, as a small-open economy that heavily relies on imports, particularly for non-oil food products, Azerbaijan is also impacted by foreign price trends. In other words, inflation in the major trading partners is found to be a crucial external factor affecting inflation in Azerbaijan. Furthermore, the non-oil weighted nominal effective exchange rate plays an essential role in driving Azerbaijani inflation. After identifying the main drivers of inflation, we estimate the models using different BVAR priors, namely Minnesota, Normal-Wishart and Sims-Zha Normal-Wishart priors. We also estimate the same variables using a standard VAR model, which serves as a multivariate benchmark for evaluating the forecasting performance of each model. Additionally, we generate inflation forecasts using a random walk model and utilise it as a univariate benchmark model. Our analysis divides the sample into two periods. 2003Q1-2018Q2 is reserved for estimation purposes, while 2018Q3-2024Q2 is used as out-of-sample forecasting. The results demonstrate that the BVAR models generally exhibit superior forecasting accuracy over the RW model, indicated by lower root mean squared forecasting error across all forecasting horizons, except for a one-quarter-ahead forecasting using the Minnesota prior. Besides, the DM test also confirms that the differences between RMSFEs are statistically significant. When comparing the forecasting abilities of BVAR models against the standard VAR model, we find that the BVAR model with the Minnesota prior shows lower forecasting performance than the VAR model up to a two-quarter-ahead timeframe, while the RMSFEs from the Normal-Wishart model are nearly identical to those from the VAR model. The Sims-Zha Normal-Wishart prior model, however, outperforms the VAR model across all forecasting horizons. Overall, the BVAR models effectively forecast inflation, as evidenced by their lower RMSFEs, making them practical tools for modelling and forecasting that policymakers should consider.

Future research should focus on extending the framework to include time-varying parameter BVARs (TVP-BVAR), real-time data updates, or forecast combination approaches. Moreover, incorporating high-frequency indicators such as real-time proxy variables or monthly price indices could improve short-term predictive performance. Finally, further comparative studies using density forecasting and forecast uncertainty measures would strengthen the evidence for Bayesian approaches in small open economies.

ADDITIONAL INFORMATION

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CONFLICT OF INTEREST

The Author declares that there is no conflict of interest.

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БАЙЄСІВСЬКА МОДЕЛЬ VAR ДЛЯ ІНФЛЯЦІЇ: ПРИКЛАД АЗЕРБАЙДЖАНУ

У цьому дослідженні розглянуто ефективність авторегресійних моделей байєсівського вектора (BVAR) у прогнозуванні інфляції споживчих цін в Азербайджані. З огляду на обмежені й нерідко низькочастотні набори макроекономічних даних країни, традиційні моделі прогнозування часто дають низьку точність прогнозування. Щоб розв'язати цю проблему, ми будуємо моделі BVAR, використовуючи три альтернативні апріорні, а саме Міннесоту, Нормаль-Вішарт і Сімса-Жа Нормального-Вішарта (фіктивні спостереження) та порівнюємо їхню точність прогнозування з еталонними моделями: одновимірним випадковим блуканням і стандартною необмеженою векторною авторегресійною моделлю (VAR). Використовуючи щоквартальні дані з 1-го по 2024-й квартал, дослідження поділяє вибірку на періоди оцінювання та прогнозування псевдо-поза вибіркою. Ми оцінюємо точність прогнозу за допомогою відносних середніх квадратичних помилок прогнозування (RMSFEs), а тест Дібольда-Маріано (DM) використовуємо для оцінки статистичної значущості різниць прогнозів. Моделі враховують ключові внутрішні та зовнішні чинники інфляції, включаючи грошову масу M2, ціни виробників обробної промисловості, реальний ненафтовий ВВП, номінальні ефективні обмінні курси та зовнішню інфляцію. Результати показують, що всі моделі BVAR перевершують модель випадкової прогулянки майже на всіх прогнозних горизонтах, а BVAR із фіктивними спостереженнями раніше стабільно дає найнижчі RMSFE. Незважаючи на те, що міннесотський пріор демонструє нижчі результати в короткострокових прогнозах, він покращується в точності на більш тривалих горизонтах. Порівняно з бенчмарком VAR, апріор Sims-Zha Normal-Wishart демонструє явну перевагу, підтверджену статистично значущими результатами тестів DM. Дослідження доповнює літературу з макроекономічного прогнозування в країнах, що розвиваються, і надає практичні наслідки для політиків. Майбутні дослідження можуть бути зосереджені на розширенні рамок для включення параметрів, що змінюються в часі, високочастотних індикаторів або прогнозів щільності невизначеності інфляції.

Ключові слова: Азербайджан, Баєс, BVAR, прогнозування ефективності, інфляція, прогнозування інфляції, RMSFE, апріор Сімс–Чжа з нормальним–Wishart розподілом

JEL Класифікація: C30, C52, C53, E31, E37